Multiple Bank Mergers and Rational Foresight

Ethan Cohen-Cole and Nick Kraninger*

November 14, 2007

Abstract

This paper presents evidence of foresight in bank merger programs. Using a search-theoretical model as a basis for estimation, the paper finds that banks that merge only once choose different partners, in rational ways, than those that merge more than once. Prior empirical research on merger patterns, efficiency, etc. has relied on the assumption that all mergers are a priori equivalent. We find evidence to the contrary: rational foresight should be incorporated into theoretical and empirical analyses. As well, we show that once foresight is incorporated, relative asset size now appears sufficient to explain variation previously described by a range of controls.

JEL Codes: G2, G34, D83

Keywords: bank mergers, multiple mergers, merger programs, foresight, search and matching

*Federal Reserve Bank of Boston. 600 Atlantic Avenue, Boston, MA 02210, USA. Cohen-Cole: 617.973.3294 email: ethan.cohen-cole@bos.frb.org. Kraninger: 617.973.3547 email: nicholas.kraninger@bos.frb.org. Many thanks are due to Todd Prono and Rich Rosen for useful comments and suggestions. All errors remain our own. The views expressed in this paper are solely those of the authors and do not reflect official positions of the Federal Reserve Bank of Boston or the Federal Reserve System.

1 Introduction

A couple of recent papers (Rosen 2004, Gorton et al. 2007) have addressed the strategic behavior of firms involved in repeated mergers. We follow and extend this line of research. In particular, we extend current merger research in two ways. One, we provide a method for the evaluation of a sequence of mergers. Two, we enable this evaluation over a full distribution of agents.

Our focus is on bank merger programs. Banks have engaged in 20 years of unparalleled merger activity that provides an outstanding laboratory for the investigation of merger, and sequential merger, behavior. As recently as 1975, there were about 14,000 banking institutions in the United States. By this year, the number had fallen to fewer than 7,000. Since the mid 1990s, bank failures have been very rare, and we attribute much of the decline in the number of institutions to merger activity. Enabling much of the volume of transactions was the passage of the Riegle-Neal (Interstate Banking and Branching Efficiency Act of 1994), which permitted almost unfettered interstate mergers.

Our primary tool will be a multi-stage model of matching that incorporates a bank's incentives to evaluate long run outcomes when deciding on a current merger opportunity. In particular, this model will allow us to look at whether an institution considers the impact of *future* merger considerations in its current decision. We find evidence both that banks have a long-run perspective in mind when making merger decisions and that the relative position of a bank vis-a-vis its competitors is significant. These manifest in a couple of ways. First, the relative size of mergers change over time. A bank that merges twice tends to buy a relatively *smaller* one second. Second, the patterns of assortative matching change. That is, a bank at the 75th quantile of the asset distribution may merge with a bank from a different point in the distribution in the first and second mergers.[1] Finally, these characteristics appear to parsimoniously capture much of the variance of merger decisions that has previously been attributed to other characteristics.

Over the past 10 years, the country has witnessed the emergence of a number of national-scale institutions. Many of these grew out of a dozen or more acquisitions; it is the relative frequency of "repeat" mergers that inspired this study. Existing literature has looked in great depth at the motivations for a single transaction. The manner of doing so typically involves making the assumption that each merger event is identical up to the selection of controls; this allows one to place the full range of merger events into some type of regression and evaluate the coefficients. While appealing, this amounts to an assumption of error exchangeability that is probably unjustified in this context. While the results have been, at times, compelling and confirming of intuition for merger motivation, one must question the logic of including Bank of America's or Citibank's first

[1] Note that this is different than the first point as relative sizes can change as the overall industry distribution changes. Positive assortative matching implies that the largest bank will merge with the largest, etc.

and tenth transactions as equivalent events.[2] Does an institution pick a small target in order to bid on a big one at a later date? If not, does it instead pick a large initial target to have more leverage in subsequent transactions? We find the latter, which we discuss in greater detail below.

To evaluate this problem, one needs a general framework that incorporates two features. One, each agent faces a potential multi-stage decision. Two, after a merger, subsequent decisions are influenced by the new combination of interests; the initial merger decision is made exclusively by the original bank. To address this, we use a multi-period search model developed in Cohen-Cole (2006) as the basis for our analysis. In addition to addressing these concerns, the model has clear and testable conclusions about the patterns of mergers that should be observed if agents have farsighted considerations.

As an example, the model predicts that mergers should show an increasing relative size (defined as the buyer asset size divided by the target asset size). Figure 1 illustrates this result. It shows the distribution of merger ratios (the ratio of asset sizes) for institutions that merged only once and institutions that merged more than once. This chart displays the ratio only for the first merger in a series. Similarly, evidence of differences between single mergers and planned merger programs can be seen in Figure 2. This shows the ratio for the 'final' merger in the series for banks that merged one, two, or three times, and we can again see possible evidence of foresight in merger planning. Notice that the distributions reflect the prediction; firms that have three mergers in the time period evaluated show larger relative merger ratios than those with fewer mergers. It is not difficult to see that the assumption of exchangeability within existing merger studies is difficult to support; in these studies, all of the three distributions in Figure 2 would be aggregated into a single distribution for analysis.

For some intuition on this result, the model used finds that the share of the acquisition surplus (to both acquirer and target) is exponentially declining in the number of future mergers. That is, if one merges with an equal today, any surplus from future acquisitions will acrue to both parties. One could imagine two possible strategies to combat this. A firm might prefer to acquire a sequence of very small firms prior to a large acquisition, thus ensuring that the surplus from the initial acquisition accrues to the firm and that negotiating authority for the final acquisition is large. Alternatively, a large acquisition might be followed by small ones such that the subsequent surplus, though shared with the initial target, would otherwise belong principally to the firm.

This paper will review the relevant literature on financial mergers and acquisitions in section 2. In the subsequent section 3, the paper will highlight the search-theoretical model and discuss how we test its principal conclusions. Section 4 discusses econometric implementation. After a review

[2] Most studies include each merger as a single observation. Thus, a bank that merges twice would have two observations in the dataset - effectively as two different institutions reflecting the then-current characteristics at the time of each merger.

of the data in section 5, we show results in section 6 and discuss and conclude in section 7.

2 Literature Review

There is a long and thorough literature on why banks merge, which banks merge and with whom, as well as on the economic impact of mergers.[3] Perhaps the most prominent lines of thought relate merger decision-making to potential efficiency gains and/or to market power. Additional research has come from exploration of the incentives created by regulatory goals and from discussions of managerial agency issues. We depart slightly from these lines of research to discuss patterns of merger activity. Simply, this paper will describe the patterns of past mergers by looking at how agents evaluate *sequential* decisionmaking.

The efficiency motivation for mergers can be subdivided into three strands: economies of scale, economies of scope, and managerial efficacy. While communications technology has removed barriers to operating a truly national or global bank, it has also made it easier for small banks to reduce overhead and function profitably. A number of papers support the conclusion that cost economies of scale only exist for relatively small banks,[4] necessitating alternative explanations for large bank mergers. One such explanation is the ability of large banks to offer a wider range of financial services under a single brand. That is, economies of scope can enable banks to capture higher market share. The scope arguments are strongest for mergers between banks and nonbanks, and therefore less applicable to this study which only examines mergers between banks. As well, there is little agreement within the banking industry on the ability of universal banks to add value. Simply, the managerial efficacy motivation dictates that superior management can create value by acquiring the assets of poorly managed institutions. Since the inferior management could not realize the bank's "true" inherent worth, the bank was perpetually undervalued. A plausible story, this explanation is very difficult to prove or disprove empirically.

Similarly, while the theory behind market power enhancing profitability is straightforward, empirical analyses have shown unclear results from increased concentration. Some existing papers demonstrate that local loan rates often increase alongside decreasing deposit rates following mergers that boost market share;[5] others find no relationship between concentration and profitability, loan rates, or deposit rates.[6] Choice of control variables on both the demand and supply side drive these conflicting conclusions. This highlights the difficulty of separately identifying market power and efficiency effects and is perhaps an area for future research.

[3] For a more comprehensive summary of bank M&A literature, see Berger *et al.* (1999).

[4] See Berger *et al.* (1987) for one example.

[5] See Berger & Hannan (1989) and Hannan (1991).

[6] See Brewer & Jackson (2004) for a recent example.

Regulatory institutions continue to have significant influence on merger and acquisition activity, even in the wake of Riegle-Neal. While that piece of legislation was not the only explanation for the large number of merger and acquisitions in the late 1990s, it epitomized the deregulatory trend. Bank holding companies have increased their out-of-state deposit holdings from 2 percent to 28 percent between 1979 and 1994, a dramatic structural shift (Berger *et al.* , 1995). In addition to Riegle-Neal, a belief in the existence of a "too-large-to-fail" threshold and an aversion to allowing high market share are the main aspects of regulation in the United States. There is some evidence that banks merge in an attempt to reach the perceived "too-large-to-fail" threshold (Saunders & Wilson, 1999). In support of this market share hypothesis, Hannan and Pilloff (2006) finds that high market share increases the likelihood of being acquired from outside the market but decreases the likelihood of being acquired by another bank in the same market. Finally, the Community Reinvestment Act (CRA), established in 1977, plays a limited role in bank mergers (Bostic *et al.* , 2002).

Existing discussion of managerial motives generally centers on empire building. By increasing bank assets, CEOs can often increase personal compensation dramatically. Managerial hubris is a more recently posited agency issue. While, as pointed out above, mergers can be legitimized by efficient management taking over inefficient management, the hubris hypothesis is that the optimism of managers leads to incorrect beliefs about their own abilities (Roll, 1986).

We change tact slightly to focus on the patterns of mergers. There are various theories on the patterns of bank mergers, however, all of them look at a current decision and the immediate consequences of that decision. In contrast, this paper looks at the long run motivations of merging firms by evaluating how banks consider not only the current merger but also its *potential* subsequent ones. Rosen (2004) examines the implications of these "merger programs" in the context of all firms and finds that the consequences of consecutive acquisitions differ markedly from those of one-off or idiosyncratic mergers. While his focus is on executive compensation, Rosen also notes that when a firm acquires multiple targets, the early acquisitions tend to increase market returns much more than later acquisitions. These results may be applicable to the financial sector, and, if so, may contribute to our understanding of bank merger behavior whether it be myopic or farsighted.

A second paper, Gorton, et al. (2007), discusses strategic merger behavior with multiple firms. Their model evaluates the decision dynamics of a small number of firms by backward induction. Even in this simple structure, they find incentives for complicated merger strategies that depend in part on the sizes of the other firms in the market. In empirical evaluation, they confirm the finding of the importance of the distribution of firms.

Using our catalog of the components needed in a comprehensive model, one can relate this paper to the prior literature. The two components, a multi-stage model and an integrated decision mechanism, respond to set of existing models and reduced form approaches that rely on the assumption of a single type of merger. That is, there are no existing empirical strategies that challenge the fundamental assumption that all mergers events are equivalent.[7]

3 Theoretical Model

In this section, we outline the structure of the multi-stage search model. We think a search model is an appropriate framework as the cost of exploring a merger with a possible partner is non-zero. Merger negotiations take time, during which other mergers are harder or impossible to consider. A search model incorporates the time-cost of looking for partners into an evaluation of decision making. For the sake of brevity, we abstract from Cohen-Cole (2006), but do not copy the model in its entirety. Broadly, the model will specify a value function for the payoffs from a merger. Merging produces an option value due to the possibility for a subsequent merger; the merged bank moves to a new position in the industry distribution. Remaining unmerged produces the option value of merging with a different firm at a later date. The subsequent merger can also be represented by a value function with similar tradeoffs. The challenge is to nest these value functions into a single framework and then to extract the implications of the second merger on the decision to undertake the first.

Begin with a continuum of banks of three types (x_a, x_b, y). Type y agents can merge only with the outcome of an x_a, x_b match (denoted x for simplicity). Thus, in order to form a two-stage merger, x_a and x_b match into x in "stage one." Once matched, the new type x may now match with type y (stage two) to produce a larger firm. This partitioning of banks is done for mathematical tractability, though the intuition is unchanged in the more general case. Firms must agree for a match to take place and surplus is divided per Nash Bargaining. This bargaining structure appropriates match surplus according to relevant size. Match-making is time consuming and thus costly. Agents face a Poisson arrival of potential partners.

A match between x_a and x_b prevents additional search of this type, creates a type $x,$ and enables search for $y.$ This is the fundamental setup that allows us to discuss a multiple-stage merger decision. For x_a and x_b, by backward induction, the process includes the problem from the second stage – a trade off between the immediate benefits of merging and the opportunity cost of further search. It also includes a similar first-stage trade-off – some immediate flow payoffs and the opportunity to participate in the second period game versus the opportunity cost of further first-stage search.

[7] Gorton, et al (2007) include a variable in their regression for recent merger activity (whether the entity had had a merger in the prior 12 months). In a non-structural sense, this accounts for prior activity.

Take a continuum of agents indexed on some publicly observable variable $x \in [0,1]$. In the empirical work, we will use total assets as the key variable. Normalize the mass to one, and let $L : [0,1] \to [0,1]$ be the type distribution and l be the positive, finite, and bounded density function $(0 < l_{\min} < l(x) < \infty)$. Agents belong to the graph in $\mathbb{R}^2$ with Lebesgue measure $\{(x,i) \,|x \in [0,1], 0 \le i \le l(x)\}$. There are two types of agents with exogenously given type distributions: $x_{a,}x_b$. There is one type of agent, x, with an endogenously given distribution based on the matching result of the first stage.

Normalize the flow output of agents x_a, x_b, and y to zero. When agents x_a and x_b are matched, they produce an endogenous flow output and merge to form an agent of type x. Agent x's type is thus endogenously determined by the first-stage matching process between x_a and x_b. At any instant of continuous time, an agent, x_a or x_b, is unmatched, matched into x, or fully matched with y. All unmatched agents engage in search: this includes all x_a, x_b, y, as well as the matched x_a and x_b (a new agent x). Type y meets only type x, and x_a, x_b meet only each other. Upon meeting, two agents each observe the other's type prior to the match decision.

The outcome of the first stage match (x_a, x_b) is a production function $g : [0,1]^2 \to [0,1]$. The outcome of the second stage (x, y) is $f : [0,1]^2 \to \mathbb{R}$. Having laid the foundations, we can move to discussion of the payoffs.

3.1 Payoffs

Each agent maximizes expected value of payoffs, discounted at rate $r > 0$. Output of matches $f(x,y)$, and $g(x_a, x_b)$ is shared. Further, x's share of match output is shared between types x_a, x_b in proportion to their initial distribution. Essentially, the relative sizes at the time of the initial merger will determine the share of payoff in the second merger. This is akin to a stock appropriation in the merged institution that is equal to the original relative asset shares. For example, assume that stock holders in x_a got 30% of the combined x_a, x_b firm. Then, 30% of the surplus from the x, y merger will be given to x_a.

Each type x, y earns endogenous flow payoff $\pi(x|y)$ when matched, and each x_a, x_b earns flow payoff $\pi(x_a|x_b)$ when matched. It is assumed that $\pi()$ is continuous, differentiable, non-negative, and Lipschitz. Because payoffs exhaust output $\pi(x|y) + \pi(y|x) = f(x,y)$ or $f(g(x_a, x_b), y)$; and $\pi(x_a|x_b) + \pi(x_b|x_a) = g(x_a, x_b)$.

3.1.1 Steady State and Surplus from Matches

It can be shown that there exists a steady-state search equilibrium in which (i) every firm maximizes expected payoff, taking all other strategies as given, (ii) if either matching weakly increases payoffs, the two agents involved accept the match, (iii) all unmatched rates are in steady state.

Let $V(x_a)$ and $W(x)$ denote the expected values of unmatched agents x_a, x respectively. Let $W(x|y)$ be the present value of x when matched with y; similarly for $V(x_a|x_b)$. Thus, note that $V(x_a|x_b) = W(x)$ by construction. Let $S(x|y) \equiv W(x|y) - W(x)$ be surplus for x when matched with y. Similarly, let $s(x_b|x_a) = s(x_a|x_b) \equiv V(x_a|x_b) - V(x_a) = W(x) - V(x_a)$ be x_a's surplus when matched with x_b into x. Surplus for agent x_a when matched twice (with x_b and y), is $S(g(x_a, x_b)|y) = S(g(x_a, x_b)|y) + s(x_a|x_b) = W(g(x_a, x_b)|y) - W(g(x_a, x_b)) + W(g(x_a, x_b)) - V(x_a)$.

While unmatched, agents x_a, x_b earn nothing. The flow rate of x, y matches is $\rho \int_{M(x)} u(y)\, dy$. The density of unmatched x is $u(x)$. If x fails to match, then at rate δ the match breaks and reverts to x_a: incurring capital loss $s(x_a|x_b)$. x earns flow profits of $\pi(x_a|x_b)$ in each period. Letting $S(x|y) = S(y|x)$, and $S(x_a|x_b) = S(x_b|x_a)$ by the Nash Bargaining solution, then noting the resource constraints: $\pi(x|y) + \pi(y|x) = f(x, y)$ and $\pi(x_a|x_b) + \pi(x_b|x_a) = f(x_a, x_b)$, we have the single-stage result:

$$S(x|y) = \frac{f(x, y) - rW(x) - rW(y)}{2(r + \delta)}. \tag{1}$$

In addition, we have

$$s(x_a|x_b) = \frac{g(x_a, x_b) - rV(x_a) - rV(x_b) + k}{2(r + u(x)\delta)}, \tag{2}$$

where $k = \rho \int_{M(x)} S(x|y)\, u(y)\, dy$. Substituting from above and rearranging yields

$$S(x|y) = \frac{f(x, y) - rW(y) - rV(x_a)}{2(r + \delta)} - \frac{r}{2(r + \delta)} \left[\frac{g(x_a, x_b) - rV(x_a) - rV(x_b) + k}{2(r + u(x)\delta)} \right].$$

Bank surplus from a merger is the difference between two terms. The first term is half the excess of flow match output (once discounted) over y's and x_a's unmatched value. That is, given some match output $f()$, the share is computed by deducting the unmatched value. Thus matching must show an improved output over remaining unmatched in order to accept a merger. The second term is one quarter the excess of flow match output over x_b's and x_a's unmatched value (twice discounted at the appropriate rates). The logic is that an unmatched x_a must share his match output *twice* – initially sharing half the first-stage match, then subsequently sharing both this initial match and the new surplus with y.

This leads to a intuition that match surplus is exponentially declining in the number of matches. Note that in the theory section of this paper, we do not restrict the payoff function from mergers to any given form. Conditional on the mergers producing non-negative payoffs and payoffs being increasing in asset size, we can make a set of claims.

3.2 Testable Implications

This model has a number of implications that we will test for in the following sections. This subsection will detail the rationale behind each of them. Effectively, the model in this paper suggests that firms make their current decisions based on how those decisions impact their future opportunity set. This is somewhat akin to agents making pricing decisions based on future inflation expectations; the key distinction is that in this context agents are basing current actions on expectations of their own behavior (rather than exclusively on an aggregate).

What can we use as a parsimonious representation of market power? To illustrate the efficacy of the approach, we look at firm total assets.[8] For each, we look at the ratio of the these measures between the larger of two merging banks and the smaller.[9] Consider the ratio of measures - these give a simple measure of the relative types involved in a merger. Using one of these ratios, we can comment on optimal merger strategy as implied by this model. We have two matched sets of initial results: first, we can comment on how future expectations drives current behavior. Second, we can discuss merger patterns conditional on first-period behavior. Disentangling these two effects seems bound to be confounded by endogeneity concerns; in fact, in this model, the decisions of the first and second stages of a merger program are inextricably linked. Thus, our econometric implementation in the next section will identify the presence of what we call "regimes." Effectively, the decision to undertake a particular merger restricts the agent to a given regime in the next round. The choice of a merger is linked to the possibilities of the next round; thus we are concerned not with the direction of causation in this model but the presence of the patterns predicted by the model. Regardless, we discuss an IV exercise to identify causation in the Results section.

4 Econometric Implementation

Our goal in this section is to evaluate the degree to which the conclusions of the model are upheld in the data. We approach this question with a relatively straightforward methodology. Our goal will be to assess the presence of the regimes indicated in the above paragraph. This allows us to use a very simple reduced form to look for the presence of a handful of key directional indicators.

To summarize, we will search for the following:

Conjecture 1 *role of future mergers on current decisions*

- The asset ratio of the 2nd merger should be a positive predictor of the asset ratio of the current merger.

[8] We also replicated our main results using firm equity, but this analysis is omitted for brevity.
[9] We do not consider acquirer or acquired designations.

- The asset ratio of the 3nd merger should be a positive predictor of the asset ratio of the current merger.

Conjecture 2 *the pattern of future mergers conditional on the current one*

- The asset ratio of the current merger should be a positive predictor of the asset ratio of the subsequent merger.
- The asset ratio of the current merger should be a positive predictor of the asset ratio of the 3rd merger.

We evaluate as follows. First define

$$ratio_{kt} = asset_{it}/asset_{jt},$$

where $asset_i$ is the asset size of firm i, the acquiring bank, and $asset_j$ is the asset size of the target bank. The subscript t indexes time. Though this is not a panel model, the time index will be useful in tracking merger order below. We also define $ratio_k$ as the asset ratio for the k'th merger in a series of mergers for bank i.

Our claims can then be evaluated as follows. For conjecture 1 above, we use:

$$\begin{aligned} ratio_{1it} &= \alpha + \beta_1 E_t ratio_{2it'} + \beta_2 E_t ratio_{3it''} + \varepsilon_i && (3) \\ ratio_{2it'} &= \alpha + \beta_4 E_t ratio_{3it''} + \eta_i, && (4) \end{aligned}$$

where E_t is the time t expectations operator. Note the time subscripts on $ratio_2$ and $ratio_3$. For clarity, $t < t' < t''$. A full list of controls is available in the next section. For implementation purposes, we make use of the rational expectation assumption in order to replace $E_t ratio_{2it'}$ and $E_t ratio_{3it''}$with actual information at time of the merger: $ratio_{2it'}$and $ratio_{3it''}$.We then inspect the significance of β_1, β_2.

For conjecture 2 above, we use:

$$\begin{aligned} Eratio_{3it''} &= \alpha + \gamma_1 ratio_{1i} + \gamma_2 ratio_{2i} + \xi_i && (5) \\ Eratio_{2it'} &= \alpha + \gamma_4 ratio_{1i} + \mu_i, && (6) \end{aligned}$$

We again use rational expectations and replace the expectations as necessary. Our logic is that the variable of interest for the recursive search problem is the asset ratio. Other variables may have an impact on decisionmaking at the time of a given mergers, but we argue are secondary to the problem studied here. A full list of variables is available in the data section. We then check the significance of γ_1, γ_2.

4.1 Comparison to Single Stage Model

A central claim of this paper is that accurate modeling of merger patterns requires the use of a multi-stage matching model. Essentially, our argument is that models that including all mergers as observations in a regression assume exchangeability of errors.[10] In the context of Cohen-Cole (2006), exchangeability can only be achieved by ordering mergers and conditioning merger decisions on the history and expectation of future ones. To evaluate this claim, we present empirical evidence of this feature by looking again at the size ratio of mergers as a central metric. A single-stage model, essentially one that considers each merger an independent event, would suggest that the size-ratio of mergers can be predicted according to some function:

$$ratio_i = \alpha + \eta_1 X_i + \zeta_i,$$

where X_i is as appropriately defined set of independent variables as above.

Thus a simple test of the importance of the multi-stage model is an evaluation of the same regression on two datasets. If a single stage model is sufficient, one should obtain simliar results for η_1 using data from banks that merge only once and using data from banks that merge more than once. Similarly, one should see similar results from the subset of second (or third) mergers only as found in the sample of first mergers only. Consider the following set regressions:

$$\begin{aligned} ratio_{1i} &= \alpha + \eta_1 X_{it} + \zeta_i & (7)\\ ratio_{2i} &= \alpha + \eta_2 X_{it} + \zeta_i & (8)\\ ratio_{3i} &= \alpha + \eta_3 X_{it} + \zeta_i & (9)\\ ratio_{1'i} &= \alpha + \eta_4 X_{it} + \zeta_i. & (10) \end{aligned}$$

Our null hypothesis is that the single-stage model is equivalent to the multi-stage one. To reject this in favor of the multi-stage version, one must find that for each pairwise combination of $\eta_j, j = 1...4$, $\eta_j \neq \eta_k$. For clarity, let η_1, η_2, η_3 be defined as the coefficients for X_i corresponding to the k'th merger in a series. The coefficient η_4 applies to $ratio_{1'}$, the ratio for all mergers considered as a single step (the whole sample of mergers in the dataset). Note here that the time index is t for all four specifications. In each case, the relevant time period is the time of the merger itself; there is no need to worry about sequencing or multiple time periods in a given regression.

[10] Essentially, exchangeability argues that the errors from any observation of a model can be "exchanged" with one of the others without changing the content of the mode. See Bernardo and Smith (1994) for information on deFinetti's representation theorem.

5 Data

We use merger data for this analysis compiled by the SNL Financial. The time period examined includes the years 1986-present. In total, 3304 completed merger events involving 1344 distinct acquiring banks comprised the final dataset. Of these, there were 481 banks that had two or more mergers during the time period and 266 banks that had three or more. These will constitute the basic building blocks of our study.

Additional information on bank characteristics was included by linking this set with data based on FDIC call reports. Where appropriate, the characteristics of the top holder were used in lieu of the subsidiary. The various control variables, when used, were drawn from the quarter prior to each acquisition. Mergers where the assets of the nonsurviving entity were less than 1 percent of the surviving entity were dropped to exclude outliers. Cases in which the acquiring bank was several hundred times the size of the target are unlikely to have a significant effect on the future merger trajectory of the acquirer and can be viewed as tangential to our discussion here. Previous papers similarly drop small acquisitions.[11]

Though our structural interpretation of the model implies relationships that should exist independent of controls, we include an appendix with a set of ad-hoc regressions to answer potential questions of omitted variable bias.[12] As will be shown, these do little to impact the key results. Briefly, those we consider for straw-man purposes are modeled primarily after Hannan and Pilloff (2006). These include return-on-assets, capital-asset ratio, inefficiency, and the age of the bank. Return-on-assets (roa) is net income over total assets; capital-over-assets (ka) is total equity capital divided by total assets; inefficiency (ineff) is defined as non-interest expenses over the difference of total income minus interest expenses; finally, age is the number of days since the bank's opening.

We also include a time trend (simple time variable) and/or time fixed effects (year dummies for 1986 through 2007 with 1986 as the excluded dummy). See Table 1 below for descriptive statistics for the data. This includes information for all merging institutions, as well as breakdown by acquirer and target institutions.

6 Results

Various empirical exercises support the proposed theoretical matching model. First and foremost it supports the conclusion that banks exhibit clear foresight in merger activity. As evidence of this

[11] Rosen (2004) drops observations where the target firm's assets are less than 5 percent of the acquirer's.

[12] To be clear, a finding that the controls impact our regressors of interest implies only that there are strong correlates of our key variable in the controls. It does not necessarily imply a confounding of the theory or the empirics that exclude the controls.

finding, we show results to address the main two conjectures raised above: the role of anticipated future merger size ratios on current mergers and the role of current mergers on future decisions.

Table 3 shows the results of various combinations of specifications related to conjecture 1. The column headers describe the dependent variable of the regression and the row descriptors describe which independent variables are used in each case. For each table, column 1 addresses the first merger for all banks. In deciding on the relative size of this merger, the size of its subsequent (the future planned one) merger impacts the current decision on the order of .4 for each 1 unit of the present merger. This confirms the first component of the first conjecture. Column 2 of this table confirms part 2 of the first conjecture - it finds a positive coefficient on the third merger in impacting the initial one. Columns 4-7 address exchangeability along a different dimension. Perhaps firms that have only two mergers in a sequence solve a slightly different problem that those that merge three times; notice that the model cannot distinguish between firms that plan to merge twice and those that intend to merge three times but have not yet carried out the third merger due to search frictions. Column 4 addresses the first merger ratio for firms that only merge twice in our dataset (thus the notation 1/2). The other columns follow similarly. These four columns show similar results as the initial three, albeit with much reduced sample sizes, lending support to the findings.

We anticipated that the second and third merger ratios may not be separately significant in all specifications due to data limitations on banks with three or more mergers; however, an F-test of joint significance was performed for regressions including both those regressors. These joint tests had p-values less than .05 in all cases.

Table 4 has results pertaining to conjecture 2. Notation follows similarly in this table; the principal distinction is that the independent variable are now prior mergers instead of future ones. Column 1 confirms the first component of conjecture 2, and column 3 confirms part 2. The second-ratio and first-ratio coefficients in Table 4 were not always separately significant but were highly significant jointly, as was the case in Table 3.

Table 2 summarizes the results from 3 and 4. This simplified table show the coefficient on the ratio variable in a number of contexts. Each reported coefficient is taken from a full regression model in the form of Equations 3 or 4 above. The upper panel (A) shows the results from conjecture 1 above: what is the impact of future merger decisions on current actions. Beginning with the upper left cell, we observe the coefficient on the effect on a current merger of a change in the ratio of the subsequent merger. The upper right cell shows the impact of the third merger on the first and the lower right cell that of the third merger on the second. The lower panel (B) shows the inverse, corresponding to conjecture 2 above. This time we observe the coefficient on the subsequent merger of a change in the size of a current merger.

6.1 Dealing with Endogeneity

As mentioned, our principal goal in this paper is to elucidate the existence of foresight in merger planning. The baseline results confirms this; it finds a dual link between the future plans conditional on present actions and present actions based on future plans. Though this is in principle sufficient for the aims of the paper, it is useful to provide additional information on the relevance importance of each merger in the joint decision.

As should be apparent, the model proposed here involves the joint determination of two variables ($ratio_k$ and $ratio_{k+1}$). This produces a simultaneous system:

$$\begin{aligned} ratio_{1it} &= \alpha + \beta_1 ratio_{2it'} + \varepsilon_i &\quad (11) \\ ratio_{2it'} &= \alpha + \gamma_1 ratio_{1i} + \eta_i, &\quad (12) \end{aligned}$$

We evaluate the system by selecting a set of appropriate instruments. In particular, to identify β_1 we will need an instrument that is uncorrelated with ε_{1i} but correlated with $ratio_2$. Effectively, we need an instrument that can be used to predict the ratio of assets at the time of the second of a series of mergers, but is unrelated with the first. Of course, this is particularly difficult to do since any set of firm characteristics that impact either of the merged entities in the first step will likely be determinants in the second.

The instruments we will use will be deviations from expected industry characteristics. While firms could potentially plan for a target future asset ratio at the time of an initial merger, as the model implies, we hold that deviations from some set of plans and market predictions cannot be part of the current of the current decision process. Recall from the model that agents define an acceptable future matching set; however, this simply defines a subset of the range of possible asset values that match with the expected future distribution of asset values.

To be explicit, we imagine that firms anticipate the future distribution of asset values and base their matching set on this expectation. Any deviations from this expectation cannot have been used at the time of the initial planning. We thus use these deviations as our instruments. To calculate the deviations, we define the expected industry characteristics as the expected values from four independent ARMA processes. We calculate the best fitting ARMA process for the first four moments of the industry asset distribution and then take the difference between the observed industry distribution and the estimated one. These 'residuals' form our four instruments of interest.

Results of the first stage regressions are available in Table 5. This illustrates a relatively low degree of correlation between the instruments and the corresponding merger ratios. We interpret this low correlation as evidence that once a firm has chosen a merger strategy (based on expectations of the future), it is optimal to maintain that strategy even if the expectations on which the plan was based turn out to be far from the mark. Our best guess as to why this occurs is due to some form of institutional inertia in planning or an unmodeled cost factor that makes changing plans slower than the quarterly information basis that we are using. Table 6 shows second stage results. As the test statistics confirm, the instruments are borderline weak, suggesting a bias toward OLS. It appears that the magnitude of the planning effect is large, though given the imprecision of the estimates, we would be reluctant to rely on the point estimates.

Broadly, the result confirm the OLS story that future plans vis-a-vis the size of merger partners impacts current decisions in a way that has not been captured by other studies.

6.2 Controls

While the control variables have been shown to be effective at predicting the probability of merger activity, they were not statistically validated in the analysis of merger ratios. When adding controls to the regressions from Table 3 and Table 4, the coefficients on past and future ratios were largely unchanged. See tables 7, 8, and 9 at the end of the paper. This could be interpreted as evidence that the plans and foresight of bank management swamp the importance of control variables during merger programs.

7 Conclusions

This paper has shown the perhaps unsurprising result that banks are rational in their long term merger planning. When making a merger decision, institutions consider not only the impact of the merger itself, but also how that merger will position the institution to merge again in the future. We have found that the multi-stage search model is valid on the dataset we explore, and it can enrich the framework for future evaluation of mergers. The tacit assumption that all mergers can enter regressions equivalently warrants additional scrutiny.

Though it is of clear research interest, we leave unexplored in this paper the consequences of merger foresight on specific valuation decisions of individual institutions. However, the model implies that institutions with long-term merger programs will pay a larger acquisition premium than those with no future plans.

References

Berger, A., & Hannan, T. 1989. The Price-Concentration Relationship in Banking. *Review of Economics and Statistics*, **71**, 291–9.

Berger, A., Hanweck, G., & Humphrey, D. 1987. Competitive Viability in Banking: Scale, Scope, and Product Mix Economies. *Journal of Monetary Economics*, **20**, 501–20.

Berger, A., Kashyap, A., & Scalise, J. 1995. The Transformation of the U.S. Banking Industry: What a Long, Strange Trip It's Been. *Brookings Papers on Economic Activity*, **22**, 55–218.

Berger, A., Demsetz, R., & Strahan, P. 1999. The Consolidation of the Financial Services Industry: Causes, Consequences, and Implications for the Future. *Journal of Banking and Finance*, **23**.

Bernardo, J., & Smith, A. 1994. *Bayesian Theory*. New York: John Wiley and Sons.

Bostic, R., Mehran, H., Paulson, A., & Saidenberg, M. 2002. Regulatory Incentives and Consolidation: The Case of Commercial Bank Mergers and the Community Reinvestment Act. Working paper, Federal Reserve Bank of Chicago.

Brewer, E., & Jackson, W. 2004. The "Risk-Adjusted" Price-Concentration Relationship in Banking. Working paper, Federal Reserve Bank of Atlanta.

Cohen-Cole, E. 2006. Group Formation, Farsighted Agents, and Search Frictions. Federal Reserve Bank of Boston, Mimeo.

Gorton, Gary, Kahl, Matthias, & Rosen, Richard. Eat or be eaten: a theory of mergers and firm size. *Journal of Finance*. Forthcoming 2007.

Hannan, T. 1991. Bank Commercial Loan Markets and the Role of Market Structure: Evidence from Surveys of Commercial Lending. *Journal of Banking and Finance*, **15**, 133–49.

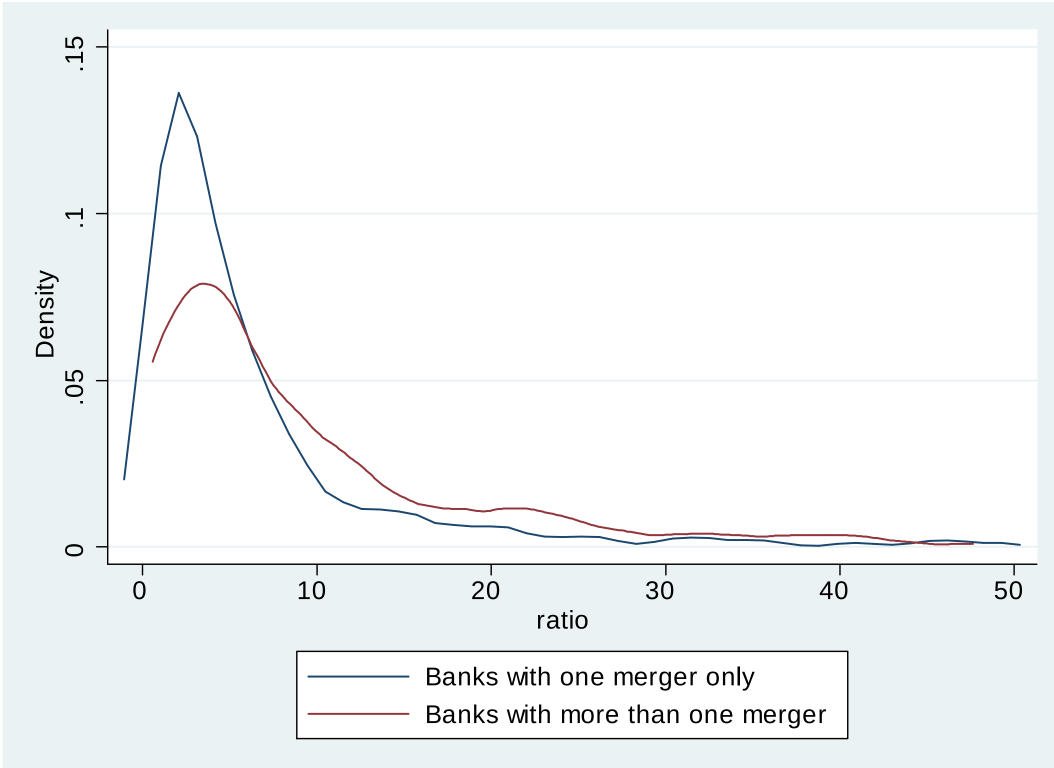
Hannan, T., & Pilloff, S. 2006. Acquisition Targets and Motives in the Banking Industry. Working paper, Federal Reserve Board.

Roll, R. 1986. The Hubris Hypothesis of Corporate Takeovers. *Journal of Business*, **59**(2), 197–216.

Rosen, R. 2004. Betcha Can't Acquire Just One: Merger Programs and Compensation. Working paper, Federal Reserve Bank of Chicago.

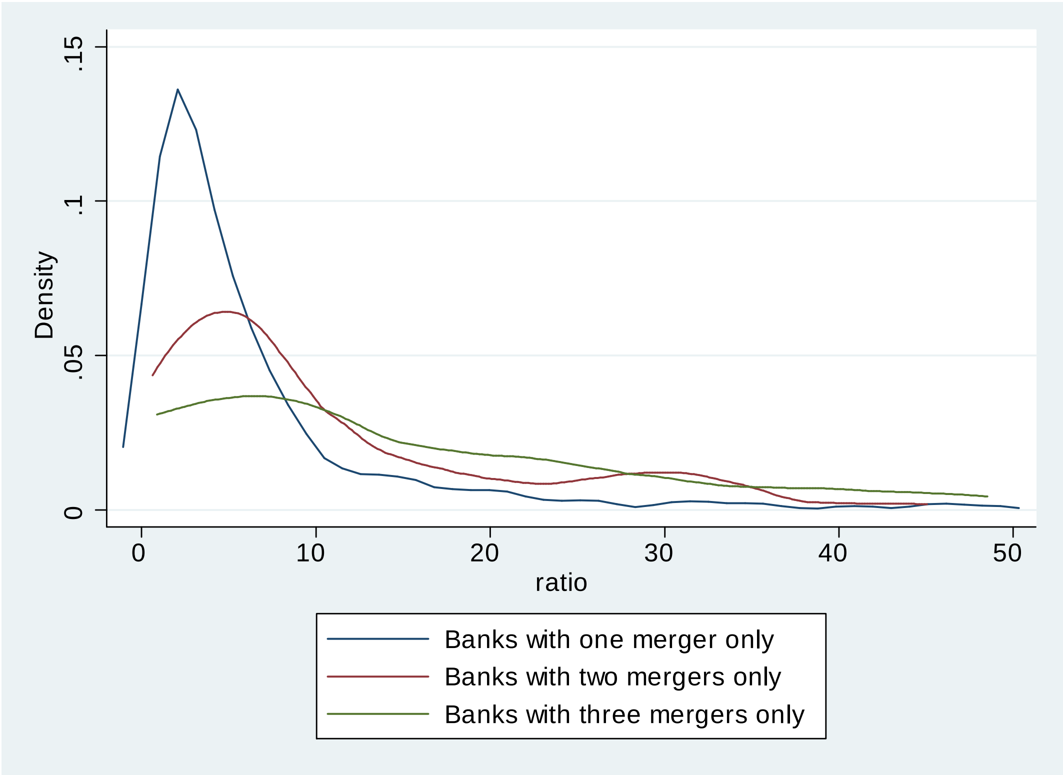
Saunders, R., & Wilson, B. 1999. Bank Capital and Bank Structure: A Comparative Analysis of the U.S., U.K., and Canada. *Journal of Banking and Finance*, **23**.

Figure 1 : Kernel densities of first merger ratio.



Note: This figure shows that banks which engage in additional mergers in the future behave differently in the present than those banks which only merge once. Banks which only merge once tend to have smaller first-ratios than banks which merge multiple times. The blue distribution represents 477 banks which only participated in one merger over the span of the data; the red distribution comprises 161 banks which engaged in more than one merger.

Figure 2 : Kernel densities of successive merger ratios.



Note: This figure shows the evolution of the banking market structure toward consolidation over time. The blue distribution represents the asset ratio of the first/last merger of the 477 banks which only merged once; the red distribution comprises the final merger ratio of the 97 banks which merged exactly twice; the green distribution reflects the final merger ratio of the 38 banks which merged exactly three times.

Table 1 : Explanatory variables and descriptive statistics.

Variable	Description	Min	Max	Mean	Std. Dev.	Median
ka	capital-to-assets ratio	-.0033174	.5544766	.0969686	.0365811	.0890661
	stats for acquirers only	.0442510	.3199723	.0958873	.0302925	.0882580
	stats for targets only	-.0033174	.5544766	.1010839	.0460722	.0920848
roa	return-on-assets ratio	-.1074567	.2410101	.0059425	.0114556	.0059688
	stats for acquirers only	-.0170804	.0586211	.0076807	.0056392	.0068893
	stats for targets only	-.1074567	.2410101	.0038017	.0176006	.0045068
ineff	non-interest expenses over the difference of total income minus interest expenses	.2121588	10.15385	.6763915	.2941916	.6358747
	stats for acquirers only	.2345913	10.15385	.6335473	.3996892	.6045817
	stats for targets only	.2121588	2.575786	.7403582	.2454603	.6934575
age	number of days the bank had been open prior to first merger in dataset	394	72920	22141.29	15252.03	23483.5
	stats for acquirers only	394	72920	25332.52	15610.21	27715
	stats for targets only	492	67290	20985.03	14593.36	23041
assets	total assets one quarter prior to merger (in thousands of dollars)	4.222	392181	1857.895	11873.06	181.012
	stats for acquirers only	5.035	392181	2242.907	16714.99	275.817
	stats for targets only	4.222	49190.23	538.0915	2973.852	64.85
first-ratio	ratio of acquirer's assets to target's assets for first merger in dataset	.020506	49.26055	7.073556	8.437436	4.105426
second-ratio	ratio of acquirer's assets to target's assets for second merger in dataset	.3284844	47.69215	12.19762	11.95277	7.402367
third-ratio	ratio of acquirer's assets to target's assets for third merger in dataset	.8005503	48.53867	13.83658	13.11138	8.789464
first-gap	time between first and second merger (in days)	2	2065	574.0435	476.0981	426
second-gap	time between second and third merger (in days)	3	1681	377.3115	385.599	230
time	number of days in dataset elapsed prior to merger	0	2445	1065.902	703.8127	985
primerate	bank prime loan rate for the month of the merger	4.75	9.5	7.936398	1.208057	8.25

Note: Year dummies for 1986-2007 were also used in the control regressions, but are not displayed here.

Table 2 : Summary of effects of previous and subsequent mergers in a merger program.

Panel A	
first-ratio on second-ratio	**first-ratio on third-ratio**
$ratio_{1it} = \alpha + \beta_1 E_t ratio_{2it'} + \beta_2 X_{it} + \varepsilon_i$	$ratio_{1it} = \alpha + \beta_1 E_t ratio_{3it''} + \beta_2 X_{it} + \varepsilon_i$
$\beta_1 = 0.419$	$\beta_1 = 0.293$
	second-ratio on third-ratio
	$ratio_{2it\prime} = \alpha + \beta_1 E_t ratio_{3it''} + \beta_2 X_{it\prime} + \varepsilon_i$
	$\beta_1 = 0.418$
Panel B	
second-ratio on first-ratio	**third-ratio on first-ratio**
$ratio_{2it'} = \alpha + \beta_1 ratio_{1it} + \beta_2 EX_{it'} + \varepsilon_i$	$ratio_{3it''} = \alpha + \beta_1 ratio_{1it} + \beta_2 EX_{it''} + \varepsilon_i$
$\beta_1 = 0.606$	$\beta_1 = 0.333$
	third-ratio on second-ratio
	$ratio_{3it''} = \alpha + \beta_1 ratio_{2it\prime} + \beta_2 EX_{it''} + \varepsilon_i$
	$\beta_1 = 0.357$

Note: These values correspond to the regression coefficients for the independent merger ratio on the dependent merger ratio. Panel A relates to Table 4 while Panel B relates to Table 3. The regressions correspond (but are not identical) to equations 3-6.

Table 3 : Current merger asset ratio on future ratios.

ratio	1st merger		2nd merger	merger 1/2	merger 1/3		merger 2/3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2nd ratio	.419	.391		.230	.399	.326	
	(.059)***	(.079)***		(.118)*	(.135)***	(.152)**	
3rd ratio		.130	.418			.255	.379
		(.081)	(.084)***			(.105)**	(.188)**
cons	6.228	6.492	11.643	5.466	6.298	3.534	9.826
	(.775)***	(1.378)***	(1.595)***	(1.037)***	(1.965)***	(1.774)**	(2.775)***
e(N)	480	264	266	214	78	76	77
e(r2)	.254	.274	.149	.104	.262	.31	.099
e(F)	51.376	22.226	24.493	3.832	8.675	8.283	4.053

Note: Various regression specifications for the relationship between the first, second, and third mergers in a merger program with the subsequent ratios included. The first-ratio regression model is $ratio_{1it} = \alpha + \beta_1 E_t ratio_{2it'} + \beta_2 E_t ratio_{3it''} + \beta_3 X_{it} + \epsilon_i$, which corresponds to equation 3. The second-ratio regression model is $ratio_{2it'} = \alpha + \beta_1 E_t ratio_{3it''} + \beta_2 X_{it'} + \varepsilon_i$, which corresponds to equation 4. The sample includes all banks which engaged in at least three merger transactions. The symbols *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 4 : Current merger asset ratio on past ratios.

ratio	3rd merger		2nd merger	merger 2/2	merger 3/3		merger 2/3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2nd ratio	.357	.282			.267	.119	
	(.064)***	(.085)***			(.123)**	(.141)	
1st ratio		.169	.606	.454		.374	.620
		(.109)	(.069)***	(.159)***		(.200)*	(.198)***
cons	12.359	11.005	7.871	6.925	11.374	8.932	7.665
	(1.397)***	(1.444)***	(.884)***	(1.378)***	(2.284)***	(2.323)***	(2.098)***
e(N)	266	266	481	215	78	78	78
e(r2)	.153	.172	.257	.105	.097	.189	.245
e(F)	31.047	15.242	76.267	8.178	4.72	3.344	9.84

Note: Various regression specifications for the relationship between the first, second, and third mergers in a merger program with the prior ratios included. The third-ratio regression model is $ratio_{3it''} = \alpha + \beta_1 ratio_{1it} + \beta_2 ratio_{2it'} + \beta_3 EX_{it''} + \varepsilon_i$, which corresponds to equation 5. The second-ratio regression model is $ratio_{2it'} = \alpha + \beta_1 ratio_{1it} + \beta_2 EX_{it} + \epsilon_i$, which corresponds to equation 6. The sample includes all banks which engaged in at least three merger transactions. The symbols *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 5 : First-stage IV regressions.

ratio				
	(1)	(2)	(3)	(4)
mean-resid	-7.02e-06	5.51e-06	-2.50e-06	-2.23e-06
	(1.00e-05)	(.00002)	(.00002)	(.00002)
var-resid		-1.71e-14	-9.05e-15	-9.06e-15
		(2.16e-14)	(2.37e-14)	(2.37e-14)
skew-resid			-.416	-.568
			(.536)	(1.695)
kurt-resid				.002
				(.023)
cons	17.340	17.226	17.285	17.290
	(.927)***	(.887)***	(.904)***	(.903)***
e(N)	3033	3033	3033	3033
e(r2)	.0001	.0004	.0007	.0007
e(F)	.339	.	.	.

Note: This table displays the first stage regressions that correspond to the IV results in Table 6.

Table 6 : Second-stage IV regression for current merger asset ratio on predicted next ratio.

ratio	all mergers	1st merger	2nd merger	3rd merger
	(1)	(2)	(3)	(4)
next merger ratio	1.470	.844	.881	.281
	(.512)***	(.247)***	(.222)***	(.273)
cons	-12.282	-.463	2.916	14.876
	(12.274)	(3.760)	(3.906)	(6.034)**
e(N)	1690	481	266	188
e(r2)	-1.14	-.002	-.035	.101
e(F)	8.234	11.655	15.57	1.043
e(Hansen J-stat)	.928	1.577	5.546	15.03
e(p-value)	.819	.665	.136	.002
e(Andersen LR-stat)	6.528	7.758	16.001	8.058
e(p-value)	.163	.101	.003	.089
e(Cragg-Donald F-stat)	1.63	1.935	4.046	2.004

Note: The excluded instruments are the distribution characteristics (mean, variance, skewness, kurtosis) of banking industry assets at the time of the subsequent merger.

Table 7 : Merger asset ratio on controls.

ratio	1st merger	2nd merger	merger 1/2	merger 1/3	merger 2/3
	(1)	(2)	(3)	(4)	(5)
surv-ka	-53.145	-1.482	-20.841	-98.934	43.155
	(9.027)***	(38.555)	(19.491)	(123.798)	(168.108)
surv-roa	247.844	-520.376	-72.983	-2685.854	2021.699
	(117.918)**	(328.147)	(194.296)	(2481.995)	(2986.131)
surv-ineff	-.031	.086	-.064	-2.720	1.200
	(.115)	(.175)	(.080)	(1.253)**	(1.864)
surv-age	-.00008	.0002	-.00007	.0003	.0003
	(.00002)***	(.0001)*	(.00005)	(.0003)	(.0005)
non-ka	26.785	25.418	21.955	-91.052	59.223
	(9.577)***	(35.806)	(22.448)	(106.094)	(84.705)
non-roa	-87.876	-25.090	-74.685	2802.937	-683.561
	(35.153)**	(131.599)	(103.630)	(2842.601)	(1672.803)
non-ineff	-.037	.260	-.005	6.763	.237
	(.051)	(.127)**	(.062)	(3.200)**	(.169)
non-age	-.00004	-.0002	7.55e-06	-.0004	-.00009
	(.00002)*	(.00008)**	(.00004)	(.0002)*	(.0002)
year dummies	included	included	included	included	included
cons	45.856	12.189	4.418	18.253	-12.051
	(1.700)***	(4.368)***	(2.396)*	(13.080)	(21.871)
e(N)	1160	377	179	58	62
e(r2)	.137	.177	.165	.487	.387
e(F)	.	.	1.48	.	.

Note: Various regression specifications for the relationship between the control variables and the first merger in a merger program. The first-ratio regression model is $ratio_{1it} = \alpha + \beta_1 X_{it} + \varepsilon_i$. The second-ratio regression model is $ratio_{2it'} = \alpha + \beta_1 X_{it'} + \epsilon_i$. The third-ratio regression model is $ratio_{3it''} = \alpha + \beta_1 X_{it''} + \epsilon_i$. The sample includes all banks which engaged in at least one merger transaction. The symbols *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 8 : Current merger asset ratio on future ratios with controls.

	1st merger		2nd merger	merger 1/2	merger 1/3		merger 2/3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2nd ratio	.460	.405		.177	.469	.469	
	(.090)***	(.114)***		(.105)*	(.389)	(.396)	
3rd ratio		.161	.426			.176	.477
		(.094)*	(.133)***			(.230)	(.176)***
surv-ka	-42.997	-83.860	107.679	-15.885	-50.919	-70.834	105.426
	(21.442)**	(50.425)*	(86.216)	(19.447)	(89.118)	(86.784)	(175.626)
surv-roa	-149.979	-555.545	-64.830	-91.866	-865.251	-1608.147	2577.924
	(262.996)	(882.582)	(1476.398)	(192.249)	(2694.466)	(2315.166)	(3000.590)
surv-ineff	-.187	-.848	.629	-.094	-2.444	-1.592	1.196
	(.121)	(.589)	(.487)	(.090)	(1.090)**	(1.148)	(1.439)
surv-age	.00002	.0003	.0008	-.00006	.0005	.0003	.0003
	(.00008)	(.0003)	(.0004)*	(.00004)	(.0003)	(.0004)	(.0005)
non-ka	18.657	17.431	40.826	19.467	-35.226	-48.785	59.370
	(20.913)	(40.412)	(56.420)	(21.948)	(86.500)	(89.859)	(77.985)
non-roa	-207.493	-256.104	25.101	-92.923	1277.346	2007.776	-239.860
	(101.051)**	(336.519)	(147.754)	(98.917)	(1936.245)	(2012.400)	(1571.001)
non-ineff	.063	1.751	.539	.012	6.204	3.371	.403
	(.082)	(1.857)	(.199)***	(.068)	(2.886)**	(3.345)	(.161)**
non-age	-.0001	-.0002	-.0002	-3.74e-06	-.0004	-.0003	-.0002
	(.00005)***	(.00008)***	(.0001)*	(.00004)	(.0002)*	(.0002)	(.0002)
year dummies	included	included	included	included	included	included	included
cons	35.450	38.273	-24.039	3.600	5.628	8.985	-34.174
	(4.419)***	(8.138)***	(11.426)**	(2.506)	(12.291)	(10.241)	(22.420)
e(N)	373	194	199	179	58	58	62
e(r2)	.379	.465	.345	.195	.556	.596	.483
e(F)	.	.	.	1.451	.	.	.

Note: Various regression specifications for the relationship between the first, second, and third mergers in a merger program with the subsequent ratios and controls included. The first-ratio regression model is $ratio_{1it} = \alpha + \beta_1 E_t ratio_{2it'} + \beta_2 E_t ratio_{3it''} + \beta_3 X_{it} + \epsilon_i$, which corresponds to equation 3. The second-ratio regression model is $ratio_{2it'} = \alpha + \beta_1 E_t ratio_{3it''} + \beta_2 X_{it'} + \varepsilon_i$, which corresponds to equation 4. The sample includes all banks which engaged in at least three merger transactions. The symbols *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 9 : Current merger asset ratio on past ratios with controls.

ratio	3rd merger		2nd merger	merger 2/2	merger 3/3		merger 2/3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2nd ratio	.329	.289			.318	.357	
	(.098)***	(.095)***			(.217)	(.222)	
1st ratio		.152	.547	.376		.269	.479
		(.131)	(.080)***	(.174)**		(.144)*	(.175)***
surv-ka	-197.858	-187.474	13.447	-29.966	-257.673	-253.378	33.744
	(58.654)***	(57.519)***	(31.431)	(25.917)	(57.983)***	(56.805)***	(143.771)
surv-roa	508.106	408.549	-163.806	-486.930	1005.120	1240.166	3942.209
	(1347.544)	(1368.319)	(261.444)	(303.852)	(1922.747)	(1745.945)	(3283.979)
surv-ineff	-.017	-.018	.053	-.027	-.013	-.016	.922
	(.010)*	(.011)*	(.102)	(.040)	(.012)	(.013)	(1.967)
surv-age	.0003	.0002	.0001	9.14e-06	.0001	1.00e-05	.0003
	(.0003)	(.0003)	(.00008)*	(.00005)	(.0004)	(.0003)	(.0004)
non-ka	98.163	106.287	37.788	52.895	181.192	193.902	78.172
	(54.385)*	(55.319)*	(31.218)	(26.664)**	(86.661)**	(80.445)**	(69.566)
non-roa	58.805	39.604	-42.207	13.362	-253.256	-266.862	-934.495
	(116.437)	(118.535)	(127.686)	(135.399)	(129.344)*	(117.510)**	(1381.286)
non-ineff	.525	.525	.253	.870	1.603	1.711	.400
	(.457)	(.462)	(.143)*	(.457)*	(.682)**	(.710)**	(.206)*
non-age	.00007	.00006	-.0002	-.0001	-.0002	-.0003	-.0003
	(.0001)	(.0001)	(.00007)**	(.00006)*	(.0001)	(.0001)**	(.0002)
year dummies	included	included	included	included	included	included	included
cons	23.208	21.942	6.570	40.107	-5.283	-7.314	-20.362
	(8.230)***	(8.097)***	(3.722)*	(3.259)***	(7.816)	(7.284)	(18.884)
e(N)	198	198	377	178	62	62	62
e(r2)	.326	.338	.369	.343	.511	.55	.519
e(F)	.	.	.	.	.	.	.

Note: Various regression specifications for the relationship between the first, second, and third mergers in a merger program with the prior ratios and controls included. The third-ratio regression model is $ratio_{3it''} = \alpha + \beta_1 ratio_{1it} + \beta_2 ratio_{2it'} + \beta_3 EX_{it''} + \varepsilon_i$, which corresponds to equation 5. The second-ratio regression model is $ratio_{2it'} = \alpha + \beta_1 ratio_{1it} + \beta_2 EX_{it} + \epsilon_i$, which corresponds to equation 6. The sample includes all banks which engaged in at least three merger transactions. The symbols *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

Pay for Performance?
CEO Compensation and Acquirer Returns in BHCs

Kristina Minnick
Department of Finance
Bentley College
kminnick@bentley.edu

Haluk Unal
Robert H. Smith School of Business
University of Maryland and
Center for Financial Research, FDIC
hunal@rhsmith.umd.edu

Liu Yang
Anderson School of Management
UCLA
liu.yang@anderson.ucla.edu

Current Version: November 2007

Abstract

We examine the effect of incentive-based compensation on bank mergers. Controlling for other characteristics, we find that banks with higher pay-performance sensitivity (PPS) are less likely to engage in mergers. However, when these high PPS managers do undertake mergers, financial markets expect good results and react positively. We find positive abnormal announcement returns for both bondholders and stockholders for banks with high PPS executives. Following acquisitions, these banks also experience significantly more improvement in their operating performance as measured by ROA.

Keywords: Pay-for-Performance Sensitivity, CEO Compensation, Acquirer Returns

JEL Classification: G34, G21

1 Introduction

Top executive pay has increased substantially over the last three decades: the average total remuneration for CEOs in S&P 500 firms (in 2002 constant dollars) increased from $850,000 in 1970 to over $14 million in 2000, and in the same period, the average value of options soared from near zero to over $7.0 million (Jensen, Murphy, and Wruck, 2002).

Despite the long-standing media campaign claiming that chief executives make too much money, economic theories recognize that performance-based compensation can better align managers' interests with shareholders', and as a result, can create value through more efficient investment decisions (e.g., Morck, Shleifer, and Vishny, 1988; McConnell and Servaes, 1990; and Jensen and Murphy, 1990). However, the empirical support for this "corporate governance" role of performance-based compensation is at best mixed. For example, Datta, Iskandar-Datta, and Raman (2001) show that when managers have high equity-based compensation, companies achieve better stock returns around acquisitions. In contrast, Harford and Li (2007) provide evidence that executive compensation can be the cause rather than the cure for growing agency problems. They show that the adverse impact of the post-merger poor stock-price performance on the executives' wealth is offset by the generous stock and option grants these executives receive after acquisitions and that these grants increase the likelihood of value-destroying acquisition decisions.

In this paper, we add to this debate by examining the relationship between executive compensation design and shareholder-bondholder interests in bank holding company (BHC) mergers. The central hypothesis of the paper is that higher performance-based compensation leads to value-enhancing merger decisions. We test this hypothesis at three levels. First, we study how pay-for-performance sensitivity in CEO compensation affects acquisition decisions for BHC. Second, we examine the merger announcement returns for shareholders and bondholders to observe the market's valuation of top executives' compensation structures. Lastly, to capture the "real" effect, we analyze the relationship between changes in operating performance around acquisition and executive compensation at time of acquisition.

Banks provide a natural experiment to assess the role of compensation in the merger decisions for a number of reasons. First, the banking industry has gone through rapid consolidation since the late 1980s, allowing us to observe a large number of cross-sectional relationships. Second, because the industry is homogeneous and most banks operate only in the financial industry, acquisitions are not diversification driven. Finally, focusing on a single and homogeneous industry alleviates the challenges that multi-industry studies face in using fixed-effect controls that may not be broad and detailed enough in terms of industry definitions. Thus, the large number of these homogeneous mergers allows a unique way to test whether executive compensation design leads to size-driven mergers that reward managers or to value-enhancing mergers that benefit stakeholders.

Our sample consists of 178 BHC merger deals in the 1990-2005 period. To capture the possible interactions among various governance measures, we construct a comprehensive governance database for our sample merging banks as well as for non-merging benchmark BHCs. This database includes both internal and external governance measures, such as board monitoring, managerial compensation, institutional ownership, and market for corporate control.

We find that both acquires and targets have lower incentive compensation, as compared with our benchmark banks, which do not participate in mergers. The multivariate regression results show that, controlling for bank and deal characteristics, banks with higher pay-performance sensitivity are less likely to engage in mergers. However, the announcement returns for BHCs with higher pay-performance sensitivity are significantly better, and this is true for both shareholders and bondholders. In other words, despite the lower propensity to merge, when these managers make acquisition decisions, they are more likely to engage in value-enhancing mergers. This is further supported when we examine changes in operating performance post-merger. We find that acquirers with higher pay-performance sensitivity prior to the acquisition also experience greater long-run improvements measured by higher return on assets.

Our findings make three contributions to the literature. First, we add to Bliss and Rosen (2001), who study the effect of CEO compensation on merger decisions in BHCs from 1986 to 1995. They find that CEOs with high performance-based compensation are less likely to make acquisitions. They argue that this is plausible because after an acquisition, the cash-based compensation generally increases due to the size effect but the performance-based compensation suffers due to the decline in stock prices. In this paper, we extend their study to explore the possibility that performance-based compensation can make value-enhancing acquisitions more worthwhile for managers. As a result, managerial incentive can serve dual roles: not only does it prevent value-destroying acquisitions from taking place, but it also motivates CEOs to make value-enhancing acquisitions. Falato (2007) finds similar results for non-financial industries.

Second, we add to the findings in the area of bank corporate governance. Banks are regulated to a higher degree than non-financial firms, but it remains unclear whether the governance issues identified as significant in non-financial firms are significant in banks (Adams and Mehran, 2003; and Capiro, Laeven, and Levine, 2003). For instance, regulatory supervision that ensures that banks comply with regulatory requirements can play a general monitoring role, which can act as a substitute for or complement to other monitoring mechanisms. The empirical evidence on the interaction of regulation and corporate governance and its impact on value is not conclusive. For example, Mehran (1995) and Belkhir (2004) find that bank performance improves when managers receive stock-based compensation. On the other hand, John and Qian (2003) argue that since banks are regulated, highly levered, and larger, they should have lower pay-performance sensitivity. Furthermore, John, Mehran, and Qian (2006) find that when regulator scrutiny is high, perk consumption becomes the larger driver as compared with risk shifting. Finally, Adams and Mehran (2002) show that unlike manufacturing firms, banks with larger boards tend to have higher value, as measured by Tobin's Q. Our paper provides new evidence that managerial incentives can serve as an effective mechanism in corporate governance for banks.

Finally, we contribute to the literature that explores the channel through which corporate governance affects firm performance. Specifically, our findings corroborate Masulis, Wang, and Xie (2007) (henceforth MWX), who show that among non-financial firms, acquirers with strong shareholder rights, measured by the anti-takeover provision index (ATP), have higher abnormal announcement returns in mergers. Consistent with MWX, we provide evidence that for BHCs, strong governance enhances value through better merger decisions. Further, we show that for BHCs, after controlling for managerial incentives, the positive effect from ATP documented in MWX becomes insignificant, suggesting that different governance schemes can serve as substitutes. That is, high pay-performance sensitivity can act as an efficient internal governance mechanism to supplement the role played by external governance mechanisms, such as the market for corporate control.

Our findings have an important policy implication. For BHC merger decisions, the pay-performance sensitivity appears to be the most important driver among all governance measures studied in this paper. It significantly affects the success of acquisition, with or without controlling for other governance measures. Both stock and bond markets view acquisitions made by CEOs with high pay-performance sensitivity as more profitable, and in the end those acquisitions lead to improvements in operating performance. In other words, market participants do care about the compensation design at BHCs, and for good reason. Hence, regulators should follow suit and include top management compensation structure as part of the supervision process.

The rest of the paper proceeds as follows: Section 2 describes our data and compares governance measures between merging and non-merging banks. Section 3 provides a model to estimate the probability of a merger and the impact of governance variables on this decision. Section 4 studies the market reaction to the merger announcement. Section 5 examines the relationship between governance and performance measured by changes in the ROA. Section 6 concludes.

2 Data

2.1 Sample Selection and Characteristics

Our acquisition sample is from Thompson Financial's SDC Platinum Mergers and Acquisitions database. We use the SIC code of 6020[1] and identify acquisitions made between January 1990 and

[1] SIC 6020 denotes Commercial Banks and Financial Institutions.

December 2005 in the banking industry that meet the following criteria:

- The acquisition is completed.
- The deal value disclosed in SDC is greater than $50 million.
- The acquirer has annual financial statement information from COMPUSTAT Bank or Call Report and stock return data from the University of Chicago's Center for Research in Security Prices (CRSP) at least a year prior to the acquisition.
- The compensation data are available either from Compustat's Execucomp database or (for the acquirers or targets before 1992) from proxy statements a year prior to the acquisition.

Our sample consists of 178 deals made by 65 acquiring BHCs (some acquirers have multiple acquisitions) and 63 target banks. Table I shows the number of transactions by year, the market cap of acquirers, and the number of acquisitions undertaken by acquirers. Consistent with the reported non-financial merger activity in MWX, 1998 proves to be the most active year for BHC mergers during our sample period. The $1990-2004$ sample-period average acquirer has a market cap of $10.39 billion, and the size of the acquirer increases over time from $3.4 billion in 1990 to $26.05 billion in 2004.[2] The BHC mergers can be considered as mega-mergers compared with non-financial mergers. Indeed, MWX report the average acquirer to have a market cap of $5.59 billion for the $1990-2003$ period, which is roughly half the size of the BHC average merger size. The average deal value over the sample period as a percentage of the acquirer's market capitalization ratio is 35% (compared with 16% in MWX's sample), and the average target is about 12% of the size of the acquirer prior to the acquisition. Panel B shows that among 65 acquirers, 29 banks (45%) have undertaken only one acquisition, and 10 banks (15%) have done at least five acquisitions over our time period.

[INSERT TABLE I HERE]

Table II presents the summary statistics for the deals. The average size of the transactions is close to $1.6 billion, and almost all deals involve a 100% ownership transfer. In terms of financing, we observe that there is a remarkable difference between the financing of non-financial and bank mergers. While in our sample only 6% of the deals were financed with 100% cash, MWX report that 46% of their non-financial merger deals were financed by 100% cash. A large percentage of mergers (72%) are between banks in different states, and 21% of the transactions are completed by banks that are first-time acquirers.

[2] The average acquirer has a market value of $4.7 billion between 1984 and 1995 in the Bliss and Rosen (2001) sample.

[INSERT TABLE II HERE]

To compare acquiring banks with their non-merging counterparts, we construct a benchmark sample using all bank-years that are not involved in acquisitions (i.e., the bank is neither an acquirer nor a target in that year) and that have information in Execucomp database. Our benchmark sample has 700 bank-years. Across the sample period, the ratio between the number of banks in our acquirer sample and the number in our benchmark sample has a mean of 37% with a standard deviation of 16%. For a robustness check, we also use an alternative benchmark sample consisting only of banks that have never participated in acquisitions. The results are qualitatively the same.

2.2 Corporate Governance Variables

In our analyses of the impact of CEO compensation on the acquisition decisions, we control for other corporate governance mechanisms. Toward that end, we compile data on internal and external governance variables. As a proxy for an internal monitoring mechanism, in addition to compensation, we use board size. The proxies for external governance mechanisms are the anti-takeover provisions and institutional ownership. Table III provides summary statistics on these variables together with firm characteristics.

[INSERT TABLE III HERE]

CEO Compensation We collect the CEO compensation data, including annual salary, bonus, new grants of restricted stock and option grants, and stock and option holdings from past grants, from Execucomp database. For bank-years before 1992, the data are hand-collected from the proxy statements whenever available. To measure the magnitude of incentive-based compensation, we calculate the pay-performance sensitivity (PPS) as defined in Core and Guay (1999). PPS measures the change of a CEO's wealth (in thousand dollars) from her stock and option holdings given a 1% change in stock price. Options are valued using the Black-Scholes formula, assuming a ten-year maturity and stock price volatility is estimated from monthly stock return in the year of the grant. Following Core and Guay (1999), we include both the existing and newly awarded grants to measure the overall wealth effect. This approach is different from that of Bliss and Rosen (2001), who consider only the percentage of equity-based compensation for the current year. In addition to calculating the total PPS (PPS), we also break it into individual components based on stock holdings (SPPS) and option holdings (OPPS). Since pay-performance sensitivities are heavily skewed to the right, we use the natural log of PPS instead of the raw value.

Table III shows that the median total compensation in acquirer banks is \$1.11 million, which represents 53% of total new compensation. Although total compensation has increased during the sample period (from \$1.70 million in 1992 to \$3.12 million in 2004), the percentage that is based on cash has decreased significantly over time. Figure 1 Panel A shows that over our sample period, cash compensation of bank CEOs as a percentage of total compensation decreased from 68% to 44%. Consistent with this decline, PPS has increased dramatically over time. Figure 1 Panel B shows the time trend of total PPS for both benchmark sample and acquiring banks, where we observe that both the option and the share components of PPS have steadily increased during the 1992-2004 period. Turning back to Table III, we observe that for every 1% increase in stock price, the acquirer CEO gains \$189,896 in wealth, 45% of which comes from the existing and newly awarded stocks. CEOs in the benchmark sample have similar total compensation structure: the median cash compensation is \$1.10 million, accounting for 53% of the total compensation. However, benchmark CEOs have higher PPS relative to the CEOs of acquiring BHCs. For every 1% increase in stock price, a benchmark CEO gains \$243,406 in wealth in contrast to the \$189,896 wealth increase for the acquiring CEO. The difference in PPS between acquirer CEO and benchmark is significant at the 10% level.

[INSERT FIGURE 1 HERE]

Board Structure It is well documented in the literature that the size and composition of a board of directors influence the effectiveness of monitoring. Smaller boards (Yermack, 1996; Jensen, 1993; and Lipton and Lorsch, 1992) with more outside directors (Weisbach, 1988; Brickley and James, 1987; and Brickley et al., 1994) tend to have higher stock returns. Following this literature, we collect information from Investors' Responsibility Research Center's (IRRC) Director database on board size (BSize), the percentage of independent directors (BIndep), and whether the CEO is also the chairman of the board (D_CEO). IRRC data are from 1996 and onward. For other years, we hand-collected information from proxy reports whenever it is available.

Consistent with Adams and Mehran (2002), we also find that BHCs have large boards. The average bank in the benchmark sample has 15 directors, as compared with an average of 17 directors in acquirer banks. More than half of the directors are independent (70% for the benchmark sample and 69% for acquiring banks). The majority of the banks have a CEO who is also chairman of the board (92% for the benchmark sample, 88% for acquiring banks, and 89% for target banks).

Anti-takeover Provisions A series of research studies in the recent literature have documented the governance role of the market for corporate control (Gompers, Ishii, and Metrick [GIM], 2003; Bebchuk, Cohen, and Ferrell [BCF], 2004; and Bebchuk and Cohen [BC], 2005). These studies show that negative relations exist between various anti-takeover-provision (ATP) measures and the firm value. MWX further find that acquirers with more ATPs, i.e., weaker shareholder rights, also have lower merger announcement returns. The GIM index is based on 24 ATPs collected by IRRC, the BCF index is based on 6 out of the 24 ATPs, and the BC index is a binary variable based on whether a firm has a staggered board. Since most of the acquisitions in the banking industry are friendly rather than hostile, we use the BCF Entrenchment index (EIndex) as the main proxy to capture the managerial entrenchment, and our results are robust based on the other two measures (the GIM and BC indexes denoted by GIndex and BCIndex).[3] The higher levels of EIndex and GIndex indicate more managerial power.

Table 3 shows that there exist no differences in terms of EIndex and GIndex between the acquirer and the benchmark BHCs. The interesting finding is that the levels of both the EIndex and the GIndex for our sample BHCs are remarkably similar to the ones reported for the non-financial sample in MWX. MWX show that average EIndex and GIndex values are 9.45 and 2.24 for $3,333$ completed non-financial acquirers. These values are 9.97 and 2.65 for our sample acquirers. Given that the threat of hostile takeovers is not nearly as high for BHCs as it is for non-financial firms, this finding raises the possibility that these anti-takeover provisions are included in corporate charters just as a matter of standard practice, unreflective of the takeover threat. In terms of having a staggered board (CBoard), our sample BHCs are above the non-financial firms. Table III shows that 72% of our acquiring BHCs have staggered boards, and MWX report this number to be 61%.

Institutional Ownership Both theory (Shleifer and Vishny, 1996; and Watts, 1988) and empirical evidence suggest that institutional ownership can beneficially influence managerial practice. For example, greater institutional holdings are associated with better investments (Smith, 1996), more-aligned compensation (Hartzell and Starks, 2003), greater performance-sensitive CEO turnover (Parrino, Sias, and Starks, 2003), and more-informative financial information (Rajgopal and Venkatachalam, 1997).

We calculate the institutional ownership using Institutional Money Manager (13f) Holdings in the CDA/Spectrum database. Acquirer banks have an average institutional ownership of 42%, with a standard deviation of 17%. Little difference exists between the acquirer banks and the benchmark.

[3]The Entrenchment Index (EIndex) is based on four "constitutional" provisions that prevent a majority of shareholders from having their way (staggered boards, limits to shareholder bylaw amendments, super majority requirements for mergers, and super majority requirements for charter amendments) and two "takeover readiness" provisions that boards put in place to prevent hostile takeovers (poison pills and golden parachutes).

Table III Panel C shows the correlation matrix of the governance variables. Banks with high pay-performance sensitivity also tend to have smaller boards, CEOs who are also the chairman of the board, and lower Entrenchment Index.

3 Probability to Acquire

Bliss and Rosen (2001) argue that acquisitions lead to higher cash compensation due to size effect but to lower stock prices due to value destruction. As a consequence, CEOs with more stock-based compensation are less likely to engage in acquisition. Bliss and Rosen's (2001) empirical findings confirm this argument. Our hypothesis takes the Bliss and Rosen (2001) arguments one step further and maintains that when these unwilling CEOs make an acquisition decision, it is likely to be value enhancing. However, before we present our central tests, it is instructive to test the applicability of the Bliss and Rosen findings to our sample. Hence, we perform similar analyses using pay-for-performance sensitivity.[4]

We estimate the following logit model:

$$D(ACQ_{i,t+1}) = c_1 + c_2 GOVERNANCE_{i,t} + c_3 CONTROLS_{i,t} + \epsilon_{i,t+1} \quad (1)$$

where $D(ACQ)$ is an indicator variable that equals 1 if an acquisition announcement is made by BHC i in year $t+1$ and 0 otherwise.

For bank characteristics, we control for size, operating performance, and the expected risk of the bank's portfolio, all of which are measured at one year prior to the acquisition announcement. We define size (Size) as the natural log of the bank's total assets, and use return on assets (ROA) as our measure for operating performance. Since banks may choose to acquire assets for risk sharing, we also control for portfolio risk using loan-loss-provision ratio (Penas and Unal, 2004). Bliss and Rosen (2001) point out that mergers may be positively or negatively auto-correlated, depending on whether the bank follows a merger strategy. Therefore, we include an indicator variable denoting whether the bank has already participated in acquisitions (D_Merger). Abnormal stock price increases may encourage merger activity due to hubris or lower financing cost. To control for this effect, we include the average stock return (Ret) as well as the volatility of return (Ret_Vol) one year prior to the acquisition announcement. We also include the level of cash holdings (Cash) to control for the agency problem generated by free cash flow in as much as higher cash holdings lead to inefficient mergers (Jensen, 1986).

[4]Bliss and Rosen use the percentage of compensation that is related to stock as their measure for incentive-based compensation, whereas our study considers the change of a CEO's wealth from both current and vested stocks and options.

In contrast to Bliss and Rosen (2001), who use only the cash compensation to total compensation ratio, we use all three pay-performance-sensitivity measures − total PPS (PPS), Option PPS (OPPS), and Stock PPS (SPPS). We also control for a larger set of internal and external governance proxies such as managerial entrenchment (E-Index and staggered boards), board structure (board size, percentage of independent directors), and institutional ownership. Table IV presents our results.[5]

[INSERT TABLE IV HERE]

Like to Bliss and Rosen (2001), we find that banks in which CEOs are better aligned with shareholder interests through the use of incentive compensation are less likely to make acquisitions. Results are robust using stock PPS, option PPS, or total PPS, with or without controlling for other governance measures. Table V presents the sensitivity of the merger probability to higher levels of performance-based compensation. Moving from the 25th percentile to the 75th percentile in total PPS decreases the probability of acquisition from 18.8% to 13.7% (a 24% relative change), and moving from one standard deviation above the mean to one standard deviation below the mean in total PPS decreases the acquisition probability from 21.3% to 12.4% (a 37% relative change). Similar results are obtained using stock PPS and option PPS. Clearly, performance-based compensation becomes a deterrent to acquisition decisions.

[INSERT TABLE V HERE]

The importance of this finding can be seen by observing that other governance variables such as entrenchment index, board structure, or level of institutional ownership do not seem to have any significant effects on acquisition probabilities, and including these variables in the regression does not affect the significance of PPS. We also find that larger banks are more likely to make acquisitions, and whether a bank has already participated in an acquisition significantly affects its probability of making another acquisition. Prior stock returns are also positively related to acquisition probability. Contrary to the prediction of free-cash-flow theory, cash holdings have negative effect on acquisition probability.

We conduct several alternative specifications for a robustness check. For example, we use an alternative benchmark sample in which we include a bank-year in the benchmark sample only if the bank has never engaged in merger activity during the sample period. We also check for different specifications using Probit models. None of these checks changes our results significantly.

[5] Our Pseudo R^2s are lower than those of Bliss and Rosen (2001), who have an average Pseudo R^2 of .50. Ours are between .08 and .15, which are similar to those in other bank-merger papers (Bostic, Mehran, Paulson, and Saidenberg, 2002).

4 Announcement Returns and Compensation

In this section, we use an event study method to examine the stock and bond price reaction to acquisition announcements by acquirer banks. Research has shown that mergers benefit all stakeholders through diversification, synergy, or implied government guarantee due to the too-big-too-fail effect (Berger and Humphrey, 1992; Becher, 2000; and Penas and Unal, 2003;). However, other studies find that mergers fail to improve a bank's operating performance or to produce positive abnormal returns to shareholders (Houston and Ryngaert, 1994; and Rhoades, 1994). In this paper, we do not intend to take any position in this debate. Rather, we focus on testing our central hypothesis that banks with better aligned managerial incentives are more likely to make value-maximizing mergers.

4.1 Stock Returns

4.1.1 Univariate Analysis

We measure acquirer announcement returns using the market model adjusted stock returns around initial acquisition announcement. The announcement dates are obtained from Thompson Financial's SDC Mergers and Acquisition Database. We compute the cumulative abnormal returns (CAR) in a three-day and a five-day window, (-1, +1) and (-2, +2), where event day 0 is the announcement date. We use CRSP value-weighted return as the market return and estimate market model parameters over the 200-day period from event day -220 to event day -21. We check the robustness of our results by using CRSP equal-weighted return as the market return and the results remain qualitatively the same.

As Table VI Panel A shows, the 3-day and 5-day CARs are widely dispersed for acquirers in our sample, ranging from -8.78% to 8.82% and from -10.64% to 12.40%, respectively. Neither the mean nor the median is significantly different from zero, similar to the announcement returns presented for BHC mergers in James and Wier (1987). Figure 2 presents the histogram of returns.

[INSERT TABLE VI AND FIGURE 2]

We next provide a univariate test of our hypothesis. To construct the test, we first sort our observations according to total PPS and form three groups of PPS so that each group has one-third of the observations. Group 1 has the least PPS and Group 3 has the most PPS. Table VI Panel B shows the statistics for each PPS group. For every 1% change in stock price, the median CEO in the Low-PPS group has an average wealth increase of $\$56,870$, as compared with an increase of $\$976,440$ for the median CEO in the High-PPS group. Panel C presents the comparison of CARs between the Low-PPS and High-PPS acquirers. We observe that on average, the Low-PPS bank has a CAR of -0.235%, whereas the High-PPS bank has a CAR of 0.475% around acquisition announcement. The difference is significant at the 10% level. We find similar results using PPS Stock and PPS Option. Figure 3 shows the comparison through box plots.

[INSERT FIGURE 3 HERE]

These findings provide initial support for our hypothesis. The next section presents other possible determinants of acquirer stock returns followed by results for multi-variate tests where we control for three categories of factors: acquirer characteristics, deal characteristics, and other governance measures.

4.1.2 Acquirer and Deal Characteristics and Other Governance Measures

Moeller, Schlingemann, and Stulz (2004) find evidence that acquirer returns are negatively related to bidder size, regardless of the method of payment or whether the target is public or private. Since banks are in general larger than non-financial firms, it is not clear whether those results hold for our sample. Penas and Unal (2003) document a significant too-big-to-fail (TBTF) factor when examining returns around acquisitions. They show that bondholders and stockholders of medium-sized banks realize the highest returns when the acquiring banks push the combined bank's asset size above the TBTF threshold. We control for the size effect by including the log of total assets (SIZE) in our regression.

Neoclassical theory suggests that acquisitions are ways to reallocate resources to their best use (Jovanovic and Rousseau, 2002). Meanwhile, agency theory such as Jensen (1986) shows that managers have incentives to overinvest for their private benefit when there exists free cash flow. Taking both arguments into account, we control for the acquirer's operating performance using return on assets (ROA) and the firms' cash holdings, adjusted by total assets (CASH).

For deal characteristics, we control for the relative size ratio, the method of payment, previous merger activity, and geographic diversification. Asquith, Bruner, and Mullins (1983) show that bidder announcement returns are positively related to relative deal size while Moeller, Schlingemann, and Stulz (2004) show that for a subsample of large bidders, the reverse is true. Our sample is more similar to Moeller, Schilingemann, and Stulz's large-acquirer sample: the market value of equity for the average (median) acquirer in our sample is \$9.5 (\$3.2) billion, as compared with \$3.1 (\$0.8) billion in Asquith, Bruner, and Mullins (1983) sample. We calculate the relative size (SIZE_RATIO) as a ratio between the deal value and the acquirer's market capitalization. For a robustness check, we also use the asset size ratio of the target banks to those of the acquirer banks prior to the merger (RelSize) as an alternative measure.

We control for the method of payment by including an indicator variable, D_Stock, which takes the value of one if the deal is more than 75% financed by equity. It is documented in the literature that acquirers experience significant abnormal returns when they pay for acquisitions with equity due to the adverse selection problem in equity issuance.

We also create a binary variable to indicate whether the acquirer has made any acquisition prior to the announcement (D_MERGER). Since interstate mergers are shown to offer either fewer opportunities for increased market power (Prager and Hannan, 1998) or fewer cost savings (Houston and Ryngaert, 1994; and Houston et al., 2001), we include a binary variable OutofState to control for geographic diversification. It takes the value of one if the merger is out-of-state and zero otherwise.

For governance measures, we control for board structure (BSIZE, B_INDEP, D_CEO), managerial entrenchment (E_Index), and institutional ownership (INST SHR). All control variables are measured at the fiscal year-end prior to the acquisition announcement. For brevity, in the rest of the paper we report only results based on the 3-day window. Results based on other event windows, such as (-2, 2), (-3, 1) and (-5, 1), are qualitatively the same.

4.1.3 Results

We use the following specification:

$$CAR_i = c_0 + c_1 GOV_i + c_3 Controls_i + \epsilon_i \tag{2}$$

where CAR is the abnormal returns for acquirer stockholders, and GOV includes governance variables such as pay-performance sensitivity (SPPS, OPPS, PPS), board size (BSize), percentage of independent directors (Indep), Dual Chair (D_CEO), entrenchment index (EIndex), and institutional ownership (INST SHR).

[INSERT TABLE VII HERE]

Table VII summarizes the results of our estimation. Columns 1-3 show that, controlling for acquirer and deal characteristics, all three PPS measures (PPS, SPPS, OPPS) have positive coefficients at the 5% significance level. In Columns 4-6 we test whether the significance of PPS is affected by the inclusion of board characteristics, EIndex, and institutional ownership variables, respectively. PPS remains significant in all three cases at the 1% level. In Column 7, we include all governance variables. PPS remains significant, and the coefficient estimate shows that a 1%

increase in the log of PPS of the CEO increases the acquirer returns 0.798%. Given that the average abnormal return is 0.26%, the impact is economically significant. These findings support our univariate test results.

To better understand the economic significance of the relationship between PPS and acquirer returns, we estimate the sensitivity of the stock market reaction to different levels of PPS. Using the specification presented in Column 7 in Table VII we estimate the abnormal return increase to one standard deviation increase in the PPS (see Table VIII). We find that the abnormal return for the High-PPS bank (PPS equals to the mean plus one standard deviation) is 1.179%, and for the Low-PPS bank (PPS equals to the mean minus one standard deviation) it is -0.154%. The difference is even more substantial when we replace PPS with SPPS or OPPS.

[INSERT TABLE VIII HERE]

Turning back to Table VII, we observe that EIndex is negative but marginally significant in Column 5. This finding implies that acquirer announcement returns are higher when the banks have fewer anti-takeover provisions. This result corroborates the evidence documented by MWX for non-financial merger cases. However, the significance of EIndex disappears when we control for all other governance measures. Interestingly, in a similar regression specification, the EIndex remains significant in MWX, indicating that different governance mechanisms can have industry specific channels to affect value. Significance of institutional ownership in Columns 6 and 7 shows that another channel of external governance mechanism is still at work. Hence, the multivariate analysis shows that for BHCs, high pay-performance sensitivity acts as an efficient internal governance mechanism to supplement the role played by external governance mechanisms such as the market for corporate control.

Examining the control variables, we find that acquirer returns are negatively related to the relative size ratio, consistent with findings from Moeller, Schlingemann, and Stulz (2004) for their large-acquirer sample. Some specifications suggest a negative relationship between cash holdings and acquirer returns, favoring the free-cash-flow hypothesis proposed by agency theory.

4.2 Bond Returns

The impact of the compensation structure of top executives has an ambiguous impact on the credit risk of the firm. If the compensation design causes greater managerial entrenchment, or if managerial pay-for-performance is structured such that the firm's investment decision benefits the shareholders by increasing the volatility of the firm's earnings at the expense of the bondholders, it will increase the credit risk of the firm. On the contrary, if the pay-for-performance structure leads to investment decisions that increase the firm value, then we obtain the prediction that bondholders benefit from the compensation structure in place.

The previous section shows that shareholders consider PPS to be an important determinant of the value-enhancing acquisition decisions of the BHCs. However, it is unclear how bondholders evaluate the relationship between PPS and acquisition decisions. If they see that these acquisitions reduce the credit risk of the firm, they must value high PPS together with the shareholders. Therefore we obtain a second hypothesis, which argues that higher performance based compensation leads to reduction in the credit risk of the firm. To test this hypothesis, we estimate abnormal bond returns around the acquisition announcement dates. Such an investigation is also warranted to further check the robustness of our findings regarding shareholder returns.

We measure bondholder abnormal returns using the LBBD database and follow Maxwell and Stephens' (2003) approach that uses a mean-adjusted-return model to account for changes in the term structure. We first calculate excess monthly holding-period return as the monthly return on a bond minus the return on a maturity-matched Treasury security. Then, using the average monthly excess return in the last 6 months as the expected excess return for the announcement month, we calculate the abnormal bond return (BAR) as the difference between the excess monthly return in the announcement month and the mean expected excess return. We should note that the LBBD database contains only monthly data rather than daily returns (Warga and Welch, 1993). But, as argued by Brown and Warner (1980) and Maxwell and Stephens (2003), this shortcoming should bias us only against finding any significance, since the effect of the announcement is diluted.

Due to data limitations, merging our sample with bond return information reduces our sample size significantly.[6] We have 136 bond return data points for 18 acquisitions. The majority of banks in the sample have multiple bonds outstanding, ranging from two to thirty issues. Previous literature uses two approaches: either treat each bond issue as a separate observation, or measure returns as a weighted average (based on market values) of the abnormal returns to all different bond issues (Maxwell and Stephens, 2003). Our reported results are based on the first method. However, we get similar results in regard to signs, significance, and coefficients for the second method.

As with the stock returns, the abnormal returns for bondholders are widely dispersed. Table IX Panel A shows the minimum, maximum, and average abnormal returns of acquirers in our sample, and Figure 4 presents the corresponding histograms. The average cumulative abnormal bond return for acquirers is -0.10% for the (0,1) window, and -0.25% for the $(-1, 1)$ window where $t = 0$ is the event month when acquisition announcements are made.

[6]The Lehman Bond database has data only up till 1998, and so we do not have any mergers post 1998.

[INSERT TABLE IX AND FIGURE 4 HERE]

Table IX, Panel B shows the breakdown of bond returns for different PPS groups based on total PPS, SPPS, and OPPS. The grouping of the PPS is similar to that of Table VI. We observe that on average, the Low-PPS bank has an abnormal bond return of -0.566% while the High-PPS group shows an abnormal bond return of 0.173%. We find similar results using PPS Stock and PPS Option. Figure 5 shows the comparison through box plots. These univariate tests establish the initial evidence that bondholders view high pay-for-performance compensation as reducing credit risk of the BHC.

[INSERT FIGURE 5 HERE]

As with stock returns, we analyze the relationship between PPS and abnormal returns in a multivariate regression setting and estimate the following specification:

$$BAR_i = c_0 + c_1 GOV_i + c_3 CONTROL_i + \epsilon_i \tag{3}$$

where BAR_i is the abnormal return for bondholders of acquirer bank i from one month before to one month after the announcement. The governance variables (GOV) and control variables ($CONTROL$) are the same as those in Equation (2).[7] Again, a positive coefficient for PPS would indicate that bondholders favor the acquisitions made by banks with high incentive-based compensation. Table X presents the results of our estimation.

[INSERT TABLE X HERE]

As with abnormal stock returns, we find very significant results for the PPS variables. Individually or together with other governance variables, PPS is significant at the 1% level. Column 5 shows that a 1% increase in PPS increases the bond returns 1.75%.

Table X also shows that larger banks experience worse bond returns than smaller banks and that higher volatility in stock returns leads to negative bond returns. Like shareholders, bondholders also react negatively to deals financed with stock and deals where the size ratio between target and acquirer is larger. It is interesting to note that bondholders react positively to acquisitions made by banks with high ROA and high cash ratios. This finding is plausible and shows that for acquirers with higher earnings and higher cash on hand, the risk of default on the bonds after acquisition is significantly reduced.

[7] We dropped the institutional ownership variable due to a limitation in data. Additionally, we drop the dual chair CEO dummy since all of our banks with bond data have a dual CEO/Chair.

5 Performance Change Following a Merger

In the previous sections, we show that acquisition announcements made by banks with high PPS have significantly higher returns for both shareholders and bondholders, suggesting that market participants expect acquisitions to deliver value in the future when CEO compensation includes higher performance-based elements. In this section, we study the change of operating performance for the acquirer following the merger, and examine whether the higher returns at the announcement can be justified by greater improvement after the merger.

The literature has mixed results on post-merger gains in banks. These papers measure performance change by focusing on operating costs per employee or the bank's efficiency ratio (where the efficiency ratio is non-interest expense divided by the sum of net interest income and non-interest income). Cornett and Tehranian (1992) and Spindt and Tarhan (1992) find increases in post-merger operating performance, whereas Berger and Humphrey (1992), Piloff (1996), and Berger (1997) do not.

We use return on assets (ROA) as our measure for operating performance in this paper, and focus on changes. First, we collect quarterly data to match the quarter before the merger to eight quarters after the announcement. Then, we calculate the change of ROA as the difference between acquirer's ROA after the acquisition and the combined acquirer-target ROA prior to the acquisition. For the "synthetic" combined ROA prior to the acquisition, we use a weighted average based on acquirer's and target's market capitalization. For a robustness check, we also perform an analysis using the event window (-1, 4), where time 0 is the quarter within which the announcement is made, and we obtain similar results.

Our base specification is as follows:

$$\Delta ROA_{it} = d_0 + d_1 GOV_{i,t-1} + d_2 CONTROLS_{i,t-1} + +\varepsilon_{it} \tag{4}$$

The dependent variable is the change in ROA for the period $t = -1$ to $t = 8$ quarters. The independent variable GOV includes the governance measures PPS, option PPS, stock PPS, managerial entrenchment, board size, dual CEO/Chair, the percentage of independent directors on the board, and institutional ownership. The firm-specific control variables include the size of the bank, the standard deviation of stock returns, acquirer's ROA, and the cash holdings of the bank.

We include a dummy variable that is equal to one if the merger is out of state. As Houston, James, and Ryngaert (2001) show, bank mergers can increase value by reducing costs and/or increasing revenues. Cost reductions can be achieved by eliminating redundant managerial positions, closing overlapping bank branches, or fixing inefficiencies, and may be greater when merging banks have geographic overlap. We also control for whether the bank has engaged in prior merger activity (D_Merger). As Houston et al. point out, there is mixed evidence as to whether prior merger activity results in worse or better post-merger performance. Banks that have already engaged in successful mergers will be more inclined to merge again. However, banks that have never engaged in mergers will be careful in selecting their first deal.

Houston and Ryngaert (1997) find that most acquiring banks issue stock to finance their mergers. Loughran and Ritter (1997) show that equity issuers experience a drop in profitability after an equity issue. Banks might be willing to make stock-financed acquisitions when they are at the apex of their earnings and predict that future profits will decline. Therefore, we control for whether the merger is stock financed (D_STOCK). Finally as shown in Rivard and Thomas (1998), larger mergers lead to increased efficiencies and better performance. We control for merger size as well (SIZE_RATIO).

Table XI shows the results of our estimation. As with return regressions, pay-for-performance sensitivity helps to predict the improvements in post-acquisition operating performance. Banks with high PPS prior to the acquisition generate bigger improvement as measured by change of ROA. This finding, together with our observations for stock and bond abnormal returns, shows how robust the influence of PPS on firm values.

[INSERT TABLE XI HERE]

We also find that larger banks with lower return volatility experience higher increases in ROA. Deals in which the target-acquirer size ratio is large also generate better post-merger performance. On the other hand, higher cash ratios lead to lower changes in return, consistent with results from stock return regressions, suggesting that banks with a large amount of cash may not invest efficiently. Our results are inconclusive in regard to stock-financed acquisitions, out-of-state acquisitions, and acquisitions that are made by banks with no prior experience.

6 Conclusion

This paper examines the effect of incentive-based compensation on bank mergers. Specifically, we examine the role of executive compensation in three areas: the probability of a merger occurring, announcement returns for both shareholders and bondholders, and changes in post-merger performance. Using a comprehensive governance database incorporating managerial compensation, board structure, anti-takeover provisions, and institutional ownership, we investigate whether performance-based compensation is beneficial or harmful to all stakeholders in bank holding companies.

Our findings show that BHCs in which the CEO's wealth is closely linked to the wealth of the shareholders through incentive-based compensation are less likely to acquire. However, when those managers do undertake mergers, financial markets expect good results and react positively. We find positive abnormal returns for both bondholders and stockholders around acquisition announcement for banks with high PPS executives. In the end, markets are correct in their expectations. Following acquisitions, banks with high PPS experience significantly bigger improvement in their operating performance as measured by ROA. As shown in the paper, strong governance through incentive compensation protects both shareholders and bondholders. The policy implication of these findings is straightforward. Executive compensation is an important governance measure that signals BHC acquisition quality. Hence, supervisory process should incorporate top executive compensation structure into its ratings of the BHCs.

Table I: Bank Acquisitions

Panel A describes the deal information in our sample by year. The first column shows the number of BHC acquisitions in the year. Deal Value is the amount of the deal, in millions. Acq. MVE denotes acquisition market value of equity, TAsset denotes target asset size, and AAsset denotes acquire asset value. All deal data are from SDC Platinum. Panel B examines the number of multiple acquirers in our sample.

Panel A: Deals by Year

	Number of Transactions		Deal Value	Acq. MVE	Deal Value/Acq. MVE	TAsset/AAsset
Year	Acquirer	Target	(in $ millions)	(in $ millions)		
1990	4	4	1,337	3,430	0.33	0.36
1991	4	0	395	1,051	0.42	0.23
1992	14	1	273	3,043	0.20	0.10
1993	13	6	364	3,624	0.23	0.11
1994	10	11	1,089	3,133	0.45	0.19
1995	11	5	271	1,378	0.31	0.12
1996	16	9	1,185	3,731	0.64	0.17
1997	21	4	832	4,800	0.40	0.13
1998	24	5	639	11,583	0.37	0.06
1999	16	7	1,306	21,438	0.25	0.11
2000	8	1	260	13,053	0.24	0.08
2001	5	0	216	9,073	0.13	0.03
2002	12	3	4,685	22,454	0.32	0.12
2003	11	6	7,601	17,369	0.40	0.12
2004	9	1	4,625	26,048	0.34	0.21
Total	178	63	1,610	10,390	0.35	0.12

Panel B: Information on Multiple Acquirers

Number of Acquisitions	Frequency	Percent
1	29	45
2	11	17
3	10	15
4	5	8
5 or more	10	15
Total	65	100

Table II: Summary of Deals in the Sample

This table shows the deal characteristics in our acquisition sample. Deal Value is the disclosed value reported by SDC. Pct. Acq. is the percentage of ownership acquired by the acquirer. D_Stock(D_Cash) is an indicator variables that equals to one if the acquisition is financed with at least 75 percent of stock(cash). OutOfState is an indicator variable which is equal to one if the acquisition involves an acquirer and a target from different states. D_Merger equals to one if the acquirer has done at least one acquisition prior to this transaction (based on data in our sample), and zero otherwise.

	Mean	Std. Dev.
Deal Value (in $ mil)	1,610	6,438
Pct Acq	99.92	0.64
D_Stock	0.821	0.38
D_Cash	0.058	0.23
OutOfState	0.72	0.45
D_Merger	0.21	0.41

Table III: Summary of Bank Characteristics

This table compares the acquirer banks with the benchmark sample. A bank is an acquirer if it has made at least one acquisition in the current year, and the benchmark sample contains all bank years that are not related to mergers. Total Assets is the total asset size of a bank. MVE is the market value of equity. Return Volatility. is the annualized standard deviation based on the monthly stock returns. ROA is the return on assets and ROE is the return on equity. PRV is the ratio of loan loss provision. Cash equals the percentage of assets held in cash. RE is the percentage of loans held in real estates. Stock PPS and Option PPS are the pay-performance sensitivity calculated using stock and options grants, respectively, based on methods developed in Core and Guay (1999). Total PPS is the sum of SPPS and OPPS. Bsize and Indep are the size of board and the percentage of independent directors, respectively. D_CEO is an indicator variable that is equal to one if there is a dual CEO and Chair. GIndex is the governance index based on Gompers, Ishii, and Metrick (2002). EIndex is the entrenchment index based on Bebchuk, Cohen and Ferrell (2004). CBoard is an indicator variable that equals to one if the bank has a staggered board, and zero otherwise. INST SHR is the percentage of shares owned by institutions. We use pairwise t-tests to examine whether there is a significant difference between the benchmark and the acquirers, or between the benchmark and the targets. *, **, *** denotes significant at 10 percent, 5 percent, and 1 percent, respectively.

Panel A: Summary Statistics

		Benchmark		Acquirer			
		Mean	Median	Mean		Median	
Firm Characteristics	Total Assets	55,891	17,223	51,081		19,902	
	MVE	7,724	2,503	9,546		3,203	
	Return Volatility	0.25	0.22	0.23	*	0.21	
	ROA(%)	1.17	1.19	1.19		1.19	
	ROE(%)	14.50	14.86	14.28		14.36	
	Cash(%)	4.49	3.72	3.91	**	3.24	*
	PRV(%)	0.87	0.56	1.00		0.79	***
	RE	0.50	0.51	0.50		0.5	
Compensation	Cash Comp($mil)	1.59	1.10	1.47		1.11	
	Cash Comp(in %)	54%	53%	53%		53%	
	Total Comp($mil)	4.17	2.32	3.88		2.18	
	Stock PPS	279.7	114.1	223.3		71.5	***
	Option PPS	216.7	87.0	210.7		68.2	
	Total PPS	509.4	243.4	448.8		189.9	**
Board	BSIZE	15.37	15	16.58	***	17	***
	Indep	0.7	0.71	0.69		0.72	
	D_CEO	0.92	1	0.88		1	
Anti-Takeover Provisions	EINDEX	2.50	3	2.65		3	
	GINDEX	10.16	10	9.97		10	
	CBoard	0.67	1	0.72		1	
Inst. Ownership	INST SHR	0.46	0.46	0.42		0.42	
N		700		163			

Table III: Summary of Bank Characteristics (cont.)

Panel B: Correlation of Governance Variables

	PPS	Bsize	Indep	D_CEO	E Index	G Index	Inst Shr
PPS	1						
BSize	-0.107**	1					
Indep	0.003	0.061	1				
D_CEO	0.154***	0.102**	0.029	1			
EIndex	-0.127***	-0.229***	-0.025	0.014	1		
GIndex	-0.074*	-0.141***	0.045	0.029	0.750***	1	
Inst ShR	0.056	-0.081*	0.105**	-0.040	-0.238***	-0.248***	1

Table IV: Probability of Acquisition

This table shows the results from logit regressions based on (1). The dependent variable is equal to one if the bank takes at least one acquisition in the next year and zero otherwise. All specifications include year dummies. *, **, *** denotes significant at 10 percent, 5 percent, and 1 percent, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bank Characteristics							
SIZE	.297**	0.252**	0.419***	0.030	0.281**	0.245**	0.448***
	(0.130)	(0.125)	(0.153)	(0.152)	(0.132)	(0.114)	(0.173)
ROA	0.586	0.461	0.212	0.418	0.506	0.588	0.889
	(0.408)	(0.399)	(0.489)	(0.502)	(0.498)	(0.424)	(0.680)
RET	1.653**	1.678**	2.261***	2.166**	1.903**	1.613**	2.337**
	(0.693)	(0.698)	(0.749)	(0.907)	(0.821)	(0.751)	(1.014)
RET VOL	-0.643	-0.724	-0.759	-1.819	-0.559	0.284	-1.659
	(1.853)	(1.878)	(2.090)	(2.236)	(2.186)	(1.971)	(2.667)
CASH	-0.181***	-0.170***	-0.202***	-0.167**	-0.273***	-0.139**	-0.225***
	(0.064)	(0.062)	(0.070)	(0.065)	(0.077)	(0.063)	(0.079)
PRV	-0.022	-0.010	-0.075	0.197	-0.098	-0.314	-0.181
	(0.224)	(0.226)	(0.248)	(0.243)	(0.265)	(0.310)	(0.327)
D_MERGER	1.212***	1.189***	1.459***	1.231***	1.309***	0.963***	1.308***
	(0.259)	(0.262)	(0.296)	(0.294)	(0.294)	(0.286)	(0.379)
Compensation Variables							
PPS	-0.214**						-0.280**
	(0.102)						(0.122)
SPPS		-0.171*					
		(0.094)					
OPPS			-0.333**				
			(0.144)				
Anti-Takeover Provisions							
ETINDEX				-0.030			0.037
				(0.110)			(0.146)
Board Characteristics							
BSIZE					0.031		0.010
					(0.031)		(0.042)
BINDEP					0.282		0.258
					(1.000)		(1.207)
D_CEO					-0.991*		-1.208**
					(0.520)		(0.544)
Ownership Characteristics							
INST SHR						-1.156	-0.742
						(0.974)	(1.264)
Const.	-2.968**	-2.802*	-2.925*	-1.128	-3.297*	-2.914*	-3.587
	(1.445)	(1.448)	(1.603)	(1.975)	(1.850)	(1.535)	(2.611)
Obs.	515	513	427	392	399	456	277
Pseudo R^2	0.10	0.10	0.14	0.12	0.14	0.09	0.17

Table V: Sensitivity of Acquisition Probability to PPS Levels

This table shows the sensitivity analysis of the probability of acquisition on different PPS levels. Estimates are based on predicted value from Table IV (1) - (3). PPS, SPPS and OPPS are the natural logarithm of Total PPS, Stock PPS and Option PPS, respectively. Holding all other variables at their mean level, we calculate the predicted probability using the 25th and 75th percentile of PPS variable, and using one standard deviation below and above the mean of PPS variable. Relative change measures the difference between the predicted value based on low-PPS and the predicted value based on high-PPS divided by the predicted value based on low-PPS.

	25 PCTILE	75 PCTILE	RELATIVE Δ	MEAN-SD	MEAN+SD	RELATIVE Δ
SPPS	0.179	0.140	-22%	0.221	0.130	-41%
OPPS	0.228	0.126	-45%	0.260	0.109	-58%
PPS	0.188	0.137	-24%	0.213	0.124	-37%

Table VI: Acquirer Stock Returns: Univariate Analysis

This table summarizes information on acquirer returns for different PPS groups. Panel A shows the cumulative abnormal stock returns (CARs) in percentage for acquirers using different event window where day 0 is the event day. We separate acquirers in three groups based on their total PPS so that each group has one third of the observation. Panel C compares CARs between acquires in the Low-PPS group (bottom one third) and acquirers in the High-PPS group (top one third). T-Tests (Signed rank tests) are performed to examine whether the mean(median) returns are significantly different between two gruops. *, **, *** denotes significant at 10 percent, 5 percent, and 1 percent, respectively.

Panel A: Summary Statistic on Acquirer Returns

	Mean	Min	Max
(-1, 1)	0.20	-8.78	8.82
(-2, 2)	0.26	-10.64	12.40
N	178		

Panel B: Summary Statistics on PPS Groups

PPS Group	Mean	Median	Min	Max	N
1	62.80	56.87	0.00	134.63	60
2	265.40	265.02	138.10	452.19	59
3	1251.96	976.44	476.35	4238.90	59
Total	524.11	254.21	0.00	4238.90	178

Panel C: Acquirer Returns by PPS Group

Abnormal Returns	Mean Returns			Median Returns		
	Low PPS	High PPS		Low PPS	High PPS	
PPS	-0.235	0.475	*	-0.203	0.664	**
SPPS	-0.155	0.409		-0.203	0.664	*
OPPS	-0.323	0.461	*	-0.301	0.538	*

Table VII: Acquirer Stock Returns: Multivariate Analysis

This table shows regression results where the dependent variable is the cumulative abnormal stock returns (CARs) around acquisition announcement for the acquirers around a 3-day window. . All variables are one-year lagged and we include year fixed effects in all specifications. Robust standard errors are reported in parentheses and.*, **, *** denotes significant at 10 percent, 5 percent, and 1 percent, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Acquirer Characteristics							
SIZE	-0.306	-0.231	-0.249	-0.175	-0.475	-0.670***	-1.258***
	(0.216)	(0.216)	(0.199)	(0.282)	(0.309)	(0.210)	(0.434)
ROA	0.514	0.870	0.426	0.018	0.792	0.293	-0.067
	(0.753)	(0.765)	(0.859)	(0.981)	(0.839)	(0.817)	(1.282)
CASH	17.712*	15.310*	20.583**	17.485	11.231	-8.935	-23.193
	(9.106)	(8.658)	(9.568)	(18.180)	(10.222)	(15.914)	(34.849)
Deal Characteristics							
SIZE_RATIO	-1.059**	-1.051**	-0.872**	-1.006**	-1.324***	-1.325***	-1.240***
	(0.416)	(0.441)	(0.405)	(0.409)	(0.332)	(0.489)	(0.457)
D_STOCK	-0.317	-0.247	-0.400	-0.500	-0.086	0.291	0.464
	(0.506)	(0.519)	(0.512)	(0.565)	(0.569)	(0.486)	(0.720)
D_MERGER	-0.340	-0.494	-0.166	-0.752	-1.049	-0.370	-0.644
	(0.532)	(0.548)	(0.562)	(0.751)	(0.725)	(0.597)	(1.111)
OUTOFSTATE	0.309	0.389	0.332	0.311	0.132	0.941	1.841
	(0.629)	(0.627)	(0.619)	(0.906)	(0.772)	(0.679)	(1.460)
Pay-for-Performance							
PPS	0.416***			0.605***	0.508***	0.484***	0.798***
	(0.129)			(0.207)	(0.136)	(0.129)	(0.253)
SPPS		0.300**					
		(0.120)					
OPPS			0.252**				
			(0.118)				
Board Structure							
BSIZE				0.091			0.279*
				(0.130)			(0.169)
B_INDEP				1.355			-2.078
				(1.743)			(2.168)
D_CEO				-1.529			-2.075
				(1.004)			(1.358)
Anti-Takeover Provisions							
E Index					-0.442*		-0.209
					(0.227)		(0.353)
Institutional Ownership							
INST_SHR						6.327***	9.010**
						(1.935)	(4.496)
Const.	1.171	0.484	0.881	-0.387	3.840	2.344	5.377
	(2.328)	(2.290)	(2.361)	(3.716)	(3.609)	(2.537)	(5.468)
Obs.	117	117	117	105	98	101	76
R^2	0.278	0.264	0.262	.33	0.335	0.326	0.439

Table VIII: Acquirer Bond Returns: Univariate Analysis

This table summarizes information on abnormal bond returns for acquirers. Panel A shows the returns in percentage using different event window where month 0 is the event month. Panel B compares returns between acquires in the Low-PPS group (bottom one third) and acquirers in the High-PPS group (top one third). T-Tests (Signed rank tests) are performed to examine whether the mean(median) returns are significantly different between two groups. *, **, *** denotes significance at 10 percent, 5 percent, and 1 percent, respectively.

Panel A: Summary Statistic on Acquirer Returns

	Mean	Min	Max
(0, 1)	-0.326	-8.77	9.455
(-1, 1)	-0.449	-9.377	10.240
N	190		

Panel B: Acquirer Returns by PPS Group

Abnormal Returns	Mean Returns		Median Returns		
	Low PPS	High PPS	Low PPS	High PPS	
PPS	-0.566	0.173	-0.231	0.390	*
SPPS	-0.504	-0.471	-0.179	0.046	
OPPS	-0.191	-0.004	0.073	0.099	

Table IX: Acquirer Bond Returns: Multivariate Analysis

This table shows the estimation of the abnormal returns around acquisition announcements for bondholders. Abnormal bond returns are measured using a three-month windown (-1, 1) where month 0 is the event month. All variables are one-year lagged and we include year fixed effects in all specifications. Robust standard errors are reported in parentheses and.*, **, *** denotes significant at 10 percent, 5 percent, and 1 percent, respectively.

	(1)	(2)	(3)	(4)	(5)
Acquirer Characteristics					
SIZE	-2.022***	-2.075***	-1.289***	-1.967***	-2.393***
	(0.756)	(0.277)	(0.437)	(0.506)	(0.295)
RET_VOL	-0.530***	-0.076	-0.699***	-0.486*	-0.271***
	(0.056)	(0.055)	(0.062)	(0.264)	(0.044)
ROA	1.704	-4.338***	2.645	-0.320	-2.007***
	(2.596)	(0.699)	(2.620)	(4.946)	(0.285)
CASH	0.466**	0.214**	0.426*	0.509**	0.652***
	(0.199)	(0.091)	(0.246)	(0.212)	(0.146)
Deal Characteristics					
SIZE_RATIO	-12.449***	-5.754***	-13.861***	-11.613***	-9.588***
	(0.664)	(0.364)	(1.543)	(1.868)	(0.612)
D_STOCK	-6.734***	-6.528***	-6.116**	-6.655***	-7.950***
	(2.260)	(0.645)	(2.504)	(0.906)	(1.101)
D_MERGER	-4.623***	-2.525***	-4.670***	-5.548*	-3.130***
	(0.523)	(0.281)	(0.817)	(2.939)	(0.164)
OUTOFSTATE	-2.961***	-0.094	-3.541***	-0.787	-2.539***
	(0.066)	(0.360)	(0.310)	(1.826)	(0.367)
Pay-for-Performance					
PPS	1.503***			1.334***	1.750***
	(0.382)			(0.200)	(0.477)
SPPS		2.581***			
		(0.356)			
OPPS			0.648***		
			(0.150)		
Board Structure					
BSIZE				0.024	
				(0.379)	
B_INDEP				-5.589	
				(12.642)	
Anti-Takeover Provisions					
E Index					0.328
					(0.307)
Obs.	136	116	136	111	121
R^2	0.457	0.448	0.44	0.47	0.518

Table X: Changes of ROA

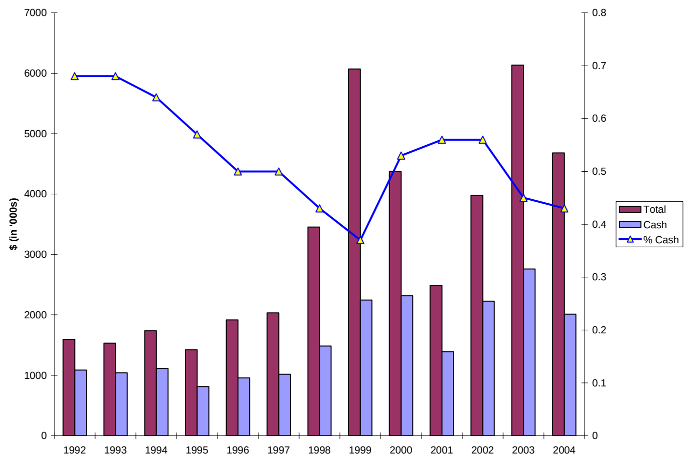
This table shows the analysis on changes of ROA around acquisitions between t-1 to t+8 quarters, where t is the event quarter. We measure the pre-acquisition ROA as the weighted average of the target 's and acquirer's ROA based on their market value. Robust standard errors are reported in parentheses and.*, **, *** denotes significant at 10 percent, 5 percent, and 1 percent, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Acquirer Characteristics						
SIZE	0.019	0.042^{**}	0.029^{***}	0.045^{***}	0.055^{***}	-0.003
	(0.013)	(0.019)	(0.009)	(0.013)	(0.002)	(0.036)
RET_VOL	-4.770^{***}	-4.542^{***}	-5.938^{***}	-6.703^{***}	-7.132^{***}	-2.832^{***}
	(1.032)	(1.505)	(0.721)	(0.768)	(0.185)	(0.969)
ROA	-0.445^{***}	-0.509^{***}	-0.426^{***}	-0.430^{***}	-0.506^{***}	-0.449^{***}
	(0.055)	(0.079)	(0.038)	(0.031)	(0.008)	(0.144)
CASH	-4.313^{***}	-4.263^{***}	-3.008^{***}	-5.069^{***}	-2.734^{***}	-0.143
	(0.453)	(0.708)	(0.294)	(0.348)	(0.076)	(1.544)
Deal Characteristics						
D_MERGER	0.061	0.028	0.127^{***}	-0.064	-0.003	0.046
	(0.039)	(0.055)	(0.028)	(0.060)	(0.007)	(0.083)
D_STOCK	0.016	-0.019	-0.028	-0.014	-0.031^{***}	-0.064
	(0.034)	(0.046)	(0.022)	(0.016)	(0.005)	(0.042)
SIZERATIO	0.418^{***}	0.399^{**}	0.539^{***}	0.272^{***}	0.081^{***}	-0.148
	(0.125)	(0.184)	(0.087)	(0.061)	(0.025)	(0.311)
OUTOFSTATE	0.006	0.023	-0.008	-0.067^{***}	-0.158^{***}	-0.170
	(0.039)	(0.056)	(0.027)	(0.021)	(0.005)	(0.121)
Pay-for-Performance						
PPS	0.067^{***}			0.137^{***}	0.046^{***}	0.049^{*}
	(0.016)			(0.012)	(0.003)	(0.024)
SPPS		0.026				
		(0.016)				
OPPS			0.043^{***}			
			(0.005)			
Board Structure						
BSIZE				-0.0002		0.013^{*}
				(0.002)		(0.008)
B_INDEP				-0.204^{***}		-0.518
				(0.063)		(0.328)
D_CEO				-0.304^{***}		0.252^{*}
				(0.035)		(0.140)
Anti-Takeover Provisions						
E Index					-0.044^{***}	-0.059^{*}
					(0.002)	(0.033)
Const.	0.203	0.278	0.173^{*}	0.016	0.891^{***}	0.822^{*}
	(0.140)	(0.197)	(0.098)	(0.118)	(0.030)	(0.495)
Obs.	57	57	57	41	46	42
R^2	0.924	0.847	0.96	0.994	0.999	0.515

Figure 1: CEO Compansation in BHCs

This figure shows the CEO compensation in bank holding companies over time. Panel A shows the cash and total compensation in dollar amounts and the percentage of cash compensation (over the total compensation) over time. Panel B presents the Stock PPS, Option PPS and Total PPS over time.

Panel A: Cash and Total Compensation



Panel B: Pay-for-Performance

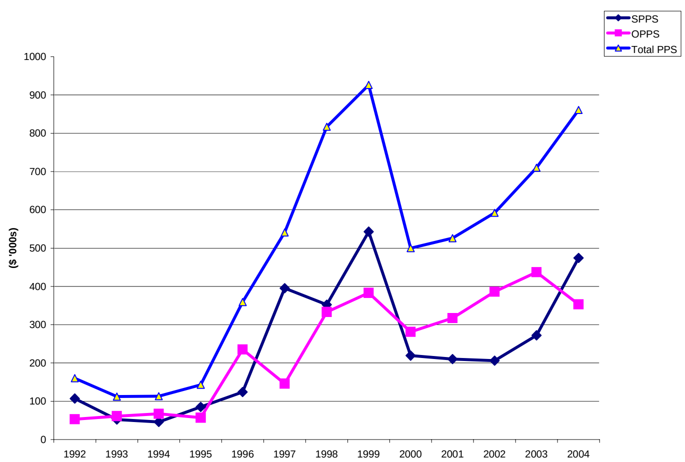


Figure 2: Histogram of Acquirer Stock Returns

This figure shows the cumulative abnormal stock returns (CARs) around the announcement. We use a three-day window, (-1, 1), and a five-day window, (-2, 2), where day 0 is the event date. We use CRSP value-weighted return as the market return and estimate market model parameters over the 200-day period from event day -220 to event day -21.

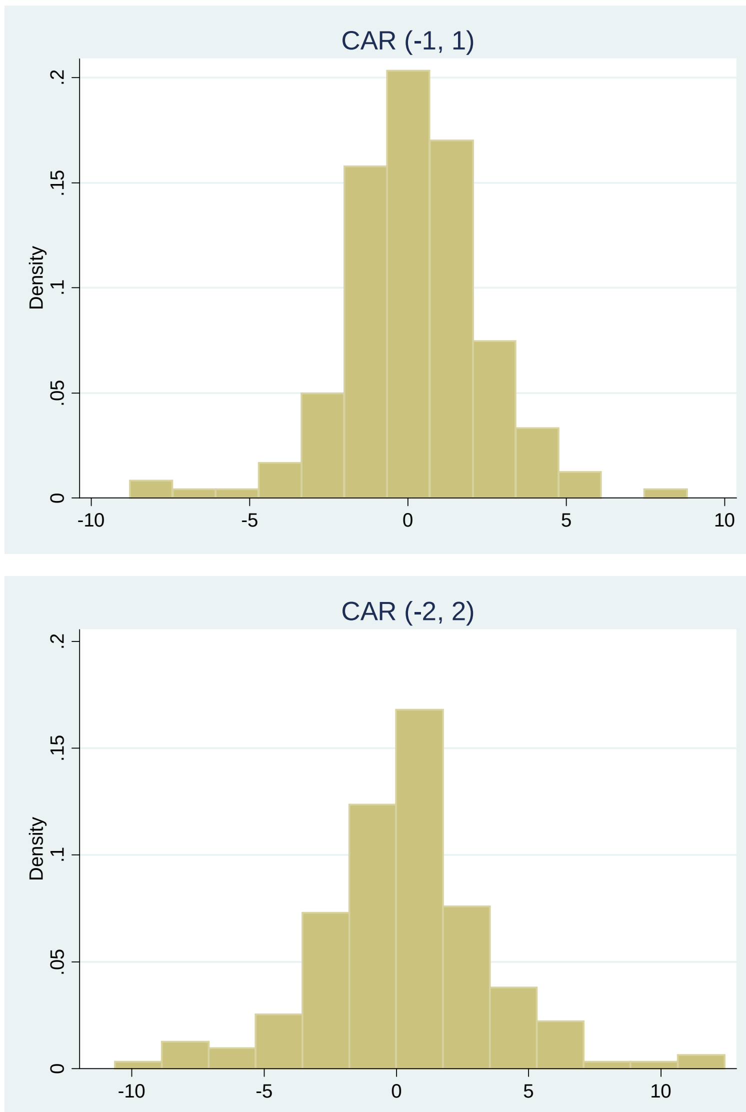


Figure 3: Acquirer Stock Returns by PPS Group

This figure shows the cumulative abnormal stock returns around the announcement for banks in different PPS groups. We use a three-day window, (-1, 1)where day 0 is the event date. We use CRSP value-weighted return as the market return and estimate market model parameters over the 200-day period from event day -220 to event day -21. We separate acquirers in three groups based on their total PPS so that each group has one third of the observation. Low-PPS group has acquires in the bottom one third and High-PPS group has acquirers in the top one third.

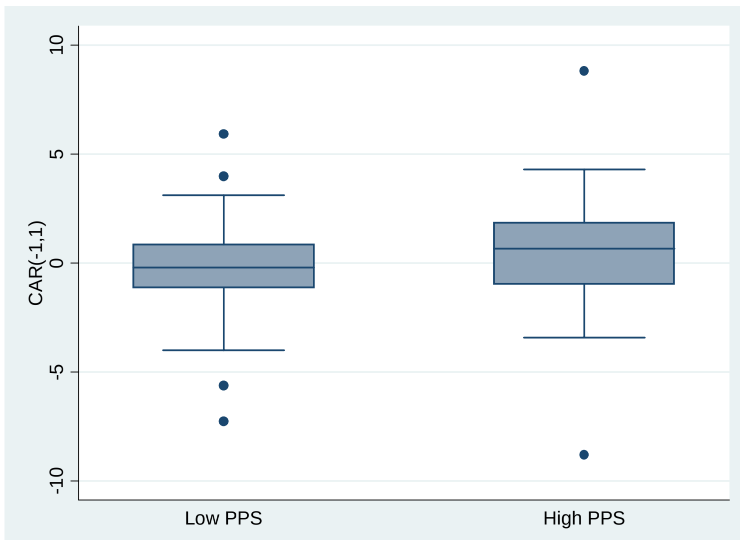


Figure 4: Histogram of Acquirer Bond Returns

This figure shows the habnormal bond returns around the annoucement. We use a three-month window, (-1, 1) and a two-month window, (-1, 0), where month 0 is the event date. We measure bondholder abnormal returns using the LBBD database and follow Maxwell and Stephens' (2003) approach.

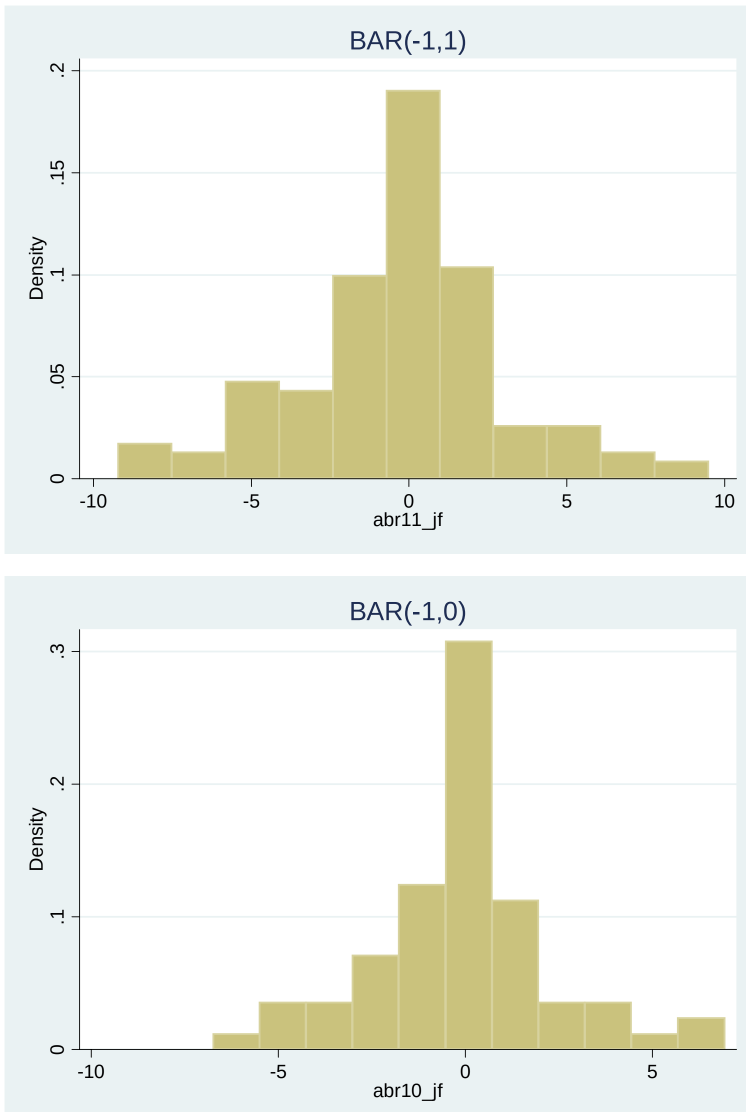
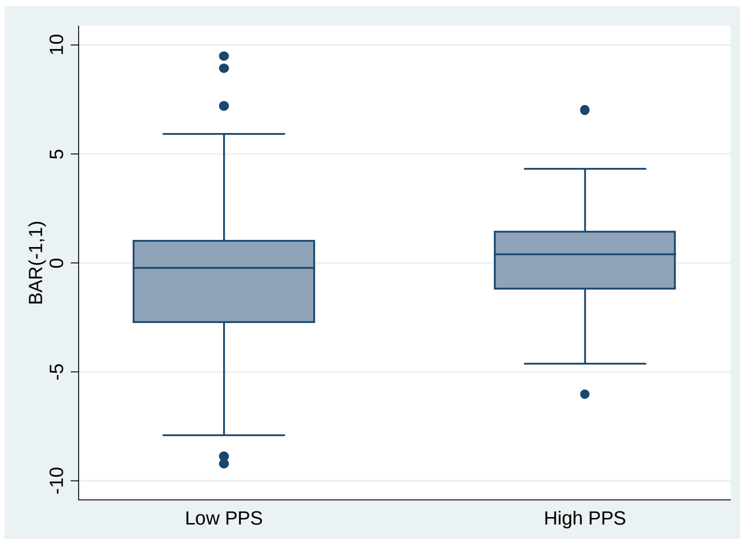


Figure 5: Acquirer Bond Returns by PPS Group

This figure shows the abnormal bond returns around the announcement for banks in different PPS groups. We use a three-month window, (-1, 1), where day 0 is the event date. We measure bondholder abnormal returns using the LBBD database and follow Maxwell and Stephens' (2003) approach.. We separate acquirers in three groups based on their total PPS so that each group has one third of the observation. Low-PPS group has acquires in the bottom one third and High-PPS group has acquirers in the top one third.



References

[1] Adams R., Mehran, H., 2003. Is Corporate Governance Different for Bank Holding Companies? Federal Reserve Bank of New York Economic Policy Review, Vol. 9, No. 1: 123-142.

[2] Adams, R. B., Mehran, H., 2002. Board Structure and Banking bank Performance. Unpublished working paper, Federal Reserve Bank of New York.

[3] Asquith, P., Bruner, R. and D. Mullins, Jr., 1983, The gains to bidding firms from merger, Journal of Financial Economics 11, 121-139.

[4] Bebchuk, L., Cohen, A., 2005. The costs of entrenched boards. Journal of Financial Economics 78, 409-33.

[5] Bebchuk, L., Cohen, A., Ferrell, A., 2004. What matters in corporate governance? Unpublished working paper, Harvard Law School.

[6] Becher, D. A., 2000. The valuation effects of bank mergers. Journal of Corporate Finance, July, 189-214.

[7] Belkhir, M., 2004. Board of Directors Size and Performance in Banking, Unpublished working paper, Université d'Orléans.

[8] Berger, Allen N., 1997. The efficiency effects of bank mergers and acquisitions: A preliminary look at the 1990s data, in Y. Amihud and G. Miller eds.: Mergers of Financial Institutions (Homewood, Ill: Business One-Irwin).

[9] Berger, A.N., Humphrey, D.B., 1992. Megamergers in banking and the use of cost efficiency as an antitrust defense. Antitrust Bulletin 37, 541-600.

[10] Bliss, R. T., Rosen, R. J., 2001. CEO compensation and bank mergers. Journal of Financial Economics 61, 107-138.

[11] Bostic, R., Mehran, H. , Paulson, A. and Saidenberg, M., 2002. Regulatory Incentives and Consolidation: The Case of Commercial Bank Mergers and the Community Reinvestment Act. FRB of Chicago Working Paper No. WP-2002-06.

[12] Brickley, J., Coles, J., Terry, R.L., 1994. Outside directors and the adoption of poison pills. Journal of Financial Economics 35, 371-390.

[13] Brickley, J. and C. James, 1987. The Takeover Market, Corporate Board Composition, and Ownership Structure: The Case of Banking, Journal of Law and Economics, Vol. 30, April, 161-180.

[14] Core, J., Guay, W., 1999. The use of equity grants to manage optimal equity incentive levels. Journal of Accounting and Economics 28, 151–184.

[15] Cornett, M. M., and Tehranian, H., 1992. Changes in Corporate Performance Associated with Bank Acquisitions. Journal of Financial Economics. 31, 211-234.

[16] Datta, S., Iskandar-Datta, M., Raman, K., 2001, Executive Compensation and Corporate Acquisition Decisions, Journal of Finance, vol. 56, 2299-2336.

[17] Falato, Antonio, 2007, Superstars or Superlemons? Top Executive Pay and Corporate Acquisitions, Working Paper, Federal Reserve Board.

[18] Gompers, P., Ishii, J., Metrick, A., 2003. Corporate governance and equity prices. Quarterly Journal of Economics 118, 107-155.

[19] Harford, J., Li, K., 2007. Decoupling CEO wealth and firm performance: The case of acquiring CEOs. Journal of Finance, forthcoming.

[20] Hartzell, J., Starks, L., 2003. Institutional investors and executive compensation. Journal of Finance 58, 2351–2374.

[21] Houston, J. F., Ryngaert, M., 1994. The overall gains from large bank mergers. Journal of Banking and Finance 18, 1155-1176

[22] Houston, J., James, C., and M. Ryngaert, 2001. Where Do Merger Gains Come From?: Bank Mergers from the Perspective of Insiders and Outsiders. Journal of Financial Economics 60, 285-331.

[23] James, C., Wier, P., 1987. Returns to Acquirers and Competition in the Acquisition Market: The Case of Banking. Journal of Political Economy 31, 355-370.

[24] Jensen, M., 1993. The modern industrial revolution, exit, and the failure of internal control systems. Journal of Finance 48, 831-880.

[25] Jensen, M., 1986. Agency Costs of Free Cash Flow: Corporate Finance and Takeovers. American Economic Review 76, 323-329.

[26] Jensen, M.,. Meckling, W., 1976. Theory of the bank: Managerial Behavior, Agency Costs, and Ownership Structure. Journal of Financial Economics 3, 4, 305- 360.

[27] Jensen, M., Murphy, K., and Wruck, E., 2004. Remuneration: Where We've Been, How We Got to Here, What are the Problems, and How to Fix Them,' unpublished manuscript.

[28] Jovanovic, B., and P. Rousseau, 2002. The Q-Theory of Mergers, American Economic Review 92, 198-204.

[29] John, K., Qian Y., 2003. Incentive Features in CEO Compensation in the Banking Industry. Economic Policy Review-Federal Reserve Bank of New York, 9(1), 109-121.

[30] John, K., Qian Y., Mehran, H., 2006. Subordinated Debt and Incentive Features of CEO Compensation in the Banking Industry, working paper.

[31] Lipton, M., Lorsch, J., 1992. A modest proposal for improved corporate governance. Business Lawyer 48, 59- 77.

[32] Loughran, T., and J. Ritter, 1997.The operating performance of firms conducting seasoned equity offerings, Journal of Finance 52, 1823-50.

[33] Macey, J. R., O'Hara, M., 2003. The Corporate Governance of Banks. Federal Reserve Bank of New York Economic Policy 9, 91-107.

[34] Masulis, R. W., Wang, C., Fei, X., 2007. Corporate Governance and Acquirer Returns. Forthcoming, Journal of Finance

[35] Maxwell, W., and C. Stephens, 2003. The Wealth Effects of Repurchases on Bondholders, Journal of Finance, 58, April 2003: 895-919.

[36] McConnell, J., and Servaes, H., 1990. Additional Evidence on Equity Ownership and Corporate Value, Journal of Financial Economics, 27, 595-612.

[37] Mehran, H. 1995. Executive Compensation Structure, Ownership, and bank Performance, Journal of Financial Economics 38, 163-184.

[38] Moeller, S., F. Schlingemann and R. Stulz, 2004. Firm Size and Gains from Acquisitions, Journal of Financial Economics 73, 201- 228

[39] Morck, R., Shleifer, A., and Vishny, R., 1988. Management Ownership and Market Valuation: An Empirical Analysis', Journal of Financial Economics, 20, 293-315.

[40] Parrino, R., R. Sias, and L. Starks, 2003. Voting with their feet: institutional ownership changes around forced CEO turnover. Journal of Financial Economics 68, 3-46.

[41] Penas, M. F., Unal, H., 2004. Gains in Bank Mergers: Evidence from the Bond Market. Journal of Financial Economics 74(1), 149-179.

[42] Piloff, S.J., 1996. Performance changes and shareholder wealth creation associated with mergers of publicly traded banking institutions, Journal of Money, Credit, and Banking, 28, August, 294-310.

[43] Prager, R. A., Hannan, T. H., 1998. Do Substantial Horizontal Mergers Generate Significant Price Effects? Evidence from the Banking Industry. Journal of Industrial Economics 46, 433-52.

[44] Rajgopal, S., Venkatachalam, M., 1997. The role of institutional investors in corporate governance: An empirical investigation. Unpublished working paper. Duke University.

[45] Rhoades, S. A., 1994. A summary of merger performance studies in banking, 1980-1993, and an assessment of the operating performance and event study methodologies. Staff Study 167 – Board of Governors of the Federal Reserve System.

[46] Rivard, R.J. and C.R. Thomas, 1997. The Effect of Interstate Banking on Large Bank Holding Company Profitability and Risk. Journal of Economics and Business 49, 61-76.

[47] Shleifer, A., Vishny, R. W., 1986. Large shareholders and corporate control. Journal of Political Economy 94, 461-488.

[48] Smith, M. 1996, "Shareholder activism by institutional investors: Evidence from CalPEPRS", Journal of Finance 51, 227 - 252

[49] Spindt, P. A., and V. Tarhan, 1992. Are There Synergies in Bank Mergers?, Working paper, Tulane University.

[50] Watts, R. L., 1988. Discussion of financial reporting standards, agency costs, and shareholder intervention. Journal of Accounting Literature 7,125-132.

[51] Warga, A., Welch, I., 1993. Bondholder losses in leveraged buyouts. Review of Financial Studies 6, 959-982.

[52] Weisbach, M. S, 1988. Outside Directors and CEO Turnover, Journal of Financial Economics, 20, 431-460.

[53] Yermack, D., 1996. Higher market valuation of companies a small board of directors. Journal of Financial Economics 40, 185-202.

Appendix: Description of Variables

Firm Specific Variables (from Compustat, Compustat Bank, CRSP and FDIC Call Reports)

- Total Assets: The total asset size of a bank
- Size: The natural logarithm of Total Assets
- MVE: Market value of equity - number of shares outstanding multiplied by the average share price
- Ret_Vol:.The annualized standard deviation based on the monthly stock returns
- Ret: The annualized stock return, calculated using monthly stock returns
- ROA The return on assets, defined as the net income divided by the total assets
- ROE The return on equity, defined as the net income divided by total shareholder's equity
- RE Ratio The ratio of real estate loans to total loans for the bank
- PRV_Ratio The total loan loss provision divided by the total loans
- Cash: The cash holdings divided by total assets

Deal Specific Variables (from SDC Plantinum)

- Acq. MV: Acquirer's market value of equity
- AAsset: Acquirer asset size
- TAsset: Target asset size
- Value: The deal value
- D_Merger: An indicator variable that equals to one if the bank has participated in acquisition before and zero otherwise
- D_Stock: An indicator variable that equals to one if more than 75% of the deal was funded with stock and zero otherwise
- D_Cash: An indicator variable that equals to one if more than 75% of the deal was funded with cash and zero otherwise
- OutofState: An indicator variable that equal to one if the acquisition involves acquirer and target from different states
- Size_Ratio The ratio of the deal value over the acquirer's market value of equity

Compensation Variables (from Excucomp and Proxy Statements)

- SPPS: The log the pay-performance sensitivity based on stock grants
- OPPS: The log of the pay-performance sensitivity based on option grants
- PPS: The log of the sum of PPS Stock and PPS Options
- Cash Comp: The amount of cash compensation in $millions

- Total Comp: The total amount of compensation in $millions.
- Percentage in Cash: The ratio of cash compensation over the total compensation.

Board Characteristics (from IRRC Director Database and Proxy Statements)

- Bsize: The size of board
- Indep: The percentage of independent directors
- D_CEO: An indicator variable that is equal to one if the CEO aslo serves as the Chair of the Board of Directors

Anti-takeover Provisions (from IRRC)

- GIndex: The governance index based on Gompers, Ishii, and Metrick (2002).
- EIndex The entrenchment index based on Bebchuk, Cohen and Ferrell (2004)
- CBoard: An indicator variable that equals to one if the bank has a staggered board, and zero otherwise.

Ownership (from 13F)

- INST SHR: The percentage of shares owned by institutions.

Does Patience Pay? Empirical Testing of the Option to Delay Accepting a Tender Offer in the U.S. Banking Sector[1]

RACHEL A. CAMPBELL & ROMAN KRAUSSL

We examine the empirical predictions of a real option-pricing model using a large sample of data on mergers and acquisitions in the U.S. banking sector. We provide estimates for the option value that the target bank has in waiting for a higher bid instead of accepting an initial tender offer. We find empirical support for a model that estimates the value of an option to wait in accepting an initial tender offer. Market prices reflect a premium for the option to wait to accept an offer that has a mean value of almost 12.5% for a sample of 424 mergers and acquisitions between 1997 and 2005 in the U.S. banking industry. Regression analysis reveals that the option price is related to both the price to book market and the free cash flow of target banks. We conclude that it is certainly in the shareholders best interest if subsequent offers are awaited.

Keywords: Option-pricing model, Mergers and acquisitions, U.S. banking industry

JEL Classification: G34, C10.

---

[1] All errors pertain to the authors. Roman Kraussl is at the Vrije University in Amsterdam, The Netherlands. Corresponding author: Dr. R. A. J. Campbell, is at Maastricht University and Erasmus University Rotterdam. Adress for correspondence :Department, Faculty of Economics and Business Administration, Maastricht University, Tongersestraat 53, 6211 LM Maastricht, the Netherlands. Tel: +31433884827. Fax: +31 433884875. Email: r.campbell@finance.unimaas.nl.
The authors would like to thank Jan Quadvlieg and Thorsten Kaiser for their help.

I. Introduction

Numerous empirical studies, including Moeller, Schlingemann and Stultz (2004), and Fuller, Netter and Stegemoller (2002) have found that acquiring companies tend to overpay for acquisitions. One possible explanation of the empirical results is that managers of bidding firms may suffer from hubris (see Roll (1986)). Another explanation is the free cash flow hypothesis. Jensen (1986) argues that empire-building managements would rather make an acquisition than increase payout to shareholders. Such managerial overconfidence during takeovers is confirmed in more recent papers by Heaton (2002) and Malmendier and Tate (2005).

Other theories expect takeover attempts to be value destroying, such as Jensen's (1986) agency cost theory and the theory of managerial entrenchment established by Shleifer and Vishny (1989). Jensen's theory is related to excess free cash flows in a company, as for example in the oil business in the 1970s. Whenever there are less investment opportunities than available free cash, often this excess capital is used for takeovers, which leads to value-reducing diversification decisions. Shleifer and Vishny's theory implies empire building by managers. Here, takeover transactions are pursued to improve the management's position by increasing the managers' value to the shareholders, without actually enhancing the value to the shareholders themselves (Weston, Mitchell & Mulherin, 2004).

There is a also an extensive literature on the management resistance to takeover, including Baron (1983), and Schwert (2000). The management of the target firm in an acquisition may turn down a tender offer for a number of reasons: It wants to retain control of the company;

the offer may not reflect the true value of the firm; or the offer may reflect the true value but management might be waiting for a better offer. The idea that management does not accept a tender offer and recommends shareholders to reject the offer, in anticipation of a better offer, is also reflected in the management being aware of the value that the option to delay accepting a tender offer has. Schwert (2000) highlights that if the goal of the target firm from taking a hostile stance to takeover is to bargain for a better offer, this can lead to a higher premium paid to target shareholders. Hard bargaining in pursuit of a higher premium potentially leads to a lower success rate. By understanding which factors, if any, have the highest explanatory power in determining the value premium for the option to delay accepting the offer, can have important implications for management's strategy in deciding to prolong the takeover bid. Just how effective is this strategy to the target company, and what is the value of this strategy to the target company's shareholders, are 2 of the important issues which the real option valuation model is able to answer.

In this paper we answer these questions by bringing together these two strands of the literature on the tendency for managers of the acquiring firm to overpay for an acquisition and the target management's resistance to takeover. There is a large literature in corporate finance that studies the information and value effects of mergers. There has also been extensive testing of option-pricing models for financial assets; however, virtually to our knowledge no research has been conducted on the empirical applications of option-based valuations models for tender offers. We value this amount by using a real option methodology to empirically value the option to delay accepting a tender offer. These results have important implications for the management of both target and bidder banks in their decisions for merger and acquisition behavior.

This research is the first to examine the empirical prediction of a real option pricing model using a large sample of data of 424 mergers and acquisitions between 1997 and 2005 in the U.S. banking industry. We argue that if firm managers suffer from empire building and hubris, they are likely to put in a higher second offer for the acquisition if the tender offer is rejected. This gives the target firm a valuable option to wait in accepting a tender offer.

Our empirical results show that market prices reflect a premium for the option to wait to accept an offer that has a mean value of almost 12.5% for a sample of 424 mergers and acquisitions between 1997 and 2005 in the U.S. banking industry. The synergy value to the acquiring bank is therefore estimated at am eighth of the market capitalization of the target bank. Regression analysis reveals that the option price is related to the free cash flows of the targets among others. We conclude that it is certainly in the shareholders best interest if subsequent offers are awaited; hence patience on behalf of target banks pays.

The remainder of the paper is organized as follows: In Section II we present the methodology and data. We define the option that will be valued by specifying the parameters needed for valuing a real option, outline the option valuation methodology adopted and present the sample selection. Section III discusses the empirical results. Conclusions are presented in Section IV.

II. Methodology and Data

II.1 The Option to Delay Accepting a Tender Offer

When a tender offer is presented at time t to the shareholders of a company, they receive an offer price P_t to sell their shares currently worth S_t to the acquirer, resulting in a gain of P_t - S_t. The shareholders may accept this offer immediately or wait with their offer of acceptance until a date T. This final date is usually specified by the acquirer but may also be determined by the applicable legislation concerning mergers and acquisitions. The shareholders in the target company therefore have the option to sell their shares now for the gain specified above or wait until date T is reached and sell their shares later for S_T.

In general, shareholders would accept the offer straight away if P_t - S_t is higher than the present value of receiving $P_t - S_T$ at time T, discounting at the risk-free rate. However, by receiving the offer P_t which elapses at time T, shareholders are presented with an American call option to wait for a higher, second, third or a final offer P_2, P_3, or P_T , which is larger than P_t and therefore represents a gain of P_T - $S_T > P_t - S_T$ or an incremental gain of $P_t - P_T$. By waiting for such an offer, the shareholders run the risk that the acquirer withdraws his bid and they receive nothing or receive a lower offer with $P_T < P_t$. Accordingly, the option to wait that is valued here has the possible payoffs of

$$\max[\, PV(P_T - S_T\ ) \,;\, P_t - S_T\ )].$$

II.2 Option Value Determinants

Current Value of the Underlying Asset (V)

The value of the underlying asset is the gain the shareholders make by accepting a tender offer and selling their shares at a premium over the market value of the shares before the announcement was made. It is therefore dependent on the difference between the final offer P_T and the target companies share price S_t , before any bid was received. This implies that $V = P_T - S_t$.

Stock price volatility (σ^2)

The price volatility of the target companies share price is a crucial element in the real option model. In our framework the stock price variance can be estimated directly, t is therefore analogous to determining the variance when valuing a regular financial option on a stock[2].

Exercise price (X)

The exercise price in the real option model is the investment that must be made in order to acquire the underlying asset. In this case if the target shareholders accept the second offer they cannot receive the premium from the first offer so by tendering their shares for a gain of V they lose $P_t – S_t$. It is important to note that X is not equal to S, because if the bid is withdrawn ($P_T = 0$) and in the case that $P_T < P_t$, the shareholders would actually lose a part of the gain they would have made if they had accepted the offer of $P_t – S_t$. The price that has to be paid to exercise the option is therefore given as $X = P_t - S_t$.

---

[2] Davis (1998), Luehrman (1998) and Damodaran (1999) point out that the variance is the most difficult part to determine in real option valuation when it cannot be observed directly, and estimation is possible but difficult and imprecise. Alternatively, Fabozzi (2005) uses a backward approach by comparing similar options with known option values to find the implied volatility.

Time to expiration (T)

The time to maturity of an American call option is the date until which the option's holder has the right to acquire the underlying asset. For valuing the option to wait, time T can be determined by a multiple of variables, such as the acquirer setting a deadline or legislation specifying a time until which the takeover process has to be completed. It is even possible that the option cannot expire in the case when a tender offered has been declared unconditional after a certain threshold and the acquisition of shares has been exceeded. For consistency we determine the time, T, by the date when the transaction is successfully completed; or in the case when the offer is withdrawn, at the time when the transaction is aborted.

Discount rates (r)

As is standard in the real option pricing literature risk neutral valuation is adopted, see Fernández (2002)[3]. To be able to apply risk-neutral valuation, discount rates equal to the respective risk-free rates over the life of the option must be chosen. In general, the higher the interest rate, the larger the call option value, because higher interest rates reduce the present value of the strike price. The risk-free rate is chosen so that it corresponds to the length of the life of the option.

Dividend payout (δ)

[3] Standard financial options are priced using the risk-free rate, resting on risk-neutral valuation made possible by a no-arbitrage argument since the underlying asset is traded and so the payoff of the option can be replicated. In many cases it is possible to use risk-neutral valuation even though the underlying asset is not traded, Constantinides (1978) and Harrison and Kreps, (1979); otherwise determining an appropriate discount rate is difficult, imprecise and very time-consuming.

The presence of discrete dividends or a continuous dividend yield on the underlying stock price decreases the value of the option and in some cases makes it optimal to exercise the option early (Hull, 2002). Dividends represent a cash-outflow of the underlying asset that cannot be captured anymore by the holder of the option and the value of the option decreases. In real option analysis the dividend yield is usually labeled the cost of delay but the effect remains the same.

II.2 Option Valuation Methodology

II.2.1 Simulating vs. Approximating Stochastic Processes

When there is no analytical solution for valuing an option, or if an analytic solution can not be applied, there are two other main approaches for valuation. Either direct simulation of the stochastic processes determining the evolution of the price of the underlying asset, or, by approximating the stochastic processes by partial differential equations. Monte Carlo simulation and lattice methods belong to the first category whereas methods of numerical integration and explicit or implicit finite difference schemes belong to the second category.

Since the option to be analyzed here is American, Monte Carlo simulation should not be used (Trigeorgis, 1996). In our framework it is more appropriate to employ a finite-difference method or a lattice approach. Geske and Shastri (1985) provide a detailed comparison of the approaches. They compare explicit and implicit finite difference methods, three types of binomial methods and the analytic Black-Scholes method for computing the values of American call and put options with and without dividends. They compare the methods along two dimensions. The method’s precision is measured by looking at the convergence of the approximation errors and stability. Efficiency of the method is measured by computing the costs associated with employing the methods. The results by Geske and Shastri (1985) indicate that the binomial approach, the implicit finite difference and the log transformed explicit finite difference method give the best results.

However, each method is especially suitable for valuing a particular type of option. Geske and Shastri (1985) recommend the binomial method for options where no (discrete) cash-outflow in the underlying asset is present and argue that it is still reasonably accurate when assuming a continuous cash-outflow (dividend yield or "cost of delay"). The explicit finite difference method has some stability problems but when transformed logarithmically is more efficient than the implicit finite difference method[4]. Their results furthermore imply that finite-difference schemes can be equivalent to a dynamic-programming-type process such as used in a lattice approach.

Following their approach, we value the option to wait using the lattice approach. A lattice approach is as precise as using a finite-difference technique but is more pragmatic since it does not involve specifying the partial differential equations to describe the stochastic process of the underlying asset.

II.2.2 Lattice Approaches

The binomial lattice approach for option valuation was first presented by Cox, Ross and Rubinstein (1979). Risk-neutral valuation is used in all lattice approaches, whether binomial

[4] See Geske and Shastri (1985). Researchers computing a smaller number of option values may prefer the binomial approximation, while practitioners in the business of computing a larger number of option values will generally find that the finite difference approximations are more efficient.

or trinomial, with the option value being determined as the discounted value of the expected option payoff. Lattice approaches determine the value of the option by constructing a multinomial tree showing all possible states of the price of the underlying asset over time. These values are obtained by using transition probabilities that determine the magnitude of the state variable at each point in time. Those time points have to be selected so that the tree converges in a manner that is accurate, stable and efficient (Trigeorgis, 1996).

In principle, accuracy and stability can be obtained by increasing the time points until maturity while efficiency can be obtained by reducing the steps. Therefore, a balance has to be chosen between obtaining accurate results and saving computing time. Convergence is necessary since each step in the tree actually can be seen as a model of its own. Hence, the sequence of probabilities must converge to a limiting probability measure (Bingham and Kiesel, 2004).

Starting at the end of the multinomial tree, corresponding to the expiration of the option, the value of the option is calculated according to whether its expected payoff is positive or 0. Using the possible option values, the values one period before expiration can be calculated. Successively all possible option values over time are calculated in a backward manner until the starting point of the binomial tree is reached and the current option value is calculated.

All lattice approaches work according to this basic structure but many changes have been proposed to incorporate multiple options, discrete cash-outflows, improve computational accuracy or incorporate more than one state variable. For instance, Hull and White (1988) propose a control variate approach to be used with lattice approaches in order to improve computational efficiency. The control variate approach reduces variance by reducing the dimensions needed in the calculation and therefore reduces estimation errors by about 50%. It requires the existence of a similar option whose value is already known, such as, for example, a European option with exactly the same parameters. Although it provides a significant improvement over standard binomial models the control variate technique cannot be used in our framework since no similar option exists.

Another extension of the lattice approach by Cox, Ross and Rubinstein (1979) is presented by Boyle (1988) who develops a method for valuing American options where two state variables need to be considered. This method also cannot be applied here as there is only one underlying asset and hence only one state variable. As mentioned by Geske and Shastri (1985) methods for incorporating discrete cash-outflows can be disregarded as they make the calculation far less efficient but only improve the results marginally. Therefore a continuous dividend yield will be used for valuing the option to wait. The lattice approach that seems most suitable for valuing the option to wait with the parameters specified above is the one developed by Trigeorgis (1996), which will be outlined in the next section.

II.2.3 Calculation

The algorithm used to value the option to wait is based on the log-transformed binomial model presented by Trigeorgis (1996). The value of V is assumed to follow the diffusion Wiener process given by

$$\frac{dV}{V} = \alpha dt + \sigma dz \, . \tag{1}$$

In this equation, α is the instantaneous expected return on V, σ is the instantaneous standard deviation and z is a standard Wiener process. For a small time interval this implies that the natural logarithm of *V* follows an arithmetic Brownian motion in continuous time or a Markov random walk in discrete time.[5] Assuming risk-neutrality and thereby implying that $\alpha = r$ means increments in lnV are independently, identically and normally distributed.

By expressing time in units of variance (in the form of $\sigma^2 T/N$) increments in lnV become normally distributed, having a mean of $\mu(\sigma^2 T/N)$ and a variance of $\sigma^2 T/N$, where the drift parameter μ is defined as $r/\sigma^2-0.5$. We also include the dividend yield which reduced the drift parameter by dividend rate *d*. To be used in a multinomial valuation model, this continuous diffusion process must be approximated by a discrete process. This is done by dividing the time to maturity into *N* subintervals of equal length.

Calculations are made for the subintervals, N, equal to 50, 100, 250, 500 and 1,000 subintervals. Within these discrete subintervals the value of the underlying asset follows a Markov random walk, increasing by an amount $\Delta lnV = H$ with probability *P* and decreasing by an amount $\Delta lnV = -H$ with probability 1-*P*. This implies that the discrete process measures the value of the underlying asset *V* as lnV expressed in units of length *H*, and measures time in units of variance *k*. This discrete process has a mean, $2PH – H$, and a variance, $H^2 - (2PH-H)^2$.

[5] A Markov random walk is a special type of a discrete-time Markov chain and describes a process which changes states at discrete time steps and where the probability of the next stage only depends on the current state, disregarding the past states (see Bingham and Kiesel, 2004).

For reasons of consistency, mean and variance of the continuous and the discrete diffusion Wiener process must be equal. Therefore, the probability of an increase H in V for one k, P must equal $0.5(1+ \mu k/H)$ and H must equal $[k+(\mu k)^2]^{-0.5}$ conditional on H being larger than μk, where k is defined as $\sigma^2 T/N$.

To be applicable in our framework, the option parameters specified in Section III must be transformed to achieve consistency between the continuous diffusion and the discrete time processes outlined above. As the previous paragraph described, these intermediate variables are defined as k (time step), μ (drift), H (state step), and P (probability).

The next step consists of calculating the terminal boundary values at the last day of the option's life. Hence, for each state i at $j = T$ the following formula is used to calculate $V_{(i)}$:

$$V_{(i)} = e^{V_{(0,0)} + i*H} \quad . \tag{2}$$

The option payoff at node $(i\ ;\ T)$ is equal to the difference between $V_{(i,T)}$ and the corresponding strike price $X_{(i,T)}$, which is defined as:

$$X_{(0,0)}\left[1+\left(tr*k/\sigma^2\right)\right] . \tag{3}$$

The final step consists of a backward iterative process which is used to calculate the option's value at the announcement day of the bid. Starting at the terminal values at $j = T$ the values of the option for the preceding node $j = T$-1 are calculated using the information for two states i present at $j = T$. This implies that according to P, the value of the option at nodes with $j = N$ is equal to the higher of the two values at the two possible states, at $j = N$ discounted for one period at the risk-free rate, equal to equation (4) or the payoff from early exercise:

$$R_{(i,\,j-1)} = e^{-rk/\sigma^2}\left[PR_{(i+1,\,j)} + (1-P)R_{(i-1,\,j)}\right]. \qquad (4)$$

II.3 Data

II.3.1 Sample Selection

Our primary data set consists of a large number of transactions for mergers and acquisitions in the U.S. banking industry over the period 1997 to 2005 retrieved from Thompson Financial's SDC Platinum. A merger occurs when an acquiring bank and a target bank agree to combine under legal procedures in the countries in which the merger participants are incorporated. Generally, mergers are friendly and require the approval of both management teams and management boards before stockholders vote. In contrast, inter-firm tender offers are generally of unfriendly nature, as the target management is by-passed by asking the stockholders to sell their stock or voting rights. Both kinds of transactions can be referred to as takeovers or acquisitions, which will be the terms that are used in the following.

In order to obtain any evidence on the value of an option to delay a tender offer it is necessary that we are meticulous in constructing the sample so that other influences can be controlled. The original data of mergers and acquisitions was reduced to a sample of 424 deals in the U.S. banking sector, which fulfilled the following 8 necessary conditions:

1. The deal type was a merger or acquisition.
2. Target and acquiring were both US based.
3. Target and acquirer belong to the banking sector with respective SIC codes: 6000, 6081, 6029, 6082, 6021, 6712 and 6022.
4. Target and acquirer were both publicly listed companies.
5. The sub-deal type must have been one or more of the following: contested bid, hostile bid, initially hostile bid became recommended bid, public takeover, recommended bid, initially recommended bid became hostile and/or unsolicited bid.
6. The deal status must have either been completed or withdrawn.
7. To avoid the issue of using equity as a signaling effect, we focus on cash transactions only [6].
8. The final stake the acquirer has in the target after completion of the transaction must be more than 50.1% to include only transactions where a change in control takes place.

II.3.2 Variables

Besides a synopsis and the general information gathered on the targets and acquiring banks, the announcement and closing dates of the deals were obtained in order to calculate the time to maturity. Furthermore, the initial offer and the final offer were compared to the target stock price one day prior to the announcement date. Also, the dividend yield one day prior to the announcement date was applied to avoid any announcement effects on the dividend yield.

[6] Travlos (1987) points out that those firms with poor returns generally pay for acquisitions with equity.

Additional data, necessary to determine the option value, e.g. dividend yield and risk free rates, was extracted from Thompson Financial's Datastream. We employ the one month US interbank rate. For all rates, averages over the respective period from the announcement until the conclusion of the deal were calculated. For the regression analyses that were conducted in order to test factors that could potentially influence the option premium, all variables used were key item variables extracted from Thompson Financial's Datastream. These were Cash Flow per Share, Market Capitalisation, Common Equity and Debt to Equity, Book Value per Share and Price to Book Value Ratios respectively.

II.3.3 Descriptive Statistics

Table 1 shows the descriptive statistics for all parameters that are needed to determine the option values for the full dataset of 424 observations. The necessary stock prices are given in absolute and in standardised form. For simplicity, all absolute numbers are given in US dollars. N is the randomly chosen amount of subintervals into which the time to maturity is subdivided for the calculation model.

Insert Table 1

III Empirical Results

By applying the model to the described data set, we obtain option premiums that are realised by delaying the decision to accept a tender offer. Table 2 presents the summary statistics for the option premium of the data set, which relies on 250 nodes. Based on a total sample of 424 bank acquisitions between 1997 and 2005, we obtain an average option premium of 12.45%.

Insert Table 2

We find that this average option premium of 12.45% is stable from year to year. Although the Group of Ten (2001) finds that the amount of takeovers and the takeover values constantly increased between 1997 and 2001, this research based on various sub samples finds that the average annual option premium does not vary significantly during the period of observation. Interesting is also the comparison between mean and median values. The median is significantly lower than the mean, which suggests that outliers exist that pushes the average premium upwards.

Moreover, in 60 observations information about competing bidders was revealed. Without competition of other potential acquirers, the option premium was at 8% significantly lower than the average. Table 2 indicates that in the case that competitors entered the bidding process, the findings suggest an option premium of 18.43%, which is clearly much greater than the average premium paid. This is in line with previous studies and the winner's curse theory first established by Rock (1986). As more bidders enter the process, the higher the bids with the winner probably paying too high a price for the takeover.

The exercise price is already corrected for the time value of money due to the risk-free discount rate. Thus, a potential premium as it is determined by this research is instantly incurred when accepting the tender offer. As the option premium is of significant size, target shareholders are always better off if the decision to accept a tender offer is delayed. Even if the offer is withdrawn and the transaction is cancelled, the chance of a future takeover is very high. Our finding of an increased premium with competition in the bidding process also suggests it is highly valuable to delay the decision to accept an initial tender offer for as long as possible. The higher the probability of other bidders in the bidding process, the greater this value.

In contrast to the positive implications for target banks shareholders, acquirers must be aware of the negative impacts, in case the option to delay accepting the tender offer is exploited. Previous research implies that majority of the return to the target company's shareholders is born by the bidder. Hence for the acquirer it is of importance to finish the transaction before any competitors enter the bidding process.

III.1 Sensitivity of the Option Parameters

It is highly interesting to gauge the sensitivity of the parameters in the option model to the option premium. The option premium is a positive function of the premium offered over the stock price at time *t(X)*. The higher the initial tender offer over the stock price at time *t*, the higher the option premium to wait in accepting the offer. There is also a similar positive relation between the option premium and the final offer premium *V*. The variance of the underlying stock price has a greater positive influence on the option premium, as can be seen in Figure 1: the more volatile the stock price during the run-up to the tender offer, the higher the premium. Figure 1 also indicates that the longer the period until the target firm has until the tender offer lapses results in a significant increase in the value of the option.

Insert Figure 1

There is a positive and highly significant relationship between the premium on the tender offer, over the stock price at the time of the offer *X*, and the value of the real option. This provides us with some empirical support for a model that incorporates the option to wait in accepting a tender offer.

At time *t* the option value can be derived for the target firm in waiting to accept the tender offer. The sensitivity of the value of the option to the final offer can be calculated, so that the target firm can evaluate the additional value of waiting to accept the tender offer. To analyze in more detail which factors are more influential in determining the value of the option to wait, it is necessary to run some preliminary regressions. The results of these regressions are presented in Figure 1. It becomes apparent that the variance (Figure 3) is the largest driver in valuing the additional value of waiting to accept a tender offer from an acquiring firm.

Insert Figure 2 & 3

The second strongest driver is the value of the underlying asset. Moreover, we see that there are highly significant positive relationships between the value of the underlying asset, the variance of the stock price in the underlying period and the size of the option premium.

III.2 Endogenous Variables

To try and determine which firm specific characteristics can best explain the size of the option premium, we analysed a variety of firm factors. Both for the acquiring firm and the target firm. The additional factors which we analyse for the target banks were, size, debt/equity ratio, earnings and price to book value. We also look at the size of acquiring firm, debt to equity ratio, FCF and price to book value of the acquiring firm. Dunis and Klein (2005) also do this for financial firms; however, use a different methodology.

Several regression analyses were conducted with the option premium as the dependent variable and several endogenous variables as independent variables. For the acquirer side, these were respectively Market Capitalisation, Debt to Equity, Cash Flow per Share, and Price to Book Value. For the target side, these were respectively Market Capitalisation, Debt to Equity, Free Cash Flow per share and Price to Book Value. Summary statistics of the regressions are provided in Table 3.

Insert Table 3

Price to book value can be seen as a proxy for company size. Hence, the size of the target company significantly influences the option premium. Furthermore, a low price to book value and the contribution to a higher option premium can be seen from the acquirer perspective. If the target firm has a very low price to book value, the acquirer is more likely to want to pay a premium for acquiring a valuable asset at a low price.

It can be deemed very likely that target size influence the option's value in some way or the other. In particular the notion that larger firms have a greater base of knowledge capital, greater efficiency gains from a reduction in overhead costs and hence greater overall benefits from synergy. Related to this, another interesting question would be to find out how previous takeover attempts and the percentage premium offered by the acquirer influence the value of the option.

Schwert (2000) finds that target firms with higher market-to-book ratios are more likely to be successfully taken over. This may provide evidence that the value of the option to delay accepting a tender offer is likely to be higher for target firms with high BV/MV. We do find evidence in support of Schwert (2000) for the US banking sector, since target firms with a high price to book value have lower option prices. However the result is not significant for MV/BV ratios, or as a ratio of the acquiring companies MV/BV.

The empirical results by Schwert (2000) also show that targets with lower debt-to-equity ratios are more likely to be successfully taken over. Does this mean that they also render larger premiums for the option value to delay accepting the offer? We find no evidence in support of the premium that US banks pay in attracting target banks being related to target banks with a specifically low or lower debt-to-equity ratio. There is some anecdotal evidence that targets avoid takeover by adding debt through a leveraged recapitalization, however our results do not show empirical support for higher premiums being paid for banks with low debt ratio for the US banking industry.

A likely explanation is in line with the hubris hypothesis of corporate takeovers presented by Roll (1986). The first offer represents the maximum amount the acquirer can offer to make the acquisition a profitable deal. However, most managers engage in only very few acquisition during their career, while at the same time these acquisitions have a profound impact on their career. It is not only due to the increase in power but also due to the publicity that is associated with such a deal. Therefore, the reason for a second (higher) offer might be, that the management of the acquiring company willingly overpays for personal reasons. Abandoning the deal could be perceived badly. Acquisitions are often presented as necessary for the future of the acquiring company. Not completing a deal would question the credibility of the management.

III.3 Robustness Analysis

As pointed out in the methodology section, the accuracy, stability and efficiency of the model is dependent on the amount of nodes included in the binomial lattice approach. A sensitivity analysis with different amounts of nodes was conducted to see the influence of a change on the final result of the option pricing model. Therefore, the initial amount of 125 nodes was doubled three times and the model was run with 125, 250, 500 and 1.000 nodes. Even though, Trigeorgis (1996) states that his application of the log-transformed binomial model with $N = 50$ nodes and came up with a result that only deviates minimally from the standard binomial model of Cox, Ross and Rubinstein (1979) with $N = 500$ nodes, this research starts with 125 nodes and the empirical results given in the tables above are obtained with $N = 250$ nodes.

When the nodes are doubled from 125 to 250, the option premium changes by more than three percent from 13.18% to 12.77%. If it is doubled again to 500 nodes, it only changes by 0.64% to 12.69%. Thus the result with $N > 250$ can be seen as reasonably accurate and stable. With regard to efficiency, the choice of 250 nodes also seems to be the best. When the amount of nodes is doubled from 125 to 250, the processing time is less than doubled from three to five seconds. If the amount of nodes is doubled further, the amount of processing time is more than doubled: from five to thirteen seconds for 500 nodes and to about 50 seconds for 1000 nodes.

IV Conclusions

This paper provides evidence, based on a large sample of actual mergers and acquisitions in the U.S. banking industry, that the real option pricing model for valuing the price of delaying in accepting a tender offer has descriptive value. This paper gives insight into the quantitative premium that can be obtained by target shareholders of a bank under acquisition from waiting to accept the tender offer. If the decision to delay accepting the tender offer is pursued, the average premium to the target shareholders amounts to 12.45%. The median values are lower with 5.2%, hinting towards large outliers in the data set. In any case the median values support the conclusion that target bank shareholders are better off by waiting when accepting a tender offer from a potential acquiring bank in the US banking industry.

By delaying the decision to accept the tender offer, potential new entrants on the bidding process may occur. We find highly significant evidence that the premium is much greater, if competitors enter the bidding process. This finding holds for the total data set, as well as for various annual sub-samples. Several characteristics of banks that could potentially increase or decrease the likelihood of a larger option premium have been researched by conducting regression analyses with endogenous variables. Of all the researched variables, only a target banks' price to book value and its earnings per share had a significant inverse relationship on the size of the option premium. A low price to book value means than an acquirer takes over a bank that seems to be worth more from its balance sheet for a lower price. A similar reasoning for target companies earnings to price ratios. Although these factors may be intuitively understood, both the coefficients of the estimates and the R^2 of the regressions were extremely low. This would indicate that other non- firm specific factors play a greater role on the size of the option premium and hence the value to the target bank in delaying the option to accept a tender offer. One explanation of the large value for the option premium is the hubris hypothesis of corporate takeovers presented by Roll (1986).

The implications from this research are exactly opposite for acquiring banks. The longer the takeover process takes and the more reluctant the target shareholders are to accept the tender offer, the higher the price for the transaction and the more likely bidders will enter the process. That increase in the price can diminish all potential gains from realising synergies and economies of scope. Hence, whether to delay accepting a tender offer depends on the perspective. For target shareholders, patience always pays!

The model developed has proved to be simple enough to be intuitively understood, yet complex enough to capture all the important factors influencing an option's value. An analytic solution to the valuation problem would decrease the time needed to calculate the option's value. However, since the development of an analytic solution is far more complex and does not necessarily improve the results, the practical and theoretical benefits of switching from a lattice model to an analytical model are limited.

The real option model outlined in this paper has found empirical evidence of a large and significant premium to the target company in delaying to accept a tender offer from an acquiring bank. Using data for a sample of 424 US banks between 1997 and 2005 we find a value of 12.45% as a premium paid. The real option methodology enables us to break down the effects of time, stock market volatility on the value to the target bank of having this option. The most crucial factor is the effect of stock market volatility on the value of the premium. Patience also pays in that it may attract competitors in the bidding process, which resulted in a significant gain in value to the option value and hence to the target bank's shareholders.

For future research it would be interesting to see if hostile takeovers render a larger option premium. We have also not yet analyzed multiple bidders (white knights), and the effect of seeking additional bidders to give the option greater value. Also, the financial ratio analysis has raised additional questions. As only two ratios of the target have been revealed to be significant, it would be of importance to find also variables for the acquiring firm that can help to predict the option premium.

References

Baron, D.P. (1983): "Tender Offers and Management Resistance", *Journal of Finance,* 38(2), 331-343.

Bingham, N.H., and R. Kiesel (2004): *Risk-Neutral Valuation - Pricing and Hedging of Financial Derivatives,* 2nd ed., Springer, London.

Black, F., M. Scholes (1973): "The Pricing of Options and Corporate Liabilities", *Journal of Political Economy,* 81(3), 637-654.

Bowe, M., and D.L. Lee (2004): "Project Evaluation in the Presence of Multiple Embedded Real Options - Evidence from the Taiwan High-Speed Rail Project", *Journal of Asian Economics,* 15, 71-98.

Boyle, P.P. (1988): "A Lattice Framework for Option Pricing with Two State Variables", *Journal of Financial and Quantitative Analysis,* 23(1), 1-12.

Constantinides, G. (1978): "Market Risk Adjustment in Project Valuation." *Journal of Finance,* 33(2), 603-616.

Cox, J.C., S.A. Ross, and M. Rubinstein (1979): "Option Pricing – 'A Simplified Approach'", *Journal of Financial Economics,* 7(3), 229-263.

Damodaran, A. (1999): "The Promise and Peril of Real Options", *Working Paper,* New York University – Stern School of Business.

Davis, G.A. (1998): "Estimating Volatility and Dividend Yield When Valuing Real Options to Invest or Abandon", *The Quarterly Review of Economics and Finance,* 38, 725-754.

Dunis, C.L., and T. Klein (2005): "Analyzing Mergers and Acquisitions in European Financial Services - An Application of Real Options", *European Journal of Finance,* August.

Fernández, P. (2002): "Valuing Real Options - Frequently Made Errors", *Research Paper No. 455,* IESE University of Navarra, January.

Geske, R. (1979): "The Valuation of Compound Options", *Journal of Financial Economics,* 7(1), 63-81.

Geske, R., and K. Shastri (1985): "Valuation by Approximation - A Comparison of Alternative Option Valuation Techniques." *Journal of Financial and Quantitative Analysis,* 20(1), 45-71.

Harrison, M., and D. Kreps (1979): "Martingales and Arbitrage in Multiperiod Security Markets", *Journal of Economic Theory,* 20, 381-408.

Heaton, J.B. (2002): "Managerial Optimism and Corporate Finance", *Financial Management,* Summer 2002, 33-45.

Hietaia, P.S., N. Kaplan, and D. T. Robinson (2003): “What is the Price of Hubris? Using Takeover Battles to Infer Overpayments and Synergies”, *Financial Management,* Autumn 2003, 5-31.

Hull, J.C. (2002): *Fundamentals of Futures and Options Markets,* 4th ed., Prentice Hall, New York.

Hull, J., and A. White (1988): “The Use of the Control Variate Technique in Option Pricing”, *Journal of Financial and Quantitative Analysis,* 23(3), 237-251.

Johnson, H.E. (1987): “Options on the Maximum or Minimum of Several Assets”, *Journal of Financial and Quantitative Analysis,* 22(3), 277-283.

Luehrman, T.A. (1998): “Investment Opportunities as Real Options - Getting Started on the Numbers”, *Harvard Business Review,* 76, July-August, 3-15.

Malmendier, U., and G. Tate (2005): “CEO Overconfidence and Corporate Investment”, Journal of Finance, 60(6), 2661-2700.

McClave, J.T., P.G. Benson, T. Sincich (1998): *Statistics for Business and Economics,* 7th ed., Prentice Hall, New York.

Margrabe, W. (1978): “The Value of an Option to Exchange One Asset for Another”, *Journal of Finance,* 33(1), 177-186.

Paddock, J.L., D.R. Siegel, and J.L. Smith (1988): “Option Valuation of Claims on Real Assets - The Case of Offshore Petroleum Leases.” *The Quarterly Journal of Economics,* 103(3), 479-508.

Quigg, L. (1993): “Empirical Testing of Real Option-Pricing Methods”, *Journal of Finance,* 48(2), 621-640.

Roll, R. (1986): “The Hubris Hypothesis of Corporate Takeovers”, *Journal of Business,* 59(2), 197-216.

Sengupta, C. (2004): *Financial Modeling - Using Excel and VBA,* John Wiley, New York.

Stulz, R. (1982): “Options on the Minimum or the Maximum of Two Risky Assets”, *Journal of Financial Economics,* 10(2), 161-185.

Trigeorgis, L. (1996): *Real Options – Managerial Flexibility and Strategy in Resource Allocation,* MIT Press, Cambridge.

Trigeorgis, L. (1993): “The Nature of Option Interactions and the Valuation of Investments with Multiple Real Options”, *Journal of Financial and Quantitative Analysis,* 28(1), 1-20.

Table 1: Descriptive Statistics of the US Dataset

Parameters	Description	Mean	Median	Std. Dev.	Min.	Max.
S_t	Target closing price 1 day prior to announcement	33.05	22.00	48.66	0.31	559.72
P_t	Initial price per share	40.53	26.94	61.93	0.45	738.6
P_T	Accepted price per share	40.80	26.60	63.38	0.45	744.06
V	$P_T - S_t$ in absolute values	7.74	4.70	23.59	-121.25	341.65
X	$P_t - S_t$ in absolute values	7.48	4.66	21.91	-121.25	335.75
V (stand.)	Value of underlying asset	0.298	0.216	0.480	-0.648	7.688
X (stand.)	Strike price	0.297	0.215	0.476	-0.648	7.688
Var	Variance	0.075	0.012	0.673	0.000	14.776
T	Time to maturity in days	161	157	74	0	967
r	Risk-free rate	3.99%	4.32%	1.89%	0.00%	13.32%
DivYie	Dividend yield	2.23%	1.89%	4.62%	0.00%	94.32%

Table 2: Summary Statistics for the Option Premium

	Mean	**Median**	**Standard Deviation**	**Minimum**	**Maximum**
Total	12.45%	5.22%	18.39%	0.00%	75.79%
With Competitor	18.43%	8.81%	25.60%	0.01%	75.79%
Without Competitor	8.00%	2.74%	14.46%	0.00%	70.49%

Table 3 – Firm specific explanatory variables for the discount in accepting a tender offer immediately

A	**Discount if accepting offer immediately**				
Target Bank Variable	(1)	(2)	(3)	(4)	(5)
Target Total Debt %	-5.87E-05	-8.70E-05			
	6.83E-05	6.63E-05			
Target Size (Market Cap)	-1.93E-10		-1.62E-09		
	1.65E-09		1.26E-09		
Target Earnings Per Share	-0.010854			**-0.019323**	
	0.013936			0.009838**	
Target Price to Book Value	-0.023623				-0.032226
	0.017891				0.016521**
R2	0.028013	0.007704	0.007314	0.017079	0.016851
Number of observations	224	224	224	224	224

B	**Discount if accepting offer immediately**				
Variable	(1)	(2)	(3)	(4)	(5)
Acquirer Total Debt %	-8.36E-05	-0.000108			
	6.62E-05	6.44E-05			
Acquirer Size (Market Cap)	-7.32E-10		-8.86E-10		
	4.86E-10		4.77E-10		
Acquirer Cash Flow per Share	-0.000156			-0.000133	
	0.000184			0.000184	
Acquirer Price to Book Value	-0.009589				-0.013631
	0.011438				0.011222
R2	0.021228	0.008974	0.010926	0.001660	0.004707
Number of observations	314	314	314	314	314

** Significant at the 5% level

Figure 1: Real option value as a function of the target bank's stock price

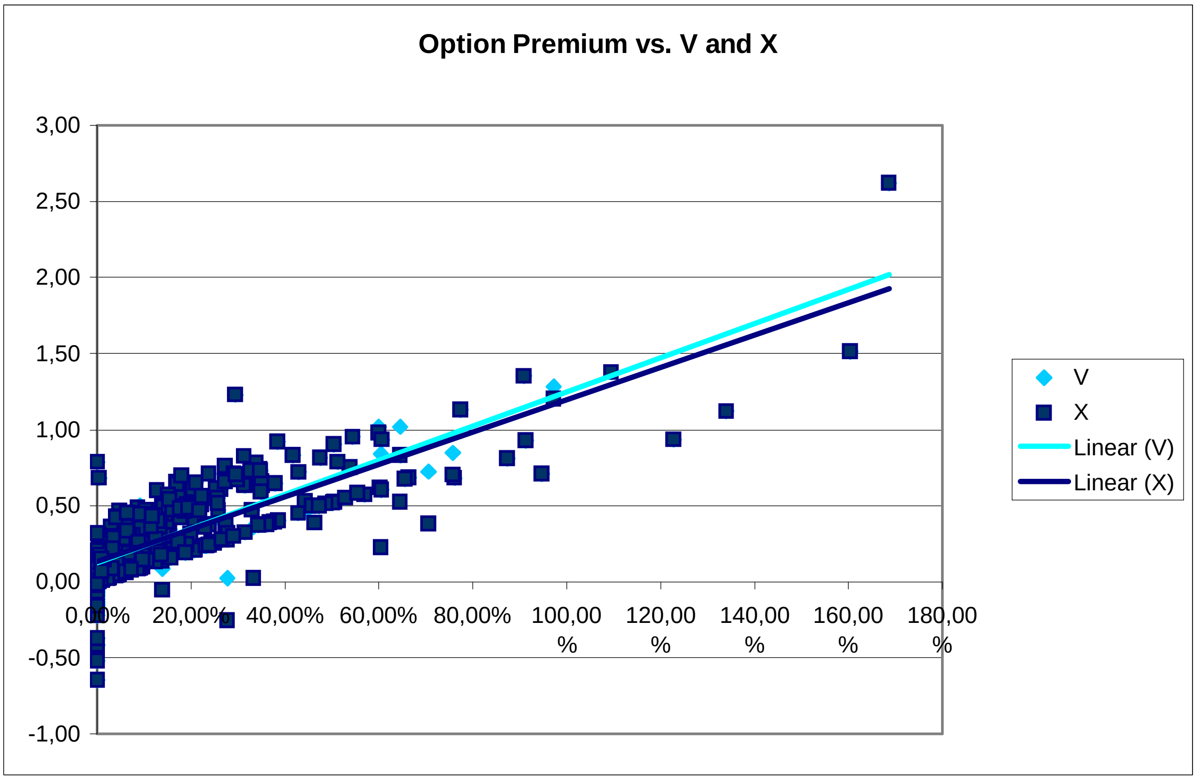


Figure 2: Real option value as a function of time

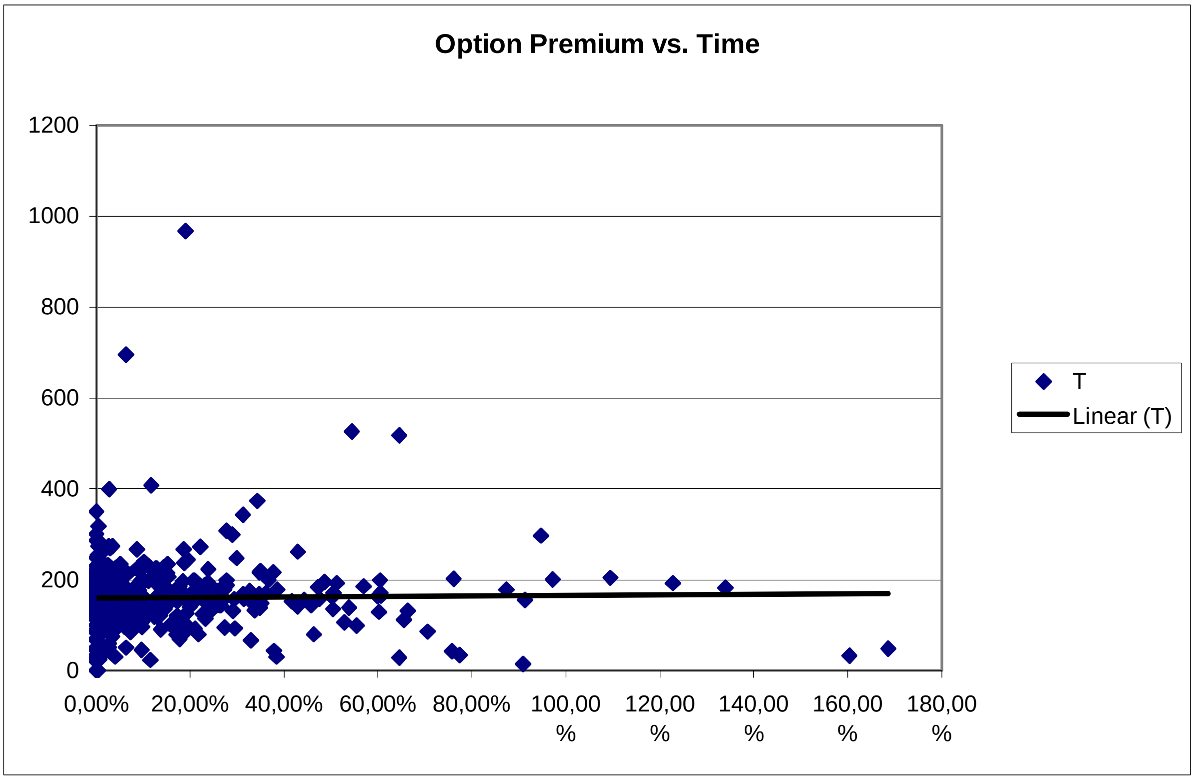
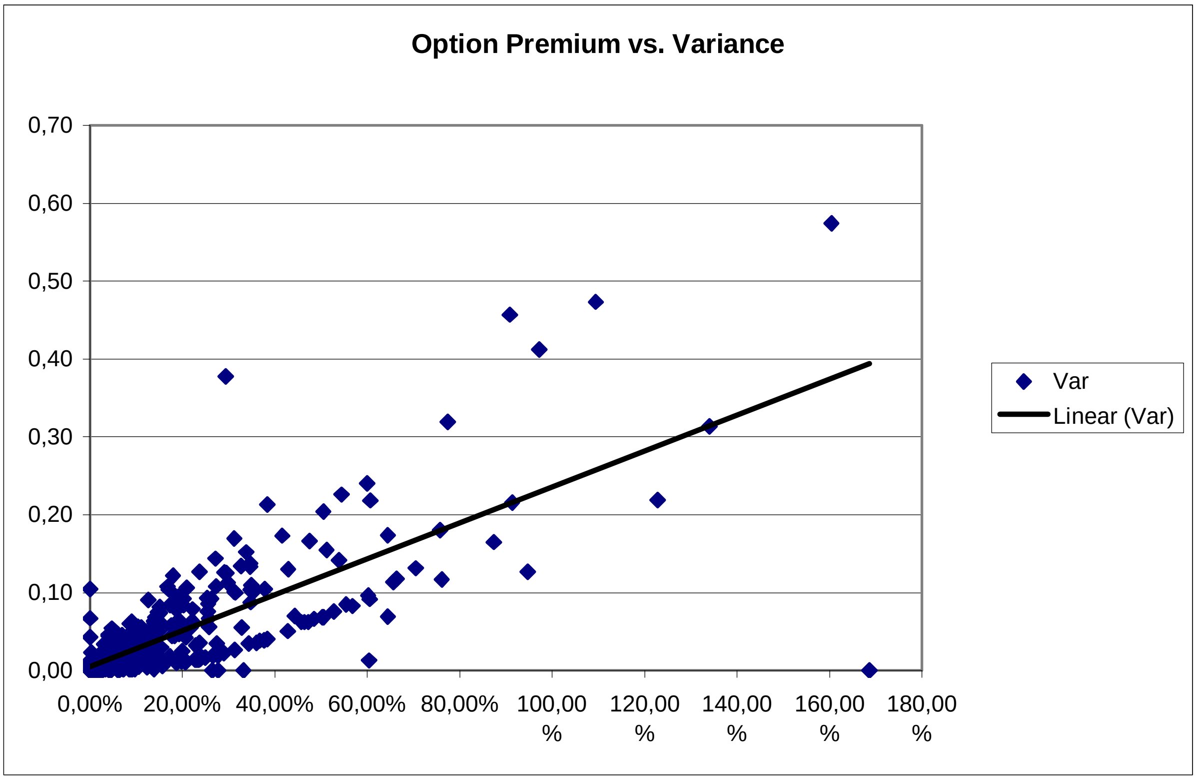


Figure 3: Real option value as a function of the target banks stock price volatility



Bank Consolidation and Soft Information Acquisition in Small Business Lending*

Yoshiaki Ogura

Institute of Economic Research
Hitotsubashi University
2-1 Naka, Kunitachi,
Tokyo 186-8603, Japan
ogura@ier.hit-u.ac.jp

Hirofumi Uchida

Faculty of Economics
Wakayama University
930 Sakaedani, Wakayama
Wakayama 640-8441, Japan
uchida@eco.wakayama-u.ac.jp

This version: October 2007

* This paper is the result of research performed at the Industrial and Financial Structure Workshop at the Research Institute of Economy, Trade, and Industry in Japan. This paper was presented at Chuo University, Kwansei Gakuin Univeristy, and the 2007 Fall Meeting of the Japan Society of Monetary Economics （Doshisha University）. We are grateful to Kenji Kustuna, Yuji Honjo, Toshihiro Okada, Kohei Daido, Eiji Okuyama, Atsushi Tanaka, and Tetsuya Shinkai for their insightful comments. We also gratefully acknowledge the financial support by the Daiginkyo Forum of the Osaka Bankers' Association. This study is also partly supported by the Grant-in-Aid for Scientific Research, Japan Society for the Promotion of Science (Subject No.18730215).

ABSTRACT

We empirically examine the impact of bank consolidation on bankers' acquisition of soft information about borrowers. Using a dataset of small businesses, we found that bank mergers have a negative impact on soft information acquisition by small banks while those by large banks that have less interest in acquiring soft information irrespective of mergers have no impact. Detailed analyses of the post-merger organizational restructuring show that the measures of an increase in organizational complexity have a negative and significant impact on soft information acquisition by small banks, while the measures of cost-cut do not have any significant impact on soft information acquisition. This result implies that the increase in organizational complexity by bank mergers hindered soft information acquisition, which is consistent with Stein's prediction [2002, J. Fin.] on the comparative advantage of simple and flat organizations in acquiring and processing soft information.

Key words: Relationship lending, soft information, bank consolidation, merger

JEL classification code: G21, G34, L22, L14, D82

I. Introduction

A surge in bank consolidation has been observed worldwide since the late 1980s and 1990s. In response to this trend, a large volume of empirical literature on the effects of bank consolidation has been developed to investigate its economic impact.[1] In several studies, researchers have examined the impact of bank consolidation on bank performance or its market value.[2] In other studies, researchers have examined the impact of bank consolidation on deposit/credit market performance.[3]

In accordance with the development of the literature on bank-borrower relationships, recent studies have shifted their focus to the impact of bank consolidation on the credit availability or performance of relationship borrowers, who are typically small businesses. Since bank consolidation usually accompanies the reevaluation of existing borrowers, it is likely to have a detrimental effect on the bank-borrower relationships and would, thus, be harmful to borrowers. In fact, numerous empirical studies have obtained evidence that is supportive of this view.[4] However, the existing evidence is indirect in the sense that these studies do not investigate the consolidation impact on the key factor that makes the bank-borrower relationship meaningful, *soft information*. Soft information is defined as information that is difficult to communicate in a

---

1 Amel, Barnes, Panetta, and Salleo [2004] and Berger, Demsetz, and Strahan [1999] provide concise literature reviews on this subject.

2 The literature along this line includes Cornnet, McNutt, and Tehranian [2004], Hosono, Sakai, and Tsuru [2006], Houston, James, and Ryngaert [2001], Humphrey and Vale [2004], Kane [2000], Knapp, Gart, and Becher [2005], Penas and Unall [2004], Rhodes [1998], Rime and Stiroh [2003], Stiroh [2000], Stiroh and Rumble [2006], and Yamori, Harimaya, and Kondo [2003].

3 As for deposit interest rates, it is found that they temporarily go down after bank mergers (Prager and Hannan [1998]) but eventually go up as efficiency gains materialize in the long-run (Focarelli and Panetta [2003]). Regarding loan interest rates, it is observed that loan rates increase in a market segment in which competition is stifled by a merger (Calomiris and Pomrojnangkool [2005]), while they go down as a result of improved cost efficiency if the market shares of merging banks are not too large (Sapienza [2002]).

4 Studies using U.S. data found that bank consolidation can decrease small business lending by merging banks, but that rivals eventually compensate for it (Berger, Saunders, Scalise, and Udell [1998], Peek and Rosengren [1998]). Studies using Italian data also found that bank-firm relationships are more likely to be terminated when the lending bank is acquired (Focarelli, Panetta, and Salleo [2002], Sapienza [2002]), but this adverse effect is compensated by other banks in the long run (Bonaccorsi-di-Patti and Gobbi [2007]). Some studies also found that in-market mergers decrease the market values of the borrowers of acquired banks (Carow, Kane, and Narayanan [2006], Karceski, Ongena, and Smith [2005]).

verifiable manner even within an organization, such as an entrepreneur's competence and employee morale (Boot [2000], Stein [2002]), and is considered to be accessible exclusively from a primary incumbent lender.[5]

In the present study, we try to provide direct evidence for the impact of bank consolidation on this key factor, the production or acquisition of soft information by banks. We propose the three hypotheses shown below about the bank-consolidation impact on the production of soft information suggested by the existing theories and statistically investigate the relative importance of these hypotheses.

First, an increase in the bank size and organizational complexity due to consolidation may deter soft information acquisition. Stein [2002] shows that information-collecting sections of banks, such as bank branches, have smaller incentive to collect soft information when the decision authority is alienated from them. This is because soft information is hardly used when making decisions, and, thus, it is rarely rewarded in such an organization. Although Stein's original theory [2002] does not include the impact of consolidation, we can naturally extend the theory to predict that bank consolidation that increases the size of an organization and widens the discrepancy between loan-decision sections and information-production sections is likely to hinder soft information production. The difference in the corporate culture among pre-merger banks may also prevent the communication of soft information. Hereafter, we call this detrimental effect of bank consolidation the *bank-complexity hypothesis*.

Second, bank consolidation entails large-scale restructuring to realize the synergy effect mainly resulting from improved cost efficiency, as found in the existing empirical literature. The restructuring includes shutdowns of duplicated branches and administrative sections. In the process of such personnel reductions and relocations, soft information production capacity may be diminished. This hypothesis, which we call the *cost-cut hypothesis*, predicts that bank mergers

[5] By investing to acquire soft information about existing borrowers, a relationship lender can make a profit from informational advantage over rival banks in the future, while borrowers can ensure credit availability for their promising projects (Sharpe [1990]).

decrease soft information acquisition by banks.

Third, a decrease in the intensity of the lending competition due to consolidation may increase soft information acquisition. As Hauswald and Marquez [2006] demonstrated, the return from the investment for information acquisition is more likely to be recouped in the future in less competitive lending markets. This theory predicts that bank consolidation that is likely to decrease competitive pressure in a lending market promotes soft information acquisition by banks. We call this the *competition hypothesis*.

A unique micro dataset collected from *the Management Survey of Corporate Finance Issues in the Kansai area* of Japan sets the stage for our empirical investigation of the consolidation impact on the production of soft information. The survey, which was conducted right after the bank consolidation wave in Japan since the late 1990s in response to the banking crisis, asked firms to evaluate to what extent their main banks knew about the responding firms, their owners or managers, industries that they belonged to, communities where they were located, and the markets of their products/services. We use these evaluations to measure soft information acquisition by main banks. The survey also provides information about the identification of the main bank of each responding firm, its financial standing, and the bank-firm relationship. Matching this information with the bank consolidation data makes it possible to test the impact of bank consolidation on soft information acquisition by banks.

Our statistical analyses show that bank mergers decrease soft information acquisition. This result is consistent with the bank-complexity hypothesis and/or the cost-cut hypothesis explained above. The analyses also show that this negative merger impact is observed only among small banks but is not observed among large banks, which are less intended to acquire soft information regardless of mergers. This implies that bank mergers hinder soft information production by small banks, whereas no deterioration of soft information is observed for large banks. The result for small banks is consistent with both the bank-complexity hypothesis and the cost-cut hypothesis explained above, while the result for large banks implies that large banks may not acquire soft information.

The additional analysis on the characteristics of merging banks shows that the post-merger increment of the organizational complexity and the post-merger cost-cut do not significantly differ by bank size. However, it shows that the post-merger complexity increment has a negative and significant impact on soft information acquisition, in particular, that by small firms, while the post-merger cost cut does not have any significant impact. Thus, our empirical result shows that the bank-complexity hypothesis is the primary factor that explains the negative impact of mergers.

In summary, we obtained results that are consistently supportive of Stein's theory [2002] or its extension. For small banks, bank mergers have a negative impact through the mechanism of the bank-complexity hypothesis, which implies that mergers complicate the managerial organization and reduce incentives to produce soft information. For large banks, no consolidation impact is observed, which implies that soft information is not likely to be produced in these banks. In addition to these findings related to bank consolidation, we also obtained evidence that directly supports Stein's theory [2002]: irrespective of whether or not bank consolidation takes place, small banks tend to acquire soft information more often than large banks do. Thus, our findings support Stein's theory [2002] on the comparative advantage of simple and flat organization in producing and processing soft information from three angles.

Consolidation decisions by banks are an exogenous variable in the context of soft information acquisition since it is hardly plausible that the primary purpose of bank consolidation is to reduce soft information production. Therefore, bank consolidation serves as a natural experiment to test the effect of the change in organizational complexity or cost reduction on soft information acquisition. In this sense, the present study provides robust evidence for Stein's organizational theory [2002] and reinforces the evidence found by Berger, Miller, Petersen, Rajan, and Stein [2005] using U.S. data and that found by Uchida, Udell, and Watanabe [2006] using

Japanese data.

The rest of the paper is organized as follows. Section II is a summary of the existing theories that can predict the effect of bank consolidation on the acquisition of soft information. Section III is an introduction of our dataset and our measures of soft information acquisition. Section IV is the result of univariate analysis. The methodology of our multivariate analysis is explained, and the main results are presented in Section V. Section VI is a detailed analysis of the bank-complexity hypothesis and the cost-cut hypothesis. The final section is a summary and conclusion of the findings.

II. Background Theory

In small business lending, loan underwriting decisions by banks are often made on the basis of qualitative information of borrowers, such as entrepreneurs' competence and enthusiasm or employee morale and skills.[6] This type of information, called *soft information*, is difficult to communicate precisely in a verifiable manner. We can present a few determinants of the intensity of bankers' soft information acquisition in the context of small business lending. In this section, we review these theories in detail and extend them to predict possible impacts that bank consolidation would have on soft information acquisition.

A. The bank-complexity hypothesis

Stein [2002] has shown that an organization in which the decision-making authority is allocated to a lower level in the hierarchy tends to acquire more soft information. Soft information is usually collected at a lower level of the hierarchy, such as loan officers at bank branches. If the authority of loan-underwriting decisions is allocated to an upper level, it is hard for soft information

[6] See, for example, Berger and Udell [2002, 2006].

to reflect on decision-making, and the effort to acquire such information is not rewarded.[7] Consequently, soft information acquisition becomes less intensive in an organization in which those who acquire soft information do not have a decision-making authority[8].

Needless to say, bank consolidation increases bank size and complicates the decision-making process within the organization. Furthermore, merged banks have diverse historical backgrounds; thus, communication across different corporate cultures becomes harder within the new organization. This may also discourage soft information accumulation by a loan officer at a branch level. Therefore, we can extend Stein's theory [2002] to predict that bank consolidation decreases soft information acquisition by banks. We call this the *bank-complexity hypothesis*.

B. The cost-cut hypothesis

An important purpose of bank consolidation is to realize a synergy effect. Financing costs for merged banks may decrease as a result of getting a too-big-to-fail status (Penas and Unal [2004]) or acquiring the ability to construct more diversified portfolios. Operation costs also decrease by trimming off duplicated branch networks and other administrative costs. In order to realize such cost efficiency, especially with respect to operation costs, merged banks need to cut down on personnel expenses and relocate personnel at the time of consolidation. Such a personnel cut or relocation can reduce the production capacity for soft information. If a merged bank considers the accumulation of soft information as a valuable asset that can yield future profits exceeding the cost efficiency resulting from a personnel cut, then the bank would try to preserve the information production capacity by limiting the personnel cut. Otherwise, the bank would discard parts of the production capacity for soft information at the time of consolidation. We refer to this

7 Liberti and Mian [2006] empirically show that loan underwriting decisions made at the upper level of the bank hierarchy tend to depend less on soft information than those made at a lower level.

8 Consistent with this prediction, studies such as those by Cole et al. [2004], Berger, Miller, Petersen, Rajan, and Stein [2005], and Uchida, Udell, and Watanabe [2006] give evidence that banks with a more complex organization tend to have weaker relationships with their borrowers than banks with a smaller and simpler organization.

deterioration of soft information as the *cost-cut hypothesis*.

C. The competition hypothesis

Some theoretical studies have been focused on the effect of increased lending competition on soft information acquisition by banks. Hauswald and Marquez [2006] show that the investment in information acquisition decreases as the number of competing banks increases in a framework of localized oligopoly. An additional market share that can be captured by information advantage becomes smaller as the number of rivals increases. Therefore, the investment in information acquisition is less likely to be recouped. This results in the decrease in the investment in soft information acquisition. Boot and Thakor [2000] also show that bankers' investments in relationship lending (sector specialization), which can be interpreted as an investment in the acquisition of soft information, decrease with the number of competing banks.[9] Bank consolidation decreases the number of competitors. It should, therefore, have a favorable impact on the investment in soft information acquisition. We call this the *competition hypothesis*.

In short, the bank-complexity hypothesis and the cost-cut hypothesis predict that a bank consolidation decreases soft information acquisition, while the competition hypothesis predicts the opposite. As a first step, we now examine the overall direction of the bank consolidation impact on soft information acquisition by banks.

III. Data

Most of our dataset is collected from the micro data of *the Management Survey of Corporate*

[9] Boot and Thakor [2000] also show (in their Theorem 3) that banks are more likely to provide relationship lending for a larger portion of borrowers as the number of rivals increases, given a certain level of upfront investment in sector specialization, in order to shield their existing customers from poachers. We do not focus on this effect in this paper, since our dataset captures how much soft information banks maintain as a result of upfront investment, rather than how intensively they utilize it.

Finance Issues in the Kansai Area of Japan, which was conducted by the Regional Finance Workshop at the Research Institute of Economy, Trade, and Industry (RIETI) in June 2005. The survey asks small and medium-sized enterprises (SME) in three prefectures in the Kansai area, Osaka, Hyogo, and Kyoto, about firm characteristics, including financial standing, management strategies, bank relationships, and loan transactions.[10]

Target firms from each prefecture are randomly chosen by employee-size categories ((1) 1-20 employees, (2) 21-50 employees, (3) 51-100 employees, (4) more than 100 employees). The target size from each prefecture is adjusted according to the relative number of enterprises in each prefecture; i.e., 5,000 firms from Osaka Prefecture, 2,500 firms from Hyogo Prefecture, and 1,500 firms from Kyoto Prefecture are selected as target firms.

A total of 2,020 of 9,000 target firms responded effectively. The response rate was 22.4%. The number of observations was reduced to 1,405 after dropping those firms whose main banks are not private banks and those for which no soft information indicators were available, which is explained below. Further, the number of observations was reduced to 987 after dropping the observations whose dependent or independent variables were not available, and those of five firms that started their businesses after April 2001. We drop these youngest firms from our analysis since it is not likely that main banks have accumulated so much soft information of these firms as it would be affected by bank consolidations. The industry composition in this final dataset is construction (12.5%), manufacturing (38.1%), information and communications (3.3%), transportation (6.4%), wholesale (20.2%), retail (5.9%), real estate (1.6%), restaurants and hotels (1.3%), and other services (10.8%).

[10] The Kansai area is the second largest metropolitan area in Japan and the business center of Western Japan. The area consists of six prefectures. Among these, the target firms were chosen from Osaka, Hyogo, and Kyoto, including those located in three major cities, Osaka, Kobe, and Kyoto, in their respective prefectures. Osaka is the second largest city in Japan.

A. Measure of soft information

The survey contains a question that enables us to obtain information about the information production by banks. Each respondent company is asked to evaluate the knowledge or satisfaction level of its main bank in terms of various factors, and six of them are related to soft information: knowledge about (Q1) the responding company itself, (Q2) owners or managers of the company, (Q3) the industry that the company belongs to, (Q4) the local community where the company is located, (Q5) the market for the products/services of the company; and satisfaction with (Q6) the frequency of contacts by loan officers of a main bank. For each of these items, responding companies grade their main banks from grade 1 (inadequate or low) to 5 (excellent or high). We use the resulting indicators as the measures of soft information acquisition by main banks.

In addition to using these indicators separately, we also use the variable SOFTINFO, which is defined by the primary principal component of the six soft-information indicators.[11] The principal component is calculated from 1,405 observations whose indicators are all available. We consider that SOFTINFO represents sufficient information that is contained in the six indicators, since it captures 57.8% of the variance-covariance of the six indicators.

A shortcoming of these variables is that the responding firms may not necessarily think only of soft information when they answer the questions. For example, an established and publicly well-known firm that submits solid financial statements to its main bank may give the bank a rating of 5 (excellent) with respect to the banks' knowledge about the responding company itself (Q1) not because the main bank accumulates soft information about the borrower but because a significant amount of hard information is available for the firm. In order to treat this potential problem, we will control the availability of hard information for main banks in the regression

[11] SOFTINFO is similar to the soft information indices in Scott [2004] and Uchida, Udell, and Yamori [2006]. However, their indices are constructed from "5 (excellent)" answers only. Our SOFTINFO makes use of "1" through "4" information as well. In addition, their indices utilize information about the respondent firms' view on the extent that their main banks *should* know about the firms with respect to the relevant items. Our SOFTINFO does not utilize this information, and, in this sense, it is more focused on the *actual* knowledge of the main banks.

analysis below.

B. Bank consolidation

We focus on five types of lending institutions in Japan that constitute the majority of main banks in our data set: city banks (banks operating nationwide), long-term credit banks (banks specializing in long-term finance), trust banks (banks that are legally allowed to operate trust services), regional banks (local banks operating within or around one prefecture), and Shinkin banks (cooperative institutions that are allowed to lend to member firms only).[12] City banks, long-term credit banks, and trust banks are the largest, operate nationwide, and provide a wide variety of services. Regional banks are smaller and usually specialize in commercial banking in specific regions. Shinkin banks are local community banks and the smallest in our sample.[13]

In response to the serious financial distress since the late 1990s in Japan, a lot of financial institutions experienced consolidation. Among these events, we focus on bank mergers and the establishments of bank holding companies.[14] We set the window period from April 2001 to June 2005. This is because the RIETI Survey was conducted in June 2005, and it is well-known that the effects of bank consolidation vanish after approximately three years (see, for example, Rhodes [1998]). During this period, the Japanese banking industry experienced a surge of bank consolidation. There were 12 incidences of the establishment of a bank holding company, 63 events of bank mergers, and 3 cases in which banks became subsidiaries of other banks. Among the 63 merger events, 5 were among city and long-term credit banks, 4 were among trust banks, 5 were among regional banks, and 49 were among Shinkin banks.

Focusing on the main banks of our sample firms, we observed 14 mergers (5 among city

[12] Member firms of Shinkin banks have 300 or fewer employees or capital of 900 million yen or less.

[13] The average total asset of each institution type in our dataset as of March 2005 is 48,059 billion JPY for major banks (city, long-term credit, and trust banks), 2,716 billion JPY for regional banks, and 918 billion JPY for Shinkin banks.

[14] As explained below, a variable representing banks' asset acquisitions from a liquidated bank is also available. Due to the small number of observations, however, detailed analysis on this variable is impossible, and the variable is generally insignificant in the regression analysis below.

banks, 3 among trust banks, 2 among regional banks, and 4 among Shinkin banks) from April 2001 to June 2005. In our 987 sample firms, 593 firms' main banks experienced a merger in this period. From this information, we define a dummy variable, Merger, which is equal to one if a firm's main bank experienced a merger during the period from April 2001 to June 2005, and, otherwise, zero.[15]

As for the establishment of a bank holding company (BHC) in this period, 8 banks among the main banks in our dataset were involved in the foundation of bank holding companies, and 2 banks became subsidiaries of other banks. In order to capture the effect of these changes in ownership structure, we define a dummy variable, BHC, which is equal to 1 if the firm's main bank established a bank holding company or became a subsidiary of another bank and, otherwise, zero. There are several banks that experienced both a merger and the establishment of a bank holding company. In this case, the dummy variable BHC is set to be equal to zero in order to isolate the merger effects from the effect of BHC establishments.

IV. Univariate Analysis

Before running regressions, we conducted a univariate analysis of our soft information measures. Table 1 is a comparison of the distribution of the responses to each of the survey questions regarding the soft information acquisition by main banks based on whether or not a main bank experienced a merger (Panel A) and whether or not a main bank established a bank holding company (Panel B). Pearson's χ^2 statistics about the independence between row items and column items are also shown. In Panel A, it is shown that the companies whose main banks experienced mergers tend to give lower grades to their main banks' knowledge about the companies. The Chi-squared tests significantly reject the independence between the merger experience and the 1-5 answers in all questions but Q3. Therefore, we can expect that bank mergers will deter soft

[15] During this period, 4 of main banks for our sample firms acquired assets from failed banks (1 regional bank and 3 Shinkin banks). We constructed Merger dummy to include these cases also.

information acquisition by merged banks, which is consistent with the bank-complexity hypothesis and/or the cost-cut hypothesis. In contrast, significant correlations are shown in Panel B between column items and row items only in Q4 and Q5. At this point, the effect of BHC establishment on soft information seems weaker than that of mergers.

Descriptive statistics are shown in Table 2 of our soft information measures that are sorted by whether or not the main bank experienced a merger (Panel A) and whether or not the main bank experienced the establishment of a bank holding company (Panel B). The points observed in Table 1 are verified in this table as well. Statistically significant differences in the mean responses to most questions are shown in Panel A, while such differences are not seen in Panel B. Furthermore, the mean of SOFTINFO is significantly lower for the firms whose main banks experienced mergers, whereas the difference is insignificant for those in which main banks founded BHCs.

Figure 1 depicts the histogram of SOFTINFO, sorted by Merge (Panel A) and BHC (Panel B). The figures suggest that SOFTINFO tends to be somewhat lower for those companies in which the main bank experienced mergers. However, the difference in the distribution of SOFTINFO by whether the main bank established a BHC is less apparent.

Finally, we examine the difference of SOFTINFO by bank size. Table 3 shows the mean levels of SOFTINFO by splitting the sample firms by bank size and merger experiences. In the table, city banks, long-term credit banks, and trust banks are classified as large banks, while regional banks and Shinkin banks are classified as small banks. First, when we simply split the sample by the size of the main banks, we find that large banks are less inclined to acquire soft information (first row). This is consistent with the original prediction by Stein [2002]. Second, mergers decrease SOFTINFO of small main banks significantly (third low), while they do not affect SOFTINFO of large main banks at all (second row). There seems to be a difference in the merger impact across bank types. We elaborate on this relative impact in a later section.

In summary, the univariate analyses show that bank consolidation, especially mergers by small banks, is likely to hinder soft information acquisition. This result is consistent with the bank-complexity hypothesis and/or the cost-cut hypothesis. In the next section, we will examine whether these findings are robust even after controlling for potential covariates.

V. Multivariate Analysis

A. Methodology

In order to examine the impact of bank consolidation on soft information acquisition after controlling for other potential factors that could also influence soft information acquisition, we run the following linear regression:

$$SOFTINFO_i = \beta_0 + \beta_1 {*} Merger_i + \beta_2 {*} BHC_i + \beta_3 {*} control\ variables_i + \varepsilon_i, \quad (1)$$

where i is the index of responding companies. The definition of the control variables is presented in Table 4 together with their descriptive statistics. We are mostly interested in the sign and the significance of the coefficient β_1. If this coefficient is negative and significant, then we can interpret that the bank-complexity hypothesis and/or the cost-cut hypothesis is stronger. If it is positive and significant, then we can interpret that the competition hypothesis is stronger.

A potential shortcoming of this dataset is that, since the information is limited to that about the *current* main bank, we cannot determine whether a firm switched main banks upon merger, although several empirical studies have shown that there are positive impacts of mergers on the probability to switch main banks (Bonaccorsi and Gobbi [2007], Focarelli, Panetta, and Salleo [2002], and Sapienza [2002]). In order to overcome this shortcoming, we include the length of the relationship with the main bank into explanatory variables to control for such main-bank switching.

If the length of the relationship is short, the implication is that the firm switched main banks recently, possibly due to a main-bank merger. Relationship terminations as an ultimate negative impact should be captured in the coefficient of the length of relationship, although we cannot single out the impact since a relationship may terminate due to reasons other than mergers. By controlling the effect of such switches, the coefficient β_1 captures a merger impact on the soft information with respect to firms that kept lending relationships with their main banks in spite of merging. In this sense, β_1 represents the most *conservative* estimate of the merger impact on soft information acquisition.

In addition to this baseline specification, we adopt two other specifications. First, to accommodate the possibility that the effects of bank consolidation differ according to the type of main bank, we use another specification that includes the interaction terms between consolidation dummies (Merger and BHC) and bank-type dummies (Regional bank and Shinkin bank). This is to capture the difference in the merger impact by bank type. Second, we also regress *each* of the six soft-information indicators on the explanatory variables by ordered logit to determine the component that is the most seriously affected by the consolidation events.

As for the control variables, a few variables are worth mentioning. First, the dummy variables of the Regional bank and Shinkin bank by themselves are used as proxies for bank size or organizational complexity, which is expected to have positive coefficients according to the original prediction by Stein [2002] that small banks are more likely to acquire soft information. Second, as reported in the previous section, the *knowledge* of the main bank about the borrowing firm may include *hard information*, such as monthly financial reporting. The variables, Audited, Financial statement, Financial reporting frequency, and Assets of a firm are used to capture such portion of knowledge.

B. Main results

The estimated coefficients are listed in Table 5. Specification (1) is the baseline regression. Specification (2) uses the asset size of banks instead of the bank-type dummies as the proxy for bank size or complexity. Specification (3) includes the interaction terms of the consolidation dummies and the bank-type dummies.

In Specifications (1) and (2), both the Merger and BHC dummies have negative coefficients. The coefficients are statistically significant for the Merger dummy, while the BHC dummy is statistically less significant. The result is consistent with the univariate one in Table 2 and supports the bank-complexity hypothesis and/or the cost-cut hypothesis, which predict that bank mergers decrease soft information acquisition.

However, the results of Specification (3) show that the type of bank matters. A negative effect of the bank merger on soft information is observed only when the main bank is a regional or a Shinkin bank. This is consistent with the results in Table 3. In other words, bank mergers have a negative impact on soft information acquisition only for small banks, and no deterioration of information is observed from the mergers of large banks. The BHC dummy is not statistically significant.

Table 6 is a summary of the estimated coefficients of the Merger and BHC dummies when the response of each question (Q1-Q6) is regressed on these dummies and other covariates by ordered logit. In Specifications (1) and (2) (Panels A and B), the coefficients of the Merger dummy are negative in all regressions and statistically significant with respect to four questions. The signs of the coefficients of the BHC dummy are generally negative although the coefficients are insignificant except for Q4 and Q5. In Specification (3) (Panel C), the coefficients of the interaction terms of the Merger dummy and the small bank dummies, Regional and Shinkin, have negative and significant coefficients. The interactions of the BHC dummy do not have statistically significant coefficients, although they have negative coefficients. The results of Specification (3) in this table are, therefore, consistent with those in Table 5.[16]

The presence of a merger impact against small banks, as opposed to its absence against large banks, is quite suggestive about the mechanism generating the negative impact of mergers on soft information acquisition. Another important and noteworthy result is that small banks seem to accumulate soft information, while large banks do not, irrespective of mergers (the first row in Table 3, or the coefficient of the Shinkin dummy in Table 5), which is consistent with the prediction of the original theory of Stein [2002].[17] Taken together, these findings suggest that it is highly likely that the increase in the complexity upon merger negatively affects the acquisition of soft information by small banks, as predicted by the bank-complexity hypothesis.

However, it is also possible that the difference of merger impacts just stems from the difference in the magnitude of an increase in organizational complexity and/or of the cost cut across bank types. For example, if a cost reduction that accompanies a merger is less severe for large banks than for small banks, the negative impact against small banks and lack of impact against large banks are nothing but the consequence of the cost-cut hypothesis. It is, therefore, interesting to examine what brings about the difference in the merger impact by bank type in detail. We investigate this issue in the next section using additional data about the characteristics of merged banks.

The result of the weaker effect of the BHC establishment as opposed to the negative and significant effect of a merger possibly reflects the fact that bank mergers accompany drastic cost reduction and often entail the shift of the authority to make lending decisions, while BHC establishments rarely entail such drastic reorganizations or cost reduction. However, we cannot deny the possibility that the BHC dummy works as a partial proxy for bank size or bank type since most banks that experienced the establishment of BHC are large banks.

[16] As mentioned above, if we change the BHC dummy to include banks that have undergone a merger and the establishment of a bank holding company, the effect of the merger dummy becomes less significant.

[17] However, it is significant at a 10% level, and another small bank dummy, the regional bank dummy, is not significant. The interaction term of the regional bank dummy and the merger dummy is significant and negative.

The estimated coefficients of a couple of control variables are worth mentioning. First, the size of the firm measured by a log of assets has positive and significant coefficients. This may well be interpreted as large firms being *well-known*. A similar effect can also be seen in the coefficients of the financial reporting frequency. These results imply that a hard-information component commingled with our soft information measures is successfully controlled by these explanatory variables. Second, the non-performing loan ratio of a main bank has a negative and significant coefficient in all the specifications. This result implies the possibility that the accumulation of non-performing loans prevents banks from actively producing soft information about borrowers, although we need more careful examination of the causality between bad loans and soft information acquisition.

VI. Bank-complexity hypothesis and cost-cut hypothesis

The analysis in the previous section revealed that a bank merger has a negative impact on soft information acquisition. This result is consistent with both the bank-complexity hypothesis and the cost-cut hypothesis. We also found the presence of a negative merger impact against small banks and its absence against large banks. The difference may be because large banks do not acquire soft information, as predicted by Stein [2002], or it may be because the extent of the complexity increment in banking organizations and/or the extent of cost reduction differs by bank type. In this section, we investigate the cause of the impact difference by bank size with additional information about the organizational complexity and organizational restructuring of main banks.

A. Univariate analysis

We define the measures of the increase in organizational complexity and the measures of cost reductions upon mergers. First, we define the measures of the complexity increase from the proxies of organizational complexity: asset size, loan size, number of bankers, and number of branches. For merged banks, we use the average increasing rate of each variable from *each* pre-merger bank to the post-merger bank. To be more specific, for each variable X (= asset size, loan size, number of bankers, or number of branches), we calculate the following measure:

Complexity measure for Merged banks

$$\textit{(X of the post-merger bank at the end of year s) / (weighted average of X of pre-merger banks at the end of year s-1)} - 1, \qquad (2)$$

where s is the year during which the merger took place. For non-merged banks as the controlling group, we use the annual increasing rate of each variable averaged throughout the window period from 2001 through 2005:

Complexity measure for non-merged banks

$$\frac{1}{5}\sum_{t=2001}^{2005}\left[\textit{(X at the end of year t) / (X at the end of year t-1)} - 1\right]. \qquad (3)$$

Second, to investigate the extent of cost reduction, we focus on the increasing rates of four variables: the number of branches, the number of bankers, overhead and personnel expenses, and ordinary expenses. For merged banks, we calculate the three-year increasing rates of each variable summed over all the pre-merger banks. That is, the cost-cut measure of variable X (=number of branches, number of bankers, overhead and personnel expenses, and ordinary expenses) is:

Cost-cut measure for merged banks

$$\textit{(X of the post-merger bank at the end of year s+2) / (X summed over all the pre-merger banks at the end of year s-1)} - 1. \qquad (4)$$

This measure represents to what extent total costs are reduced as a whole among banks involved in the merger. We take the three-year period because it is likely to take more than one year to complete the cost reduction. For non-merged banks as the controlling group, we use the annual increasing rates of these variables averaged through the window period, but this time they are multiplied by three to match the duration of merged banks' rates:

Cost-cut measure for non-merged banks

$$3\cdot\frac{1}{5}\sum_{t=2001}^{2005}\left[\{\textit{(X at the end of year t) / (X at the end of year t-1)} - 1\}\right] = 3 * (2). \qquad (5)$$

Table 7 is a comparison of the means of the measures for the complexity increment in banking organization (Panel A) and for cost reduction (Panel B). Panels A-1 and B-1 are calculated from all banks, panels A-2 and B-2 are calculated from large banks only (Regional = Shinkin = 0), and panels A-3 and B-3 are calculated from small banks only (Regional or Shinkin = 1). Panels A-4 and B-4 show the statistics for the test of the difference in means.

Panel A clearly shows that mergers increased the organizational complexity. The test statistics show that the differences in the means of all the measures for merged banks and non-merged banks differ at a 1% level of significance. This remains the case when banks are classified according to type. The last column shows that the increase in organizational complexity upon merger does not differ significantly according to the size of the merging banks.

Panel B shows that banks that experienced a merger cut down on all the items presented in the table by some 20% or more on average within two years after a merger. In contrast, banks without any merger events decrease the items by smaller rates. The difference in the magnitude of the cost cut between merged banks and non-merged banks is significant, although the statistical significance is weaker than that of the complexity increment. If banks are sorted by type, the difference becomes more insignificant. The decrease in the number of bankers is more precipitous for merged banks than for non-merged banks, but, as to other cost-cut measures, non-merged banks reduce costs as much as merged banks. The difference between large banks and small banks is not significant again (the last column).

In summary, we conclude that mergers are accompanied by a significant complexity increment, whereas cost reduction due to mergers is not very extensive since banks that did not experience mergers also reduced costs. This finding, therefore, implies that the bank-complexity hypothesis is more likely to hold than the cost-cut hypothesis.

As for the difference in the merger impact across bank types, the last column shows that there is no difference in the magnitude of the complexity increment or in cost reduction between large banks and small banks. This implies that the finding in section V.B that the impact of a merger differs by bank type does not stem from a difference in the extent of the complexity increment or the post-merger cost reduction across bank types. Rather, this supports the interpretation along the line of the original theory of Stein [2002] predicting that large banks do not normally produce soft information and that, as a result, no deterioration is observed upon merger.

B. Multivariate analysis

We further investigate the impact of the increment in organizational complexity and cost cut by multivariate analysis. In this analysis, in place of bank consolidation dummies in Specification (2) in the previous section, we use each of the complexity measures or the cost-cut measures. Table 8 contains excerpts of the major results of this analysis.

The results show that the complexity measures have a negative impact on SOFTINFO (Panel A), while the cost-cut measures have a positive impact (Panel B). The significance of the estimated coefficients is not strong in either specification except that the complexity increment measured by the amount of loans has a negative and significant impact on SOFTINFO. The significance levels of the other complexity measures are, at worst, significant at a 20% level, while the coefficients of cost-cut measures are by far less significant. This result provides more evidence for the significance of the bank-complexity hypothesis, although the significance of the result is weaker.

Finally, the difference in the impact is examined according to bank type. Panel C of Table 8 contains a report of the results. In Specifications (1) and (2), the complexity measures have negatively significant impacts on SOFTINFO when the main bank is a regional bank. When the main bank is a Shinkin bank, the coefficients of the cross terms are insignificant, but the p values are small. The interactions of bank-type dummies and cost-cut measures (not reported) do not have any statistically significant coefficients. Thus, it is more likely that the bank-complexity hypothesis is the primary hypothesis that explains the negative impact of mergers on soft information acquisition by small banks.

VII. Summary and Conclusion

In this paper, we have found that:

(1) Bank mergers have a negative impact on soft information acquisition by small banks, whereas no impact is observed for large banks (Tables 3, 5, and 6).

(2) The increase in organizational complexity upon merger has a significant impact on information acquisition by small banks, while the cost reduction upon merger does not (Table 8).

(3) The magnitudes of the cost reduction and the complexity increments upon merger do not vary according to bank size (Table 7).

(4) When a merger does not take place, small banks are likely to acquire soft information more extensively than large banks (Tables 3, 5, and 6).

Finding (1) is consistent with the bank-complexity hypothesis and/or cost-cut hypothesis for small banks. Finding (2) suggests that the former is the primary mechanism that generates the negative impact of mergers against soft information acquisition by small banks. Finding (3) proves that the asymmetric impact by bank size does not come from the difference in the magnitude of complexity increments or cost reduction upon merger by bank size. Rather, as confirmed in Finding (4), the asymmetry in the merger impact is likely to come from the lack of the production of soft information by large banks in a typical operation, which supports the prediction of the original theory of Stein [2002].

Thus, our findings support the theory by Stein [2002] on the comparative advantage of simple and flat organization in producing and processing soft information from three angles. First, small banks acquire more soft information than large banks do in a typical operation. Second, when a merger takes place, it complicates managerial organization and deters the production of soft information or the maintenance of that accumulated in small banks (the bank-complexity hypothesis). Third, such an effect is not observed in large banks that accumulate little soft information before mergers.

The promotion of bank mergers is a popular policy for improving the stability of the banking sector. Our analysis suggests that there can be a proviso against this prescription, i.e., soft information accumulated through existing bank-firm relationships might be deteriorated by bank mergers, which could be economically costly for small banks and their borrowers. However, to the best of our knowledge, no thorough analysis of the welfare impact of bank mergers taking into account the production of information by banks has ever been conducted.[18] Empirical studies that integrate both the impact on information production, which we investigated in this paper, and the efficiency improvement by synergy effects are required in order to evaluate the overall welfare impact of bank consolidation. More general and extensive empirical/theoretical studies on this subject remain to be done.

[18] As an exception, Hauswald and Marquez [2006] suggest the possibility that bank mergers improve economic efficiency by decreasing duplicated information acquisition costs.

REFERENCES

Amel, D., Barnes, C., Panetta, F., and Salleo, C. “Consolidation and Efficiency in the Financial Sector: A Review of the International Evidence.” *Journal of Banking and Finance*, 28:2493-2519, 2004.

Berger, A., Demsetz, R., and Strahan, P. “The Consolidation of the Financial Services Industry: Causes, Consequences, and Implications for the Future.” *Journal of Banking and Finance*, 23:135-194, 1999.

Berger, A., Goldberg, L., and White, L. “The Effects of Dynamic Changes in Bank Competition on the Supply of Small Business Credit.” *European Finance Review*, 5:115-139, 2001.

Berger, A., Miller, N., Petersen, M., Rajan, R., and Stein, J. “Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks.” *Journal of Financial Economics*, 76:237-269, 2005.

Berger, A., Saunders, A., Scalise, J., and Udell, G. “The Effects of Bank Mergers and Acquisitions on Small Business Lending.” *Journal of Financial Economics*, 50:187-229, 1998.

Berger, A., and Udell, G. “Small Business Credit Availability and Relationship Lending: The Importance of Bank Organizational Structure,” *Economic Journal*, 112:32-53, 2002.

Berger, A., and Udell, G. “A More Complete Conceptual Framework for SME Finance,” *Journal of Banking and Finance*, 31:2945-2966, 2006.

Bonaccorsi di Patti, E., and Gobbi, G. “Winner or Losers? The Effects of Banking Consolidation on Corporate Borrowers.” *Journal of Finance*, 62:669-696, 2007.

Boot, A., “Relationship Banking: What Do We Know?” *Journal of Financial Intermediation*, 9:7-25, 2000.

Boot, A., and Thakor, A. “Can Relationship Banking Survive Competition?” *Journal of Finance*, 55:679-713, 2000.

Calomiris, C., and Pornrojnangkool, T. “Monopoly-Creating Bank Consolidation? The Merger of Fleet and BankBoston.” *NBER Working Paper Series*, 11351, 2005.

Carow, K., Kane, E., and Narayanan, R. “How Have Borrowers Fared in Banking Megamergers?” *Journal of Money*, *Credit*, *and Banking*, 38:821-836, 2006.

Cole, R., Goldberg, L., and White, L. “Cookie Cutter vs. Character: The Micro Structure of Small Business Lending by Large and Small Banks.” *Journal of Financial and Quantitative Analysis*, 39:227-251, 2004.

Cornett, M., McNutt, J., and Tehranian, H. “Performance Changes around Bank Mergers: Revenue Enhancements versus Cost Reductions.” *Journal of Money*, *Credit*, *and Banking*, 38:1013-1050, 2006.

Focarelli, D., and Panetta, F. “Are Mergers Beneficial to Consumers? Evidence from the Market for Bank Deposits.” *American Economic Review*, 93:1152-1172, 2003.

Focarelli, D., Panetta, F., and Salleo, C. “Why Do Banks Merge?” *Journal of Money*, *Credit*, *and Banking*, 34:1047-1065, 2002.

Hauswald, R., and Marquez, R. “Competition and Strategic Information Acquisition in Credit Markets.” *Review of Financial Studies*, 19:967-1000, 2006.

Hosono, K., Sakai, K., and Tsuru, K. “Consolidation of Cooperative Banks (*Shinkin*) in Japan: Motives and Consequences.” *RIETI Discussion Paper Series*, 06-E-034, 2006.

Houston, J., James, C., and Ryngaert, M. “Where Do Merger Gains Come from? Bank Mergers from the Perspective of Insiders and Outsiders.” *Journal of Financial Economics*, 60:285-331, 2001.

Humphrey, D., and Vale, B. “Scale Economies, Bank Mergers, and Electronic Payments: A Spline Function Approach.” *Journal of Banking and Finance*, 28:1671-1696, 2004.

Kane, E. “Incentives for Banking Megamergers: What Motives Might Regulators Infer from Event-Study Evidence?” *Journal of Money*, *Credit*, *and Banking*, 32:671-701, 2000.

Karceski, J., Ongena, S., and Smith, D. "The Impact of Bank Consolidation on Commercial Borrower Welfare." *Journal of Finance*, 50:2043-2082, 2005.

Knapp, M., Gart, A., and Becher, D. "Post-Merger Performance of Bank-Holding Companies, 1987-1998." *Financial Review*, 40:549-574, 2005.

Liberti, J., and Mian, A. "Estimating the Effect of Hierarchies on Information Use," London Business School Working Paper, 2006.

Peek, J., and Rosengren, E. "Bank Consolidation and Small Business Lending: It's Not Just Bank Size That Matters." *Journal of Banking and Finance*, 22:799-819, 1998.

Penas, M., and Unal, H. "Gains in Bank Mergers: Evidence from the Bond Markets." *Journal of Financial Economics*, 74:149-179, 2004.

Prager, R., and Hannan, T. "Do Substantial Horizontal Mergers Generate Significant Price Effects? Evidence from the Banking Industry." *Journal of Industrial Economics*, 46:433-452, 1998.

Rhoades, S. "The Efficiency Effects of Bank Mergers: An Overview of Case Studies of Nine Mergers." *Journal of Banking and Finance*, 22:273-291, 1998.

Rime, B., and Stiroh, K. "The Performance of Universal Banks: Evidence from Switzerland." *Journal of Banking and Finance*, 27:2121-2150, 2003.

Sapienza, P. "The Effects of Banking Mergers on Loan Contracts," *Journal of Finance*, 57:329-367, 2002.

Scott, J. "Small Business and the Value of Community Financial Institutions," *Journal of Financial Services Research*, 25:207-230, 2004.

Sharpe, S. "Asymmetric Information, Bank Lending, and Implicit Contracts: A Stylized Model of Customer Relationships," *Journal of Finance*, 45:1069-1087, 1990.

Stiroh, K. "How Did Bank Holding Companies Prosper in the 1990s?" *Journal of Banking and Finance*, 24:1703–1745, 2000.

Stiroh, K., and Rumble, A. "The Dark Side of Diversification: The Case of U.S. Financial Holding

Companies." *Journal of Banking and Finance*, 30:2131-2161, 2006.

Stein, J. "Information production and capital allocation: decentralized versus hierarchical firms," *Journal of Finance*, 57:1891–1921, 2002.

Uchida, H., Udell, G., and Watanabe, W. "Bank Size and Lending Relationships." *NBER Working Paper Series #13005*, (conditionally accepted for publication from *Journal of Japanese and International Economies*), 2007.

Uchida, H., Udell, G., and Yamori, N. "Loan Officers and Relationship Lending," *RIETI Discussion Paper Series 06-E-031*, 2006.

Yamori, N., Harimaya, K., and Kondo, K. "Are Banks Affiliated with Bank Holding Companies More Efficient Than Independent Banks? The Recent Experience Regarding Japanese Regional BHCs." *Asia-Pacific Financial Markets*, 10:359-376, 2003.

Table 1 Distribution of responses to the survey questions on soft information

Each cell contains the number of respondent companies concerning the questions asking to what extent their current main banks are satisfied with the bank's knowledge about (Q1) the responding company, (Q2) the owners or managers of the company, (Q3) the industry that the company belongs to, (Q4) the local community where the company is located, and (Q5) the major market of the company; and with (Q6) how often a loan officer of the main bank contacts the company. In Panel A, the distribution is presented by whether the company's main bank experienced a merger (Merger=1) or not (Merger=0) during the period from Apr. 2001 through Jun. 2005, whereas, in Panel B, the distribution is presented by whether the company's main bank established a bank holding company (BHC=1) or not (BHC=0) during the same period. "Pearson χ^2" and "P-values" are statistics for the hypothesis testing about the independence between row items and column items. *, **, and *** indicate that the hypothesis of no-independence is rejected at a significance level of 10%, 5%, and 1%, respectively.

A. Distribution of grades, sorted by Merger.

Reply to each question	Q1		Q2		Q3		Q4		Q5		Q6	
(5:excellent- 1:inadequate)	Merger=0	Merger=1	Merger=0	Merger=1	Merger=0	Merger=1	Merger=0	Merger=1	Merger=0	Merger=1	Merger=0	Merger=1
5	124	150	125	137	42	38	66	39	32	22	62	57
4	206	305	189	285	135	214	116	164	92	182	168	250
3	50	105	67	131	185	287	183	334	230	313	141	214
2	11	27	11	29	29	46	26	48	37	62	17	54
1	3	6	2	11	3	8	3	8	3	14	6	18
Number of observations	987		987		987		987		987		987	
Pearson χ^2	9.15		15.52		6.39		29.15		18.15		17.16	
P-value	0.057*		0.004***		0.172		0.000***		0.001***		0.002***	

B. Distribution of grades, sorted by BHC.

Reply to each question	Q1		Q2		Q3		Q4		Q5		Q6	
(5:excellent- 1: inadequate)	BHC=0	BHC=1	BHC=0	BHC=1	BHC=0	BHC=1	BHC=0	BHC=1	BHC=0	BHC=1	BHC=0	BHC=1
5	254	20	240	22	74	6	101	4	49	5	109	10
4	459	52	433	41	320	29	263	17	259	15	379	39
3	143	12	175	23	425	47	461	56	482	61	319	36
2	34	4	38	2	69	6	63	11	92	7	68	3
1	7	2	11	2	9	2	9	2	15	2	22	2
Number of observations	987		987		987		987		987		987	
Pearson $\chi^2_{(4)}$	4.09		3.22		2.13		12.58		7.97		2.61	
P-value	0.393		0.522		0.711		0.014**		0.093*		0.625	

Table 2 Descriptive statistics for soft information variables

Descriptive statistics for the variables representing the acquisition of soft information are shown. "Response to Q1" through "Response to Q6" are variables explained in Table 1 (with a 1-5 value). SOFTINFO is the first principal component of the principal component analysis over "Response to Q1" through "Response to Q6" variables. In Panel A, the statistics are presented for "Merger=0" firms vs. "Merger=1" firms, whereas, in Panel B, they are presented for "BHC=0" firms vs. "BHC=1" firms, where the definitions of "Merger" and "BHC" are the same as in Table 1. *, **, and *** indicate that the sample mean of each group is different at a significance level of 10%, 5%, and 1%, respectively (two-sided test).

A. Descriptive statistics for soft information variables, sorted by Merger

	Merger=0					Merger=1					
Variables	No. of Obs.	Mean	S.D.	Min.	Max.	No. of Obs.	Mean		S.D.	Min.	Max.
Response to Q1	394	4.109	0.782	1	5	593	3.954	**	0.838	1	5
Response to Q2	394	4.076	0.800	1	5	593	3.857	***	0.892	1	5
Response to Q3	394	3.467	0.810	1	5	593	3.384		0.776	1	5
Response to Q4	394	3.548	0.873	1	5	593	3.300	***	0.765	1	5
Response to Q5	394	3.287	0.776	1	5	593	3.229		0.776	1	5
Response to Q6	394	3.668	0.846	1	5	593	3.462	***	0.898	1	5
SOFTINFO	394	0.370	1.778	-7.465	4.198	593	-0.085	***	1.783	-7.465	4.198

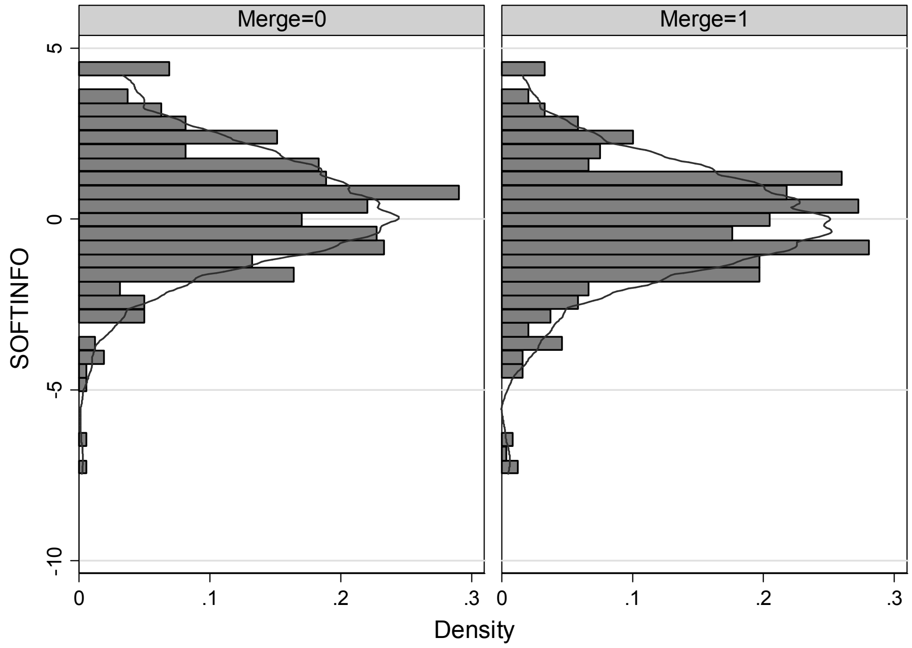
B. Descriptive statistics for soft information variables, sorted by BHC

	BHC=0					BHC=1					
Variables	No. of Obs.	Mean	S.D.	Min.	Max.	No. of Obs.	Mean		S.D.	Min.	Max.
Response to Q1	897	4.025	0.815	1	5	90	3.933		0.859	1	5
Response to Q2	897	3.951	0.861	1	5	90	3.878		0.885	1	5
Response to Q3	897	3.425	0.790	1	5	90	3.344		0.796	1	5
Response to Q4	897	3.428	0.819	1	5	90	3.111	***	0.756	1	5
Response to Q5	897	3.262	0.780	1	5	90	3.156		0.733	1	5
Response to Q6	897	3.541	0.889	1	5	90	3.578		0.821	1	5
SOFTINFO	897	0.125	1.782	-7.465	4.198	90	-0.182		1.897	-7.465	4.198

Figure 1　Histogram of SOFTINFO by the merger experience of main banks

Histogram of the variable SOFTINFO (for its definition, see Table 2).　In Panel A, the histograms of the firms in which the main bank experienced a merger ("Merge=1") and did not ("Merge=0") are compared.　In Panel B, the histograms of the firms in which the main bank established a bank holding company ("BHC=1") and did not ("BHC=0") are compared.

A. Sorted by Merge



B. Sorted by BHC

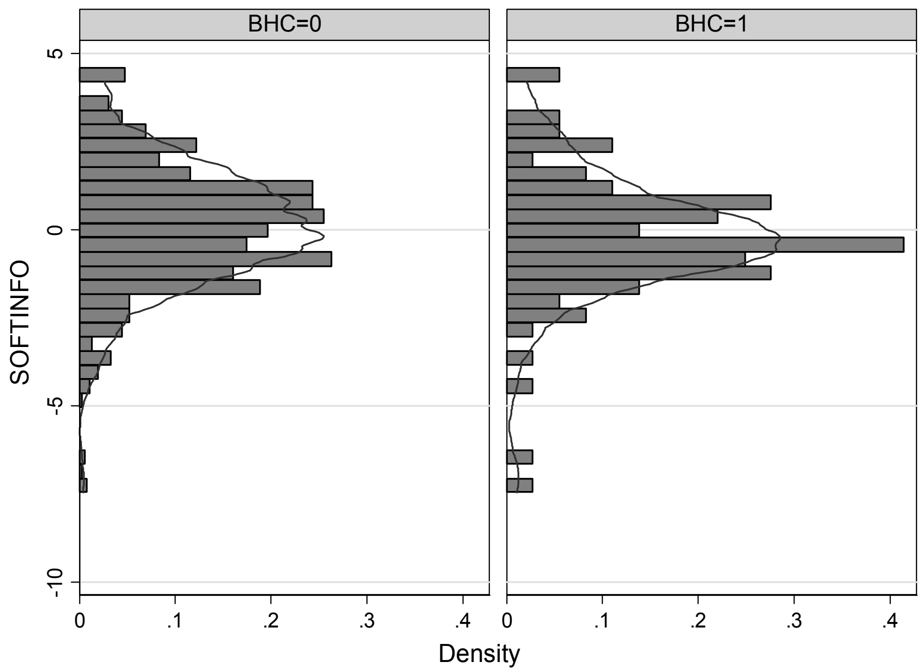


Table 3 Difference in SOFTINFO by bank size and merger

P-values for the test about the difference in the means of SOFTINFO among two groups are also shown. For the definition of SOFTINFO, see Table 2. *** indicates the statistical significance at a 1% level in each mean difference *t*-test.

Mean of SOFTINFO (s.d.)	# of obs.	Mean of SOFTINFO (s.d.)	# of obs.	t-test H_0: |(1)-(2)|=0 p-value
(1) Large banks		(2) Small banks		
-0.065	653	0.415	334	0.000
(0.069)		(0.100)		***
A. Large banks only				
(1) Merged banks		(2) Non-merged banks		
-0.057	569	-0.125	84	0.738
(0.074)		(0.186)		
B. Small banks only				
(1) Merged banks		(2) Non-merged banks		
-0.748	24	0.505	310	0.001
(0.445)		(0.101)		***

Table 4 Descriptive statistics of covariates

Variables	No. of Obs.	Mean	S.D.	Min	Max	Definition
Regional bank	987	0.202	0.401	0	1	A dummy equal to 1 if the main bank is a regional bank and 0 otherwise.
Shinkin bank	987	0.137	0.344	0	1	A dummy equal to 1 if the main bank is a Shinkin bank and 0 otherwise.
Audited	987	0.122	0.327	0	1	A dummy equal to 1 if the firm is audited and 0 otherwise.
Financial reporting frequency	987	2.606	3.106	1	13	Frequency of submission of the financial statements to the main bank (months).
Financial statement	987	0.978	0.148	0	1	A dummy equal to 1 if the firm has a financial statement and 0 otherwise.
Total assets of the firm	987	36.720	111.552	0.004	2417.644	Assets of the firm (100 million JPY).
Firm profit in the last two yrs. (deficit, surplus)	987	0.098	0.298	0	1	A dummy equal to 1 if the firm reported deficit two years ago and surplus in the previous year and 0 otherwise.
Firm profit in the last two yrs. (surplus, deficit)	987	0.067	0.250	0	1	A dummy equal to 1 if the firm reported surplus two years ago and deficit in the previous year and 0 otherwise.
Firm profit in the last two yrs. (deficit, deficit)	987	0.054	0.226	0	1	A dummy equal to 1 if the firm reported deficit both 2 years ago and in the previous year and 0 otherwise.
Paying dividend	987	0.424	0.494	0	1	A dummy equal to 1 if the firm pays dividends and 0 otherwise.
Firm age	987	50.218	24.008	4.333	135.667	Firm age (years old).
Years of relationship with the main bank	987	27.605	16.019	0	100	Years of the relationship of the firm with its main bank (years).
Time distance from the main bank	987	19.220	19.273	5	180	Time distance from the firm to its main bank (minutes: categorical).
Subsidiary of other companies	987	0.108	0.311	0	1	A dummy equal to 1 if the firm is a subsidiary of other company and 0 otherwise.
Visit by non-main banks increased	987	0.611	0.488	0	1	A dummy equal to 1 if the visits by loan officers of non-main banks increased and 0 otherwise.
Number of bank branches	987	43.747	38.796	1	139	Number of bank branches in the city where the firm is located.
Asset acquisition	987	0.037	0.190	0	1	A dummy equal to 1 if the main bank acquired assets of a liquidated bank during the period from April 2001 to June 2005.
Assets of the main bank	987	48.521	37.295	0.262	91.130	Total assets of the main bank (trillion JPY).
Loan/deposit of the main bank	987	0.696	0.176	0.178	1.390	Loan/deposit ratio of the main bank.
Capital ratio of the main bank	987	0.037	0.012	0.022	0.127	Capital ratio of the main bank.
Non-performing loan ratio of the main bank	987	0.023	0.011	0.008	0.098	{(loans to borrowers in legal bankruptcy) + (past due loans in arrears by 6 months or more) + (loans in arrears by 3 months or more and less than 6 months) + (restructured loans)} / (total loans outstanding) of the main bank.

Table 5　Effects of mergers and BHCs on soft information

Dependent variable: SOFTINFO.　OLS with robust standard errors.　The definitions of “Merger” and “BHC” are the same as in Table 1.　Other covariates are as shown in Table 3.　Constant terms are omitted from the table.　*, **, and *** indicate that the coefficient is different from zero at a significance level of 10%, 5%, and 1%, respectively (two-sided test).

Independent variables	(1)		(2)		(3)	
Merger (0,1)	-0.893	**	-0.868	***		
	(0.391)		(0.284)			
BHC (0,1)	-0.703	*	-0.758	**		
	(0.422)		(0.354)			
Merger*major bank (0,1)					-0.450	
					(0.588)	
Merger*regional bank (0,1)					-1.239	***
					(0.462)	
Merger*Shinkin bank (0,1)					-1.461	**
					(0.597)	
BHC*major bank (0,1)					-0.401	
					(0.628)	
BHC*regional bank (0,1)					-0.027	
					(0.784)	
Audited (0,1)	-0.223		-0.227		-0.213	
	(0.169)		(0.170)		(0.167)	
Fin. reporting frequency	0.031	*	0.030	*	0.032	*
	(0.018)		(0.017)		(0.017)	
Financial statement (0,1)	-0.425		-0.429		-0.479	
	(0.375)		(0.375)		(0.390)	
Assets (log)	0.401	***	0.402	***	0.408	***
	(0.051)		(0.051)		(0.051)	
Firm profit in the last two yrs.	0.152		0.168		0.136	
(deficit, surplus)	(0.195)		(0.195)		(0.192)	
Firm profit in the last two yrs.	-0.409	**	-0.419	**	-0.437	**
(surplus, deficit)	(0.203)		(0.205)		(0.205)	
Firm profit in the last two yrs.	0.152		0.158		0.155	
(deficit, deficit)	(0.258)		(0.257)		(0.258)	
Paying dividend (0,1)	-0.336	***	-0.341	***	-0.345	***
	(0.126)		(0.127)		(0.126)	
Firm age (log)	0.009		0.009		0.013	
	(0.129)		(0.129)		(0.130)	
Years of relationship with MB (log)	0.042		0.037		0.033	
	(0.074)		(0.074)		(0.074)	
Time Distance from MB (log of min.)	-0.128	*	-0.124	*	-0.128	*
	(0.068)		(0.068)		(0.068)	
Subsidiary of other companies	-0.561	***	-0.553	***	-0.567	***
	(0.209)		(0.210)		(0.209)	
Visit by non-MBs increased (0,1)	0.154		0.151		0.137	
	(0.114)		(0.114)		(0.114)	

(Table 5 continued)

(Table 5 continued)

Number of bank branches (log)	-0.039		-0.042		-0.050	
	(0.061)		(0.061)		(0.061)	
Regional bank (0,1)	0.415				0.740	
	(0.420)				(0.625)	
Shinkin bank (0,1)	1.178	*			1.570	*
	(0.655)				(0.895)	
Assets of MB (log)			-0.139			
			(0.093)			
Asset acquisition (0,1)	-0.189		-0.061		-0.284	
	(0.286)		(0.275)		(0.290)	
Loan/deposit of MB	1.569	*	0.489		1.418	
	(0.807)		(0.438)		(0.871)	
Capital ratio of MB	-13.227	**	-13.940	**	-11.514	*
	(6.272)		(6.519)		(6.348)	
Non-performing loan ratio of MB	-19.236	**	-17.681	**	-17.095	**
	(7.621)		(7.203)		(8.453)	
Industry Dummies	YES		YES		YES	
Urban dummies (Osaka, Kobe, Kyoto)	YES		YES		YES	
Adjusted R-squared	0.127		0.126		0.128	
Number of observations	987		987		987	

Table 6 Effects of mergers and BHCs on each component of soft information

Dependent variable: Response to each question (1-5) (see Table 1). Ordered logit. The definitions of "Merger" and "BHC" are the same as in Table 1. Other covariates are as shown in Table 3. *, **, and *** indicate that the coefficient is different from zero at a significance level of 10%, 5%, and 1%, respectively (two-sided test).

A. Specification (1) (the set of explanatory variables is the same as Specification (1) in Table 5).

	Q1	Q2	Q3	Q4	Q5	Q6
Merger (0,1)	-0.349	-0.888 **	-0.924 *	-1.021 **	-0.887 **	-0.019
	(0.462)	(0.424)	(0.476)	(0.499)	(0.448)	(0.414)
BHC (0,1)	-0.203	-0.543	-0.778	-1.361 ***	-0.952 **	0.425
	(0.479)	(0.416)	(0.485)	(0.498)	(0.471)	(0.412)
Pseudo R-squared	0.057	0.056	0.053	0.055	0.044	0.048
Number of observations	987	987	987	987	987	987

B. Specification (2) (the set of explanatory variables is the same as Specification (2) in Table 5).

	Q1	Q2	Q3	Q4	Q5	Q6
Merger (0,1)	-0.585 *	-0.567 *	-0.720 **	-1.086 ***	-0.786 **	-0.407
	(0.338)	(0.318)	(0.350)	(0.357)	(0.332)	(0.325)
BHC (0,1)	-0.480	-0.363	-0.729 *	-1.514 ***	-0.912 **	0.105
	(0.395)	(0.366)	(0.406)	(0.417)	(0.398)	(0.364)
Pseudo R-squared	0.055	0.056	0.051	0.056	0.043	0.047
Number of observations	987	987	987	987	987	987

C. Specification (3) (the set of explanatory variables is the same as Specification (3) in Table 5).

	Q1	Q2	Q3	Q4	Q5	Q6
Merger*major bank (0,1)	-0.168	-0.030	-1.160	-0.809	-1.285	0.921 *
	(0.566)	(0.933)	(1.206)	(0.790)	(1.082)	(0.495)
Merger*regional bank (0,1)	1.097	-0.524	-1.790 ***	-3.312 ***	-1.535 ***	0.439
	(1.591)	(0.895)	(0.600)	(0.664)	(0.470)	(0.526)
Merger*Shinkin bank (0,1)	-1.280 **	-1.562 ***	-0.840	-0.902	-0.907	-1.331 *
	(0.624)	(0.569)	(0.717)	(0.781)	(0.680)	(0.706)
BHC*major bank (0,1)	-0.140	0.258	-1.107	-1.317	-1.473	1.244 **
	(0.614)	(0.963)	(1.221)	(0.807)	(1.101)	(0.556)
BHC*regional bank (0,1)	0.382	-0.289	-0.114	-0.329	-0.138	1.052
	(0.826)	(0.653)	(0.935)	(0.751)	(0.975)	(0.696)
Pseudo R-squared	0.059	0.057	0.054	0.060	0.045	0.052
Number of observations	987	987	987	987	987	987

Table 7 Complexity increment measures and cost-cut measures

The degrees of the increment in organizational complexity (Panel A) and cost reduction (Panel B) are compared between banks that experienced a merger (Merged) and those that did not (Non-merged). For Merged banks, a complexity measure of X (= Asset, Loan, …) is calculated as (X of post-merger bank at s+1) / (weighted average of X of pre-merger banks at s-1)-1, while a cost-cut measure X is calculated as (X of post-merger bank at s+2) / (sum of X of pre-merger banks at s-1) -1, where s is the year a merger took place; for Non-merged banks, each complexity measure is the average annual increase in X throughout the window period, and each cost-cut measure is three times the average annual increase. P-values for the test about the difference in the means are also shown. ***, **, and * mean that the means are statistically different at a 1%, 5%, and 10% significance level, respectively.

[A. Complexity measures]

Variables	[A-1 All banks]				[A-2 Large banks]				[A-3 Small banks] (Regional, Shinkin)				[A-4 Difference in means]			
	Merged		Non-merged		Merged		Non-merged		Merged		Non-merged		Merged vs. Non-merged (all banks, P-value)	Merged vs. Non-merged (large only, P-value)	Merged vs. Non-merged (small only, P-value)	Large vs. Small (merged only, P-value)
	mean (s.d.)	# of obs.	mean (s.d.)	# of obs.	mean (s.d.)	# of obs.	mean (s.d.)	# of obs.	mean (s.d.)	# of obs.	mean (s.d.)	# of obs.				
Asset	1.059	10	0.011	43	0.884	5	-0.010	2	1.234	5	0.012	41	0.000	0.072	0.007	0.664
	(0.843)		(0.033)		(0.782)		(0.062)		(0.955)		(0.032)		***	*	***	
Loan	0.979	10	-0.005	43	0.753	5	-0.040	2	1.206	5	-0.003	41	0.000	0.046	0.009	0.537
	(0.799)		(0.030)		(0.594)		(0.050)		(0.978)		(0.028)		***	**	***	
Number of bankers	1.112	8	-0.032	43	1.010	4	-0.006	2	1.213	4	-0.033	41	0.000	0.018	0.021	0.800
	(0.757)		(0.037)		(0.506)		(0.011)		(1.026)		(0.038)		***	**	**	
Number of branches	1.033	8	-0.013	43	0.937	4	-0.008	2	1.128	4	-0.013	41	0.000	0.005	0.006	0.740
	(0.563)		(0.035)		(0.320)		(0.013)		(0.783)		(0.036)		***	***	***	

[B. Cost-cut measures]

Variables	[B-1 All banks]				[B-2 Large banks]				[B-3 Small banks] (Regional, Shinkin)				[B-4 Difference in means]			
	Merged		Non-merged		Merged		Non-merged		Merged		Non-merged		Merged vs. Non-merged (all banks, P-value)	Merged vs. Non-merged (large only, P-value)	Merged vs. Non-merged (small only, P-value)	Large vs. Small (merged only, P-value)
	mean (s.d.)	# of obs.	mean (s.d.)	# of obs.	mean (s.d.)	# of obs.	mean (s.d.)	# of obs.	mean (s.d.)	# of obs.	mean (s.d.)	# of obs.				
Number of bankers	-0.260	6	-0.096	43	-0.270	4	-0.017	2	-0.240	2	-0.100	41	0.004	0.031	0.043	0.784
	(0.090)		(0.112)		(0.107)		(0.034)		(0.069)		(0.113)		***	**	**	
Number of branches	-0.178	6	-0.039	43	-0.178	4	-0.025	2	-0.178	2	-0.040	41	0.023	0.101	0.348	1.000
	(0.106)		(0.105)		(0.088)		(0.040)		(0.183)		(0.107)		**			
Overhead & personnel expenses	-0.180	7	-0.056	43	-0.180	5	0.038	2	-0.181	2	-0.060	41	0.074	0.117	0.353	0.994
	(0.144)		(0.090)		(0.157)		(0.064)		(0.162)		(0.089)		*			
Ordinary expenses	-0.435	7	-0.134	43	-0.488	5	-0.339	2	-0.305	2	-0.124	41	0.039	0.633	0.536	0.640
	(0.273)		(0.253)		(0.262)		(0.246)		(0.355)		(0.252)		**			

Table 8 Impacts of the complexity increment and cost-cut on SOFTINFO

OLS with robust standard errors. ***, **, and * mean that the respective means are statistically different at a 1%, 5%, and 10% level of significance, respectively. The independent variables shown below are the relevant measures shown in Table 7.

A. Complexity increment measures only

	(1)	(2)	(3)	(4)
Asset	-0.184			
	(0.119)			
Loan		-0.226 *		
		(0.136)		
Number of bankers			-0.250	
			(0.180)	
Number of branches				-0.293
				(0.206)
Adjusted R^2	0.119	0.120	0.143	0.143
Number of observations	981	981	728	728

B. Cost-cut measures only

	(1)	(2)	(3)	(4)
Number of bankers	0.587			
	(0.609)			
Number of branches		0.099		
		(0.823)		
Overhead & personnel expenses			0.431	
			(0.470)	
Ordinary expenses				0.240
				(0.259)
Adjusted R^2	0.145	0.144	0.122	0.122
Number of observations	715	715	963	963

C. Impact of the complexity increment by bank type

	(1)		(2)		(3)	(4)
Asset	0.082					
	(0.127)					
Asset * Regional bank dummy	-1.314	**				
	(0.550)					
Asset * Shinkin bank dummy	-0.567					
	(0.387)					
Loan			0.107			
			(0.151)			
Loan * Regional bank dummy			-1.267	**		
			(0.502)			
Loan * Shinkin bank dummy			-0.551			
			(0.386)			
Number of bankers					0.031	
					(0.207)	
Number of bankers					-2.152	
* Regional bank dummy					(3.993)	
Number of bankers					-0.517	
* Shinkin bank dummy					(0.414)	
Number of branches						0.036
						(0.233)
Number of branches						-1.533
* Regional bank dummy						(3.135)
Number of branches						-0.609
* Shinkin bank dummy						(0.484)
Adjusted R^2	0.126		0.126		0.150	0.150
Number of observations	981		981		728	728

Bank market structure, competition, and SME financing relationships in European Regions

Steve Mercieca[a] Klaus Schaeck[b,*] Simon Wolfe[a]

Abstract

How do concentration and competition in the European banking sector affect lending relationships between small and medium sized enterprises (SMEs) and their banks? Recent empirical evidence suggests that concentration and competition capture different characteristics of banking systems. Using a unique dataset on SMEs for selected European regions, we empirically investigate the impact of increasing consolidation and competition on the number of lending relationships maintained by SMEs. We find that the negative effect on the number of lending relationships arising from more concentrated banking systems is offset by a positive impact from increased competition. Our results also suggest that characteristics of the local banking market considerably impact on the number of lending relationships.

JEL classification: G20; G21; G28
Keywords: SME financing; relationship banking; bank market structure

* Corresponding author.
[a] University of Southampton, School of Management, Highfield, Southampton SO17 1BJ
[b] Cass Business School, Faculty of Finance, 106 Bunhill Row, London EC1Y 8TZ
Email-addresses: S.Merceica@soton.ac.uk (Steve Mercieca); Klaus.Schaeck.1@city.ac.uk (Klaus Schaeck); ssjw@soton.ac.uk (Simon Wolfe)

Acknowledgements
We thank conference participants at the conference "Small business banking and financing: a global perspective" in Cagliari, Italy, and seminar participants at the University of Southampton for helpful comments and suggestions. All remaining errors are our own.

1 Introduction

An accelerating number of mergers and acquisitions (M&As) over the past decade, and changes in the regulatory and institutional environment financial institutions operate in have markedly affected the structure and competitive nature of banking markets. As the industry continues to shift and consolidate, relationships between banks and their customers may be altered, possibly impacting on the provision of banking services. This is of particular concern to small and medium size enterprises (SMEs) in Europe,[1] since they predominately depend on bank financing.

Numerous studies focus on the nature of relationships established by different types of banks (Berger et al., forthcoming), the determinants of the role of banks (Elsas, 2005; Harhoff and Körting, 1998; Elsas and Krahnen, 1998), the benefits of bank-borrower relationships (Berger and Udell, 2006; Elyasiani and Goldberg, 2004; Farinha and Santos, 2002; Ongena and Smith, 2001; Boot, 2000; Petersen and Rajan, 1995; Brick and Palia, 2007), the effect of competition on bank orientation (Degryse and Ongena, 2007), and the number of bank relationships maintained by large corporations (Ongena and Smith, 2000).

To the best of our knowledge, however, the extant literature has not yet investigated the determinants of the number of bank relationships maintained by SMEs. Moreover, how do observed changes in bank market structures affect the number of bank relationships maintained by SMEs? Further, how do characteristics of the local banking market impact on the number of bank financing relationships? This paper seeks to answer exactly these questions.[2]

In Europe, 23 million SMEs account for 99% of all companies, employ around 75 million people, and generate one in every two new jobs.[3] Given their important role, these institutional changes in banking systems give rise to major policy concerns. Our empirical enquiry focuses on SMEs since information-based intermediation theory (Diamond, 1984; Ramakrishnan and Thakor,

---

[1] The EU defines SMEs as enterprises that employ fewer than 250 people, have an annual turnover not exceeding €50 million, and/or annual balance sheet total not exceeding €43 million.

[2] For the purpose of our research 'bank financing relationship' refers to SME financing for the following purposes: firm start-up; product development; purchases of fixed assets; cash flow; reduction/avoidance of overdraft facilities; trading and trading costs; other business/company acquisition; expansion/growth; share capital; working capital; retirement of co-director; management buy-in/buy-out; bridge financing; seasonal production/trading; research; general corporate purposes; staffing; debtors financing; bills payable; work in progress funding; stock purchase; tax payments; replacement machinery; acquisitions; and business development.

[3] Observatory for European SMEs, Enterprise Directorate-General of the European Commission, (2004), Brussels.

1984; Bhattacharya and Thakor, 1993; Stein, 2002) suggests that SMEs are less likely to have as many bank relationships as have large corporations.

First, SMEs and their lenders frequently belong to the same socio-economic setting, which reduces information asymmetries, eases monitoring, and reduces costly information acquisition information about borrowers. This implies that opaque firms like SMEs find it optimal to borrow from one bank. However, 'hold up' problems arise with repeated lending from only one bank if the relationship lender extracts rents from the firm (Sharpe, 1990; Rajan, 1992). Thus, a limited number of bank relationships is optimal for SMEs, this also reduces the probability of being denied credit (Thakor, 1996; von Thadden, 1995).

Second, empirical evidence indicates that the number of bank relationships is increasing, although not uniformly, in firm size (Petersen and Rajan, 1994; Berger and Udell, 1995; Houston and James, 1996; Ongena and Smith, 2000).

Third, another reason why SMEs are less likely to maintain many bank relationships relate to their typical rural locations where sophisticated intermediaries. Typically, large banks do not have a physical presence in these rural locations because SMEs do not demand diversified supplies of financial services (Ferri and Messori, 2000).

Finally, SMEs are less likely to maintain relationships with larger institutions as the lending technology required for processing 'soft' information is less well developed in larger banks (Williamson, 1988; Stein, 2002; Berger and Udell, 2002; Cole et al, 2004; Berger et al., 2005a).[4] These final two arguments indicate that SMEs have a reduced pool of banks to obtain financing from.

Our cross-country analysis is also related to the literature on financial system architecture. First, while Staikouras and Koutsomanoli-Fillipaki (2006) and Schaeck and Cihak (2007) report increasing degrees of competition in European banking systems, Goddard et al. (2007), de Guevara et al.

---

[4] Relatedly, the literature on relationships maintained by local and regional banks proposes a 'long term interaction hypothesis' according to which banks taking part in community life share relationships of various kinds, not solely economic (Bannerjee et al., 1994; Besley and Coate, 1995). Through such relationships, they can acquire information that would be available to an outsider only at a cost. Consequently, banks operating in local and rural communities may take advantage of such information in their financing activities, placing them in a better position to deal with asymmetric information and agency problems.

(2005), and Amel et al. (2004) simultaneously observe a wave of consolidation across European banking systems resulting from an increasing number of M&As. This raises fears that consolidation decreases the number of banks specialising in relationship banking (e.g. community banks) with possibly detrimental welfare effects for local firms, especially SMEs, these firms' access to credit, and, ultimately, economic growth.[5] As a result, positive effects for the provision of banking services arising from increased competition in banking systems may be offset by higher degrees of concentration.

As part of our empirical investigation, we seek to answer this question because the extant literature on the effect of market structure and competition on SME financing offers two competing theories: Whereas proponents of the 'market power' notion (Elsas, 2005; Boot, 2000; Boot and Thakor, 2000, Ongena and Smith, 2000) contend that concentration decreases firms' access to credit, advocates of the 'information hypothesis' (Dell'Ariccia and Marquez, 2005; Petersen and Rajan, 1995) argue that less competition improves credit availability.

We propose that these contrasting findings may be due to the way competition is determined in empirical studies that frequently proxy competition with concentration measures. This assertion places our paper into a growing body of work by Beck et al. (2006), Claessens and Laeven (2004), Carbo et al. (2006), Schaeck et al. (2006), and de Guevara et al. (2005) indicating that concentration is a poor proxy for competition and that concentration and competition describe different characteristics of banking systems.

Second, following Ongena and Smith (2000), who report evidence that well developed financial systems with stronger protection of creditor rights help explain the number of bank relationships, we also test for the effect of differences in legal and financial system arrangements in the spirit of the studies motivated by La Porta et al. (1997), Levine (1999), Demirgüç-Kunt and Maksimovic (1998), and Beck et al. (2006). Our analysis helps evaluate whether the effects uncovered by Ongena and Smith (2000) are also valid for SMEs in Europe.

[5] Such developments have been extensively studied for the US, see, for instance, Craig and Hardee (2007), Berger and Udell (2002), Cole et al. (2004) and Berger and Frame (2005).

Third, we focus on Europe since EU banking systems have been undergoing significant changes following the launch of the Single Market Programme, transition to the Euro, and recent EU enlargements. While these developments are aimed at creating a level playing field for competition in European banking, the EU banking landscape is still largely influenced by linguistic and cultural differences that thwart setting up banking relationships across national boundaries. Such impediments may be due to 'exogenous economic borders', i.e. legal origin and system, supervisory and corporate governance practices, political framework, language and culture, and 'endogenous economic borders'. These are information-based, and arise from bank-firm relationships, adverse selection, and information sharing between intermediaries (Buch, 2001). Evidence for the conjecture that linguistic minorities and smaller non-financial firms prefer a more local character of the banks they do business with across EU regions is provided by Affinito and Piazza (2005). We therefore also explore whether differences across European regions help explain the number of bank relationships.

The purpose of our paper is to extend the literature on bank relationships in three distinct ways: First, this research is to the best of our knowledge the first empirical analysis of the determinants of the number of SME-bank financing relationships exclusively based on European data. Second, to disentangle effects from competition and concentration, we simultaneously consider independent effects arising from competition and concentration for SME-bank relationships. Third, we focus on selected European regions to investigate the importance of the socio-economic environment for SME-bank financing relationships. As Guiso et al. (2004, p. 937) point out 'if local market conditions matter, they should matter the most for small firms, which have difficulty in raising funds at a distance, than for large firms'.

We obtain data from the Centre for Business Research of the University of Cambridge regarding scope and scale of the relationship between 552 SME borrowers and their banks from Emilia-Romagna in the north-east of Italy, Bavaria in the south of Germany, and the south-east region of the UK. These regions are traditionally characterised by areas rich in innovative SMEs as well as local and regional banks, which are the main source of financing for SMEs.[6] This dataset, augmented with information on financial system architecture and local market conditions, provides an excellent setting to conduct our empirical investigation as the survey data can be matched with local bank market data. As detailed further below, this is particularly beneficial since we anticipate socio-economic factors to be paralleled by local financial systems. In addition, a regional focus permits better accounting for information asymmetries banks are exposed to when aiming to establish relationships with SMEs.

Four key findings emerge from our analysis: (1) Adverse effects of increasing consolidation for the number of bank relationships maintained by SMEs are fully offset by increased competition. To this extent, our results highlight that concentration measures do not serve as a proxy for competition in banking systems. (2) Factors such as regional GDP growth, regional population and an innovative environment are positively related to the number of bank relationships. (3) The number of bank relationships is increasing in the amount of bank finance used, and if the bank plays an active role in advising SMEs. (4) Regulatory restrictions on banking activities and financing and legal obstacles decrease the probability of maintaining multiple bank relationships.

The plan for the paper is as follows: Section 2 briefly explains the methodology and also describes the dataset. We present empirical results in Section 3. Section 4 contains sensitivity checks and Section 5 offers concluding remarks.

2 Data and Variables

We explain in Section 2.1 the information on SMEs obtained from survey data. Section 2.2 presents the motivation and description for the choice of the firm, bank, regional, and country-specific variables.

2.1 Survey Data

Our primary source for firm information is the *Survey of the Financing of Small and Medium-sized Enterprises in Western Europe,* conducted by the Centre for Business Research at the

[6] Further details regarding composition of these three regions are provided in Martin et al. (2001). Ferri and Messori (2000) present additional details regarding socio-economic characteristics and regional financial sub-systems in Italy.

University of Cambridge in 2001.[7] This survey focuses on the financing of SMEs in three different regions of Europe: Emilia-Romagna in Italy, Bavaria in Southern Germany, and the south-east of England. The survey is based on a questionnaire containing 191 questions for Germany and the UK, and 188 questions for Italy.[8] The questionnaire was sent out to over 800 SMEs and yielded 247 responses for the UK, 161 for Italy and 114 for Germany. Questions from the survey cover a variety of topics including the main markets serviced, the type of finance used, whether firms have used bank finance, and the role that banks play. Moreover, the questionnaire also provides details about the nature of the SMEs' type of business, size, employment growth, and turnover.

Summary statistics for the survey (and the other explanatory variables) are presented in Table 1. The UK makes up 47% of the sample with Germany and Italy accounting for 22% and 31% respectively. Italy shows the highest incidence of multi-bank relationships with the UK exhibiting the lowest.[9] Our definition of bank financing includes financing that is intended for, *inter alia*, acquisition investment, cash-flow, tax, and for enabling the SME to remain a going concern. It excludes SMEs having a relationship solely through having a checking or savings account with a bank. 42% of the SMEs in the sample do not use banks for their financing activities. This implies that they either use other forms of financing such as borrowing from family and friends, or use their own reserves for financing purposes. Such notion of self-financing is consistent with Beck et al. (2005a) who show that small firms finance a lesser proportion of their investment with formal sources of external finance.

The survey does not provide actual figures for turnover. Rather, the SMEs are classified into five categories, whereby higher values indicate greater turnover. Both average turnover and average number of employees for all SMEs are greater for those that move from zero to one and from one to more than one bank financing relationships. This is in line with previous studies highlighting that size is positively correlated with the number of bank relationships, e.g. Petersen and Rajan (1994). Descriptive statistics for the country-specific and regional variables are also presented in Table 1.

---

7 The survey data can be obtained from http://www.data-archive.ac.uk/findingData/snDescription.asp?sn=4955.

8 The questionnaire is accessible on the University of Cambridge website (http://www.data-archive.ac.uk/doc/4955%5Cmrdoc%5Cpdf%5C4955userguide.pdf).

9 These figures corroborate results obtained by other authors. For Italy, Pagano et al. (1998) report the mean number of bank credit relationships per firm to be 13.9 and Ongena and Smith (2000) report a mean of 15.2. For German firms, Elsas and Krahnen (1998), and Ongena and Smith (2000) report mean figures of 6.0 and 8.1 respectively. Ongena and Smith (2000) report mean figures of 2.9 relationships for UK firms.

[TABLE 1 about here]

2.2 Other Explanatory Variables[10]

Bank market structure variables

In order to test our hypothesis that concentration and competition among banks have independent effects for the number of financing relationships maintained by SMEs, we include the *Herfindahl-Hirschman index* (HHI), calculated as the sum of the squared market shares. This index is widely used as a measure to describe concentration in banking markets (Cetorelli, 1999). In addition, we use the 3-bank concentration ratio for a sensitivity test provided in Section 4 below.

To disentangle the effects arising from concentration and competition, we include the Panzar and Rosse (1987) *H-Statistic* to gauge competition. Claessens and Laeven (2004) argue that H is a more appropriate measure for the degree of competition than previously used proxies of competition. Shaffer (2004) highlights the analytical strength and superiority of the H-Statistic over other measures of competition since it is formally derived from profit-maximising equilibrium conditions.[11] It overcomes criticism put forward against concentration ratios that are frequently used to infer competition as it does not require assumptions about the market.[12] The H-Statistic gauges market power by the extent to which changes in factor input prices translate into equilibrium revenues. Vesala (1995) has shown that higher values of H signify more competition. We anticipate that concentration is inversely related to the number of relationships maintained by SMEs whereas the H-Statistic is expected to be positively related. Appendix II presents the calculations for the H-Statistic.

Regional market structure variables

Regional indicators for Emilia-Romagna, Bavaria, and the south-east of the UK are retrieved from REGIO, Eurostat's harmonised regional statistical database. We extract information on *Regional GDP*, *Regional Population*, and *Regional Patent Applications* to the European Patent

[10] We present definitions for the explanatory variables in Appendix I.

[11] For a detailed overview on computation of the H-Statistic see Claessens and Laeven (2004).

[12] Shaffer (2004) stresses that the definition of a banking market is likely to affect inferences regarding competition, when competition is inferred from concentration ratios. This is due to the fact that banking markets in small countries are likely to extend beyond a single nation's borders and because large banks operate globally. Moreover, Cetorelli (1999) underscores that competition cannot be determined by simply looking at market structure, since bank behaviour can only be measured accurately through direct empirical analysis of individual bank data.

Office. We expect these variables to positively impact upon the number of bank financing relationships.

To control for the nexus between SMEs and the business environment, we obtain the variables *Time to start Business* and *Cost to start Business* from the World Bank Doing Business Survey (2005). These regressors capture important factors that enhance or constrain business investment, productivity and growth respectively. We expect them to be positively related to the number of bank relationships.

Control variables

We also adapt variables from the World Business Environment Survey (WBES)[13] survey that assesses whether financial and legal obstacles affect firm growth. The survey asks enterprise managers to rate the extent to which financing and legal problems present obstacles to the operation of businesses. The variables take values of 1-4, with 1 indicating no obstacle and 4 indicating a major obstacle. The variables *Financing* and *Legal obstacle* are incorporated into the model to examine the impact such obstacles have on SME financing relationships as Schiffer and Weder (2001) maintain that small firms are more likely to face obstacles in obtaining finance and accessing legal systems.

We include *Banking Freedom* (obtained from the Heritage Foundation) to assess the openness of the banking system. Higher values indicate fewer restrictions on banking freedom. It is a composite index of whether foreign banks are allowed to operate freely, the difficulties faced when setting up domestic banks, government influence over the allocation of credit, and whether banks are free to provide insurance products and securities to customers. The index is expected to be positively associated with the number of financing relationships.

Additionally, we use *Access to Financial Services* to capture the geographic penetration of the banking system measured by the number of bank branches relative to area, and *Stock Market Capitalization/GDP*, to gauge the influence of stock market development on the number of bank relationships given that well developed securities markets might function as a substitute for the

[13] The World Business Environment Survey was conducted in 1999 and 2000 over 10,000 firms in 80 countries (World Bank database). Variables include financing constraints, GDP growth, private credit, domestic bank share, and foreign bank share. A detailed discussion of the survey is provided by Batra et al. (2003).

transaction services of banks. We assume that *Access to Finance* is positively correlated with the number of relationships as countries with better access to financial services providers offer more opportunities for SMEs to set up multiple lending relationships. By contrast, if SMEs can obtain funds from the stock market, we anticipate that a well developed equity market will be negatively related to the number of financing relationships.

We employ *Turnover* as a measure of firm size as we expect SMEs to maintain more financing relationships as they increase in size. Moreover, Detragiache et al. (2000) have shown that larger firms may have to rely on multiple banking to allow banks to diversify firm-specific credit risk. Additionally, firm complexity and growth opportunities are likely to increase with size, and larger borrowing requirements also induce SMEs to rely on multiple banking.

To determine the impact of entrepreneurial innovation on SME bank financing, we make use of a *Research and Development* (R&D) dummy variable that takes on the value one if the SME engages in R&D or zero otherwise. Von Thadden (1995) uses a measure of R&D to denote the amount of innovation intensity to capture entrepreneurial control rents. A negative correlation between entrepreneurial control rents and the probability of single banking also supports the hypothesis that multiple banking serves to reduce rent appropriation by banks. Conversely, Yosha (1995) shows that R&D intensity may be associated with single banking if information leakages to competitors are more likely with multiple lenders.

We use *Age* to assess whether the year of incorporation impacts the number of financing relationships. Older firms may face less severe adverse selection problems when seeking finance and should be more likely to have access to financial services as they have survived the critical start-up period and have generated reputational effects throughout the intervening years (Diamond, 1991).

To capture organisational form and distinguish between firm type, we include a dummy variable *Firm Type* that takes on the value one if the SME is private or zero otherwise. Public firms will have easier access to the capital markets and this might impact the number of bank relationships they maintain. As in Degryse and van Cayseele (2000), we include this variable as the degree of informational asymmetry varies with organisational form due to agency conflicts between owners, managers, and creditors.

We also investigate *Ownership Change* on the number of bank relationships as changes in ownership structure tend to coincide with changes in financing relationships. The *Amount of Bank Finance Used* is employed to assess how much the SME depends on financing from banks.

To account for the banks' bargain power over the borrowers and the degree of monitoring exerted by the bank, we employ the variable *Bank Role* (Elsas, 2005). This regressor provides information on whether the bank has a seat on the SMEs board, and whether it offers sales, marketing, technical or management advice to the firm.

Distance determines whether proximity between borrower and lender has any impact on the number of relationships. Given that SMEs are considered opaque and given that the collection of 'soft' information is facilitated by geographic proximity, we anticipate that distance will be positively related to the number of bank relationships.[14] As a measure of relationship strengths, we utilize a dummy variable *Bank Terms,* that takes on the value one if the SME views the terms given by the bank as favourable or zero otherwise.

We also employ two dummy variables for bank type, which take on the value one if the bank is a regional or a national bank respectively, or zero otherwise. Since a particular SME can obtain bank financing from either *Regional* or *National banks*, or both, the two bank types are not mutually exclusive and are both included in the quantitative analysis. Banks with different organisational structures may use different lending technologies to produce soft information. Small regional banks may have a comparative advantage in producing soft information, while banks with multi-layered hierarchies may perceive this as a comparative disadvantage.

[14] Several studies examine whether distance between lender and borrower has been changing over time and provide contrasting results. Petersen and Rajan (2002), Cyrnak and Hannan (2000), and, Wolken and Rohde (2000) all find that distance has increased, whilst Degryse and Ongena (2004), in contrast, find that distance has not increased.

3 Results

Concentration and competition

We use firm-level regressions of the number of bank relationships on firm, market structure, and regional and country-specific variables. The dependent variable is the multi-bank relationship variable. SMEs are classified as having no bank financing relationship, having one relationship, and having multiple bank financing relationships.[15] We employ a Tobit specification because the dependent variable is discrete-valued and truncated at the number of bank relationships below one.

[TABLE 2 about here]

Table 2 presents the main results. Column (1) is the canonical model. To examine the effects of concentration and competition, we include the HHI, the H-Statistic, and an interaction term between HHI and the H-Statistic in columns (2)-(5). The objective of these regression specifications is to establish whether concentration and competition capture the same characteristics of banking systems (and hence can be used interchangeably), or, if they independently affect the number of bank relationships. If so, this would suggest that it is inappropriate to proxy the degree of competition in banking systems with measures of market structure such as the HHI.

The HHI enters in column (2) positively and significantly, highlighting that SMEs in more concentrated markets are more likely to engage in more than one bank relationship. One reason may be that SMEs try to avoid hold-up problems in concentrated markets (Berger et al., forthcoming). This result however is reversed once the direct measure of competition, the Panzar and Rosse (1987) H-Statistic is included in the regression specification. In column (3), we only include the H-Statistic to gauge competition. This variable enters significantly with a positive sign, indicating that SMEs maintain more bank relationships in more competitive systems. Greater competition widens the spectrum of banks to choose from. Moreover, SMEs that might be experiencing difficulties could potentially find it easier to develop new bank relationships in a more competitive environment. Likewise, banks might also start providing better terms to clients in a bid to attract further business in a competitive environment. Our results contrast with Farinha and

[15] The survey data do not provide the precise number of bank relationships beyond one. This hampers the use of a Poisson model that could otherwise be used to estimate the actual number of lending relationships.

Santos (2002) who do not find that bank competition in the region where the firm is located plays a role in its decision to switch from single to multiple relationships.

Importantly, when these two variables enter the regression simultaneously in column (4), the HHI changes the sign of the coefficient, and retains its significance. This key finding persists throughout the remainder of the paper. In line with previous work by Ongena and Smith (2000) and Dewatripont and Maskin (1995), concentration reduces the number of relationships.[16] Moreover, if the banking market is concentrated, and if an SME's existing relationship is experiencing difficulties for one reason or another, then it will be harder to obtain services when the number of players in the market is limited. This result is aligned with the Structure-Conduct-Performance (SCP) paradigm, which states that market power reduces access to credit.

By contrast, competition continues to positively affect the number of bank relationships. The results concerning HHI and the H-Statistic are intuitive: Firms operating in concentrated markets can only choose between a few providers of financing and therefore have fewer bank relationships, whereas competition increases the number of bank relationships. This result provides important evidence that independent effects arise from market structure and competition. Thus, our finding suggests that competition should not be proxied by the degree of concentration. In addition, this result is related to the results by Craig and Hardee (2007), who demonstrate that credit availability for small firms declines as a result of consolidation in banking. This adverse effect is however mitigated by the fact that small businesses substitute bank financing through alternative sources such as capital leasing firms, mortgage companies and financial brokers.

To shed more light on the effects attributable to competition and concentration, we include an interaction term between the H-Statistic and the HHI. The two variables are centered on the mean in this regression to mitigate collinearity problems arising from correlations between the interaction term and its components (Zou and Adams, 2006).[17] If centered, the individual

---

[16] In a related study, Craig and Hardee (2007) show that small businesses operating in areas dominated by large banks tend to hold less debt than firms in areas with fewer large banks. They interpret this result as suggestive evidence for a negative effect of consolidation on access to credit.

[17] Centering variables involves subtracting from each observation of the component parts the mean of that variable before constructing the interaction term.

components reflect the effect of competition when concentration is held at the mean value (and vice versa). Thus, the total effect of H or the HHI on the number of bank relationships depends on the estimated coefficient of the interaction term. For instance, a negative coefficient for the interaction term indicates that the higher the degree of competition, the lower the effect of concentration on the number of bank relationships (and vice versa). Column (5) shows that both H-Statistic and HHI retain their respective signs and level of significance when the interaction term is included. The interaction term enters positively and significantly, implying that the effect of H on the number of relationships is greater in more concentrated markets.

Visual inspection of the magnitude of the coefficients for H and HHI in column (4) already indicates that their respective positive and negative effects cancel out. To further investigate this, we evaluate the independent effects arising from competition and concentration, using a logit model with marginal effects, and compute the impact of increasing these two variables by one percent on the probability of engaging in an additional relationship. The dependent variable is recoded for this test to take on the value zero if the SME only maintains one bank financing relationship or one if the SME makes use of more than one bank relationships. We report marginal effects, because the magnitude of the change in the probability of setting up an additional lending relationship depends on the initial values of all the independent variables and their coefficients. The results are provided in Appendix III, column (4).

While increasing the HHI by one percent (0.001*-0.3542) decreases the probability of having an additional bank relationship by 0.04 percent, this effect is more than offset by increasing competition. In fact, increasing the H-Statistic by one percent (0.001*0.4737) increases the probability of having an additional bank relationship by 0.05 percent. This calculation illustrates that the adverse ramifications arising from increased consolidation in banking are totally offset by greater competition in banking.

Among the control variables in Table 2, we find that *Firm Age* increases the number of bank relationships, and so do *Turnover, Distance,* and the *Amount of Bank Finance Used.* The dummy variables for *Bank Role* and *Bank Terms* also enter significantly with a positive sign. The more influential a bank, the more likely the SME seeks additional bank relationships. This could reflect the SMEs' awareness that the lender is trying to extract rents. Likewise, if firms perceive banks' terms to be favourable, they increasingly establish multiple lending relationships (Harhoff and Körting, 1998). The dummy variables for *National* and *Regional Bank* also enter positively and significantly. Doing business with a regional bank increases the number of bank relationships as the regional bank may not be able to provide as broad a range of services as required by the SME (Berger et al. forthcoming). On the other hand, doing business with a national bank may not be sufficient as the SME may want to retain a relationship with a local lender that is better able to process 'soft' information.

By contrast*, Firm Type, Ownership change,* and *R&D investment* enter negatively and significantly in Table 2. Private firms are less likely to have more than one bank relationship when compared to public firms, suggesting that more opaque firms tend to have less bank relationships as providers of funds that do not have access to 'soft' information will incur greater monitoring costs. The negative effect of ownership change may reflect banks' reluctance to provide services to firms that change ownership and require an assessment of whether the new SME management is able to provide them with the necessary creditworthiness requirements. The weakly inverse association of bank relationships with R&D investment could be driven by the SMEs' concern about possible information leakages.

It is important to acknowledge that including variables that capture competition and concentration considerably improve upon the fit of the model. While the regression in column (2) only explains about 40 percent of the variation in the number of bank relationships, the pseudo R^2 increases to 46 percent when both H and HHI enter the regression equation simultaneously in column (4).

Regional and financial system characteristics

In Table 3, we investigate the effect of characteristics of the local banking market and of the wider financial system. As we are not specifically interested in the control variables, we constrain the subsequent discussion to regional and financial system characteristics and the effects of the H-Statistic and the HHI.

[TABLE 3 about here]

In terms of *Access to Financial Services*, measured by the ratio of bank branches per sq km, we find that a higher density of branch offices makes it easier to access providers of financial services.

The econometric tests corroborate our conjecture that regional factors affect the number of bank relationships. Higher *Regional GDP growth*, a larger *Regional Population*, and more *Regional Patents* are all significantly positively associated with our dependent variable. SMEs are likely to expand in scope and scale when the local economy prospers and innovates. This makes them diversify their financing relationships. Moreover, our result concerning regional population is aligned with Affinito and Piazza (2005) whose results indicate that an economically active local population requires wider access to banking services.

Stock Market Capitalization/GDP shows negative and significant association with multi-bank relationships. We attribute this result to the fact that SMEs operating in environments with better developed stock markets have a substantial part of their financial needs met through equity. A similar result, although not significant, is reported by Ongena and Smith (2000).

Both H-Statistic and HHI retain their respective sign and level of significance throughout all regressions in Table 3, suggesting that our inferences also hold when regional and financial system characteristics are accounted for.

Institutional characteristics

We examine the effects of the institutional environment and design features of the regulatory system in Table 4.

[TABLE 4 about here]

Both *Financing* and *Legal obstacles* are negatively related to the number of bank financing relationships. As financing obstacles increase, SMEs are less inclined to have more than one bank relationship since the environment makes it harder to develop new opportunities. Moreover, SMEs with one relationship are likely to be prone to maintain and nurture an existing bank relationship, anticipating that having one healthy banking relationship benefits the firm. Likewise, legal obstacles require greater knowledge of the legal environment (something which SMEs might not have or only develop over time of being in business, given their local/community nature). As shown in Beck et al. (2005a), the extent to which financial and legal underdevelopment constrain a firm's growth depends very much on a firm's size. Smallest firms are consistently the most adversely affected by all obstacles. In fact, our results are aligned with the 'soft budget' constraint hypothesis (see also Ongena and Smith, 2000), proposing that inefficient judicial systems motivate firms to maintain more bank relationships.

With respect to the *Cost to start a business*, we find that higher costs induce firms to engage in multiple relationships. As anticipated, the more costs businesses incur towards their set-up, the more use of financial support they will need, particularly in instances where they do not have self-financing. The advice provided by banks that have assisted SMEs during their set-up may prove invaluable for SMEs. Similarly, *Time to start a business* also increases the number of financing relationship. This could be due to the fact that financing working capital is spread across a number of lenders in the early stages of a business as each lender individually may not be keen on committing large volume loans to the start-up company.

In line with our expectation, *Banking freedom* enters positively and significantly, suggesting that institutional factors conducive to a more open environment facilitate the establishment of multiple bank relationships.

The HHI retains its sign and level of significance throughout all regressions in Table 4. The H-Statistic also remains significant with the anticipated sign in all but one specification. It is only rendered insignificant when *Banking freedom* is controlled for. Thus, our inferences regarding concentration and competition are insensitive to controlling for the institutional setting.

4 Sensitivity Tests

We embark on a set of robustness tests to investigate if our results are sensitive to the way competition and concentration are measured.[18]

[TABLE 5 about here]

---

[18] We also ran the regressions for regional and financial system characteristics (Table 3), and for the institutional environment (Table 4) with the alternative measures of concentration and competition. We obtain virtually identical results with respect to the effects of competition and concentration. The results can be obtained from the authors on request.

Table 5 presents four regressions. In column (1) and (2) we employ an alternatively computed H-Statistic as a measure of competiton. This H-Statistic is calculated using the ratio of interest revenue to total assets instead of the ratio of total revenue to total assets as dependent variable (see also Molyneux et al., 1994). The alternative H-Statistic enters significantly with a positive sign, suggesting that the way H is calculated does not affect the inferences.

Columns (3) and (4) replace the HHI with the 3-bank concentration ratio to gauge the degree of concentration in banking systems. This variable is frequently used in studies of bank concentration (e.g. Beck et al., 2006). The findings are not affected. We therefore conclude that measurement errors of concentration do not drive our findings.

Finally, we exploit the fact that out dataset only provides information on the number of bank relationships for zero, one, or multiple bank relationships and test the sensitivity of our results to the specification of the econometric model. As alluded to in Section 3, we employ a logit model and calculate marginal effects. Our findings regarding the effects of competition, concentration, and the regional, financial system, and institutional characteristics are corroborated. The results from this final sensitivity check are presented in Appendix III.

5 Concluding Remarks

Against a background of increasing concentration and competition in European banking systems and marked changes in the regulatory environment which financial institutions operate in, this paper seeks to establish the effect of such changes on the determinants of the number of SME bank financing relationships in three distinct European regions. To the best of our knowledge, this study provides the first insight of the determinants of financing relationship of SMEs in Europe.

Employing a new dataset from a cross-sectional survey of SMEs, we uncover independent effects arising from competition and concentration on the number of lending relationships maintained by SMEs. Small and medium sized firms maintain more relationships in more competitive banking systems. This result is consistent with the ‘market power’ hypothesis in the literature.

Importantly, our results substantiate the assertion in recent empirical work that competition and concentration describe different characteristics of banking systems. More precisely, the findings underscore that decreasing effects on the number of bank relationships arising from increased consolidation in banking are offset by increased competition. Furthermore, this conclusion is robust to alternative measures of competiton and concentration.

Our study also analyses measures that capture information on the local economic environment and regarding design features of the institutional system on the country-level. In that respect, we find that regional GDP growth, regional population, and a stimulating local entrepreneurial environment foster the establishment of multiple lending relationships, whereas legal and financing obstacles are an impediment to multiple relationships.

These findings bear important policy implications: In particular, the results imply that measures of market structure such as the HHI and the 3-bank concentration ratio may be inappropriate proxies for the degree of competition in banking as we reveal that both structure and conduct affect SMEs' financing relationships in opposite directions. Moreover, the frequently raised concern among policymakers and in the media about the adverse ramifications from an increase of consolidation in banking concerning the provision of banking services to SMEs is not justified, given that these negative effects are fully offset by the increased competition in banking. In addition, the finding that legal obstacles are an impediment to diversifying lending relationships indicates that policies aimed at encouraging SMEs to expand in scope and scale (which often requires setting up additional bank relationships) are bound to be unsuccessful if legal institutions are not amended accordingly. Finally, removing barriers and obstacles that hamper setting up multiple bank relationships imposed on banks will enable SMEs to develop and mature by making use of more sophisticated financial services, thus ultimately promoting economic growth.

Data limitations concerning the comparatively small sample size suggest that our results have to be taken with a note of caution. Nonetheless, our findings complement a growing body of empirical work in the banking literature suggesting that concentration and competition describe different characteristics of banking systems.

This paper can be extended in other directions. Obviously, it would be interesting to examine our hypotheses with a larger cross-country sample, including less developed economies. Another intellectually appealing avenue for future work would be to analyse the effect of the availability of venture capital and private equity on SME financing and the way SMEs interact with their banks. Finally, an examination of how different lending technologies are affected by concentration and competition also seems worthwhile.

References

Affinito, M., and M. Piazza (2005) What determines banking structures in European regions? Bank of Italy, Working Paper

Amel, D., C. Barnes, F. Panetta, and C. Salleo (2004) Consolidation and efficiency in the financial sector: A review of the international evidence, Journal of Banking and Finance, Vol. 28, pp. 2493 - 2519

Banerjee, A. V., T. Besley, and T. W. Guinnane (1994) Thy neighbours keeper: The design of a credit cooperative theory and a test. Quarterly Journal of Economics, Vol. 109, pp. 491 - 515

Barth, J. R., G. Caprio, Jr. and R. Levine (2001) The regulation and supervision of banks around the world - A new database (Vol.1). World Bank. Mimeo.

Batra, G., D. Kaufmann, and A. Stone (2003) The Firms Speak: What the World Business Environment Survey Tells us about Constraints on Private Sector Development. World Bank. Mimeo.

Beck, T., A. Demirgüç-Kunt and R. Levine (2006) Bank concentration, competition, and crises: First results. Journal of Banking and Finance, Vol. 30, pp. 1581-1603

Beck, T., A. Demirguc-Kunt, and V. Maksimovic (2005a) Financial and legal constraints to growth: Does firm size matter? Journal of Finance, Vol. 60, pp. 137-177

Beck, T., A. Demirgüç-Kunt, and M. S. Martinez Peria (2005b) Reaching out: Access to and use of banking services across countries: World Bank. Mimeo.

Beck, T., A. Demirgüç-Kunt, and R. Levine (2000) A new database on financial development and structure. World Bank Economic Review, Vol. 14, pp. 597-605

Berger, A., N. L. F. Klapper, M. S. Martinez Peria and R. Zaidi (2007) Bank ownership type and banking relationships. Journal of Financial Intermediation, forthcoming

Berger, A., N. H. Miller, M. A. Petersen, R. G. Rajan, and J. Stein (2005) Does function follow organizational form? Evidence from the lending practices of large and small banks. Journal of Financial Economics, Vol. 76, pp. 237 – 269

Berger, A., N. and S. W. Frame (2005) Small business credit scoring and credit availability. Federal Reserve Bank of Atlanta Working Paper #2005-10, May 2005

Berger, A. N., and G. Udell (2006) A more complete conceptual framework for SME finance. Journal of Banking and Finance, Vol. 30, pp. 2945-2966

Berger, A., N. and G. F. Udell (2002) Small business credit availability and relationship lending: The importance of bank organisational structure. Economic Journal 112, F32-F53

Berger, A. N. and G. Udell (1995) Relationship lending and lines of credit in small firm finance. Journal of Business, Vol. 68, pp. 351 - 382

Besley, T. and S. Coate (1995) Group Lending, repayment incentives and social collateral. Journal of Development Economics, Vol. 46, pp. 1 - 18

Bhattacharaya, S., and A. V. Thakor (1993) Contemporary banking theory. Journal of Financial Intermediation, Vol. 3, pp. 2 - 50

Boot, A.W.A, (2000), 'Relationship Banking: What do we know? Journal of Financial Intermediation, Vol. 9, pp. 7-25

Boot, A.W.A., and A. V. Thakor (2000) Can relationship banking survive competition? Journal of Finance, Vol. 55, pp. pp. 679-713

Brick, I. E. and D. Palia (2007) Evidence of jointness in the terms of relationship lending. Journal of Financial Intermediation, Vol. 16, pp. 425-476

Buch, C.M. (2001) Distance and International Banking. Institute of World Economics WP, no. 1043, Kiel, Germany

Carbo, S., D. Humphrey, J. Maudos, and P. Molyneux (2006) Cross-country comparisons of competition and pricing power in European banking. Paper available at: http://www.unicatt.it/convegno/UC-LSE/paper/Carbo-Humphrey-Maudosc-Molyneux.pdf

Cetorelli, N. (1999) Competitive analysis in banking: Appraisal of the methodologies. Economic Perspectives, Federal Reserve Bank of Chicago, Vol. 23, pp. 2-15

Claessens, S. and L. Laeven (2004) What drives bank competition? Some international evidence. Journal of Money, Credit and Banking, Vol. 36 (3), pp. 563-583

Cole, R. A., L. G. Goldberg and L. J. White (2004) Cookie-cutter versus character: The micro structure of small business lending by large and small banks. Journal of Financial and Quantitative Analysis, Vol. 39, pp. 227-251

Craig, S. G., and P. Hardee (2007) The impact of bank consolidation on small business credit availability. Journal of Banking and Finance, Vol. 31, pp. 1237-1263

Cyrnak, A., and T. Hannan (2000) Non-local lending to small businesses. Board of Governors of the Federal Reserve System. Working Paper.

De Guevara, J. F., J. Maudos, and F. Perez (2005) Market power in European banking sectors. Journal of Financial Services Research, Vol. 27, pp. 109-137

Degryse, H., and P. van Cayseele (2000) Relationship lending within a bank-based system: Evidence from European small business data. Journal of Financial Intermediation, Vol. 9, pp. 90 - 109

Degryse, H., and S. Ongena (2007) The impact of competition on bank orientation. Journal of Financial Intermediation, Vol. 16, pp. 399-424

Degryse, H., and S. Ongena (2004) The impact of technology and regulation on the geographical scope of banking. Oxford Review of Economic Policy, Vol. 20, pp. 571-590

Dell'Ariccia, G., and R. Marquez (2005) Competition Among Regulators and Credit Market Integration," Journal of Financial Economics, Vol. 79, pp. 401-430

Demirgüç-Kunt, A., and V. Maksimovic, V. (1998) Law, finance, firm growth. Journal of Finance, Vol. 53, pp. 2107 - 2137

Detragiache, E., P. Garella, and L. Guiso (2000) Multiple versus Single Banking Relationships: Theory and Evidence. Journal of Finance, Vol. 55, pp. 1133 - 1161

Dewatripont, M., and E. Maskin (1995) Credit and efficiency in centralised and decentralised economies. Review of Economic Studies, Vol. 62, pp. 541 - 555

Diamond, D. (1991) Monitoring and reputation: The choice between bank loans and directly placed debt. Journal of Political Economy, Vol. 99, pp. 688 - 721

Diamond, D. (1984) Financial Intermediation and delegated monitoring. Review of Economic Studies, Vol. 51, pp. 393 - 414

Elsas, R. (2005) Empirical determinants of relationship lending. Journal of Financial Intermediation, Vol. 14, pp. 32-57

Elsas, R., and J. P. Krahnen (1998) Is Relationship Lending Special? Evidence from credit-file data in Germany. Journal of Banking and Finance, Vol. 22, pp. 1283 - 1316

Elyasiani, E., and L. G. Goldberg (2004) Relationship lending: A Survey of the Literature. Journal of Economics and Business, Vol. 56, pp. 315 - 330

European Commission (2004) Observatory for European SMEs, Enterprise Directorate-General of the European Commission. Brussels

Farinha, L.A, and J. A. Santos (2002) Switching from Single to Multiple Bank Lending Relationships: Determinants and Implications. Journal of Financial Intermediation, Vol. 11, pp. 124 - 151

Ferri, G., and M. Messori (2000) Bank-firm relationships and allocative efficiency in Northeastern and Central Italy and in the South. Journal of Banking and Finance, Vol. 24, pp. 1067 - 1095

Goddard, J., P. Molyneux, O. S. J. Wilson, and M. Tavakoli (2007) European banking: An overview, Journal of Banking and Finance, Vol. 31, pp. 1911-1935

Guiso, L., P. Sapienza, and L. Zingales (2004) Does local financial development matter? Quarterly Journal of Economics, Vol. 119, pp. 929-969

Harhoff, D., and T. Körting (1998) Lending Relationships in Germany – empirical evidence from survey data. Journal of Banking and Finance, Vol. 22, pp. 1317 - 1353

Houston, J., and C. James (1996) Bank information monopolies and the mix of private and public debt claims. Journal of Finance, Vol. 51, pp. 1863 - 1889

La Porta, R., F. Lopez-de-Silanes, A. Shleifer and R. W. Vishny (1997) Legal determinants of external finance. Journal of Finance, Vol. 52, pp. 1131 - 1150

Levine, R. (1999) Law, finance, and economic growth. Journal of Financial Intermediation, Vol. 8, pp. 8 - 35

Martin, R., D. Sunley, and D. Turner (2001) The restructuring of local banking systems across Europe: implications for regional business development. Cambridge Centre for Business Research, University of Cambridge

Mercieca, S., K. Schaeck, and S. Wolfe (2007) Small European banks: Benefits from diversification? Journal of Banking and Finance, Vol. 31, pp. 1975-1998

Molyneux, P., D. M. Lloyd-Williams, and J Thornton (1994) Competitive conditions in European banking. Journal of Banking and Finance, Vol. 18, pp. 445-459

Ongena, S., and D. C. Smith (2001) The Duration of Bank Relationships. Journal of Financial Economics, Vol. 61, pp. 449 - 475

Ongena, S., and D. C. Smith (2000) What determines the number of Bank Relationships? Cross Country Evidence. Journal of Financial Intermediation, Vol. 9, pp. 25-56

Pagano, M., F. Panetta, and L. Zingales (1998) Why do companies go public? An empirical analysis. Journal of Finance, Vol. 53, pp. 27 – 64

Panzar, J. C. and J. N. Rosse (1987) Testing for monopoly equilibrium. Journal of Industrial Economics, Vol. 35, pp. 443–456

Petersen, M.A., R. G. and Rajan (2002) Does distance still matter? The information revolution in small business lending. Journal of Finance, Vol. 57, pp. 2533 - 2570

Petersen, M.A., and R. G. Rajan (1995) The effect of credit market competition on lending relationships. Quarterly Journal of Economics, Vol. 110, 406-443

Petersen, M.A., and R. G. Rajan (1994) The benefits of firm-creditor relationships: Evidence from small business data. Journal of Finance, Vol. 49, pp. 3 - 37

Rajan, R.G. (1992) Insiders and outsiders: The choice between informed and arm's-length debt. Journal of Finance, Vol. 47, pp. 1367 - 1400

Ramakrishnan, R.T.S., and A. V. Thakor (1984) Information reliability and a theory of financial intermediation. Review of Economic Studies, Vol. 51, pp. 415- 432

Shaffer, S. (2004) Patterns of competition in banking. Journal of Economics and Business, Vol. 56, pp. 287–313

Sharpe, S.A. (1990) Asymmetric information, bank lending and implicit contracts: A stylized model of customer relationships. Journal of Finance, Vol. 45, pp. 1069 - 1087

Schaeck, K., and M. Cihak (2007) Bank market structure, competition and stability: Evidence from the micro level. IMF Working paper, forthcoming, Washington, D.C.: International Monetary Fund

Schaeck, K., M. Cihak, and S. Wolfe (2006) Are more competitive banking systems more stable? IMF Working Paper 06/143, Washington, D. C.: International Monetary Fund

Schiffer and Weder (2001) Firm size and the business environment: Worldwide survey results. Discussion Paper No. 43, International Finance Corporation, Washington, D.C.

Staikouras, C. and A. Koutsomanoli-Fillipaki (2006) Competition and concentration in the new European banking landscape. European Financial Management, Vol. 12, pp. 443 - 482

Stein, J.C. (2002) Information production and capital allocation: decentralized versus hierarchical firms. Journal of Finance, Vol. 57, pp. 1891 - 1921

Thakor, A.V (1996) Capital requirements, monetary policy, and aggregate bank lending: Theory and empirical evidence. Journal of Finance, Vol. 51, pp. 279 - 324

Vesala, J. (1995) Testing for competition in banking: Behavioural evidence from Finland. Helsinki: Bank of Finland

Von Thadden, E.L (1995) Long-term investments, short-term investment and monitoring. Review of Economic Studies, Vol. 62, pp. 557-575

Williamson, O. (1998) Corporate Finance and corporate governance. Journal of Finance, Vol. 43, pp. 567 - 591

Wolken, J., and D. Rohde (2002) Changes in the location of small businesses' financial suppliers between 1993 and 1998. Federal Reserve Board Memo.

World Bank (2004) Doing Business in 2004: Understanding Regulation. The World Bank. Washington, D.C.

Yosha, O. (1995) Information disclosure costs and the choice of financing source. Journal of Financial Intermediation, Vol. 4, pp. 3 - 20

Zou, H. and M. B. Adams (2006) The corporate purchase of property insurance: Chinese evidence. Journal of Financial Intermediation, Vol. 15, pp. 165-196

Appendix I: Definitions of explanatory variables

Variable	Description	Source
Multi-bank relationships	Whether SME has 0, 1, or more than 1 bank relationship	Cambridge SME Survey
Turnover	Turnover for year 2001. Variable takes value of 1if< £499k; value of 2 if between £500k and £999k; value of 3 if between £1m - £9.9m; value of 4 if between £10m –over.	Cambridge SME Survey
Year	Ranges between 1700 and 2001 and is measured as the difference between 2001 and the year the SME began trading.	Cambridge SME Survey
Ownership	Takes value of 1 if the company is still under the same ownership, 0 otherwise.	Cambridge SME Survey
Employees	Employees for year 2001. Variable takes value of 1 if between 1 – 5; value of 2 if between 10 - 19; value of 3 if between 20 - 49; value of 4 if between 50 – 99; value of 5 if >=100.	Cambridge SME Survey
R&D Expenditure	Take value of 1 if SME invests in R& D, 0 otherwise.	Cambridge SME Survey
Type of Company	Whether the SME is public or private company (1=public, 0 otherwise).	Cambridge SME Survey
Bank Role	Takes value of 1 if bank plays a role for SME being either a seat on the firm's board; technical advice; management advice; marketing and sales advice; and other roles; 0 otherwise.	Cambridge SME Survey
Bank Terms	Takes value of 1 if bank's terms are reasonable, 0 otherwise.	Cambridge SME Survey
Regional Bank	1 if Regional Bank 1 if National bank or 0 otherwise. Italian regional banks are Cooperative, Local and Regional banks; with National and other banks considered as National Banks. Germany regional banks are Sparkassen, Raiffeisen, Volksbank, Regionale Privatbank; with Uberregionale Privatbank, Postbank, Spardabank, Sonstige and other banks considered as National Banks. UK regional banks are Clearing banks; with Investment Banks considered as National Banks.	Cambridge SME Survey
Distance	Distance of bank from firm. Variable takes value of 1 if < 10 miles; value of 2 if between 10 – 49 miles; value of 3 if >= 50 miles.	Cambridge SME Survey
Time to start business	Time in days to set up a business	World Bank Survey (2005)
Cost to start business	Cost, measured in percent of income per capital, to set up a business	World Bank Survey (2005)
Banking freedom	An indicator of relative openness of banking and financial system, averaged over the period 1995-99: specifically whether the foreign banks and financial services firms are able to operate freely, how difficult it is to open domestic banks and other financial services firms, how heavily regulated the financial system is, the presence of state-owned banks, whether the government influences allocation of credit, and whether banks are free to provide customers with insurance and invest in securities (and vice-versa). The index ranges in value from 1 (very low) to 5 (very high), calculated as 6 minus the banking freedom index of the Heritage Foundation.	Barth et al. (2001)
Financing obstacle	Firms to rate on scale of 1-4, how problematic specific financing issues are for the operation and growth of their business. These are i) collateral requirements of banks and financial institutions; ii) bank paperwork and bureaucracy; iii) high interest rates; iv) need for special connections with banks and financial institutions; v) banks lacking money to lend; vi) access to foreign banks; vii) access to non-bank equity; viii) access to export finance; ix) access to financing for leasing equipment; x) inadequate credit and financial information on customers; and xi) access to long-term loans.	Beck et al. (2005a)
Legal Obstacle	Businesses asked whether i) information on laws and regulations was available; ii) if the interpretation of laws and regulations was consistent; and iii) if they were confident that the legal system upheld their contract and property rights in business disputes 3 years ago, and continues to do so now. Businesses asked whether their country's courts are i) fair and impartial; ii) quick; iii) affordable; iv) consistent; and v) enforced decisions.	Beck et al. (2005a)

Access to financial services	Measure of the outreach of the financial sector in terms of access to banks' physical outlets. Question asked: 'How many bank branches do deposit money banks have (combined for all banks) in your country?' (Italy, Germany, UK: Regulator Survey, 2002)	Beck et al. (2005b)
Stock Market Cap. / GDP	Value of listed shares divided by GDP. Indicator of Stock Market Size.	Beck et al. (2000)
Regional GDP	Gross domestic product (GDP) at current market prices	REGIO Database
Regional Population	Economically active population by sex and age	REGIO Database
Regional Patent applications	All Patent applications to the EPO by priority year at the regional level.	REGIO Database
3-bank concentration ratio	Sum of the market shares of the 3 largest banks in terms of total assets	Beck et al. (2006)
Herfindahl-Hirschman index	Sum of the squared market shares in terms of total assets	BankScope and authors' calculations
H-Statistic	Measure of the degree of competition	BankScope and authors' calculations

Appendix II: Computation of the H-Statistic

We present in this appendix a brief overview of the Panzar and Rosse (1987) H-Statistic that we utilise to gauge competition. This statistic is widely used in empirical work to test for banking competition (e.g. Shaffer, 2004; Molyneux et al., 1994; Claessens and Laeven, 2004).

The H-Statistic is derived from reduced-form revenue equations and measures market power by the extent to which changes in factor input prices are reflected in revenue. Assuming long-run equilibrium, a proportional increase in factor prices will be mirrored by an equiproportional increase in revenue under perfect competition. Under monopolistic competition, however, revenues increase less than proportionally to changes in input prices. In the monopoly case, increases in factor input prices will be either not reflected in revenue, or will tend to decrease revenue.[19] The magnitude of H can be interpreted in the following way:

$H \leq 0$	indicates monopoly equilibrium
$0 < H < 1$	indicates monopolistic competition
$H = 1$	indicates perfect competition

We obtain data from BankScope and include all savings, co-operative, and commercial banks operating in Italy, Germany, and in the UK in 2001. To estimate H-Statistics, we follow the method in Schaeck and Cihak (2007) and split our sample into small and large banks since potential differences in the way these banks compete will bias H. Small banks often operate locally and tend to face stronger competition from other small banks in retail markets. By contrast, large institutions compete in different lines of business, e.g. corporate and investment banking, and compete globally. We use a cut-off point of 450 million EUR to distinguish between small and large banks[20] and estimate the following reduced-form revenue equation cross-sectionally for each one of the three countries in 2001

$$\ln(R) = \alpha + \beta_1 \ln(W_1) + \beta_2 \ln(W_2) + \beta_3 \ln(W_3) + \gamma_1 \ln(Y_1) + \gamma_2 \ln(Y_2) + \gamma_3 \ln(Y_3) + \gamma_4 \ln(Y_4) + \varepsilon . \tag{A.1}$$

[19] Therefore, the magnitude of the H-Statistic can serve as a measure for the degree of competition, assuming that the bank faces a demand with constant elasticity and a Cobb-Douglas production technology (Vesala, 1995).

[20] This cut-off point is aligned with the literature on small banks in Europe (Mercieca et al., 2007).

R is the ratio of total revenue to total assets (as a proxy for the output price of loans and other services). This dependent variable includes total interest revenue, fee income, commission income, and other operating income to reflect that banks compete in many different activities. The variable W_1 is the ratio of interest expenses to total deposits and money market funding (as a proxy for input price of deposits), W_2 is the ratio of personnel expenses to total assets (proxy for input price of labour), and W_3 denotes the ratio of other operating and administrative expense to total assets (proxy for input price of equipment and fixed assets). To take account of risk-taking behaviour and size, Y_1 captures the ratio of deposits to deposits and money market funding, Y_2 is the ratio of net loans to total assets, Y_3 is the ratio of equity to total assets, and Y_4 captures bank size, measured as total balance sheet assets. All variables enter the equation in logs. The H-Statistic is calculated as the sum of the coefficients $\beta_1 + \beta_2 + \beta_3$.

It is well known that the H-Statistic assumes long-run equilibrium (Molyneux et al., 1994). Consequently, we perform the following analysis to investigate long-run equilibrium and estimate Equation (1) with the pre-tax return on assets as dependent variable.

$$\begin{aligned} \ln(ROA) = \alpha + \beta_1 \ln(W_1) + \beta_2 \ln(W_2) + \beta_3 \ln(W_3) \\ + \gamma_1 \ln(Y_1) + \gamma_2 \ln(Y_2) + \gamma_3 \ln(Y_3) + \gamma_4 \ln(Y_4) + \varepsilon \end{aligned} \quad \text{(A.2)}$$

The modified H-Statistic is the equilibrium statistic and it is again calculated as $\beta_1 + \beta_2 + \beta_3$. We test if the equilibrium statistic $E = 0$, using an F-test. This test aims to establish whether input prices are uncorrelated with industry returns since a competitive system will equalise risk-adjusted rates of return across banks in equilibrium. If this hypothesis is rejected, the market is assumed to be in disequilibrium. The results from our equilibrium test indicate that the three markets under consideration are in long run equilibrium.

Appendix III: Logit model with marginal effects

	(1)	(2)	(3)	(4)	(5)
Firm Age	0.3419	0.2842*	0.1577	0.2196	0.2192
	(0.3916)	(0.4015)	(0.4153)	0.4116)	(0.4118)
Firm Type	2.1840***	0.6639	0.9274**	0.3444**	0.3630*
	0.3521)	(0.4317)	(0.4019)	(0.4430)	(0.4415)
Ownership change	-1.3149***	-0.2647***	-0.5539	-0.1538	-0.1681
	(0.3131)	(0.3762)	(0.3541)	(0.3837)	(0.3821)
R&D investment	-0.5234	-0.4272	-0.3190	-0.3422	-0.3203
	(0.3305)	(0.3536)	(0.3584)	(0.3662)	(0.3649)
Turnover	0.6384**	0.4051	0.2010*	0.3916	0.6859
	(0.1753)	(0.1848)	(0.1006)	(0.1891)	(0.0266)
Distance	0.4761	0.2207*	0.1843*	0.0440***	0.0558***
	(0.3444)	(0.3767)	(0.4027)	(0.4112)	(0.4112)
Bank Role	0.2015**	1.0787*	0.6395***	0.2040***	0.1922***
	(0.3658)	(0.4484)	(0.4054)	(0.5028)	(0.5021)
Bank Terms	0.7253*	1.1786***	0.8404*	1.1305**	1.1129**
	(0.4110)	0.4919)	(0.4942)	(0.5341)	(0.5346)
Amount of bank finance used	0.0248	0.2266**	0.1096**	0.1793*	0.2102**
	(0.1360)	(0.1496)	(0.1404)	(0.1524)	0.1481)
Regional bank	2.6376***	2.8666***	2.7788***	2.8243***	2.8171***
	(0.7082)	(0.7426)	(0.7533)	(0.7427)	(0.7416)
National bank	2.1809***	2.9124***	1.6683**	2.2350***	2.2420**
	(0.6108)	(0.6259)	(0.6935)	(0.6879)	(0.6878)
HHI		0.8680***		-0.3542**	0.9709***
		(0.5558)		(0.7479)	(0.4806)
H-Statistic			0.6129***	0.4737***	0.3427*
			(0.8737)	(0.1486)	(0.3634)
HHI*H-Statistic					0.9833
					(0.5541)
Pseudo R^2	0.44	0.53	0.54	0.57	0.56
Observations	305	305	305	305	305

Dependent variable: Multi-bank relationships with 0 being a firm with one bank relationship, 1 being a firm with more than one bank relationship. ***, **, * indicates statistical significance at the 1%, 5%, and 10% level respectively. Robust standard errors in parentheses.

Table 1: Descriptive statistics

			Italy				Germany				UK	
Bank Relationships		0	1	>1		0	1	>1		0	1	>1
Total Observations	161				114				247			
% of Total Observations		12.4	16.1	71.4		55.3	20.2	24.6		54.3	42.9	2.8
Oldest Trading SMEs		1932	1927	1905		1900	1868	1602		1926	1926	1959
Youngest SMEs		1999	1999	2001		2001	2001	2001		2001	2001	1998
(year of incorporation)												
Changed ownership		8	8	39		46	15	15		119	95	6
Turnover -Average		2.8	2.5	3.2		2.11	2.57	2.75		1.49	2.02	2.14
Private Company		4	9	33		48	20	20		131	106	7
Public Company		16	17	82		15	3	8		3	0	0
Employees - Average		2	1.58	2.23		2.11	2.70	3.11		1.46	1.93	2.57
R&D Investment (1=yes)		20	12	65		41	12	13		50	49	3
Distance (miles) - Average		0	1.12	1.10		0	1.13	1.25		0	1.41	1.43
Favourable Terms (1=yes)		0	26	94		0	20	22		0	85	4
Regional Bank		0	23	105		0	9	24		0	101	6
National Bank		0	3	10		0	15	20		0	2	2
HHI	0.0483				0.0859				0.0828			
Concentration Ratio	0.3216				0.4551				0.3846			
H-Statistic (average)	0.4718				0.6694				0.6474			
Amount of Bank Finance Used (Average)	1.88				1.18				0.75			
Branches/sq. km	102.05				116.90				45.16			
Regional GDP	109.06				369.60				238.30			
Regional Population	1.865				6.177				4.156			
Regional Patent Applications (number)	754				5902				1930			
Stock market cap/gdp	0.6007				0.6356				1.6958			
Legal Obstacles	2.27				2.14				1.51			
Financing Obstacles	1.98				2.60				2.21			
Time to start business (days)	23				45				18			
Cost to start business (% of income/capita)	16.7				5.8				0.9			
Banking Freedom	2.14				2.71				1.00			

Table 2: Tobit model

	(1)	(2)	(3)	(4)	(5)
Firm Age	0.1575**	0.1571**	0.1277**	0.1048*	0.1078*
	(0.0610)	(0.0605)	(0.0566)	(0.0551)	(0.0648)
Firm Type	-0.3542***	-0.3493***	-0.1303**	0.0177	0.0183
	(0.0582)	(0.0580)	(0.0618)	(0.0662)	(0.0531)
Ownership Change	-0.3037***	-0.3001***	-0.1595**	-0.0674	-0.0534
	(0.0527)	(0.0525)	(0.0526)	(0.0535)	(0.0520)
R&D investment	-0.1183**	-0.1150**	-0.0936*	-0.0890*	-0.0639
	(0.0527)	(0.0525)	(0.0491)	(0.0470)	(0.0521)
Turnover	0.0637**	0.0617**	0.0269	0.0091	0.0833
	(0.0279)	(0.0278)	(0.0264)	(0.0256)	(0.0221)
Distance	0.1996***	0.2037***	0.2427***	0.2464***	0.2455***
	(0.0506)	(0.0506)	(0.0478)	(0.0457)	(0.0415)
Bank Role	0.3084***	0.3553***	0.4010***	0.2530***	0.3012***
	(0.0621)	(0.0694)	(0.0599)	(0.0628)	(0.0513)
Bank Terms	0.2165***	0.2242***	0.2085**	0.1618***	0.2010***
	(0.0651)	(0.0652)	(0.0605)	(0.0584)	(0.0602)
Amount of bank finance used	0.0450**	0.0427**	0.0507**	0.0652**	0.0783**
	(0.0225)	(0.0225)	(0.0210)	(0.0203)	(0.0304)
Regional bank	1.1774***	1.1628***	1.0929***	1.0772***	1.0885***
	(0.0844)	(0.0845)	(0.0788)	(0.0756)	(0.0801)
National bank	0.9196***	0.8535***	0.7108***	0.8399***	0.8395***
	(0.0852)	(0.0946)	(0.0827)	(0.0845)	(0.0851)
HHI		0.6357**		-2.818***	-0.5148***
		(0.4152)		(0.5353)	(0.0568)
H-Statistic			1.7312***	2.9655***	1.6779***
			(0.2435)	(0.3302)	(0.0401)
HHI*H-Statistic					0.3175***
					0.0748
Pseudo R^2	0.40	0.40	0.42	0.46	0.46
Observations	522	522	522	522	522

Dependent variable: Multi-bank relationships with 0 being a firm with no bank relationships, 1 being a firm with one bank relationship and 2 representing firms with more than one bank relationship. ***, **, * indicates statistical significance at the 1%, 5%, and 10% level respectively.

Table 3: Regional and financial system characteristics

	(1)	(2)	(3)	(4)	(5)
Firm Age	0.0986*	0.1027**	0.1033**	0.1048**	0.1055**
	(0.0560)	(0.0551)	(0.0578)	(0.0552)	(0.0487)
Firm Type	0.0068	0.0179	0.0161	0.0177	0.0163
	(0.0673)	(0.0662)	(0.0600)	(0.0662)	(0.0503)
Ownership Change	-0.0468	-0.0683	-0.0678	-0.0674	-0.0672
	(0.0542)	(0.0535)	(0.0441)	(0.0535)	(0.0555)
R&D investment	-0.1064**	-0.0890**	-0.0903**	-0.0890**	-0.0869*
	(0.0474)	(0.0470)	(0.0378)	(0.0470)	(0.0441)
Turnover	0.0067	0.0093	0.0103	0.0091	0.0171
	(0.0259)	(0.0256)	(0.0274)	(0.0256)	(0.1228)
Distance	0.2796***	0.2433***	0.2479***	0.2464***	0.2490***
	(0.0454)	(0.0457)	(0.0401)	(0.0457)	(0.0456)
Bank Role	0.1082**	0.2572***	0.2498***	0.2530***	0.2544***
	(0.0672)	(0.0628)	(0.0633)	(0.0628)	(0.0629)
Bank Terms	0.1409**	0.1731**	0.1624**	0.1618**	0.1583**
	(0.0599)	(0.0584)	(0.0678)	(0.0584)	(0.0661)
Amount of bank finance used	0.0687***	0.0699**	0.0689**	0.0652**	0.0515***
	(0.0205)	(0.0203)	(0.0204)	(0.0204)	(0.0167)
HHI	-0.4442***	-1.5006***	-1.8143***	-0.6918***	-0.2560***
	(0.4857)	(2.6788)	(3.4093)	(0.8705)	(0.5624)
H-Statistic	1.6382**	0.8170***	0.9812***	0.4081***	1.7352***
	(0.7317)	(1.3338)	(1.7122)	(0.4618)	(0.3872)
Regional bank	1.1540***	1.0729***	1.141***	1.0749***	1.0812***
	(0.0741)	(0.0744)	(0.0756)	(0.0763)	(0.0741)
National bank	0.8693**	0.8341***	0.8011***	0.8398***	0.8387***
	(0.0867)	(0.0801)	(0.0845)	(0.0792)	(0.0830)
Access to financial services	0.0080**				
	(0.0037)				
Regional GDP growth		0.0078***			
		(0.0018)			
Regional population			0.5959***		
			(0.1405)		
Regional patents				0.0001***	
				(0.3253)	
Stock market cap/GDP					-0.3130***
					(0.0739)
Pseudo R^2	0.47	0.46	0.46	0.46	0.45
Observations	522	522	522	522	522

Dependent variable: Multi-bank relationships with 0 being a firm with no bank relationships, 1 being a firm with one bank relationship and 2 representing firms with more than one bank relationship. ***, **, * indicates statistical significance at the 1%, 5%, and 10% level respectively.

Table 4: Access to finance and institutional environment

	(1)	(2)	(3)	(4)	(5)
Firm Age	0.1033**	0.1048**	0.0018**	0.1067*	0.1060*
	(0.0549)	(0.0551)	(0.0008)	(0.0552)	(0.0552)
Firm Type	0.0129	0.0177	0.0346	0.0181	0.0165
	(0.0662)	(0.0662)	(0.0657)	(0.0662)	(0.0661)
Ownership Change	-0.0641	-0.0674	-0.0592	-0.0659	-0.0677
	(0.0514)	(0.0535)	(0.0534)	(0.0536)	(0.0535)
R&D investment	-0.1023**	-0.0890**	-0.0924**	-0.1077*	-0.0871*
	(0.0523)	(0.0470)	(0.0467)	(0.0609)	(0.0470)
Turnover	0.0201	0.0091	0.0414	0.0244	0.0188
	(0.0226)	(0.0256)	(0.1201)	(0.1217)	(0.1213)
Distance	0.2458***	0.2464***	0.2478***	0.2451***	0.2469***
	(0.0409)	(0.0457)	(0.0458)	(0.0460)	(0.0459)
Bank Role	0.2531***	0.2530***	0.2554***	0.2535***	0.2528***
	(0.0633)	(0.0628)	(0.0627)	(0.0628)	(0.0629)
Bank Terms	0.1637**	0.1618**	0.1584**	0.1603**	0.1621**
	(0.0567)	(0.0584)	(0.0583)	(0.0585)	(0.0584)
Amount of bank finance used	0.0697**	0.0652**	0.0642**	0.0670***	0.0672**
	(0.0213)	(0.0203)	(0.0199)	(0.0199)	(0.0199)
HHI	-0.4185***	-0.0278*	-0.6160***	-0.2796***	-0.4929***
	(0.4833)	(1.0147)	(0.7499)	(5.7435)	(0.5457)
H-Statistic	0.6323***	0.9785***	0.3025***	0.2618***	1.7976
	(0.9175)	(0.3634)	(0.3257)	(5.5940)	(0.3792)
Regional bank	1.0768***	1.0772***	1.0778***	1.0731***	1.0751***
	(0.0761)	(0.0756)	(0.0752)	(0.0756)	(0.0755)
National bank	0.8341***	0.8399***	0.8570***	0.8369***	0.8383***
	(0.0847)	(0.0845)	(0.0844)	(0.0846)	(0.0846)
Legal obstacles	-1.1850***				
	(0.2794)				
Financing obstacles		-0.7608***			
		(0.1794)			
Time to start business			0.0257***		
			(0.0066)		
Cost to start business				0.3564***	
				(0.0846)	
Banking Freedom					0.4141***
					(0.0977)
Pseudo R^2	0.46	0.46	0.45	0.48	0.45
Observations	522	522	522	522	522

Dependent variable: Multi-bank relationships with 0 being a firm with no bank relationships, 1 being a firm with one bank relationship and 2 representing firms with more than one bank relationship. ***, **, * indicates statistical significance at the 1%, 5%, and 10% level respectively.

Table 5: Robustness tests with alternative measures of competition and concentration

	(1)	(2)	(3)	(4)
Firm Age	0.1210**	0.1048*	0.1167**	0.1048*
	(0.0559)	(0.0551)	(0.0571)	(0.0551)
Firm Type	-0.0864	0.0177	-0.0403	0.0177
	(0.0627)	(0.0662)	(0.0673)	(0.0662)
Ownership Change	-0.1312**	-0.0674	-0.1101**	-0.0674
	(0.0527)	(0.0535)	(0.0542)	(0.0535)
R&D investment	-0.0910*	-0.0890*	-0.1006**	-0.0890*
	(0.0484)	(0.0470)	(0.0484)	(0.0470)
Turnover	0.0206	0.0091	0.0214	0.0091
	(0.0261)	(0.0256)	(0.0263)	(0.0256)
Distance	0.2469***	0.2464***	0.2312***	0.2464***
	(0.0472)	(0.0457)	(0.0467)	(0.0457)
Bank Role	0.3794***	0.2530***	0.1532**	0.2530***
	(0.0582)	(0.0628)	(0.0595)	(0.0628)
Bank Terms	0.1990***	0.1618**	0.1531**	0.1618***
	(0.0597)	(0.0584)	(0.0599)	(0.0584)
Amount of bank finance used	0.0539**	0.0652**	0.0678**	0.0652**
	(0.0207)	(0.0203)	(0.0209)	(0.0203)
Regional bank	1.0841***	1.0772***	1.1279***	1.0772***
	(0.0777)	(0.0756)	(0.0774)	(0.0756)
National bank	0.7205***	0.8399***	1.0075***	0.8399***
	(0.0806)	(0.0845)	(0.0796)	(0.0845)
H-Statistic (total revenue)				1.1291***
				(0.2601)
H-Statistic (interest revenue)	0.8101***	0.9775***		
	(0.3612)	(0.4429)		
HHI		-2.0537***		
		(0.4786)		
3-bank concentration ratio			1.6763***	-1.2038***
			(0.2138)	(0.2295)
Pseudo R^2	0.43	0.46	0.44	0.46
Observations	522	522	522	522

Dependent variable: Multi-bank relationships with 0 being a firm with no bank relationships, 1 being a firm with one bank relationship and 2 representing firms with more than one bank relationship. ***, **, * indicates statistical significance at the 1%, 5%, and 10% level respectively.

Detecting Information Pooling: Evidence from Earnings Forecasts after Brokerage Mergers *

Serena Ng
Dept. of Economics
University of Michigan and Columbia University

Matthew Shum
Dept. of Economics
Johns Hopkins University

October 25, 2007

Abstract

Forecast improvements can be expected if the two partners involved in a brokerage merger pool information and expertise. We examine four large mergers of brokerage firms in the last decade to study the incidence of and explanations for forecast improvements after the mergers. At the brokerage-level, we find that for two of the four mergers, forecast improvements appear more pronounced in subsamples of stocks for which both of the pre-merger analysts were retained in the merged brokerage. At the analyst-level, we find only weak evidence of forecast improvements after the merger. However, we find evidence that after a merger, a stock is more likely to be assigned to an analyst with overall better forecasting performance before the merger. This suggests that analyst selection can be a mechanism generating the post-merger forecasting improvements.

JEL classification numbers: G14, D83
Keywords: information pooling, earnings forecasts, brokerage mergers

*The authors may be contacted via e-mail at `serena.ng@columbia.edu` (Ng) and `mshum@jhu.edu` (Shum). We thank Liran Einav, Andreas Lehnert, Pai-ling Yin, Nicholai Iskrev, and participants at the Federal Reserve Board, the 2005 Winter Econometric Society Meetings, and the Tuck IO conference for suggestions. Yonatan Ben Shalom, Eric Millis and Migiwa Tanaka provided outstanding research assistance. Two anonymous referees and the editor provided suggestions which greatly improved the paper. We gratefully acknowledge the contribution of Thomson Financial for providing earnings per share forecast data, available through the Institutional Brokers Estimate System.

1 Introduction

In the last two decades, there have been a very large number of mergers in the financial sector. This merger wave can perhaps be attributed to two large shifts in government policy during this period. First, starting in the mid-1980s, restrictions on interstate banking were loosened, triggering a consolidation wave among former state-level commercial banks. Then in 1999, the Gramm-Leach-Bliley Act took effect and effectively repealed the Glass-Steagall Act, which for decades restricted commercial banks from offering investment banking services, and vice versa.

Not only have the causes of mergers in the financial sector been varied, so have the effects of these mergers. Mergers are large complicated events, which affect the merging firms in many aspects, including stock market valuations, hierarchical and organizational structure, and leading to substantial employee turnover. However, empirical work on the effects of these mergers have, for the most part, only focused on the effects of mergers on stock market valuations of the merged entities, or on the pricing of financial products offered by the merging firms (such as loan or deposit interest rates quoted by commercial banks).

A well-accepted view of financial companies — whether commercial or investment banks, or insurance companies – is that they provide intermediation services in markets in which there are information asymmetries between the suppliers and demanders of credit (eg. Diamond (1984)). Given the importance of information in the activities of financial companies, it is surprising that little is known about the informational effects of mergers among financial companies at the empirical level.

In this paper, we seek to understand the informational effects of a merger between financial firms by focusing on a specific service offered by financial companies: earnings forecasting. We focus on one particular type of informational effect of a merger, namely, the *pooling* of information and informational resources which, prior to the merger, were privately owned by each of the merging firms. The forecasting enterprise is fundamentally information based. The accuracy of a particular forecast depends on the resources that a brokerage firm devotes to collecting information, and on the assigned analyst's ability to synthesize that information. What makes a forecast especially good or bad often depends on the access to and interpretation of an analyst's private information.

These features of the earnings forecast enterprise make it well-suited for investigating information pooling. Prior to the merger, each of the merging brokerages would have assigned an analyst to cover a given stock, eg. Apple Inc. After the merger, both of these analysts could potentially be retained in the merged brokerage. By comparing the post- vs. pre-merger changes in forecast accuracy across stocks for which both of the pre-merger analysts were retained, versus those for which only one of the analysts was retained, we can measure the importance of information pooling, which should only be present for those stocks where both of the pre-merger analysts were retained. We also distinguish the effects of information pooling from analyst selection, which is the possibility that better-abilitied analysts are more likely to be retained following the merger.

Our empirical analysis is based on the comparison of the accuracy of earnings forecasts before and after four large mergers of brokerage firms in the IBES database. The IBES dataset contains detailed analyst-level information for each forecast and allows us to track performance at the stock- and analyst-level, both before and after the merger, which is ideal for addressing the presence of information pooling via the exercise described above.

At the brokerage-level, we find some evidence consistent with information pooling for two of the four mergers. For these two mergers, we find that forecast improvements appear more pronounced in subsamples of stocks where information pooling should be strongest. These subsamples include the stocks which were covered by both of the merging brokerages before the merger, as well as the stocks where both of the pre-merger analysts were retained in the merged brokerage. This evidence persists even after controlling for changes in the timing of forecast released after the mergers. These two mergers were also the ones where the merging firms were most equal in forecasting ability before the mergers, which perhaps made information pooling more likely.

At the analyst-level, our evidence is more mixed. For one of the four mergers, we find that while the post-merger forecasts of analysts employed before the merger at the acquired (target) brokerage benefit from the presence of the analyst who covered the same stock at the acquiring (bidder) brokerage, the bidder analysts do not benefit as much from having the target analysts around. For the other three mergers, however, we have no robust evidence of information pooling.

Finally, we also consider whether the post-merger forecast improvements can be attributed to analyst selection. We find no evidence that better analysts are more likely to be retained in the merged brokerage following the merger. This confirms anecdotal evidence that in the wake of job uncertainty due to the mergers, many of the best analysts at the merging firms were poached away by competing brokerages, so that the analysts remaining at the merged brokerage following the merger are not the best analysts working at the two brokerages before the merger. However, in the cases where both of a stock's pre-merger analysts were retained in the merged brokerage, we find strong evidence (for three of the four mergers), that the stock is likely to be assigned after the merger to the analyst with the better overall pre-merger forecasting performance. This suggests that analyst selection can be a mechanism generating the post-merger forecasting improvements.

Two bodies of empirical work are related indirectly to this paper. First, a number of papers have focused on the informational aspects of the earnings forecasting enterprise. Hong, Kubik, and Solomon (2000) focus on analysts' career concerns and the tendency towards herding, and Kandel and Pearson (1995) look for evidence that competing analysts have differential interpretations of public information regarding a stock. Bernhardt and Kutsoati (1999) look for evidence in the data consistent with a model in which analysts are compensated for the relative (rather than absolute) accuracy of their forecasts. However, none of these papers have focused on information pooling, which is the topic of this paper.

Second, there is a literature on measuring the effects on mergers among financial institutions, especially commercial banks (including Prager and Hannan (1993), Sapienza (2002), Focarelli and Panetta (2003), Panetta, Schivardi, and Shum (2006), Calomiris and Pornrojnangkool (2005)). All of these studies examine the effect of mergers on the interest rates subsequently offered and charged by the merged banks. Panetta, Schivardi, and Shum (2006) examined whether merging banks pooled information regarding borrowers which they had in common (before the merger) and found no evidence for information pooling. To our knowledge, however, this is the first paper on mergers among financial institutions which explores the micro-effects of the mergers – in our case, the employment turnover caused by the mergers – on earnings forecasts.

Finally, while there is a large theoretical literature in industrial organization on information pooling (cf. Vives (1999), ch. 8), the empirical work on information pooling has been limited. There are several studies of the effects of information sharing within trade organizations. Genesove and Mullin (1999) presents a case study of the sugar producers in the early part of the twentieth century, and Snyder and Doyle (1999) examined how automobile manufacturers' announcements of their future production plans in a prominent trade journal affected the manufacturers' actual production levels.

In the next section, we present a simple framework for looking at the effects of information pooling. In Section 3, we introduce the data, and discuss the four mergers which we focus on in this paper. Sections 4 and 5 contain the empirical results, and Section 6 concludes.

2 Information pooling, analyst selection, and forecast improvements

In this section, we explore the relationship between forecast improvements, and how they can be explained by information pooling and analyst selection. We also present several definitions of forecast improvements which we will use in our empirical work. Hereafter, we will use the word "firm" to denote a brokerage firm, which forms earnings forecasts, while reserving the word "stock" to denote publicly-traded companies about which forecasts are being made.

Consider two competing brokerage firms, $j = 1, 2$, who have assigned, respectively, analysts A_1 and A_2 to forecast a variable v_i, which is the quarterly earnings per share of stock i. Prior to the merger, brokerage 1's forecast of v_i is $x_{i,1}$, and brokerage 2's forecast of v_i is $x_{i,2}$.[1] Let $z_{i,j}$, $j = 1, 2$ denote the private information of brokerage j, which is used to form brokerage j's forecast $x_{i,j}$ using the forecasting function $h_j(z_{i,j}), j = 1, 2$. The forecast is related to the true value by

$$\begin{aligned} h_1(z_{i,1}) &= x_{i,1} = v_i + e_{i,1} \\ h_2(z_{i,2}) &= x_{i,2} = v_i + e_{i,2} \end{aligned}$$

where $e_{i,1}$ and $e_{i,2}$ are forecast errors. For simplicity, assume that $x_{i,1}$ and $x_{i,2}$ are unbiased for v_i, so the pre-merger mean squared forecast error is

$$\text{MSE}_{i,j}^{pre} = \sigma_{i,j}^2 = var(e_{i,j}),\ j = 1, 2.$$

Now suppose a merger occurs between firms 1 and 2. Consider the case when both analysts A_1 and A_2 continue to work at the merged brokerage. If $z_{i,1}$ and $z_{i,2}$ are still available, the post merger forecast is $x_i^{post} = h(z_{i,1}, z_{i,2})$ for some function $h(\cdot)$, which is not necessarily the same as h_1 or h_2. Let MSE_i^{post} denote the post-merger forecast error. We look for two types of forecasting improvements.

1. Brokerage-level improvements To define brokerage-level improvements, we need to compare the merged brokerage post-merger performance to a benchmark for the two brokerages' individuals performances before the merger. Given $x_{i,1}^{pre}$ and $x_{i,2}^{pre}$, we use a benchmark equal to $w_1\text{MSE}(x_{i,1}^{pre}) + w_2\text{MSE}(x_{i,2}^{pre})$, a weighted average of the two brokerages' individual pre-merger forecast accuracies, for weights $0 \leq w_1 \leq 1$ and $w_2 = 1 - w_1$. Then brokerage-level improvements for stock i are defined as the event that

$$\Delta\text{MSE}_i = \text{MSE}_i^{post} - \left[w_1\text{MSE}_{i,1}^{pre} + w_2\text{MSE}_{i,2}^{pre} \right] \leq 0. \quad (1)$$

In the empirical work, we will, for the most part, weigh the two brokerages' pre-merger forecast errors equally (ie. $w_1 = w_2 = \frac{1}{2}$).

One premise of information pooling is that the merging brokerages share information and expertise regarding stock i. Therefore, forecast improvements for stocks which were not covered by both brokerages before the merger is not evidence of information pooling. Furthermore, to the extent that information and expertise is

[1] While the stock subscript i is not required for the discussion in this section, we include it to facilitate comparison of the equations in this section with those in subsequent section, in which the stock subscript will be important.

analyst-specific, information pooling should imply that the improvements are more prominent for stocks where both of the pre-merger analysts continued to work at the merged brokerage following the merger. These considerations will guide our empirical work below.

2. Analyst-level improvements While it is possible for both analysts to continue forecasting stock i after the merger, it also seems reasonable for the merged brokerage to consolidate resources and release one forecast instead. Provided that at least one of the pre-merger analysts covering stock i in the two merging brokerages continues to forecast stock i after the merger, we can also compare the forecast performance of this analyst on stock i before and after the merger. For a stock which is forecast by analyst j after the merger, we say that analyst j's forecasting accuracy of stock i improved relative to his pre-merger performance if

$$\Delta \text{MSE}_{i,j} \equiv \text{MSE}_{i,j}^{post} - \text{MSE}_{i,j}^{pre} \leq 0. \tag{2}$$

The main difference between the analyst-level and brokerage-level forecast change measures is that we can only compute the analyst-level change $\Delta\text{MSE}_{i,j}$ if analyst j covers the stocks both before and after the merger, but the brokerage-level change ΔMSE_i can be computed even if the analyst who covers stock i after the merger did not cover it before the merger.

Again, a precondition for information pooling is that the analyst chosen to produce the forecast after the merger has access to the skills, information, and expertise of the analyst who covered stock i for the other brokerage prior to the merger. For this reason, information pooling should imply that analyst-level forecasting improvements are more likely for those stocks where both of the pre-merger analysts are retained in the merged brokerage. Of course, it will be rare for both pre-merger analysts who covered stock i before the merger to be assigned to cover the same stock after the merger. It is more likely that one analyst will be assigned to other stocks. However, the mere presence of both analysts who had experience with stock i in the merged brokerage means that the post-merger analyst has access to knowledge and information about stock i not available before the merger.

To understand the way that information pooling leads to forecast improvements, suppose for simplicity that the merger leads to a linear aggregation of information. The pooled post-merger forecast is

$$x_i^{post} = \psi_1 h_1(z_{i1}) + \psi_2 h_2(z_{i2}) = \psi_1 x_{i1}^{pre} + \psi_2 x_{i2}^{pre}, \quad 0 \leq \psi_1 \leq 1 = 1 - \psi_2. \tag{3}$$

The MSE (which is also the variance) of the post-merger forecast is

$$\text{MSE}_i^{post} = \psi_1^2 \sigma_1^2 + \psi_2^2 \sigma_2^2 + 2\psi_1 \psi_2 \rho \sigma_1 \sigma_2 \tag{4}$$

where $\rho = Corr(e_1, e_2)$. For fixed values of ψ_1, and σ_1, MSE_i^{post} is increasing in ρ and σ_2. Intuitively, under linear forecast aggregation, the primary benefit of information pooling is variance reduction. Forecast improvements are thus larger when σ_2 is smaller. Also, averaging the forecasts will lead to a larger reduction in variance when the errors of the individual forecasts are negatively correlated ($\rho < 0$) because the errors offset. This implies that the forecast improvements, at both the brokerage and analyst-level, will depend on the relative ability of the analysts involved and are more likely when ρ is small or negative. Indeed, for some configuration of the parameters and depending on the benchmark, information pooling may not even lead to better forecasts.

2.1 Analyst selection

Typically, mergers of financial institutions lead to a great deal of employment turnover, and the mergers studied in this paper are no exception. The possibility therefore arises that forecasting improvements can also be due to analyst selection. Analyst turnover following a merger can lead to two types of analyst selection. First, if the analysts who remained in the merged firm were systematically better than those who left, a brokerage-level improvement might result. Second, after a merger, the better of the bidder and target analyst can be chosen to forecast a given stock.

In the context of the simple model from the previous section, analyst selection amounts to letting ψ_1 in Eq. (3) be a binary indicator chosen using the criterion

$$\psi_1 = \begin{cases} 1 & \text{if MSE}_{i,1}^{pre} < \text{MSE}_{i,2}^{pre} \\ 0 & \text{otherwise} \end{cases}$$

so that the better analyst in the pre-merger period is chosen to cover each stock in the post-merger period.

Observationally, both information pooling and analyst selection can appear very similar, because both imply that post-merger forecasts should be more accurate than pre-merger forecasts, and the second type of analyst selection implies that having both of the pre-merger analysts around should lead to better post-merger forecasts, because the firm is able to choose the better analyst to forecast the stock after the merger. However, because our dataset contains detailed information on analyst turnover and assignment to stocks, we can directly measure the importance of both types of analyst selection after the mergers, and hence distinguish information pooling from analyst selection.

3 Data

Our dataset of analyst forecasts is derived from the IBES (Institutional Brokers Estimate System) database, which is a comprehensive database containing every forecast and forecast revision formed by analysts for a near-complete sample of brokerage firms and securities. For a given stock (e.g. IBM) and forecast period (a quarter, e.g. 92III), we observe every earnings per share (EPS) forecast and revision which was submitted by analysts working at brokerage firms surveyed in the dataset. The dataset contains forecasts from the beginning of 1983 to the middle of 2002. In this paper, we focus only on quarterly EPS forecasts, since these are the most common forecasts in the database.[2] We also observe the actual realized earnings for each stock in each quarter for which forecasts are available.

For the remainder of this paper, we refer to the acquiring brokerage as the **bidder firm**, and the acquired brokerage as the **target firm**. We use the terms **bidder analyst** to refer to the analyst who covered a given stock at the bidder firm before the merger, and **target analyst** to refer to the analyst who covered this stock at the target firm before the merger. Finally, for a given stock i and analyst j, we use the term **rival analyst** to denote the analyst covering stock i during the pre-merger period at the brokerage other than the one where analyst j works. For example, for a bidder analyst, her rival analyst is the analyst covering the same stock at the target firm before the merger.

In the IBES dataset, we are able to track a particular analyst across different employers. Particularly, for each stock covered by both the bidder and target firms before the merger, we are able to tell whether the particular analyst who covered this stock at the target firm remained employed at the bidder firm after the merger. This will be a crucial component for our tests for the presence of information pooling.

3.1 Four mergers of brokerage firms

In order to identify mergers among brokerage firms in the IBES data, we used the SDC Mergers and Acquisition database to obtain information on all mergers within SIC four-digit sector 6311 ("Investment and Commodity Firms, Dealers, and Exchanges"). From this list, we identified four sizable mergers among brokerage firms. Since the number of mergers is small, we will do our analysis on a merger-by-merger basis, and rely on the variation across time, across stocks, and across analysts to identify the information pooling effects. The four mergers are listed in Table 1. Generally, all four of these mergers represented attempts by the bidder

[2] The second-most common forecasts are annual earnings forecasts but, for a given year, they are derived simply as the sum of the quarterly earnings forecasts for the four quarters which make up that year.

Table 1: List of Mergers Used in the analysis

Merger	A	B	C	D
Bidder Brokerage	Paine Weber	Morgan Stanley	Credit Suisse First Boston	UBS Warburg Dillon Read
Merger Date	12-94	05-97	11-00	11-00
Earliest EPS	2-10-82	5 19-82	7-13-81	4-18-84
Latest EPS	11-27-00	5-16-02	5-16-02	5-16-02
Target Brokerage	Kidder Peabody	Dean Witter Reynolds	Donaldson Lufkin and Jenrette	Paine Webber
Earliest EPS	2-17-82	7-30-81	5-19-82	2-10-82
Latest EPS	12-19-94	4-28-97	10-10-00	11-27-00

Notes:

1. Earliest EPS is the date for which we have an earnings forecast from this brokerage firm.
2. Last EPS is the date for which we have an earnings forecast from this brokerage firm.

firms to expand the scope of their retail business by purchasing another brokerage. Merger A, between Paine Webber and Kidder Peabody, was portrayed in the press as a "company in trouble" deal, in which the second-tier brokerage (Paine Webber) bought a top-tier investment bank with a strong research department (KP) at an opportune time. Just prior to the merger, KP was reeling in the aftermath of a trading scandal involving its chief government bond trader, Joseph Jett, and had already laid off 10% of its workforce. Subsequently, KP's owner, General Electric, was looking to sell the company.

Merger B was another diversifying merger, in which high-end investment bank Morgan-Stanley was portrayed as wanting to get in on the more down-market retail brokerage operations of Dean Witter.[3] As an indicator of the differences in operations between the merging parties, we note that in 1996, the year before the merger, Morgan-Stanley was the chief underwriter in 43 IPOs, with a combined offer amount of over $7 billion, while Dean Witter underwrote only 4, with a combined offer amount of just under $1 billion.[4]

Mergers C and D occurred only within a few months of each other, and both were perceived to be attempts by Swiss banks to geographically diversify their lines of business (into the American market). Merger C was a merger between two top-of-the-line investment banks (CSFB and DLJ underwrote, respectively, 57 and 36

[3]For a time in the 1980s, Dean Witter operated service desks in Sears department stores.

[4]These figures, as well as those in the following paragraph, are drawn from `www.ipodata.com`.

Table 2: Analyst employment before and after mergers

Merger	Pre-merger[a]	Post-merger[b]
Merger A:		
Paine Webber	45	34
Kidder Peabody	54	9
New		13
Total	99	56
Merger B:		
Morgan Stanley	77	69
Dean Witter	41	5
New		13
Total	118	102
Merger C:		
CS-FB	130	104
DLJ	86	17
New		39
Total	216	160
Merger D:		
UBS	98	71
Paine Webber	70	40
New		24
Total	168	135

[a]Defined as number of analysts who provided forecasts at brokerage within one year before the merger

[b]Defined as number of analysts who provided forecasts at brokerage within one year after the merger

IPOs in 1999), and concerns were raised about whether CSFB would be able to retain many of DLJ's brokers and analysts. Merger D was characterized similarly as a geographically diversifying merger, with the difference being that both Paine Webber's and UBS's American investment banking operations were smaller than those of, respectively, DLJ and CSFB. A common effect of all four mergers is that they precipitated a large degree of turnover. This turnover will be an important source of variation for detecting information pooling, because an important exercise that we do is to compare changes in forecast accuracy for stocks where both pre-merger analyst were retained, versus stocks where only one (or none) of the pre-merger analysts were retained. Table 2 shows the number of analysts employed by the merging units before and after their respective mergers varied substantially.[5] After all four mergers, the number of analysts grew in all four post-merger brokerages (relative to the pre-merger number of analysts in the bidder firms). In percentage terms, the larger increases in the number of analysts occurred after Merger B, where the number of analysts increased by 32.5% (from 77 to 102 analysts), and Merger D, where the increase was 37.8% (from 98 to 135).

The retainment percentages also depend on whether an analyst worked at the bidder or target firm before the merger. Clearly, a higher percentage of analysts from the bidder firm than target firm were retained. For Merger A, 34 out of 45 Paine Webber analysts were retained, but only 9 out of 54 Kidder-Peabody analysts. This pattern holds across all four mergers. Indeed, only for Merger D were more than half of the analysts from the target firm retained, while more than half of the analysts from the bidder firm were retained in all four mergers. Furthermore, across all the mergers, a substantial percentage of the post-merger analysts were new hires, which make up from 20-25% of the post-merger analyst workforce.

Clearly, these four mergers feature very different brokerages, but we note that the improvement of the research group was not a stated objective for merger in any of these four mergers. Hence, it would not be surprising to find that these mergers had no substantial impact on forecast performance. However, if information pooling is important, then these mergers may have provided opportunities for the merged brokerage to experience incidental forecasting improvements via the sharing of private information and expertise, even when these improvements were not a fundamental reason for the mergers.

3.2 Measuring forecast accuracy

The main empirical exercise in this paper is to examine whether forecast accuracy was improved in the merged brokerage following a merger. We utilize a standardized forecast error,

$$FE_{ijt} = \frac{f_{ijt} - a_{it}}{p_{it}} \tag{5}$$

where f_{ijt} denotes broker j's forecast of the earnings per share (EPS) of stock i, for the period t, and a_{it} the actual realized EPS. For each stock i and quarter t, we only consider analyst j's final forecast, and do not focus on the forecast revision process.

The error $f_{ijt} - a_{it}$ is standardized by dividing by p_{it}, the price per share of stock

[5]Because analyst turnover is common without or without mergers, we look at analysts employed at the brokerages in the year before the merger to isolate the turnover due to the mergers.

i on the first trading day of quarter t.[6] FE, as defined in this way, can be positive or negative, depending on whether or not $f_{ijt} > a_{it}$. Additionally, we also follow Lim (2001) by deleting observations when $|f_{ijt} - a_{it}| > 10$, and also only consider stocks i and quarters t where $p_{it} \geq 1$.[7]

Because FE can be both positive and negative, and it is still an open questions as to the unbiasedness of analyst forecasts, it is not enough to compare averages of FE across different time periods or stocks. Hence, we focus on the mean-squared error (hereafter MSE) of FE.[8]

We focus on how the MSE's changed across different stocks before and after the merger. Accordingly, we calculate the MSE of FE_{ijt} for each stock i, brokerage j, over a range of pre-merger and post-merger quarters. Specifically, define the pre- and post-merger MSE for a given stock i and brokerage j as

$$\begin{aligned} \text{MSE}_{ij}^{pre} &= 10^6 \times \frac{1}{K} \sum_{t=merg-K}^{merg-1} FE_{ijt}^2, \quad j = bidder,\ target \\ \text{MSE}_{i}^{post} &= 10^6 \times \frac{1}{K} \sum_{t=merg+1}^{merg+K} FE_{ijt}^2, \end{aligned} \tag{6}$$

where $merg$ denotes the quarter of the merger. To ensure that we isolate the effects of the mergers, we only consider forecasts within the K quarters before and after the merger. In this paper, we use a value $K = 8$ for our empirical results.[9] Furthermore, because earnings are defined on a per-share basis, the standardized forecast errors are usually very small, so that we scale up by a factor of 10^6 in computing the MSE.

3.3 Summary statistics: all stocks

In Table 3, we present summary statistics of forecast accuracy for the four mergers. For each merger, we report the median and mean, as well as the 10-th and 90-th quantiles, of $\text{MSE}_{i,bidder}^{pre}$, $\text{MSE}_{i,target}^{pre}$, and MSE_{i}^{post}, across all stocks which were forecast at least twice in the two years preceding the merger (for the pre-merger MSE measures), and the stocks which were forecast at least twice following the merger (for the post-merger MSE measure). First, note that the distribution of

[6] In normalizing by p_{it}, we follow many of the empirical studies which utilize the IBES data, including Rajan and Servaes (1997), Keane and Runkle (1998), and Lim (2001).

[7] The results are qualitatively robust to using alternative cutoff thresholds.

[8] Note that in the illustrative model if the previous section, forecasts are always unbiased, in which case the MSE simplifies to the variance of FE.

[9] Some stocks i were not forecast by brokerage j in each of the K quarters before and after the merger. In these cases, we compute the MSE as the average of the squared forecast errors only for those quarters in which the stock was forecast.

Table 3: Pre- and Post-Merger Mean-squared Errors in Merging Brokerages

		(a)	(b)		(c)		
Merger	Statistic	Pre-merger			Post-merger		
		MSE^{pre}_{bidder}	MSE^{pre}_{target}	(a)=(b)?	MSE^{post}	(c)=(a)?	(c)=(b)?
A	median	3.93	2.32	**	4.11	–	**
	mean	1873.8	1431.2		4808.3		
	10%	0.06	0.05		0.06		
	90%	262.47	164.01		235.59		
	#stocks	440	381		504		
B	median	5.03	2.43	***	4.81	–	***
	mean	2259.7	317.1		2128.2		
	10%	0.05	0.07		0.10		
	90%	290.00	405.74		305.32		
	#stocks	852	418		764		
C	median	6.86	6.90	–	3.69	***	***
	mean	9173.1	2717.5		10207.6		
	10%	0.19	0.09		0.12		
	90%	538.54	497.98		309.43		
	#stocks	1238	749		967		
D	median	5.91	6.74	–	3.92	**	***
	mean	651.14	3706.2		462.69		
	10%	0.14	0.01		0.09		
	90%	302.89	640.03		210.98		
	#stocks	948	494		797		

***: reject equality at 1%
**: reject equality at 5%
*: reject equality at 10%

MSE's is highly skewed to the right. Across all the mergers, the mean MSE generally exceeds the 90-th quantile of the MSE distribution, both before and after the merger. For this reason, in this paper, we employ median (quantile) regressions because, for such a skewed distribution, the median is a better measure of the central tendency of the MSE distribution than the mean.

Table 3 shows that Mergers A and B were quite different from Mergers C and D. In Mergers A and B, the target firms appeared to be better than the bidder firms, in terms of median MSE before the merger. For Merger A, the median MSE for target firm Kidder Peabody was 2.32, while for bidder firm Paine Webber it was

3.93. Column 5 of Table 3 shows that these differences in medians were statistically different from zero at a 5% significance level. For these two mergers, however, the post-merger median MSE was virtually the same as the median of the bidder firm's pre-merger MSE, and substantially higher than the target firm's pre-merger MSE. For example, the median MSE after Merger A was 4.11, which is just slightly higher than Paine Webber's pre-merger median of 3.93. Hence, for these two mergers, we have evidence that worse-performing bidder firms acquired better-performing target firms, and that forecasting accuracy actually deteriorated after the merger, relative to the target firms' pre-merger forecasting accuracy.[10]

The numbers for Mergers C and D tell a different story. The two mergers involved partners which, in terms of their pre-merger forecast accuracy, were rough equals. For example, the median pre-merger MSE's for Credit Suisse–First Boston and Donaldson, Lufkin, and Jenrette were, respectively, 6.86 and 6.90 (and statistically not different from each other). However, there were clear improvements in forecasting accuracy, as the post-merger median MSE in both of these mergers was lower, and statistically different (at the 1% level) from the pre-merger median MSE for both the bidder and target firms.

The simple model of forecasting improvements in the previous section assumes that analysts' forecasts are always unbiased, whereas the MSE (our measure of forecast performance) summarizes both the bias and variance of the forecasts. In Table 4, we report the bias and standard deviation of the forecast errors for each merger, and also before and after the merger.

Across all the results, the magnitude of the standard deviation is much larger than that of the bias. For example, for Merger A, the median pre-merger bias of the forecast errors for the bidder brokerage is -0.0526, but the corresponding standard deviation is 1.7728. Hence, even though the theoretical discussion in the previous section assumed a model where analysts' forecasts are unbiased, the results here suggest that this may not be a bad approximation, because in the data the variance component of the MLE far exceeds the bias component.

3.4 Summary statistics: affected stocks

An important subset of stocks which we focus on in this paper are those which were covered by both the bidder and target firms prior to the merger, and continued to be covered by the merged brokerage following the merger. This particular subset of stocks will be referred to as the **affected** stocks in the rest of this paper. Comparisons of affected and non-affected stocks play an important role in our tests for

[10]This is somewhat surprising for Merger B, because the bidder firm in this merger (Morgan Stanley) is widely considered a better research brokerage than the target firm in that merger (Dean Witter).

Table 4: Pre- and Post-Merger Mean-squared Errors in Merging Brokerages
Mean-squared errors broken down into Bias and Standard Deviation Components

		(a)	(b)	(c)	(d)	(e)	(f)
Merger	Statistic	Pre-merger				Post-merger	
		Bias_{bid}	Stdev_{bid}	Bias_{bid}	Stdev_{bid}	Bias_{bid}	Stdev_{bid}
A	median	-0.0526	1.7728	-0.0547	1.2589	-0.0507	1.8335
	mean	3.5671	9.3330	3.0644	7.4749	4.7202	9.9199
	#stocks	439		380		504	
B	median	-0.0163	2.1013	-0.0435	1.3353	-0.0203	2.0598
	mean	2.7800	9.6790	1.4225	4.7287	3.2028	9.6862
	#stocks	852		418		764	
C	median	-0.2681	2.3221	-0.0775	2.3132	-0.3311	1.7190
	mean	-0.8429	14.0994	2.1434	11.7908	-1.1986	12.5897
	#stocks	1238		749		967	
D	median	-0.1873	2.1069	-0.0326	2.4658	-0.2810	1.7178
	mean	0.9947	8.3386	3.7317	12.7572	0.3163	20.7542
	#stocks	948		494		797	

information pooling.

In Table 5, we report the same statistics as in Table 3, but only for the affected stocks. Across all four mergers, the bidder firm tends to produce more accurate forecasts of the affected stocks than the target firm before the merger, even though this difference is statistically significant only for Mergers C and D. For Mergers C and D, the median post-merger MSE is significantly lower than the pre-merger MSE for the target firm. For Merger B, the evidence here indicates a deterioration in forecast accuracy, relative to the pre-merger performance of both bidder and target firms. For Merger A, we find no evidence of changes in forecasting accuracy after the merger. These numbers seem to suggest that brokerage-level forecast improvements are driven by the pre-merger forecast performance of the bidder firm. Specifically, if the bidder and target firms are roughly equal-abilitied before the merger, then forecast improvements obtain; if the bidder firm is worse than the target firm, then there are no forecasting improvements.

4 Empirical results

In this section, we examine whether the changes in forecasting accuracy documented in Tables (3) and (5) can be attributed to information pooling by seeing whether forecast improvements appear more pronounced in subsamples of stocks

Table 5: Mean Squared Errors of Forecasts: Affected Stocks

		(a)	(b)		(c)		
Merger	Statistic	Pre-merger			Post-merger		
		$\text{MSE}^{pre}_{bidder}$	$\text{MSE}^{pre}_{target}$	(a)=(b)?	MSE^{post}	(c)=(a)?	(c)=(b)?
A	median	0.89	1.00	–	1.29	–	–
	mean	45.81	139.50		129.35		
	10%	0.02	0.03		0.02		
	90%	32.46	74.37		53.17		
	#stocks	137					
B	median	0.79	1.30	–	3.25	***	**
	mean	70.78	69.69		138.74		
	10%	0.01	0.02		0.05		
	90%	31.58	65.26		132.34		
	#stocks	197					
C	median	1.51	3.03	***	1.76	–	**
	mean	154.62	338.78		1278.7		
	10%	0.04	0.05		0.08		
	90%	54.58	112.45		92.54		
	#stocks	383					
D	median	1.04	3.59	***	1.78	–	**
	mean	27.10	83.64		172.52		
	10%	0.03	0.07		0.07		
	90%	45.29	166.79		144.71		
	#stocks	224					

***: reject equality at 1%
**: reject equality at 5%
*: reject equality at 10%

where information pooling should be stronger, such as the affected stocks, and the stocks for which both of the pre-merger analysts were retained in the merged brokerage.

4.1 Brokerage-level forecast improvements

We start by documenting the brokerage-level forecast improvements. Define

- $\text{AFFECTED}_i = 1$ if stock i was an affected stock and hence covered by both the bidder and target firms prior to the merger.

We also define two more dummy variables to isolate subsamples of the affected stocks where information pooling should be even stronger:

- $\text{BOTHSTAY}_i = 1$ if both the analysts who covered stock i at the bidder and target firms before the merger were retained in the merged brokerage.
- BOTHCOVER_i=1 if both analysts cover stock i within two years after the merger after the merger.

Note that the subsample of stocks with $\text{BOTHCOVER}_i = 1$ is included in the subsample with $\text{BOTHSTAY}_i = 1$, which is in turn included in the subsample of affected stocks ($\text{AFFECTED}_i = 1$).

Information pooling is fundamentally about the sharing of private information and expertise, so that forecast improvements should be more prominent for the affected stocks, when presumably both brokerages possess some information and expertise. If the information or expertise required in the forecasting enterprise is analyst-specific, then information pooling should be more pronounced when $\text{BOTHSTAY}_i = 1$. Information pooling should be even more pronounced when $\text{BOTHCOVER}_i = 1$, especially if information were very time-sensitive and changes quickly, so that pooling occurs only when both analysts are still actively covering the stock in the post-merger period.

In this section, brokerage-level forecast improvements are defined as

$$\Delta\text{MSE}_i \equiv \begin{cases} \text{MSE}_i^{post} - \frac{1}{2}[(\text{MSE}_{i,bidder}^{pre} + \text{MSE}_{i,target}^{pre})] & \text{if AFFECTED}_i = 1 \\ \text{MSE}_i^{post} - \text{MSE}_{i,bidder}^{pre} & \text{if only bidder covers stock } i \\ \text{MSE}_i^{post} - \text{MSE}_{i,target}^{pre} & \text{if only target covers stock } i \end{cases}$$

with $\Delta\text{MSE}_i < 0$ indicating forecast improvements. Notably, ΔMSE_i is defined differently depending on whether stock i is an affected stock. This is because for non-affected stocks, only one of the brokerages – usually the bidder firm – covers the stock before the merger. For the affected stocks, our base case is to compare the post-merger forecast to a equally weighted pre-merger forecast. Robustness to this definition of forecast improvement will be considered below.

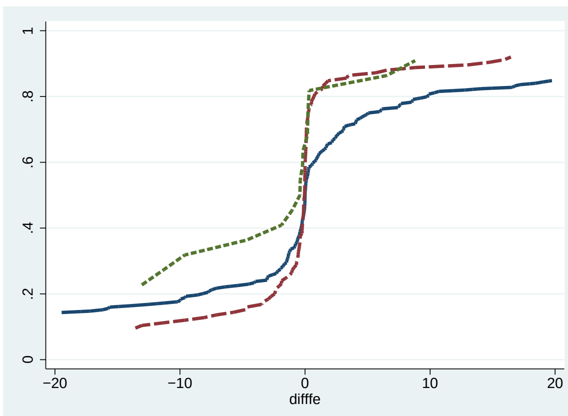
Under information pooling, ΔMSE_i should be more negative when $\text{AFFECTED}_i = 1$ than when $\text{AFFECTED}_i = 0$, and even more negative when $\text{BOTHSTAY}_i = 1$ and $\text{BOTHCOVER}_i = 1$. Some insight can be obtained from Figure (1), which presents the empirical cumulative distribution functions of ΔMSE_i, for the various subsamples of interest. Across all the mergers, the CDF for $\text{AFFECTED}_i = 1$ (in the solid lines) tends to lie above and to the left of the CDF for the $\text{AFFECTED}_i = 0$ subsample of stocks (in the dashed lines), especially for values of ΔMSE greater than zero. This suggests that the values of ΔMSE_i are smaller (in a distributional

Figure 1: Empirical Cumulative Distribution Functions for Brokerage-level Forecast Improvements

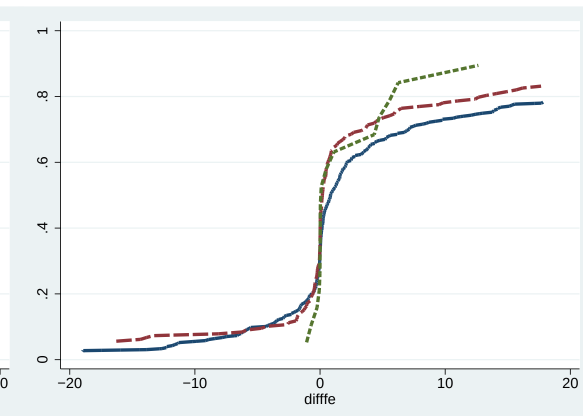
$$\text{X-Axis: } \Delta\text{MSE}_i = \text{MSE}_i^{post} - (0.5 * \text{MSE}_{i,bid}^{pre} + 0.5 * \text{MSE}_{i,tar}^{pre})$$

Y-Axis: empirical cumulative distribution function

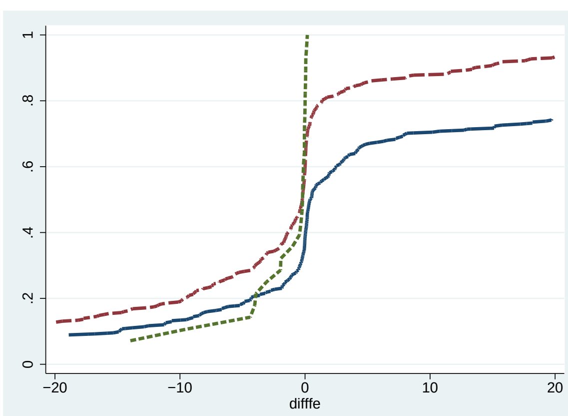
Solid line: stocks for which $\text{AFFECTED}_i = 0$
Dashed line: stocks for which $\text{AFFECTED}_i = 1$
Dotted line: stocks for which $\text{AFFECTED}_i = 1$ and $\text{BOTHSTAY}_i = 1$



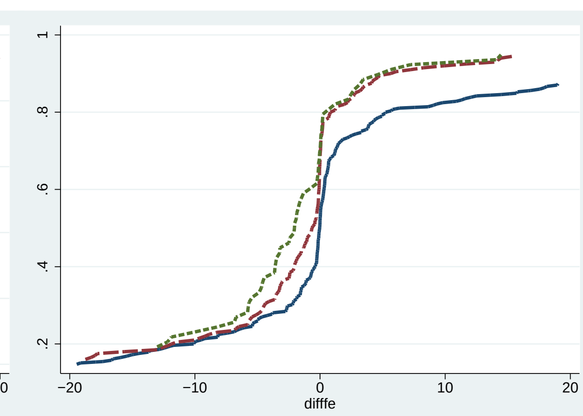
Merger A



Merger B



Merger C



Merger D

sense) when both brokerages forecast the stock before the merger, which is consistent with information pooling. Conditional on AFFECTED$_i = 1$, we then single out those stocks with BOTHSTAY$_i = 1$. The empirical CDF's for this subsample shows that while the differences are not as sharp as between the AFFECTED$_i = 0$ and AFFECTED$_i = 1$, in all four mergers, there are substantial ranges of quantiles where the dotted CDF lies above and to the left of the other two CDFs. This suggests that forecast improvements are larger when AFFECTED$_i = 1$ and even larger when both AFFECTED$= 1$ and BOTHSTAY$= 1$.

To provide a more formal analysis, consider LAD (least absolute deviation) estimation of the model:[11]

$$\Delta\text{MSE}_i = \alpha + \beta \cdot \text{AFFECTED}_i + \gamma \cdot Z_i + \text{error}_i \tag{7}$$

where a negative β would be consistent with information pooling. The results from this regression are reported in Columns A1, B1, C1, and D1 of Table 6. Since each observation in this regression is a stock, we also include stock-level covariates Z_i to control for additional variation across observations. In the reported specifications, these covariates are AVGMCAP$_i$ and SDEVMCAP$_i$ which measure, respectively, the average and standard deviation of market capitalization of stock i during the eight quarters preceding each of the four mergers studied in this paper. We use AVGMCAP$_i$ to proxy for stock i's size, and SDEVMCAP$_i$ to measure its volatility.[12]

The existing literature on analyst forecasts (eg. Zitzewitz (2001), Gallo, Granger, and Joon (2002)) has stressed the relationship between forecast timing and accuracy. Particularly, later forecasts are usually more accurate because they contain the information revealed in earlier forecasts, so that forecast improvements after the merger could arise simply from the merged firm choosing to release forecasts later, and not from information pooling. To control for this possibility, we create a stock-level variable, DIFFTIMING$_i$, defined as

$$\begin{aligned}\text{DIFFTIMING}_i = &\text{Avg(Days bef EOQ)}_i^{post}\\ &- [\frac{1}{2}\text{Avg(Days bef EOQ)}_i^{pre,bid} + \frac{1}{2}\text{Avg(Days bef EOQ)}_i^{pre,targ}]\end{aligned} \tag{8}$$

where Avg(Days bef EOQ)$_i$ is the average number of days before the end-of-quarter for which a forecast for stock i was released. DIFFTIMING$_i$ measures changes in

[11] As we remarked before, we employ LAD regressions here because the results appeared very sensitive to outliers in OLS regressions.

[12] In other specifications (not reported for brevity), we have used shares outstanding, and premerger share prices as covariates. The results reported here are robust.

Table 6: Brokerage-level Forecast Improvements

Results from median (quantile) regression; Dependent variable: ΔMSE$_i$

	Merger A			Merger B			Merger C			Merger D		
Variable	(A1) Est (Stder)	(A2) Est (Stder)	(A3) Est (Stder)	(B1) Est (Stder)	(B2) Est (Stder)	(B3) Est (Stder)	(C1) Est (Stder)	(C2) Est (Stder)	(C3) Est (Stder)	(D1) Est (Stder)	(D2) Est (Stder)	(D3) Est (Stder)
AFFECTED	-0.0632	-0.0533	—[a]	-0.1296	-0.1702	—[a]	-1.9489***	-1.9861***	-1.9211***	-1.0251***	-0.3195	-0.3195
	0.1169	0.1284		0.4938	0.4920		0.4233	0.3754	0.3678	0.3377	0.2455	0.3982
BOTHSTAY		-0.2943			0.6485			0.2022	0.6836		-1.5029***	-2.4190***
		0.2373			1.1351			0.6345	0.9391		0.5683	0.5454
BOTHCOVER									-6.3008***			0.9161
									2.2577			0.9825
Stock controls:												
DIFFTIMING	0.0025***	0.0025***		0.0117***	0.0116***		0.0219***	0.0219***	0.0209***	0.0147***	0.0151***	-0.0151***
	0.0009	0.0009		0.0032	0.0031		0.0036	0.0032	0.0031	0.0028	0.0032	0.0028
CONSTANT	-0.0262	-0.0262		0.7270**	0.7218**		1.5552***	1.5525***	1.4767***	0.2819	0.2727	0.2727
	0.0671	0.0680		0.2974	0.2888		0.3043	0.2637	0.2589	0.2208	0.2503	0.2240
N	407	407	407	561	561	561	744	744	744	539	539	539
med(ΔMSE$_i$)	-0.0126			0.4747			0.0148			-0.1550		
med(DIFFTIMING)	5.4			28.9			-24.5			-28.4		
#(AFFECTED=1)	137			197			383			224		
#(BOTHSTAY=1)	25			21			31			87		
#(BOTHCOVER=1)	2			1			4			17		

***: statistically significant at 1%; **: statistically significant at 5%; *: statistically significant at 10%

Coefficients for stock-level controls AVGMCAP and SDEVMCAP are not reported for convenience.

[a]: Results were not reliable, due to small number of observations with $BOTHCOVER = 1$.

forecast timing after the merger, with positive values indicating that forecasts were released earlier, on average, after the merger. Since more negative values of the LHS variable ΔMSE_i indicate more forecast improvements, we expect the regression coefficient on DIFFTIMING to be positive, implying that earlier forecasts lead to less forecast improvements after the merger.

For Mergers C and D, the coefficient on AFFECTED is negative and significant (the coefficients are, respectively, -1.9489 and -1.0251). Moreover, the magnitudes of these coefficients are economically nontrivial, in that they are large in comparison to the magnitudes of the unconditional median of the dependent variable, reported at the bottom of the table. Hence, for these two mergers, the regression results confirm the graphical evidence from Figure (1) that information pooling might be present.

Among the stock-level controls, the coefficient on DIFFTIMING is positive and significant across all four mergers, and all specifications of the regression. This is in the expected direction, and indicates that for stocks where the forecast was released sooner following the merger, the forecast improvements were smaller. At the bottom of the table, we present the unconditional median of the DIFFTIMING variable across the four mergers, which shows that forecasts tended to be released sooner after Mergers A and B, but later following Mergers C and D.

Next, we narrow our focus to smaller subsets of stocks for which information pooling should be stronger. In Columns A2, B2, C2, and D2 of Table 6, we report results for the regression when BOTHSTAY is added as a right-hand side variable. Only for Merger D is the coefficient on BOTHSTAY_i negative and significant (and equal to -1.5029), indicating larger forecasting improvements for the stocks for which both pre-merger analysts were retained. This is evidence of a stronger notion of information pooling.[13]

Finally, we further narrow the analysis to those stocks where both analysts continue to produce forecasts in the post-merger period. The results from the regression with the BOTHCOVER_i dummy included are reported in Columns C3 and D3 of Table 6 (we were only able to run this regression for Mergers C and D, but to the small number of observations where BOTHCOVER_i=1). The coefficient on BOTHCOVER_i is negative and significant only for Merger C, but not in Merger D. Hence, for Mergers C and D, we obtain evidence indicating that a stronger notion of information pooling (as captured by the negative coefficients on either the BOTH-

[13]The finding that information pooling is more prominent when both of the pre-merger analysts were retained also provides support against an alternative explanation for improved analyst performance following a merger, namely that retained analysts may work harder following a merger because of increased job security concerns following the merger. This alternative story does not provide an explanation for why a retained analyst's performance improves more after the merger when her former rival is also retained.

STAY or BOTHCOVER variables) may be an explanation for the post-merger forecast improvements. From Table 3, we see that these two mergers were the ones where the merging firms were most equal in forecasting ability before the mergers, which perhaps made information pooling more likely.

4.1.1 Robustness

One worry with the above regressions is that the changes in forecasting accuracy after the merger could simply reflect changes in forecasting accuracy around the time of the mergers due, for instance, to unanticipated business-cycle movements, but not directly related to the mergers. As a robustness check, we expand the sample to include the changes in MSE's for brokerages which did not participate in any merger, as a control group. The idea is that any time-specific factors affecting forecasting accuracy should impact on both the merging and non-merging brokerages, whereas the effects of the merger (such as information pooling) should predominantly affect the merging brokerages only. The modified regression is

$$\begin{aligned}\Delta\text{MSE}_{i,k} =&\alpha + \alpha_1 \cdot \text{MERGE}_k + \beta \cdot \text{AFFECTED}_i + \beta_1 \cdot \text{AFFECTED}_i * \text{MERGE}_k \\ &+ \gamma \cdot \text{BOTHSTAY}_i + \gamma_1 \cdot \text{BOTHSTAY}_i * \text{MERGE}_k + \alpha Z_i + \text{error}_{i,k}\end{aligned} \tag{9}$$

where the k subscript denotes different brokerage firms, and MERGE_i is a binary indicator for whether brokerage k is the merged brokerage. The sample includes all brokerages k and stocks i for which forecasts were submitted for at least two quarters before and after the merger. The main benefit from including the observations from the non-merging firms is that we can estimate the coefficient on MERGE_i, which measures the part of the forecasting changes due specifically to the mergers, and not due to changes across time in forecasting abilities which are common across all brokerages. The interaction of AFFECTED and BOTHSTAY with MERGE are now used to capture the incremental effects of the AFFECTED and BOTHSTAY indicators on the forecasting changes of the merged brokerage. A finding that β_1 and β_2 is negative would suggest that forecast improvements result from the merger, and are not due to time specific effects.[14]

The results are reported in Table (7). The coefficient on the interaction terms are negative and significant in most of the regressions, the sole exception being the negative but insignificant coefficient on AFFECTED*MERGE in Merger D. This furnishes strong evidence that the mergers had distinctive effects on the forecasting performance of the merged brokerage, relative to others non-merging brokerages. Moreover, comparing these results with the corresponding results in Table

[14] In these regressions, BOTHSTAY and MERGE are always equal to zero for the observations of the non-merging firms.

Table 7: Brokerage-level Forecast Improvements: Including Observations from Non-merging Brokerages

Results from median (quantile) regression; Dependent variable: ΔMSE_i

	Merger A	Merger B	Merger C	Merger D
Variable	Est (Stder)	Est (Stder)	Est (Stder)	Est (Stder)
MERGE	0.5025***	0.1583	0.2844	-0.1946
	0.0500	0.1823	0.2936	0.3020
AFFECTED	-0.0741***	-0.2453***	-0.3296***	0.1059**
	0.0208	0.0618	0.0630	0.0525
AFFECTED*MERGE	-0.5257***	-0.0214***	-0.6999**	-0.1543
	0.0790	0.2506	0.3245	0.3356
BOTHSTAY	0.3633***	2.8797***	0.2855***	0.0467
	0.0422	0.1393	0.1479	0.1646
BOTHSTAY*MERGE	-0.6916***	-12.5833***	-12.8695***	-3.3433***
	0.1511	0.5213	0.4813	0.5436
Stock controls:				
DIFFTIMING	0.0017	0.0073***	0.0058***	0.0047***
	0.0001	0.0004	0.0004	0.0004
CONSTANT	0.0426***	0.4863***	0.5847***	0.1816***
	0.0132	0.0412	0.0508	0.0388
N	5908	5312	4219	4149

***: statistically significant at 1%; **: statistically significant at 5%; *: statistically significant at 10%

Coefficients for stock-level controls AVGMCAP and SDEVMCAP are not reported for convenience.

(6), the most striking change is that the effect of BOTHSTAY on the merged brokerage (which is equal to the sum of the coefficients on BOTHSTAY and BOTHSTAY*MERGE) is now more negative, and significant, across all four mergers.[15] Thus, these results demonstrate even clearer evidence of information pooling.

For the second set of specification checks, we consider alternative definitions of

[15] From inspections of the data, this appears to be driven by the fact that the average value of ΔMSE across all observations in this regression (from both the merging and non-merging firms) is positive, indicating worsening forecasts. On the other hand, the values of ΔMSE in the merging firms are, on average, either negative or slightly positive. Hence, compared with the overall sample, the values of ΔMSE in the merging firms are smaller, which explains the negative and significant coefficient on BOTHSTAY.

the dependent variable ΔMSE_i. Because improving forecast precision may not be and is likely not the goal of the mergers, what is deemed an improvement from a statistical perspective need not be an improvement from the brokerages' perspectives. In the regressions in Table (6), we measured brokerage-level forecast improvement as the difference between the post-merger MSE and the simple average (ie. taking $w_1 = w_2 = \frac{1}{2}$ in Eq. (1) of the pre-merger MSEs of the bidder and the target firm. This was used because simple averaging favors neither the bidder nor the target firm, nor does not it weigh the better performing brokerage pre-merger more or less than the weaker brokerage.[16]

Nevertheless, to assess the robustness of the results, we re-ran the regression (7) for alternative values of the weights w_1 and w_2, including the special cases of putting all the weight on the bidder firm and none on the target firm, and vice versa. The robustness check consists of reconsidering the brokerage-level regressions reported in Table (6) for alternative definitions of ΔMSE_i. We do not report the results for the sake of brevity, but summarize them here. The regression results are similar to those reported in Table (6) when we put larger weight on the pre-merger MSE of the target firm. It is only when we put increasingly heavy weights on the MSE of the bidder firm that the negative coefficients on AFFECTED and BOTHSTAY become less significant.[17] For Mergers A and C, however, we find that the results reported in Table (6) are robust across a wide range of alternative weighting schemes. Overall, we find that although the results are not uniform over all alternatives values of w_1 and w_2, the evidence for information pooling at the brokerage level occurring in the form of forecast improvements holds up for most values of the weights.

4.2 Analyst-level forecast improvements

While the evidence above suggests that brokerage-level forecast improvements occurred after three of the four mergers, we do not know if these improvements extend to the analyst level. Indeed, the benefits of information pooling may be larger at the analyst level especially for the analysts who were substandard prior to the mergers. To focus on analyst-level forecast changes, define

$$\Delta\text{MSE}_{i,j} \equiv \text{MSE}_{i,j}^{post} - \text{MSE}_{i,j}^{pre}$$

as a measure of the change in analyst j's forecast accuracy for stock i. Again, $\Delta\text{MSE}_{i,j} < 0$ indicates forecast improvements.

[16]Furthermore, the forecast combination literature finds that simple averaging often outperforms more sophisticated forms of averaging. See, for example, Timmermann (2005). Thus in a sense, simple averaging forms a harder to beat benchmark.

[17]However, the results reported in Table (6) are robust even when we set $w_1 = 0.85$, where w_1 denotes the weight on the bidder firm's MSE in the pre-merger benchmark.

In order to measure analyst-level forecasting changes, we have to restrict our sample to stocks which were covered, in the post-merger period, by either the bidder or target analyst. Let j denote the analyst who covers stock i after the merger. As in the previous section, we define dummy variables which indicate subsets of stocks where information pooling should be strongest. We now define

- RIVALSTAY$_{i,j} = 1$ if analyst j's former rival (ie. the analyst who covered stock i in the other brokerage before the merger) was retained in the merged brokerage.

The dummy variable equals one in two circumstances. First, if analyst j, covering stock i, worked at the bidder firm before the merger, then RIVALSTAY$_{ij} = 1$ if the analyst who covered stock i at the target firm before the merger was retained at the merged brokerage after the merger. Second, if analyst j, covering stock i, worked at the target firm before the merger, then RIVALSTAY$_{ij} = 1$ if the analyst who covered stock i at the bidder firm before the merger was retained at the merged brokerage after the merger.

Figure (2) plots the CDFs of ΔMSE$_{i,j}$ separately for RIVALSTAY$_{i,j} = 0$ (in solid lines) and RIVALSTAY$_{i,j} = 1$ (in dashed lines). Compared to the brokerage-level graphs in Figure 1, forecast improvements are less apparent here. For Mergers A, B, and D, substantial portions of the RIVALSTAY$_{i,j} = 1$ graphs lie to the right of the RIVALSTAY$_{i,j} = 0$ graphs, indicating a deterioration in forecasting accuracy after the mergers. Only for Merger C is there evidence of forecast improvements.

Hence, from the graphs, the evidence for analyst-level forecast improvements is more mixed, which is confirmed in regression results. We run the LAD regression of:

$$\Delta\text{MSE}_{i,j} = \alpha + \beta \cdot \text{RIVALSTAY}_{ij} + \gamma Z_i + \delta W_j + \text{error}_i$$

separately for (i) the subsample of stocks covered in the post-merger period by the bidder analyst, which we call the "bidder stocks"; and (ii) the subsample covered by the target analyst, which we call the "target stocks". A finding that $\beta < 0$ would be consistent with the presence of information pooling.

In addition to the stock-level control variables Z_i , we also include analyst-specific covariates to control for possible analyst heterogeneity. These covariates W_j are: (1) PREMSE$_j$, analyst j's pre-merger mean-squared forecast error, taken across all the stocks covered by analyst j in the two years prior to the merger; and (2) DIFFNUM$_j$, the difference between the total number of stocks covered by analyst j in the year after the merger, versus the year before the merger. The first covariate controls for analyst-specific forecasting ability, while the second covariate controls for the "attention" that analyst j pays to each stock that she covers. Because of the small number of stocks where RIVALSTAY=1, only five of the eight regressions had reliable results, and are reported in Table 8.

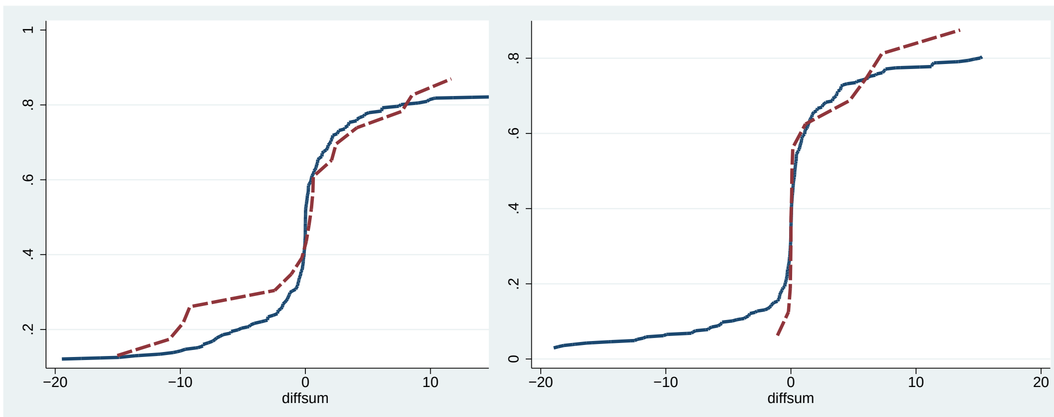
Figure 2: Empirical Cumulative Distribution Functions for Analyst-level Forecast Improvements

X-Axis: $\Delta\text{MSE}_{i,j} = \text{MSE}_{i,j}^{post} - \text{MSE}_{i,j}^{pre}$, for stocks i and analyst j [a]

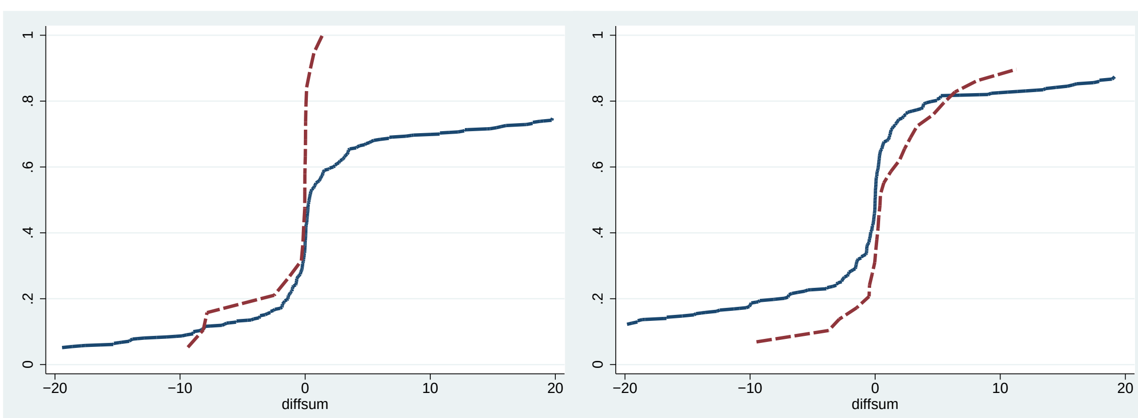
Y-Axis: empirical cumulative distribution function

Solid line: stocks i for which $\text{RIVALSTAY}_{i,j} = 0$

Dashed line: stocks i for which $\text{RIVALSTAY}_{i,j} = 1$



Merger A   Merger B



Merger C   Merger D

[a] : $j \in \{bid, tar\}$ denotes analyst who forecast stocks after the merger. That is, $j = bid$ if stock was forecast by bidder analyst after the merger, and $j = tar$ if stock was forecast by target after the merger.

Table 8: Analyst-level forecast improvements

Results from median (quantile) regression; Dependent variable: $\Delta MSE_{i,j}$

	Merger A		Merger B		Merger C		Merger D	
	(A1) Bidder stocks[a]	(A2) Target stocks[b]	(B1) Bidder stocks	(B2) Target stocks	(C1) Bidder stocks	(C2) Target stocks	(D1) Bidder stocks	(D2) Target stocks
Variable	Estimate (Stder)	Estimate (Stder)	Estimate (Stder)	Estimate (Stder)	Estimate (Stder)	Estimate (Stder)	Estimate (Stder)	Estimate (Stder)
RIVALSTAY	—[c]	-17.1619***	0.5514	—[c]	-0.7928	—[c]	0.2634	-9.3631***
		6.1988	0.9530		1.2877		0.5882	2.6488
DIFFTIMING		0.0580	0.0145***		0.0113*		0.0060*	0.0585***
		0.0446	0.0034		0.0064		0.0035	0.0150
PREMSE		-0.0180***	-0.0001		0.0000		-0.0015***	-0.092**
		0.0037	0.0004		0.0000		0.0004	0.0036
DIFFNUM		2.8192***	-0.1250*		0.0854		-0.0274	-0.1013
		0.3728	0.0667		0.1461		0.0810	0.1688
CONSTANT		17.5660***	0.3992		1.0538***		0.5067	1.7853
		5.1054	0.2925		0.3790		0.2450	1.1748
N	222	60	330	22	292	75	187	166
med(ΔMSE_i)	0.0031	0.3911	0.3451	0.0360	0.3303	-0.0074	0.1472	-0.5195
med(DIFFTIMING)	19.6	-7.4	43.8	-67.4	-5.8	-41.2	-6.2	-32.0
#(RIVALSTAY=1)	3	24	16	1	19	4	27	18

***: statistically significant at 1%; **: statistically significant at *5%; *: statistically significant at 10%

Coefficients for stock-level controls AVGMCAP and SDEVMCAP are not reported for convenience.

[a]: stocks which were covered in post-merger period by analyst who worked at bidder brokerage before merger

[b]: stocks which were covered in post-merger period by analyst who worked at target brokerage before merger

[c]: There were not enough stocks with RIVALSTAY$= 1$ to obtain reliable estimates for this regression.

For the bidder stocks, we find no evidence for information pooling. For Mergers B, C, and D, the coefficient on RIVALSTAY is statistically indistinguishable from zero. For the target stocks, however, there is some evidence of information pooling. For the two mergers where we had enough data to run this regression, we find a negative and significant coefficient on RIVALSTAY: -17.16 for Merger A, and -9.36 for Merger D. These results suggest that information pooling occurs primarily for the target analysts covering a stock in the merged brokerage when the bidder analyst is also retained, but assigned to other stocks.

For the other control variables, we find that the coefficient on the timing variable DIFFTIMING continues to be positive, and significant in four of the five regressions.

4.2.1 Robustness and additional results

As with the brokerage-level regressions, we also considered analyst-level regressions (analogous to Eq. (7) that include the changes in MSE of the non-merging brokerages as a control group in the sample, to isolate the effects due specifically to the mergers. because the results in Table 8 The regression is

$$\begin{aligned}\Delta\text{MSE}_{i,j} =& \alpha + \alpha_1 \cdot \text{MERGE}_j + \beta \cdot \text{RIVALSTAY}_i + \beta_1 \cdot \text{RIVALSTAY}_i * \text{MERGE}_j \\ &+ \gamma Z_i + \delta W_j + \text{error}_{i,j}\end{aligned} \tag{10}$$

where the j subscript denote different analysts, and MERGE_j is a binary indicator for whether analyst j works at the merged brokerage after the merger. A finding that β_1 is negative would suggest that there are changes in forecasting accuracy due to the merger, and not just to time effects. [18] Table (9) report the results, separately for the subsamples of bidder and target stocks in each merger. The results weaken the earlier results in Table 8. For the target stocks, the coefficient RIVALSTAY*MERGE remains negative and significant for Merger D, but no longer for Merger A. For the bidder stocks, the coefficient on this interaction continues to be small and insignificant. This regression shows that only for Merger D do we have robust evidence of information pooling, and only for the target stocks.

As our strongest test of information pooling, we also investigate an implication of information pooling motivated in section 2, whereby post-merger forecast improvements should be inversely related to the pre-merger correlation in the forecast errors of the analysts. Let ρ_i be the correlation between the errors in the bidder and target firms' pre-merger forecasts of stock i. In order to compute this correlation,

[18] In these regressions, RIVALSTAY and MERGE are always equal to zero for the observations of the non-merging firms.

Table 9: Analyst-level forecast improvements: Including forecasts of analysts at non-merging brokerages

Results from median (quantile) regression; Dependent variable: $\Delta \text{MSE}_{i,j}$

	Merger A		Merger B		Merger C		Merger D	
	(A1) Bidder stocks[a]	(A2) Target stocks[b]	(B1) Bidder stocks	(B2) Target stocks	(C1) Bidder stocks	(C2) Target stocks	(D1) Bidder stocks	(D2) Target stocks
Variable	Estimate (Stder)	Estimate (Stder)	Estimate (Stder)	Estimate (Stder)	Estimate (Stder)	Estimate (Stder)	Estimate (Stder)	Estimate (Stder)
MERGE	—[c]	-1.5495	0.1102	—[c]	-0.1462	—[c]	0.0454	-0.1107
		3.2081	0.1387		0.1769		0.2209	0.3168
RIVALSTAY		0.5547	-0.0427		-0.5051***		-0.3079***	0.0124
		1.6502	0.1041		0.1321		0.0975	0.1368
RIVALSTAY*MERGE		1.3354	-0.5257		0.2274		0.3834	-2.5030***
		3.8299	0.3885		0.5127		0.3995	0.4296
PREMSE		-0.0020**	0.0000***		-0.0000		-0.0000	0.0000
		0.0008	0.0000		0.0000		0.0000	0.0000
DIFFNUM		-0.2229	-0.0151		-0.0110		-0.0133	0.0027***
		0.1678	0.0096		0.0100		0.0117	0.0007
DIFFTIMING		0.0376***	0.0060***		0.0097***		0.0038***	0.0125***
		0.0089	0.0005		0.0007		0.0008	0.0012
CONSTANT		-0.1246	0.2877***		0.5176***		0.3326***	0.6658***
		1.7813	0.0510		0.0542		0.0624	0.1053
N	1257	346	2022	108	2529	574	1300	1463

***: statistically significant at 1%; **: statistically significant at *5%; *: statistically significant at 10%

Coefficients for stock-level controls AVGMCAP and SDEVMCAP are not reported for convenience.

[a]: stocks which were covered in post-merger period by analyst who worked at bidder firm before merger

[b]: stocks which were covered in post-merger period by analyst who worked at target firm before merger

[c]: There were not enough stocks with RIVALSTAY$= 1$ to obtain reliable estimates for this regression.

we restrict attention to the stocks which were forecast by both bidder and target firms during at least two quarters before the merger, and for which both analysts were retained in the merged firm. In Table 10, we consider the regression

$$\Delta\text{MSE}_{i,j} = \alpha + \gamma \cdot \text{NEGCOR}_i + \text{error}_{i,j} \tag{11}$$

where NEGCOR_i is a dummy variable that is equal to one if $\rho_i < 0$. The discussion in section 2 suggests that the coefficient on NEGCOR should be negative. This is because a negative correlation will lead to larger forecast improvements, and more negative values for $\Delta\text{MSE}_{i,j}$. From the bottom of Table 10, we see that the number of stocks when NEGCOR_i=1 is a small fraction of the sample, so that we pooled both the bidder and target stocks observations to run the regression.[19]

The results show that the coefficient on NEGCOR is *positive* and significant for Mergers A,B,C, which rejects the strong implication of information pooling which we are testing. This may not be surprising because the results in section 2 were derived from a very stylized modeling framework.

5 Analyst selection

As shown earlier, all four mergers led to a great deal of employment turnover. The possibility therefore arises that forecasting improvements can also be due to analyst selection. As we explained in Section 2 above, analyst turnover following a merger can lead to two types of analyst selection. First, if the analysts who remained were systematically better than those who left, a brokerage-level improvement might result. Second, after a merger, the better of the bidder and target analyst can be chosen to forecast a given stock. In both of these cases, the forecast improvement would not be due to information pooling.

While information pooling and analyst selection can be observationally very similar, our data permit us to look for direct evidence of analyst selection by examining patterns in analyst retention and the post-merger assignment of analysts to stocks in our data. We examine the two types of analyst selection in turn.

1. Analyst selection in retention We start with the first type of analyst selection, and examine whether the better-abilitied analysts were retained in the merged firm, after the merger. Table 11 compares the pre-merger MSEs of the forecast errors, for the analysts who were retained following the mergers, and those who were not retained. The top of Table 11 shows that the difference in the median pre-merger MSE between the retained and non-retained analysts is insignificant across three

[19]The brokerage-level covariates AVGMCAP and STDMCAP are also included in the regressions, but the coefficients are not reported for the sake of brevity.

Table 10: Regressions of Change in Mean Squared Error of Forecast on Pre-Merger Correlation

	Merger A	Merger B	Merger C	Merger D
Variable	Estimate (Stder)	Estimate (Stder)	Estimate (Stder)	Estimate (Stder)
NEGCOR	58.0008***	12.5190	7.9645***	-0.1487
	7.6633	11.6276	1.1970	3.9765
DIFFTIMING	-0.0447	0.2972***	-0.0105	-0.0005
	0.0817	0.1169	0.0099	0.0343
CONSTANT	4.1991	-11.9197	-1.5000	-1.3910
	5.4377	10.2791	0.6856	1.6906
#(NEGCOR=1)	2	3	2	12
med(ρ_i)	0.511	0.398	0.500	0.513
N	24	14	25	76

These regressions also included the stock-level controls AVGMCAP and STDMCAP.

***: statistically significant at 1%

**: statistically significant at 5%

*: statistically significant at 10%

[a]: stocks which were covered in post-merger period by analyst who worked at bidder firm before merger

[b]: stocks which were covered in post-merger period by analyst who worked at target firm before merger

[c]: There were not enough target stock observations with NEGCOR$= 1$ to permit estimation of this regression

of the mergers. However, the difference is negative and significant for Merger C (-0.1312) which is evidence of analyst selection.

Once we break down the numbers among the bidder and target firms, the evidence for analyst selection becomes even more mixed. For bidder analysts, the median MSE amongst retained analysts is less than that of non-retained analysts across all four mergers, which is evidence of positive selection. However, this difference is significant only in Mergers A and C. For example, for the bidder analysts in Merger C, the median MSE for the non-retained analysts is 0.3074, but lower (0.0309) for the retained analysts. For the target analysts, the selection is generally in the *adverse* direction, with the median MSE of retained analysts higher than that of non-retained analysts in three of the four mergers (except Merger C). Only

Table 11: Are retained analysts adversely or positively selected?
Pre-Merger MSE Among Retained and Non-retained Analysts

Status[a]	Employer[b]		Merger A	Merger B	Merger C	Merger D
Retained	Both	Med. MSE	0.0387	0.0173	0.0354	0.0550
		N^c	40	60	110	100
Not Retained	Both	Med. MSE	0.0538	0.0294	0.1666	0.0658
		N	47	24	93	48
Δ Med MSE	Both		-0.0151	-0.0121	-0.1312**	-0.0108
Retained	Bidder	Med. MSE	0.0366	0.0100	0.0309	0.0410
		N^d	31	55	93	61
Not Retained	Bidder	Med. MSE	0.0898	0.0144	0.3074	0.0774
		N	8	8	31	22
Δ Med MSE	Bidder		-0.0532**	-0.0044	-0.2765*	-0.0364
Retained	Target	Med. MSE	0.1770	0.1222	0.1409	0.0742
		N	9	5	17	39
Not Retained	Target	Med. MSE	0.0307	0.0335	0.1586	0.0621
		N	39	34	62	26
Δ Med MSE	Target		0.1463	0.0887*	-0.0177	0.0121

***: significant at 1%
**: significant at 5%
*: significant at 10%

[a] Was analyst retained or not retained, in merged brokerage?

[b] Analyst's pre-merger employer (either bidder or target firm)

[c] The total number of analysts in each column may be fewer than the number of pre-merger analysts given in Table 2, because in this table, we eliminate analysts who do not provide at least four quarterly forecasts for a given stock.

[d] The total number of analysts in each column may be fewer than the number of pre-merger analysts given in Table 2, because in this table, we eliminate analysts who do not provide at least four quarterly forecasts for a given stock.

in Merger B, where the median MSE for retained analysts is 0.1222 and for non-retained analysts is 0.0335, is the difference significant.

2. Analyst selection in post-merger stock assignment To examine the second type of analyst selection, arising if the better of the bidder and the target analyst might be chosen to forecast a given stock, we restrict our attention to the subset of the affected stocks which were (i) forecast by either the bidder or target firm

Table 12: Determinants of post-merger stock assignment

Sample is restricted to affected stocks which were (i) forecast by either the bidder or target firm analyst, after the merger; and (ii) *both* the bidder and target analysts were retained in the merged brokerage.

		Merger A	Merger B	Merger C	Merger D
	Total N	23	20	27	73
of which:					
(A):	#(analyst w/lower stock MSE chosen):	14	9	14	27**
(B):	#(analyst w/lower overall MSE chosen):	20***	18***	20**	35
(C):	#(analyst w/longer tenure chosen):	2***	14*	7**	40
(D):	#(analyst from bidder brokerage chosen):	1***	19***	24***	27**

Stars denote significance of a test for whether the probability is equal to $\frac{1}{2}$, with 3/2/1 stars denoting a p-value below 1/5/10% under the null hypothesis that $p = \frac{1}{2}$. The t-test statistic is $\frac{\hat{p}_N - \frac{1}{2}}{\sqrt{\frac{1}{N}\frac{1}{2}^2}}$, where $\hat{p}_N$ denote the fraction of stocks which satisfy each criterion. Asymptotically, this statistic is distributed standard normal under the null that $p = \frac{1}{2}$.

analyst, after the merger; and for which (ii) *both* the bidder and target analysts were retained in the merged brokerage. In Table 12, we investigate whether stocks were systematically assigned to analysts with better abilities, based on pre-merger forecasting performance.

In row (A), we consider whether the stock was assigned to the analyst who was better at forecasting this particular stock before the merger. We find no evidence of this. For Mergers A, B, and C, we could not reject that the stock was assigned randomly. For Merger D, our evidence indicates that the stock is more likely to be assigned to the analyst who was worse at forecasting this particular stock before the merger.

However, row (B) provides a partial explanation of this. Here, we consider whether the stock was assigned to the analyst with better *overall* performance (across all stocks that he/she forecast) before the merger. We find strong evidence in favor of this hypothesis. For Mergers A, B, and C, the overwhelming majority of stocks are assigned to the analyst with the better overall pre-merger performance, strong evidence of analyst selection in stock assignment. Only for Merger D do we find no evidence of this type of analyst selection.

Table 13: Determinants of post-merger assignment of analysts to stocks

Results from probit regressions where left-hand side variable is $\mathbf{1}(\text{analyst } j \text{ assigned to stock } i \text{ after merger})$.
Sample is restricted to affected stocks which were (i) forecast by either the bidder or target firm analyst, after the merger; and (ii) *both* the bidder and target analysts were retained in the merged brokerage.
Each observation is a (stock i, analyst j).

	Merger A	Merger B	Merger C	Merger D
	Estimate (Stder)	Estimate (Stder)	Estimate (Stder)	Estimate (Stder)
STOCK_BEST$_{ij}$	–[a]	-1.0690	-0.3063	-0.0973
		0.8992	0.4279	0.2234
OVERALL_BEST$_j$		1.7817***	1.1130***	0.5783**
		0.8432	0.4092	0.2365
TENURE$_j$		0.5309	-0.4728	-0.1592
		0.6643	0.2983	0.0986
BIDDER$_j$		2.4935**	0.9021*	-1.0958***
		1.0261	0.5158	0.2323
Constant		-2.9731*	-0.2274	0.4729*
		1.6782	0.8540	0.2888
N		46	63	170

[a]: could not estimate due to collinearity of the regressors.

These findings are echoed in Table 13, which contains results from probit regressions where the dependent variable is an indicator for whether an analyst j is assigned to cover stock i after the merger. As right-hand side variables, we included the two indicators of pre-merger forecasting superiority used in Table 12 (STOCK_BEST and OVERALL_BEST), as well as two additional analyst-level controls which likely influence stock assignment after the merger. These two controls are TENURE, measured as the number of years than the analyst was employed before the mergers, and BIDDER, an indicator for whether the analyst worked at the bidder firm before the merger. The one consistent result across the three mergers for which we were able to run the regression is the positive and significant coefficient on OVERALL_BEST, an indicator for whether analyst j had the better overall forecasting performance before the merger. The signs and magnitudes for the other variables varied across the mergers.

Summing up, our analysis of turnover and coverage patterns in this section yields no evidence for the first type of analyst selection, that better analysts are more likely to be retained in the merged brokerage following the merger. This confirms anecdotal evidence that in the wake of job uncertainty due to the mergers, many of the best analysts at the merging firms were poached away by competing brokerages, so that the analysts remaining at the merged brokerage following the merger are not the best analysts working at the two brokerages before the merger. However, in the cases where both of a stock's pre-merger analysts were retained in the merged brokerage, we find strong evidence (for three of the four mergers), that the stock is likely to be assigned after the merger to the analyst with the better overall pre-merger forecasting performance. This suggests that analyst selection can be a mechanism generating the post-merger forecasting improvements.

6 Conclusions

We exploit four large mergers of brokerage firms in the last decade to examine whether the patterns of changes in forecasting accuracy following the mergers can be attributed to information pooling. Given the large differences between the brokerages involved in the mergers, and the motives for the merger, it is not surprising that our results varied across mergers. However, several conclusions can be drawn. First, at the brokerage-level, we find some evidence of information pooling across two of the four mergers (Mergers C and D), in that forecast improvements were larger in the subsample of stocks which were covered by both of the merging brokerages before the merger, and the subsample where both of the pre-merger analysts were retained in the merged brokerage. These are indeed situations where information pooling should be strongest. Furthermore, the merging brokerages in these two mergers were of roughly equal forecasting ability before the mergers, which perhaps made information pooling more likely.

Second, at the analyst-level, we find no general evidence of forecast improvements, except for Merger D. For this merger we found that the post-merger forecasts of analysts from the target firm benefit more from the presence of the analyst who covered the same stock at the bidder firm around than vice versa. We also find evidence that after a merger, a stock is more likely to be assigned to an analyst with overall better forecasting performance before the merger. This suggests that analyst selection can be a mechanism generating the post-merger forecasting improvements.

Finally, the results for Merger D yield the strongest evidence consistent with information pooling. Only for this merger do we find evidence consistent with information pooling in both the brokerage-level regressions and the analyst-level regressions (for the target stocks only). Moreover, only for this merger do we find no evidence of analyst selection. This finding of information pooling after Merger D also corroborates to some extent the coverage of this merger in the business press. Particularly, the general perception is that the analysts from Paine Webber (the target brokerage) were absorbed into the merged brokerage without much problem (cf. *Crain Communications, Inc.* (2000)). Perhaps this post-merger collegiality between the Paine Webber and UBS analysts explains the evidence of information pooling that we found for this merger.

References

BERNHARDT, D., AND E. KUTSOATI (1999): "Can Relative Performance Compensation Explain Analysts' Forecasts of Earnings?," Tufts University Dept. of Economics discussion paper 99-09.

CALOMIRIS, C., AND T. PORNROJNANGKOOL (2005): "Monopoly-Creating Bank Consolidation? The Merger of Fleet and BankBoston," mimeo, Columbia Business School.

Crain Communications, Inc. (2000): "One on One: UBS didn't buy us to change (us). They recognize the value of a financial advisor (Interview with Paine Webber's Mark Sutton)," September 11, pg. 58.

DIAMOND, D. (1984): "Financial Intermediation and Delegated Monitoring," *Review of Economic Studies*, 51, 393–414.

FOCARELLI, D., AND F. PANETTA (2003): "Are mergers beneficial to consumers? Evidence from the market for bank deposits," *American Economic Review*, 93, 1152–1172.

GALLO, G., C. GRANGER, AND Y. JOON (2002): "Copycats and Common Swings: The Impact of the Use of Forecasts in Information Sets," IMF Staff Reports, vol. 49, no. 1.

GENESOVE, D., AND W. MULLIN (1999): "The Sugar Institute Learns to Organize Information Exchange," in *Learning by Doing in Markets, Firms, and Countries*, ed. by N. Lamoreaux, D. Raff, and P. Temin. University of Chicago Press.

HONG, H., J. KUBIK, AND A. SOLOMON (2000): "Security Analysts' Career Concerns and Herding of Earnings Forecasts," *RAND Journal of Economics*, 31, 121–144.

KANDEL, E., AND N. PEARSON (1995): "Differential Interpretation of Public Signals and Trade in Speculative Markets," *Journal of Political Economy*, 103, 831–872.

KEANE, M., AND D. RUNKLE (1998): "Are Financial Analysts' Forecasts of Corporate Profits Rational?," *Journal of Political Economy*, 106, 768–805.

LIM, T. (2001): "Rationality and Analysts' Forecast Bias," *Journal of Finance*, 56, 369–385.

PANETTA, F., F. SCHIVARDI, AND M. SHUM (2006): "Do Mergers Improve Information? Evidence from the Loan Market," Manuscript, Bank of Italy and Johns Hopkins University.

PRAGER, R., AND T. HANNAN (1993): "Do Substantial Horizontal Mergers Generate Significant Price Effects? Edvidence from the Banking Industry," *Journal of Industrial Economics*, 46, 433–452.

RAJAN, R., AND H. SERVAES (1997): "Analyst Following of Initial Public Offerings," *Journal of Finance*, 52, 507–529.

SAPIENZA, P. (2002): "The effects of banking mergers on loan contracts," *Journal of Finance*, 57, 329–266.

SNYDER, C., AND M. DOYLE (1999): "Information Sharing and Competition in the Motor Vehicle Industry," *Journal of Political Economy*, 107, 1326–1364.

TIMMERMANN, A. (2005): "Forecast Combinations," forthcoming in *Handbook of Econometrics*.

VIVES, X. (1999): *Oligopoly Pricing*. MIT Press.

ZITZEWITZ, E. (2001): "Measuring Herding and Exaggeration by Equity Analysts and Other Opinion Sellers," Manuscript, Stanford University GSB.

M&A operations and performance in banking

Elena Beccalli

Università degli Studi di Macerata and London School of Economics [*]

Pascal Frantz

London School of Economics

Abstract

This paper investigates whether M&A operations influence the performance of banks. Using a sample of 714 deals involving EU acquirers and targets located throughout the world over the period 1991-2005, we analyse whether M&A operations are reflected in improved performance (measured using both standard accounting ratios and cost and alternative profit X-efficiency measures). Despite the extensive and ongoing consolidation process in the banking industry, we find that M&A operations are associated to a slight deterioration in return on equity, cash flow return and profit efficiency and contemporaneously to a marked improvement in cost efficiency. Hence, the improvements in cost efficiency appear to be transferred to bank clients. These changes in (cost and profit) efficiency are directly determined by the M&A operations, and would not have occurred in the absence of any M&A operation. Moreover, these changes exhibit a particularly negative trend for cross-border deals to testify the importance of geographical relatedness in order to achieve better post-M&A performance.

JEL classification code: G21, G34

Keywords: Banking; Mergers and acquisitions; EU and US; Cost and profit efficiency

---

[*] Elena Beccalli, Accounting and Finance Department, London School of Economics and Political Science, Houghton Street, London WC2A 2AE

Tel. 0044 20 7955 7737; Fax 0044 20 7955 7420; E-mail: e.beccalli@lse.ac.uk

1 Introduction•

This paper investigates the effect of mergers and acquisitions on the performance of banks and explores the sources of any merger-induced changes in performance. It is motivated by the relative dearth of empirical evidence on the impact of mergers and acquisitions involving European banks. Overall the handful of studies on merger and acquisition (M&A) activities in the EU banking industry provides mixed results. For instance, Altunbas and Ibanez (2004) report that bank mergers taking place in the EU banking industry between 1992 and 2001 do lead on average to improved accounting profitability. Altunbas, Molyneux, and Thornton (1997) provide empirical evidence suggestive of limited opportunities for cost savings from large mergers in the banking industry. Vander Vennet (2002) reports a limited improvement in profit efficiency but not in cost efficiency with reference to cross-border deals only.

This inconclusive evidence appears counterintuitive given that an intensive process of M&A operations transformed the banking industry in the US over the last decades (DeLong and DeYoung, 2007), and that the pursuit of a further integration trough cross-border M&A operations in retail banking is one of the main objectives pursued by the European Central Bank in the EU (Trichet, 2007). The main aim of our paper is to use a comprehensive approach, involving cost efficiency, profit efficiency, and accounting ratios, in order to test directly whether mergers involving European banks did lead to improvements in performance between 1991 and 2005.

To our knowledge, this is the first study involving a large sample of EU acquiring banks in deals with target banks located throughout the world (including, among the others, US and EU banks). None of the previous studies compare the evidence from all the performance measures (accounting ratios, cost efficiency and profit efficiency). None of the existing studies disentangle the total change in performance into the part due to the M&A operation itself and the part that would have occurred anyway. Our paper therefore aims to investigate the impact of M&A operations on accounting profitability measures and on (cost and alternative profit) X-efficiency for a large sample of 714 deals with EU acquirers and targets located in any country of the world over the period 1991-2005 and to extend and integrate the existing literature by enlarging the geographical coverage of the sample, by contemporaneously testing several performance measures, and by distinguishing the part of the change in performance due to the M&A itself.

• This paper is part of a research project - promoted by Arel ('Agenzia di ricerche e legislazione' founded by Nino Andreatta) and sponsored by UniCredit - co-ordinated by Paolo Gualtieri. The authors are grateful for the research assistance offered by Francesco Pisano and Livia Spata, and for the constructive comments offered by Philip Molyneux, Giovanni Petrella, Agostino Fusconi and Francesco Cesarini.

In spite of the extensive and ongoing consolidation process in the banking industry, we find that M&A operations are associated to a slight deterioration in return on equity, cash-flow returns, and profit efficiency and a pronounced improvement in cost efficiency in a period of 5 to 6 years following the deals. Hence, the improvements in cost efficiency appear to be transferred to bank clients rather than to bank shareholders. Interestingly, these changes in performance are directly determined by the M&A operations and would not have occurred in the absence of any M&A operation. Moreover, these changes exhibit a particularly negative trend for cross-border deals: in domestic deals, cost efficiency improves more markedly than in cross-border deals whilst returns on equity and profit efficiency remain unchanged instead of diminishing. This testifies the importance of geographical relatedness in order to achieve better post-M&A performance. Finally, in the years before the M&A operation, target banks exhibit weaker performance than acquirers in terms of profit efficiency, cash-flow returns, returns on equity, personnel expenses and operating costs. Besides, banks involved in M&A operations (both acquirers and targets) are more efficient and profitable than their peers not involved in M&A operations.

Furthermore, an important set of institutional, regulatory, bank-specific and deal-specific variables has a significant influence on the changes in cost and profit efficiency. The management of acquiring banks should tend to direct investments to those countries that guarantee better regulatory quality together with higher freedom from government. Moreover, to achieve positive changes in efficiency in the medium-term, transactions should be domestic, paid in equity (not in cash), and result in a combined bank with a higher focus on traditional banking activities.

The paper is organised as follows. Section 2 provides a literature review and notes the motivation for our study. Section 3 outlines the methodological approach, and illustrates the sample and data. Finally section 4 describes the empirical results, and section 5 concludes.

2 Literature and motivations

Surprisingly, the available empirical evidence suggests that M&A operations in the US banking industry have not had a positive influence on performance (DeLong and Deyoung, 2007; Amel, *et al*., 2004; Berger, Demsetz, and Strahan, 1999). Overall these studies provide mixed evidence and many fail to show a clear relationship between M&As and performance. Some of the previous literature has examined the impact of M&A operation on cost efficiency as measured by simple accounting cost ratios (Rhoades, 1990, 1993; Pilloff, 1996; DeLong and DeYoung, 2007), the impact on cost X-efficiency (Berger and Humphrey, 1992; DeYoung, 1997; Peristiani, 1997; Berger, 1998; Rhoades, 1998), the impact on profitability ratios such as ROE and ROA (Berger and Humphrey, 1992; Pilloff, 1996; Knapp *et al.*, 2006; DeLong and DeYoung, 2007), and the impact on profit X-efficiency (Akhavein *et al.*, 1997; Berger, 1998). Neither the earlier studies nor more recent analysis find evidence of clear positive effects of M&A operations on the performance of US banks.

Most of the empirical evidence on the impact of M&A operation on X-efficiency relates to the US banking sector and to the estimation of cost efficiency only. The evidence shows that very minor or absent improvements in cost X-efficiency were achieved by M&A operations during the '80s (De Young, 1997; Peristiani, 1997). By using a thick frontier approach on a sample of 348 deals, DeYoung (1997) finds that 58% of the banks in the sample generated cost efficiency. Interestingly, mergers in which the acquiring bank had recent experience with acquisitions were more likely to generate post-merger cost efficiency gains. As regard to 4,900 transactions occurred between 1980 and 1990, Peristiani (1997) suggests that acquirers failed to improve X-efficiency after the merger, but acquiring banks experienced moderate gains in scale efficiency relative to a control sample. As regard to the '90s, there is mixed empirical evidence (Rhoades, 1998; Berger, 1998). For nine deals involving relatively large banks during the early 1990s, Rhoades (1998) finds that four of the nine mergers were clearly successful in improving cost X-efficiency but five were not, although all nine of the mergers resulted in significant cost cutting. For deals involving both large and small banks from 1990 to 1995, Berger (1998) instead finds very small improvements in cost X-efficiency.

Although most of the studies focus on cost efficiency, few attempts have been done to estimate the effects on profit efficiency for US banks (Akhavein *et al.*, 1997; Berger, 1998). By investigating US "megamergers" (i.e. both partners with more than $1 billion in assets) over the period 1980-1990, Akhavein *et al.* (1997) find improvements in profit efficiency (+16% in comparison to other big banks). Most of the improvement is from a better risk diversification and increased revenues, including a change in the output composition from securities in the bank portfolio to loans. The highest improvement is recorded for the banks with the lowest efficiencies prior to the merger, who therefore had the greatest capacity for improvements. Berger (1998) finds similar results in a study that includes all US bank mergers, both large and small, from 1990 to 1995.

The handful of studies on the M&A activities in the EU banking industry also seem to conclude that performance improvements are seldom realised. These studies have examined the impact of M&A operation on cost X-efficiency (Vander Vennet, 1996, 2002; Altunbas, Molyneux and Thornton, 1997), the impact on profitability ratios such as ROE and ROA (Vander Vennet, 1996; Altunbas and Ibáñez, 2004), and the impact on profit X-efficiency (Huizinga *et al.*, 2001, Vander Vennet 2002). Altunbas, Molyneux and Thornton (1997) estimate a hybrid translog cost function for a pooled sample of French, German, Italian and Spanish banks for 1988 only. Their results suggest only limited opportunities for cost savings from big-bank mergers, and instead an increase in total costs appears more likely. As regard to a sample of 492 M&A operations related to

EU banks over the period 1988-1993, Vander Vennet (1996) shows that domestic mergers among equal-sized partners significantly increase the accounting profitability of the merged banks, whereas improvements in cost efficiency are observed only for cross-border acquisitions (and not for domestic operations). Domestic takeovers are found to be influenced predominantly by defensive and managerial motives such as size maximization. For a small sample of 52 bank mergers over the period 1992-1998, Huizinga *et al.* (2001) find that the cost efficiency of merging banks is positively affected by the deal, while the relative degree of profit efficiency improves only marginally. In a specific focus on cross-border deals among EU banks, Vander Vennet (2002) refers to a sample of 62 operations executed by banks headquartered in the EU, Norway and Switzerland between 1990 and 2001. In the short period after the deal, he finds a limited improvement in profit efficiency, but no improvement in cost efficiency. His analysis also reveals large differences in the cost and profit efficiency of the acquirer and target pre-deal. Altunbas and Ibáñez (2004) as regard to 262 deals taking place in the EU banking sector between 1992 and 2001 find that, on average, bank mergers resulted in improved accounting profitability (ROE).

Several explanations for this puzzling evidence have been provided: absence of best-practices guidelines for planning and executing increasingly large and complex acquisitions (DeLong and DeYoung, 2007), failure in considering the mean-reversion behaviour in industry-adjusted performance (Knapp *et al.*, 2006); longer time (up to five years) needed to realise efficiency gains, leading to more favourable prices for consumers (Focarelli and Panetta, 2003), difficulties of integrating broadly dissimilar institutions (Altunbas and Ibáñez 2004; Vander Vennet, 2002), increased costs associated with changes in post-merger risk profiles and business strategies (Demsetz and Strahan, 1997; Hughes *et al.*, 1999).

Nevertheless all the above studies just refer to the overall change in performance by comparing in a dynamic analysis (according to the definition by Berger, 1998 and 1999) the post-M&A performance with the pre-M&A performance. However, some of this difference could be due to a continuation of firm-specific performance before the merger or to economywide and industry factors, as stated by Healy *et al.* (1992). Healy *et al.* (1992) however do not specifically investigate the banking industry and just refer to the impact on operating cash flow returns of the 50 largest US mergers over the period 1979 and 1984.

In short, none of the above studies consider a large sample of EU acquiring banks involved in deals with target banks located throughout the world; none compare the evidence from all the performance measures; and none disentangle the total change in performance into the part due to the M&A operation itself and the part that would have occurred anyway. Our paper therefore aims to extend and integrate the existing literature by enlarging the geographical coverage of the sample, by contemporaneously testing several performance measures, and by distinguishing the part of the change in performance due to the M&A itself. These elements constitute the main novelties of this analysis.

3 Methodology

Our study uses a variety of ways to investigate the relationship between bank performance measure in the pre- and post- deal period. The initial approach to test this relationship follows the traditional banking literature on M&A and performance measures (reviewed above). By conducting ANOVA tests, we thus compare:

i) Performance values for target and acquirer in the pre-M&A period;

ii) Performance values for banks involved in M&A operations and banks not involved in any M&A operations. To take into account that the performance measure can be affected by both bank-specific influences and industry-wide trends, the relevant benchmark is the industry-adjusted performance of the banks under study. This industry-adjusted performance, also know as abnormal performance, is obtained as the performance measure for each M&A bank minus the (average) performance of the industry control sample (all other banks operating in the same country of the M&A bank in each year under investigation, excluding those that were also involved in an M&A during the same year);

iii) Performance for the combined bank resulting after the M&A deal and weighted average of the performance of the target and acquirer prior to the M&A deal (with total assets as weights). This provides a measure of the change in performance.

In this paper, the performance measure used in these models refers either to accounting profitability (measured by annual ROE and cash flow return) or to global measures of operational efficiency (estimated by both cost and alternative profit X-efficiency). The statistical significance of the industry-adjusted figures is based on t-statistics, and on the non-parametric Wilcoxon test to assess the significance in the case of non-normality. To ensure that industry-adjusted figures are not driven by outliers, the portion of positive cases is also reported. The dynamic analysis covers a medium-long term period either starting six years before and ending six years after a deal (6B-6A) or starting three years before and ending three years after (3B,3A). For each of the years surrounding the deal, we calculate the mean value of the relevant ratios for the banks involved. For accounting ratios we also calculate median values, as they are more susceptible to outliers. The year of the deal itself is left out of the analysis as it can be considered as a transition period strongly affected the accounting practices regarding M&As.

The measure of the change in performance – as described here above - provides some informative (but not conclusive) evidence about the impact of M&A operations on performance. The difference in the performance prior- and after- the deal, could be also due to economy-wide and industry factors, or the a continuation of firm-specific performance before the operation (Healy *et al.*, 1992). Because of these changes in the industry mean over time, accounting measure typically move to the industry mean in a process known as mean reversion (Fama and French, 2000; Knapp *et al.*, 2006). To further investigate the relationship between pre- and post- deal industry-adjusted performance, we split the overall change into its several determinants by using the following cross-sectional regression:

$$AdjPer_{M\&A,post} = \alpha + \beta AdjPer_{M\&A,pre} + \varepsilon \qquad (1)$$

where *AdjPer* is the average annual industry-adjusted performance for each M&A (as previously noted, performance measures are both accounting values and X-efficiency estimation). $AdjPer_{M\&A,post}$ refers to the post-M&A period (i.e. to each of the 6 years after the deal), whereas $AdjPer_{M\&A,pre}$ refers to pre-M&A period, known as base period, which represents the weighted average of the performance measure of the target and acquirer in the 3 years (or alternatively in the 6 years) prior to the M&A.

Following the interpretation of Healy *et al.* (1992), the slope coefficient β captures any correlation in performance between the pre- and post- M&A years so that $\beta AdjPer_{pre,M\&A}$ measures the effect of the pre-M&A performance on the post-M&A performance. This implies that β is independent from the M&A operation. The intercept α is therefore independent of pre-M&A performance, and is the measure of the impact of the M&A operation on performance.

To control for the determinants of the change in performance, several regulatory, bank-specific and deal-specific variables are used as control variables. The estimated regression equation is:

$$AdjPer_{M\&A,\,pre\,vs\,post} = \alpha + \beta\left(CV_{A,\,pre}, CV_{T,\,pre}, CV_{C,\,post}\right) \qquad (2)$$

where CV are the control variables:

a) deal-specific: year of the deal, dummy for cross-country and domestic deals;
b) bank-specific: size (where size is measured as ln total assets) of acquirer (A), target (T), and combined bank resulting from the deal (C); risk of the business (where risk is measured by the standard deviation of ROE) of acquirer, target, and combined bank; proportion of traditional banking (measured by loans/total assets) for acquirer, target and combined entity;
c) regulatory and institutional: financial freedom (a measure of banking security as well as independence from government control), freedom from government (defined to include all government transfers and state-owned enterprises), investment freedom (an assessment of the free flow of capital, especially foreign capital), regulatory quality (the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development).

3.1 Data set and sample

The data set is obtained by combining three sources: Thomson One Banker M&A for data on the M&A operations; Thomson Financial Datastream for prices of listed banks, benchmark, and economic indexes; Bankscope for balance sheet and profit and loss data of the banks involved in M&A operations (M&A sample) and of banks not involved (control sample).

The sample is limited to credit institutions as defined in the Second Banking Directive (excluded are deals involving securities firms, insurance companies, investment banks or finance companies). It comprises M&A deals announced between 1/1/1991 and 31/12/2005 in which the acquirer is a EU bank and the target is a bank operating in any country of the world. The initial M&A sample refers to 970 observations, but the final one contains 714 deals (394 domestic and 320 cross-border transactions) for which full financial information about the participating banks is available. It is a unique sample, bigger than any other sample used for the analysis of M&A operations in the banking industry. Table 1 shows the total number of deals constituting the sample in each country and year, and the total panel under observation. Table 2 highlights the home country of target and acquirer in cross-border deals over the years under observation.

In any given year, the control sample consists of all banks which match the nationalities of acquirers and targets and have not engaged in any merger or acquisition during that year. As shown in Table 3, the control sample consists of 7,963 observations over the life span of this study. For any M&A deal, there is a control for both the acquirer and the target. By default, in the X efficiency studies, the control for any performance measure related to an acquirer (target) is the mean performance of all the banks in the same country than the acquirer (target), and same year. Accounting ratios however do exhibit significant skewness. In accounting studies, by default, the control for any performance measure related to an acquirer (target) is hence the median performance of all the banks in the same sector of activity than the acquirer (target)[1], in the same country, and same year.

3.2 Accounting ratios as performance measure

This paper introduces two main accounting-based ratios in order to assess performance as far as shareholders are concerned: return on equity (ROE) and cash-flow return (CFR). A firm's ROE is defined by default as the ratio of net income over the market value of equity obtaining at the beginning of the financial year. This ratio relies on the properties of accrual accounting in order to

[1] Sectors of activities consist of bank holdings and holding companies, commercial banks, cooperative banks, investment banks and securities houses, medium and long-term credit banks, non-banking credit institutions, real estate and mortgage banks, savings banks and specialized government credit institutions.

assess performance. Whilst widely used, this ratio is however affected by the method of accounting for the acquisition or merger. Hence we also assess performance through cash-flow returns. A firm's cash-flow return is defined by default as the ratio of operating cash-flow over the market value of equity obtaining at the beginning of the financial year. The operating cash-flow is furthermore derived as net revenue (interest revenue, commission income, and trading income) less cost of generating revenues (interest expense, commission expense, and trading expense), less personnel expenses, and other administrative expenses. The cash-flow return performance measure, unlike return on equity, is unaffected by depreciation and goodwill. This market-based performance measure is however affected by changes in expectations about future cash-flows, and hence market values. Regardless of the performance measure used, we do exclude the year in which the acquisition or merger is taking place because of differences between the acquisition and merger methods in timing the consolidation of the acquirer with the target.

3.3 Operating efficiency as performance measure

In addition to traditional accounting ratios, we introduced a more advanced measure of operational productivity at the global level, the so-called X-efficiency (Leibenstein, 1966). It generally accepted in the empirical banking literature that frontier analysis provides an overall, objectively determined, numerical efficiency value (known as X-efficiency) and ranking of firms that is not otherwise available (Berger and Humphrey, 1997). This attribute makes frontier analysis particularly valuable in assessing and informing government policy regarding financial institutions, such as determining the efficiency effects of mergers and acquisitions for possible use in antitrust policy.

X-inefficiency is a measure of managerial best practice, and represents the distance of the position of equilibrium of each bank from the optimal operative frontier. X-efficiency can be framed as:

1. Cost efficiency, which provides a measure of how close a bank is to the cost sustained by the best practice bank to produce a given mix of outputs (assuming that the banks are operating under the same conditions). A bank is said to be cost minimising when it consumes a lower quantity of inputs for the production of a given amount of outputs or, in other words, produces the same amount of outputs using less inputs and, in this way, enjoys a cost advantage;
2. Profit efficiency, which provides a measure of how close a bank is to the realisation of the maximum level of profit given its level of outputs (generally known as alternative profit X-inefficiencies). A bank is said to be profit maximising when it produces a greater quantity of outputs given the amount of inputs employed. It indicates that the bank

produces more outputs (or outputs of a higher quality) using the same amount of inputs and, thus, is able to apply a price premium.

Following Berger and Mester (1997), we prefer to choose a parametric approach – as opposed to a non-parametric approach – as it is particularly effective in representing the concepts of cost and profit efficiency. We employ the standard Stochastic Frontier Approach (SFA) to generate estimates of cost and alternative profit efficiencies for each bank over the years 1991-2005 along the lines first suggested by Aigner *et al.* (1977). Specifically, we employ the Battese and Coelli (1995) model of a stochastic frontier function for panel data with firm effects which are assumed to be distributed as truncated normal random variables ($\mu \neq 0$) and are also permitted to vary systematically with time (see for more details on the SFA methodology Coelli *et al.*, 1998).

The functional form for the frontier is a Fourier flexible (FF) form, which is a global approximation that dominates the conventional translog form. The characteristic of global approximation is particularly important in the case of the study of the effects of M&As on banks around the world, because the scale of banks, the diversification of their products and services and the levels of their inefficiency are often heterogeneous (see, for example, Gallant 1981; McAllister and McManus 1993; Mitchell and Onvural, 1996). It combines the stability of the translog specification around the average of the sample and the flexibility of the Fourier specification for the observations that are far from the average. The FF functional form, including a standard translog and all first- and second-order trigonometric terms, as well as a two-component error structure is estimated using a maximum likelihood procedure. This is specified as follows:

$$\begin{aligned}
\ln TC &= \alpha_0 + \sum_{i=1}^{3} \alpha_i \ln Q_i + \sum_{j=1}^{3} \beta_j \ln P_j + \tau_1 T + \lambda_1 \ln E + \\
&+ \frac{1}{2}\left[\sum_{i=1}^{3}\sum_{j=1}^{3} \delta_{ij} \ln Q_i \ln Q_j + \sum_{i=1}^{3}\sum_{j=1}^{3} \gamma_{ij} \ln P_i \ln P_j + \phi_{11} \ln E \ln E \right] + \\
&+ \sum_{i=1}^{3}\sum_{j=1}^{3} \rho_{ij} \ln Q_i \ln P_j + \sum_{j=1}^{3} \kappa_{j1} \ln P_j \ln E + \sum_{i=1}^{3} \varsigma_{i1} \ln Q_i \ln E + \\
&+ \sum_{i=1}^{3} \left[a_i \cos(z_i) + b_i \sin(z_i) \right] + \\
&+ \sum_{i=1}^{3}\sum_{j=1}^{3} \left[a_{ij} \cos(z_i + z_j) + b_{ij} \sin(z_i + z_j) \right] + \varepsilon
\end{aligned} \tag{3}$$

where: TC is a measure of the total cost of production (including labour costs, depreciation, other operating and administrative costs and interests paid on deposits); Qi represent bank outputs (with 1.0 added to avoid taking the log of zero): Q1 = total loans, Q2 = securities, Q3 = off balance sheet business; Pi are bank input prices for labour (= personnel expenses/total assets), price for loanable funds (= interest expenses/total deposits) and price for physical capital (depreciation and other capital expenses/fixed assets). Equity capital (E) is included to control for differences in bank risk preferences (Mester, 1996). z_i are the adjusted values of the log output $\ln Q_i$ such that they span the interval [0.1·2.π, 0.9·2.π] to reduce approximation problems near the endpoints.[2] ε is the two-component stochastic error term. $\alpha, \beta, \delta, \gamma, \tau, \lambda, \phi, \rho, \kappa, \varsigma$ are parameters to be estimated.

While there continues to be debate about the definition of input and output used in the function, we follow the traditional intermediation approach of Sealey and Lindley (1977), in which inputs (labour, physical capital and deposits) are used to produce earning assets. Two of our outputs (loans and securities) are earnings assets, and we also include off balance sheet items as a third output.[3]

The alternative profit function has the same specification as the above, the only difference being that the dependent variable is replaced with ln profits (π+θ), as specified in Berger and Mester (1997). π is a measure of operating profits (interest revenues + commission income + trading income – total costs). To exclude negative values, $\pi + \theta = \pi + \left|\pi^{\min}\right| + 1$, where $\left|\pi^{\min}\right|$ is the absolute value of the minimum value of profits in the sample.

We adopt a common cross-country frontier for banking industries across the world that also includes real growth in GDP as a country-specific control variable used in the panel. This model controls for environmental differences across countries and investigates the effects of these variables on measured efficiency (Beccalli, 2004). This methodology essentially allows for a firm-specific and time-varying intercept shift in the distribution of the inefficiency term, and this intercept shift is itself a function of the exogenous environmental variables that vary across countries (Battese and Coelli 1995).

This study applies Fourier terms (both for the cost frontier and the alternative profit frontier) only for the outputs, leaving the input price effects to be defined entirely be the translog terms (see Berger, Leusner, and Mingo, 1997; Mitchell and Onvural, 1996; Gallant, 1982). Moreover, the usual input price homogeneity restrictions are imposed on logarithmic price terms only, and not on the trigonometric terms (as in Altunbas, Gardener, Molyneux, Moore, 2001). Accordingly, TC, P_1 and

---

[2] $z_i = \mu_i(\ln Q_i + w_i)$, where μ_i and w_i are scaling factors, limiting the periodic sine and cosine trigonometric functions within one period length 2π (see for a discussion: Gallant, 1981; for an application: Mitchell and Onvural, 1996).

[3] Although off balance sheet items are not earning assets, they do represent an increasing source of income for all types of banks and are therefore included in order to avoid understating total output (Jagtiani and Khanthavit, 1996).

P_2 are normalised by the price of physical capital, P_3. Finally, all the values are expressed in real terms (GDP deflator for each country with 1991 as a base year).

4 Empirical results

We first examine unadjusted performance (cost efficiency, profit efficiency, accounting profitability and their determinants) for acquirers and targets in each of the six years before the deal. The values highlighted in Table 4 show that the level of profit efficiency is higher for acquirers in comparison to targets in each of the 6 years before the deal (and the difference is statistically significant): the higher values for the acquirers range between 1.3% (one year before the deal) and 3.2% (six years before the deal). The level of cost efficiency tends to be higher for acquirers than for targets in most of the years before the deal but not statistically significant. Interestingly, instead, the determinants of cost efficiency (labour costs and operating costs) show a clearly better performance for acquirers in comparison to targets: these costs are always lower for the acquirer in comparison to the target. In particular, personnel costs of the acquiring banks are on average 3.7% to 4.7% lower than the personnel costs of the acquired banks. In the remaining part of this section, we will control for the performance of acquirers' and targets' peers. (Note that first we will present the evidence on the accounting measures and then move to the results on efficiency).

To investigate performance as far as shareholders are concerned, we use the return on equity (ROE), where equity is measured at the beginning of the financial year. As shown in Table 5 (Panel A), acquirers do outperform their peers in each of the five years prior to the mergers and acquisitions by 2 to 3%. There is also some evidence reported in Table 5 (Panel B) suggesting that targets do outperform their peers in the two years prior to the mergers and acquisitions[4]. Acquirers furthermore outperform targets in a period starting five years prior to the mergers and ending three years prior to the mergers [Table 5 (Panel C)]. As shown in Table 5 (Panel D), there is not much evidence that firms engaging in M&A do outperform their peer post-merger (first year only). There is furthermore evidence suggesting that firms engaging in mergers and acquisitions experience a decrease in their performance post-merger. As shown in Table 5 (Panel E), in the five years following the mergers, the median industry-adjusted ROE is about 1%. This compares with a median weighted average of the acquirer's industry-adjusted ROE and target's industry-adjusted ROE of about 2% in the five years prior to the merger.

The study's main findings so far, superior bottom-line performance by acquirers pre-merger and lack of evidence of any increase in bottom-line performance post-merger, are robust to alternative specifications of return on equity and peer performance. For example, these findings still

[4] The latter result is however not robust to alternative specifications of ROE.

obtain if return on equity is derived on an average basis (that is, if equity is measured as the average of the beginning of the financial year and end of the financial year values) or if peer performance is derived as the average (as opposed to the median) return on equity of all banks in the same year, sector of activity, and country[5].

Any decrease in post-merger industry-adjusted ROE may however not be due to the merger or acquisition. In order to control for the effect of pre-merger performance on post-merger performance, we regress post-merger industry-adjusted ROE on pre-merger industry-adjusted ROE, the regression intercept capturing the direct effect of the merger on performance. As shown in Table 6, the regression intercept is negative and statistically significant in the second, third, and fourth year following the merger.

We then distinguish between domestic and cross-border mergers and acquisitions. There is strong evidence suggesting that acquirers do outperform targets prior to domestic mergers and acquisitions [Table 7 (Panel A)]. In contrast, there is not much evidence suggesting that targets do outperform acquirers prior to cross-border mergers and acquisitions [Table 7 (Panel A)]. There is no statistically significant evidence suggesting that firms engaging in domestic mergers and acquisitions experience a decrease in their performance post-merger following the mergers and acquisitions [Table 7 (Panel B)]. In contrast, there is strong evidence suggesting that firms engaging in cross-borders mergers and acquisitions experience a decrease in their performance from the second to the fifth year following the mergers and acquisitions [Table 7 (Panel B)].

The superior returns on equity experienced by acquirers pre-merger are driven by superior net margins as opposed to superior asset turnover [Table 8 (Panel A)]. In contrast, compared with their peers, targets suffer from lower asset turnover in each of the four years prior to the mergers and lower net margins in the two years prior to the mergers [Table 8 (Panel B)]. There is no evidence of any statistically significant improvement in industry-adjusted asset turnover or net margin post-merger [Table 8 (Panel C)].

Compared with their peers, acquirers have a lower personnel expense as a function of revenue in each of the five years prior to the mergers and acquisitions [Table 9 (Panel A)]. This is also true for targets in some of the earlier years prior to their acquisitions [Table 9 (Panel B)]. The ratio of personnel expense over revenue is however increasing post-merger [Table 9 (Panel C)]. The same picture arises when analysing the ratio of other administrative expenses over revenue.

We then turn our attention to cash-flow returns. As shown in Table 10 (Panel A), acquirers do outperform their peers in each of the five years prior to the mergers and acquisitions. There is however no evidence suggesting that targets do outperform their peers in any of the five years prior

[5] Empirical evidence on robustness is available from the authors on request.

to the mergers and acquisitions [Table 10 (Panel B)]. Acquirers furthermore outperform targets in a period starting the three years prior to the mergers and ending three years prior to the mergers [Table 10 (Panel C)]. There is furthermore strong evidence suggesting that firms engaging in mergers and acquisitions experience a decrease in their performance post-merger [Table 10 (Panel D)].

We now focus our attention on efficiency measures. The industry-adjusted values (Table 11) show that banks involved in M&A operations are more efficient than banks not involved in M&A (control sample) on average in the years under investigation (1991-2005): the cost efficiency of banks involved in M&A is 4% higher than the cost efficiency of banks not involved in M&A operations, whereas profit efficiency is on average 6% higher. It is interesting to note that profit efficiency of the M&A banks is higher than that of the control sample in any of the years under investigation (and the difference is always statistically significant). The industry-adjusted values of profit efficiency and costs efficiency are also shown for all the countries under investigation (Table 12): with few exception profit efficiency is higher (and the difference is statistically significant) for M&A banks than for non-M&A banks, whereas cost efficiency exhibit a more heterogeneous behaviour across countries.

To further examine the industry-adjusted performance of M&A banks in comparison to their non-M&A peers, we distinguish between acquirers and targets (Table 13). Both acquirers and targets are more efficient (both in profit and cost terms) than non-M&A banks, and the higher performance of both is statistically significant (in line with the findings on ROE and CFR). However, adjusted-values do not provide confirmation of the better performance of acquirers in comparison to targets as regard to profit efficiency, differently from the evidence on unadjusted efficiency values and from the evidence on adjusted median ROE values. This result seems therefore to be due to the higher standard deviation induced by the use of the control sample.

The comparison of the efficiency values of the combined bank emerging from the deal and the pre-values of the merging banks interestingly outlines improvements in cost efficiency in the post-deal period in comparison to pre-deal period, both when the base year prior to the deal refers to 3 and 6 years [Table 14 (Panel A)]. In each of the six years after the deal, cost efficiency is higher than the cost efficiency before the deal, and this happens in up to 80% of the cases (six years after the deal). Moreover, it emerges that improvements in cost efficiency become more evident the longer the time after the deal, with a trend strictly monotonic (from +3.01% in year one after the deal to 5.10% in year six after the deal). By disentangling the sample into domestic and cross-border deals [Table 14 (Panel B and C)], the analysis emphasis that the higher improvements in cost efficiency are associated to domestic deals.

The picture on the profit efficiency side is however different. Profit efficiency decreases in the post deal period in comparison to the pre-deal period [Table 14 (Panel A)], and the decrease becomes more evident the longer the number of years of the deal (as previously documented by the accounting profitability measure). The average decrease of profit efficiency varies between –1.17% (one year after the deal) and –5.33% (six years after the deal) in comparison to the weighted average of profit efficiency for the target and acquirer in the six years prior to the deal. Interestingly, by distinguishing between domestic and cross-border operations [Table 14 (Panel B and C)], the decrease in profit efficiency is particularly evident for cross-border operations; instead it does not emerge for domestic operations (as found as regard to ROE).

The previous findings emphasise that the impact of M&A operations on banks' performance is negative on the profit efficiency side and positive on the cost efficiency side: M&A operations are associated with lower profit efficiency and higher cost efficiency. This finding seems to suggest that the improvements in cost efficiency are transferred outside the bank, as bank revenues suffer a decrease after the operation. It could be argued that cost benefits are transferred to bank clients (and not to bank shareholders), especially in cross-border operations. The need to enter into new markets forces banks not to apply a price premium at least in the medium-term.

To better investigate the above preliminary evidence, we disentangle the overall change in (cost and profit) efficiency in order to isolate the variation specifically determined by the M&A operation, by using the OLS regressions previously outlined in equation (1). Several interesting results emerges for the overall sample of deals [Table 15 (Panel A)]. First, the explanatory power of the relationship is particularly high: by comparing the average of (both cost and profit) efficiency in the 6 years after the deal to the average efficiency in the 3 year before the deal, the R^2 is above 50%, a much higher value than the one traditionally found (e.g. as regard to cash flow return the R^2 is 10% in Healy *et al.*, 1992). Moreover, the decreasing trend over time in the values of the coefficient β clearly shows that there is a strong mean reversion trend in the industry-adjusted (cost and profit) efficiency measures. This provides clear evidence of the highly competitive nature of the banking industry. Finally, the value of the intercept α (a measure of the impact of the M&A operation itself) is positive and statistically significant for cost efficiency as regard to the overall sample both when the reference is to the 3 and 6 years prior to the deal. However, the value of the intercept α as regard to profit efficiency is not significantly different from zero (Panel A). This would suggest that the M&A operation itself does have a positive impact on cost efficiency, but does not have any (either positive or negative) impact on profit efficiency.

This surprising evidence imposes to further investigate the impact of the M&A operation itself by emphasising the level of geographical relatedness of the acquirer and target bank. To this aim, by distinguishing between domestic and cross-border operations, the analysis reveals that when the dependent variable is profit efficiency, the value of the intercept α is positive for domestic operations (Panel B) and negative for cross-border deals (Panel C). This implies that cross-border

M&As have a negative impact on profit efficiency, whereas domestic M&As have a positive impact on profit efficiency. When the dependent variable is cost efficiency, the value of the intercept α is higher for domestic operations in comparison to cross-border operations. Overall, this suggests that for domestic deals the improvements in cost efficiency and in profit efficiency are due to the M&A operation itself, and not to the behaviour in X-efficiency that would have occurred in absence of any M&A operation. Contrarily for cross-border deals, decreases in profit efficiency occur because of the M&A operation itself, while the improvements in cost efficiency are lower than what observed for domestic deals. Consequently, this evidence emphases the importance of geographical similarities in order to achieve better post-M&A performance: geographical relatedness creates value.

The potential determinants of the changes in cost and profit efficiency due to M&A operations are proxied here by institutional/regulatory, bank-specific and deal-specific variables. Table 16 sets out their definitions and statistics. The first category comprises freedom from government (an index measuring the incidence of all government expenditures and state-owned enterprises in the economy) and regulatory quality (a measure of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development). The second category includes the period in which the deal takes place, the method of payment used to regulate the operation (cash vs. equity), and the geographical nature of the operation (domestic vs. cross-border). The third category refers to the size of the banks involved in the operation (big, medium, and small measured on the basis of total assets), the focus of the banks involved in the so-called traditional banking (proxied by the amount of loans over total assets), and the degree of riskiness of the bank business (measured by the standard deviation of ROE).

In order to identify the impact of these determinants on the changes in the efficiency levels due to the M&A operation, we test equation (2) (Table 17). As regard to the regulatory and institutional variables, the change in profit efficiency (post vs. pre deal) is positively associated to the levels of freedom from government and regulatory quality characterising the home country of the target, whereas it is negatively associated to the same indexes qualifying the home country of the acquirer. (Note that given the magnitude of the coefficient, regulatory quality seems by far the most relevant determinant of the change). Deals better able to create profit efficiency are those in which acquiring banks direct their investments in countries better ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development and with lower government expenditures and state-owned enterprises. As regard to deal-specific conditions, cash payment has a negative impact on profit efficiency. Moreover, the cross-border nature of an M&A operation has a negative impact on cost efficiency. The realisation of the M&A deal in the periods 2000-2005 and 1994-1999 causes a negative impact on cost efficiency, whereas it is negative for profit efficiency only for the period 1994-1999. As regard to structural bank-specific variables, a size qualified as “medium” (comprising all the banks in the second terzile in terms of the natural logarithm of total assets) for the target in the pre-deal period results in a negative impact on both cost and profit efficiency. Also a “big” size for both the acquirer and the combined bank determines a negative impact on profit efficiency. The higher concentration of the acquirer in the pre-deal period on traditional banking activities over the total bank activities (proxied by the proportion of loans over total assets) has a negative impact on both cost and profit efficiency; whereas the impact is positive when the combined bank resulting from the operation shows a higher concentration on traditional banking. Finally, the level of riskiness (proxied by the standard deviation of the ROE) of the activity of both the acquirer, the target, and the combined entity resulting form the M&A is always positively associated to the changes in profit and cost efficiency.

5 Conclusions

This paper investigates whether M&A operations influences the performance of banks. Using a sample of 714 deals involving EU acquirers and targets located throughout the world over the period 1991-2005, we analyse whether M&A operations are reflected in improved performance (measured using both standard accounting ratios and cost and alternative profit X-efficiency). Despite the extensive and ongoing consolidation process in the banking industry, we find that M&A operations are associated to a slight deterioration in profit efficiency and contemporaneously to a pronounced improvement in cost efficiency in the 6 years after the deal (in comparison to the 3/6 years prior to the deal). Hence, the improvements in cost efficiency appear to be transferred to bank clients rather than to bank shareholders. Interestingly, these changes in (cost and profit) efficiency are directly determined by the M&A operations, and would not have occurred in the absence of any M&A operation. Moreover, these changes exhibit a particularly negative trend for cross-border deals: in domestic deals, cost efficiency improves more markedly than in cross-border deals, and profit efficiency remains unchanged instead of diminishing. This testifies the importance of geographical relatedness in order to achieve better post-M&A performance. Finally, in the years before the M&A operation, target banks exhibit an inferior performance than the acquirers in terms of profit efficiency, profitability accounting ratios, personnel expenses and operating costs. Besides, banks involved in M&A operations (both acquirers and targets) are more efficient and profitable than their peers not involved in M&A operations.

Furthermore, an important set of institutional, regulatory, bank-specific and deal-specific variables has a significant influence on the changes in cost and profit efficiency. The management of acquiring banks should tend to direct investments to those countries that guarantee better regulatory quality together with higher freedom from government. Moreover, to achieve positive changes in efficiency in the medium-term, transactions should be domestic, paid in equity (not in cash), and result in a combined bank with a higher focus on traditional banking activities.

References

Aigner, D.J., Lovell, C.A.K., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. Journal of Econometrics 6, 21-37.

Akhavein, J.D., Berger, A.N., D.B., Humphrey, D.B., 1997. The Effects of Megamergers on Efficiency and Prices: Evidence from a Bank Profit Function. Review of Industrial Organization 12, 95-139.

Altunbas, Y., Gardener, E.P.M., Molyneux, P., Moore, B., 2001. Efficiency in European banking. European Economic Review 45, 1931-1955.

Altunbas, Y., Ibáñez, D.M., 2004. Mergers and acquisitions and bank performance in Europe. The role of strategic similarities. ECB Working paper n. 398, Frankfurt.

Altunbas, Y., Molyneux, P., Thornton, J., 1997. Big-Bank Mergers in Europe: An Analysis of the Cost Implications. Economica 64 (254), 317-329.

Amel, D., Barnes, C., Panetta, F., Salleo, C., 2004. Consolidation and efficiency in the financial sector: A review of the international evidence. Journal of Banking and Finance 28(10), 2493-2519.

Battese, G.E., Coelli, T.J., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics 20, 325 -332.

Beccalli, E., 2004. Cross-Country Comparisons of Efficiency Evidence from the UK and Italian Investment Firms. Journal of Banking and Finance 28, 1363-1383.

Berger, A.N., 1998. The efficiency effects of bank mergers and acquisitions: A preliminary look at the 1990s data, in Amihud, Y. and G. Miller (eds.), Bank mergers and acquisitions, Kluwer Academic Publishers: Boston, 79-111.

Berger, A.N., Demsetz, R.S., Strahan, P.E., 1999. The consolidation of the financial services industry: Causes, consequences, and implications for the future. Journal of Banking and Finance 23, 135–194.

Berger, A.N., DeYoung, R., Genay, H., Udell, G.F., 2000. The Globalization of Financial Institutions: Evidence from Cross-Border Banking Performance. Brookings – Wharton Papers on Financial Services, n. 3, 23 - 125.

Berger, A. N., Humphrey, D.B., 1997. Efficiency of Financial Institutions: International Survey and Directions for Future Research. European Journal of Operational Research 98, 175-212.

Berger, A.N., Humphrey, D.B., 1992. Megamergers in Banking and the Use of Cost Efficiency as an Antitrust Defense. Antitrust Bulletin 37, 541–600.

Berger, A.N., Leusner, J.H., Mingo J.J., 1997. The efficiency of bank branches. Journal of Monetary Economics 40, 141-162.

Berger, A.N., Mester, L.J., 1997. Inside the black box: what explains differences in the efficiency of financial institutions?. Journal of Banking and Finance 21, 895 - 947.

Coelli T.J., Prasada Rao D.S., Battese, G., 1998. An Introduction to Efficiency and Productivity Analysis. Kluwer Academic Publishers, Norwell.

DeLong, G., DeYoung, R., 2007. Learning by Observing: Information Spillovers in the Execution and Valuation of Commercial Bank M&As. Journal of Finance 62, 181-216.

Demsetz, R.S., Strahan, P.E., 1997. Diversification, size, and risk at bank holding companies. Journal of Money, Credit, and Banking 29, 300–313.

DeYoung, R., 1997. Bank mergers, X-efficiency, and the market for corporate control. Managerial finance 23, 32-47.

Fama, E.F., French, K.R., 2000. Forecasting profitability and earnings. Journal of Business 73, 161-175.

Focarelli D., Panetta F., 2003. Are mergers beneficial to consumers? Evidence from the market for bank deposits. The American Economic Review 93(4), 1152-1172.

Gallant, A.R., 1981. On the bias in flexible functional forms and essentially unbiased form: The Fourier flexible form. Journal of Econometrics 15, 211-245.

Healy, P.M., Palepu, K.G., Ruback, R.S., 1992. Does corporate performance improve after mergers?, Journal of financial economics 31, 135-175.

Jagtiani, J. e Khanthavit, A., 1996. Scale and scope economies at large banks, including off balance sheet products and regulatory effects. Journal of Banking and Finance 20, 1271-1287.

Knapp, M., Gart, A., Chaudhry, M., 2006. The impact of mean reversion of bank profitability on post-merger performance in the banking industry. Journal of banking and finance 30, 3503-3517.

Hughes J.P., Lang, W.W., Mester, L.J., Moon, C.-G., 1999. The dollars and sense of bank consolidation. Journal of banking and finance 23, 291-324.

Huizinga, H.P., Nelissen, J.H.M., Vander Vennet, R., 2001. Efficiency effects of bank mergers and acquisitions in Europe. Working Paper Ghent University n. 106.

Leibenstein, H., 1966. Allocative efficiency vs. “X-efficiency”. American Economic Review 56, 392-415.

McAllister, P., McManus, D., 1993. Resolving the scale efficiency puzzle in banking. Journal of Banking and Finance 17, 389-405.

Mester, L.J., 1996. A study of bank efficiency taking into account risk-preference. Journal of Banking and Finance 20, 1025-1045.

Mitchell, K., Onvural, N.M., 1996. Economies of scale and scope at large commercial banks: Evidence from the Fourier Flexible functional form. Journal of Money, Credit and Banking 28, 178-199.

Peristiani, S., 1997. Do Mergers Improve the X-Efficiency and Scale Efficiency of U.S. Banks? Evidence from the 1980s. Journal of Money. Credit, and Banking 29(3), 326-337.

Pilloff, S.J., 1996, Performance changes and shareholder wealth creation associated with mergers of publicly traded banking institutions. Journal of Money, Credit, and Banking 28, 294–310.

Rhoades, S.A, 1998. The Efficiency Effects of Bank Mergers: An Overview of Case Studies of Nine Mergers. Journal of Banking and Finance 22, 273-91.

Rhoades, S.A., 1993. Efficiency effects of horizontal (in-market) bank mergers, Journal of Banking and Finance 17, 411–422.

Rhoades, S.A., 1990. Billion Dollar Bank Acquisitions: a Note on the Performance Effects. Working Paper, Board of Governors of the Federal Reserve System, Washington, DC.

Vander Vennet, R., 1996. The effect of mergers and acquisitions on the efficiency and profitability of EC credit institutions. Journal of Banking & Finance 20 (1996) 1531-1558.

Vander Vennet, R., 2002. Cross-border mergers in European banking and bank efficiency. Working Paper Ghent University n. 152.

Table 1: Number of M&A deals (by country and by year); 1991 -2005

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	Total
Austria				1	2	1	4	2	5	1				1		17
Belgium							4	4	2	1	4	2	1	2		20
Denmark	1		1	2		1	2	2	2	3		2		2		18
Finland			1	1												2
France	11	7	9	17	8	9	7	6	5	4	9	3	4	10		109
Germany	2	5	3	10	7	5	15	8	9	11	2	1		2		80
Greece								2	6	3	1	2	2			16
Hungary											1		1	3		5
Iceland													2	4		6
Ireland					2											2
Italy	1		3	16	22	8	14	12	22	28	20	16	11	5		178
Luxembourg							1	2		1	1		1	2		8
Netherlands			2	1	2	3	1	3	3	3		2	1		1	22
Norway				2	1	3	2						1	3		12
Poland							2	1	6	2	4		1	1		17
Portugal		2	2	1	2	2	1	2	3	11			1			27
Spain	6	6	3	3	4	9	8	11	11	12	6	6	5	3		93
Sweden								2	8	2	3	1	1	2		19
Switzerland		4	4	6	1	2	5	1	1	1		1	2			28
Turkey															1	1
UK	1	3	1	3	3	5	5	2	4	2	1	1	1	2		34
Total	22	27	29	63	54	48	71	60	87	85	52	37	35	42	2	714

Table 2: Number of cross-border M&A deals (by country); 1991 -2005

	Home country acquirer																			
Home country target	AU	BE	DE	FR	GE	GR	HU	IS	IR	IT	LU	NE	PL	PO	SP	SE	CH	TR	UK	Total
Argentina				1						1		1			12					15
Australia																	1		2	3
Austria		1		1	4				1				1				1			9
Belgium		1		1	1						1									4
Brazil				2								4		1	5				1	13
Bulgaria				2		1	1													4
Canada				1						1										2
Chile					1										5					6
Colombia															6				1	7
Croatia					1		1			1										3
Czech Republic	2			1	3					2										8
Denmark					1			1								6				8
Estonia																3				3
Finland																1				1
France		2		4	4					2	2	2		1	1		4		3	25
Germany				5						3		2			2	1				13
Greece				3	2															5
Hungary	3				4		1			2		1	1		1					13
India		1																		1
Ireland			1																2	3
Italy	1			5	5							4			4				1	20
Lebanon				1																1
Luxembourg		2	1	2																5
Mexico															13					13
Morocco				2	1															3
Netherlands					1						1									2
Norway			1					3								2				6
Poland	1	5	2	1	13							1	4	3		3				33
Portugal				1								1			7					9
Romania				3		3	1			1										8
Slovak Rep		1					1			4										6
Slovenia				1																1
South Africa				1	1									1					1	4
South Korea				1	3															4
Spain				3	3	1				2	4			3					4	20
Sweden			2																	2
Switzerland				1	1					2							1			5
Thailand												1								1
Turkey				1															1	2
United Kingdom		1	1	1	2					1					3			1	1	11
United States				2								4		1	4		1		3	15
Venezuela															3					3
Total	7	14	8	47	51	5	5	4	1	22	8	21	6	10	66	16	8	1	20	320

AU: Austria; BE : Belgium; DE: Denmark; FR: France; GE: Germany; GR: Greece; HU: Hungary; IS: Iceland; IR: Ireland; IT: Italy; LU: Luxembourg; NE: Netherlands; PL: Poland; PO: Portugal; SP: Spain; SE: Sweden; CH: Switzerland; TR: Turkey; UK: United Kingdom

Table 3: Number of banks in the control sample (by country and by year)

	Year														
Country	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	Total
Argentina		1	1	2	3	3	5	5	5	5	5	5	6	6	6	58
Australia	8	8	9	10	10	10	10	10	10	11	12	14	14	14	12	162
Austria			1	1	6	7	8	9	8	7	6	6	6	6	1	72
Belgium					1	1	5	5	4	5	5	5	5	5		41
Brazil	4	5	6	6	8	10	9	10	9	10	14	16	16	16	15	154
Canada	3	3	4	10	10	11	11	12	12	12	14	16	15	16	15	164
Chile				1	4	4	5	7	6	7	7	7	7	7	7	69
Colombia								1	1	2	2	3	4	4	3	20
Denmark	6	7	8	11	14	14	14	14	14	14	14	14	15	15	3	177
Finland	2	2	3	3	3	3	3	3	3	4	4	4	4	4		45
France	9	12	15	16	17	17	17	17	25	29	31	31	31	31	4	302
Germany	4	4	5	6	6	6	6	4	5	7	8	8	8	6	1	84
Greece		1	2	5	5	6	8	8	10	10	10	11	11	11	1	99
Hungary	1	1	1	2	2	2	1	1	2	3	3	3	3	3	1	29
India											13	19	16	17	18	83
Ireland	2	3	3	3	3	3	3	4	4	4	4	5	5	4	1	51
Italy	3	3	10	11	15	16	18	20	21	25	27	28	29	29	1	256
Lebanon			1	1	2	2	2	2	2	2	2	2	2	1	1	22
Luxembourg		1	1	1	1	2	3	3	3	3	2	2	2	2		26
Mexico	1	1	1	1	1	1	2	2	3	3	5	5	6	5	5	42
Morocco	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	27
Netherlands	3	3	3	3	3	5	5	5	5	5	5	5	6	6		62
Norway	2	3	4	5	6	7	7	8	8	10	11	12	14	14		111
Poland						2	5	5	6	7	8	8	9	9		59
Portugal	2	4	4	4	4	4	5	5	5	5	5	5	5	5		62
Romania										1	1	1				3
Slovenia					1	1	1	1	1	1	1	1	1	1		10
South Africa	5	5	6	6	7	7	10	12	13	13	13	13	12	12	4	138
South Korea		1	3	4	4	4	5	5	4	5	7	8	9	9	8	76
Spain	8	8	7	8	8	8	9	9	9	9	9	9	9	9	1	120
Sweden	3	3	3	4	4	4	4	4	5	6	7	9	9	9		74
Switzerland	4	5	8	10	11	13	13	13	14	18	16	16	17	14	11	183
Thailand			1	1	2	2	4	7	10	13	20	20	20	22	18	140
Turkey	1	1	1	1	1	1	1	1	1	1	2	6	9	9	7	43
United Kigdom	9	9	9	10	13	16	18	20	23	25	27	29	31	31	10	280
United States	21	23	214	223	237	248	262	303	344	359	391	468	488	498	484	4563
Venezuela	1	1	1	1	1	2	3	3	3	5	7	7	7	7	7	56
Total	103	119	336	371	414	443	483	539	599	649	721	824	854	860	648	7963

Table 4: Comparison of unadjusted values of efficiency and return on equity for acquirer and target prior to the M&A deal

Panel A. Acquirers. Unadjusted values for cost efficiency, profit efficiency and returns on equity

	N. Obs	Cost efficiency		Profit efficiency		ROE		NTB		NM		TOER		PER	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
B1	721	0.8042	0.1019	0.7963	0.0780	0.1278	0.0772	0.6404	3.0359	0.0733	0.0640	0.0228	0.0092	0.0125	0.0050
B2	674	0.8038	0.0935	0.7997	0.0764	0.1209	0.0644	0.5741	1.0761	0.0660	0.0485	0.0225	0.0089	0.0124	0.0051
B3	612	0.7953	0.1002	0.7999	0.0758	0.1204	0.0631	0.7479	1.4417	0.0589	0.0565	0.0221	0.0086	0.0123	0.0049
B4	529	0.7940	0.1012	0.8018	0.0688	0.1138	0.0656	0.8394	1.2418	0.0556	0.0637	0.0223	0.0086	0.0123	0.0045
B5	464	0.7879	0.1021	0.8016	0.0665	0.1164	0.0760	1.1760	1.8698	0.0555	0.0549	0.0233	0.0088	0.0127	0.0048
B6	410	0.7809	0.1039	0.8106	0.0614			1.1755	1.4886	0.0585	0.0501	0.0225	0.0081	0.0123	0.0047

Panel B. Targets. Unadjusted values for cost efficiency, profit efficiency and determinants

	N. Obs	Cost efficiency		Profit efficiency		ROE		NTB		NM		TOER		PER	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
B1	222	0.7928	0.1177	0.7705	0.1318	0.1039	0.1396	0.3494	0.9433	0.0631	0.1260	0.0268	0.0190	0.0158	0.0115
B2	212	0.7910	0.1165	0.7700	0.1281	0.1109	0.1101	0.3474	0.4488	0.0599	0.0746	0.0264	0.0151	0.0155	0.0105
B3	187	0.7896	0.1198	0.7821	0.1267	0.1281	0.1136	0.4241	0.5923	0.0648	0.0677	0.0257	0.0137	0.0148	0.0095
B4	155	0.7849	0.1076	0.7835	0.1161	0.1197	0.1415	0.3936	0.5513	0.0560	0.0781	0.0264	0.0136	0.0148	0.0101
B5	137	0.7796	0.1127	0.7765	0.1287	0.1120	0.1455	0.4810	0.7428	0.0404	0.0752	0.0278	0.0153	0.0150	0.0093
B6	120	0.7734	0.1214	0.7867	0.1212			0.4291	0.3298	0.0315	0.1075	0.0275	0.0138	0.0159	0.0110

Panel C. Acquirer versus targets. Unadjusted values for cost efficiency, profit efficiency and determinants

	N. Obs	Cost efficiency		Profit efficiency		ROE		NTB		NM		TOER		PER	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
B1	209	0.0091	0.1376	0.0132*	0.1392	0.0505***	0.2217	0.1032**	0.5620	0.0226*	0.13126	-0.0065***	0.0207	-0.0046***	0.0123
B2	194	0.0129	0.1390	0.0244**	0.1325	0.0236***	0.0987	0.1030*	0.5616	0.0114	0.0827	-0.0050***	0.0147	-0.0044***	0.0109
B3	168	0.0094	0.1345	0.0190*	0.1395	0.0118	0.1101	0.0888	0.9359	-0.0048	0.0622	-0.0047***	0.0137	-0.0037***	0.0097
B4	130	0.0084	0.1369	0.0161	0.1242	0.0132	0.1383	0.3355	1.1665	0.0033	0.0776	-0.0056***	0.0131	-0.0040***	0.0112
B5	106	0.0056	0.1328	0.0312**	0.1322	0.0238**	0.1228	0.5244	2.0823	0.0123	0.0700	-0.0060***	0.0165	-0.0040***	0.0105
B6	95	-0.0021	0.1480	0.0322**	0.1284	0.0661***	0.2381	0.0498	0.1307	0.0209*	0.0711	-0.0056***	0.0152	-0.0047***	0.0128

Return on Equity (ROE) = Net income/Total Equity (end of the year); Non Traditional Banking (NTB) = OBS/Total assets; Net margin (NM) = Net income/Revenues (= Interest income + Commission income + Trading income); Total Operating Expense Ratio (TOER) = Total non-interest operating expense/Total assets; Personnel expense ratio (PER) = Personnel costs/Total assets. ***, **, * T-test respectively statistically significant at 1%, 5% and 10%.

Table 5: Comparison of return on equity before and after the deal

Panel A: Acquirers' Pre-Merger Performance						
Year	Acquirer		Acquirer Industry-Adjusted			
	Median ROE (%)	N	Median ROE (%)	N	% +	Z Score
B5	10.6	426	2.57	396	73.5	10.60***
B4	11.1	485	2.28	442	74.4	10.60***
B3	11.9	553	2.49	501	72.9	11.04***
B2	11.6	641	2.25	566	69.3	10.21***
B1	12.2	691	2.07	618	63.1	8.82***
Panel B: Targets' Pre-Merger Performance						
Year	Target		Target Industry-Adjusted			
	Median ROE (%)	N	Median ROE (%)	N	% +	Wilcoxon Test Z Score
B5	9.1	151	1.11	116	57.8	1.75*
B4	9.7	177	1.96	135	60.7	1.87*
B3	10.0	215	0.54	169	55.0	1.99*
B2	10.1	254	1.22	206	57.8	1.96**
B1	11.0	272	1.56	224	60.3	2.21**
Panel C: Acquirers' versus Targets' Pre-Merger Performance						
Year	Industry-Adjusted ROE (%)			Wilcoxon Test		
	Acquirer	Target	Difference	N	% +	Z Score
B5	2.57	1.11	2.41	78	59.0	2.96***
B4	2.28	1.96	1.14	91	53.8	2.12**
B3	2.49	0.54	0.57	119	52.9	1.73*
B2	2.25	1.22	0.00	157	48.4	1.08
B1	2.07	1.56	0.02	169	50.3	1.10
Panel D: Post-Merger Performance						
Year	Combined Firm		Combined Firm Industry-Adjusted			
	Median ROE (%)	N	Median ROE (%)	N	%+	Z Score
A1	12.4	675	2.09	111	65.8	3.03***
A2	11.6	663	0.80	94	58.5	1.60
A3	11.5	629	0.83	83	59.0	1.27
A4	11.6	565	-0.34	68	48.5	0.99
A5	12.4	493	0.21	51	51.0	0.35

Panel E: Post-Merger versus Pre-Merger Industry-Adjusted Performance								
Pre-Merger			Post-Merger			Post versus Pre Wilcoxon Test		
Years	Median ROE(%)	N	Years	Median ROE(%)	N	Change (N)	%+	Z Score
B2B1	2.09	186	A1A2	1.80	117	0.00 (102)	45.1	0.02
B3B1	2.00	189	A1A3	1.33	118	-1.00 (104)	39.4	2.00**
B5B1	1.94	191	A1A5	0.99	119	-2.50 (104)	31.7	3.26***

ROE = Net income / Total Equity (beginning of the year). N: number of observations. % of positive cases under the Wilcoxon test. ***, **, * statistical significance at 1%, 5% and 10%.

Table 6: Regression of Post-Merger on Pre-Merger Industry Adjusted Mean ROE

Panel A: Regression of Annual Post-Merger Industry-Adjusted ROE on Average Pre-Merger Industry-Adjusted ROE						
	α	β	R	R^2	Adj.R^2	N
A1, B3B1	-0.012 (0.008)	0.383** (0.194)	0.216	0.047	0.035	82
A2, B3B1	-0.035*** (0.011)	1.010*** (0.245)	0.455	0.207	0.195	67
A3, B3B1	-0.029*** (0.009)	0.530** (0.231)	0.306	0.093	0.076	53
A4, B3B1	-0.021** (0.008)	0.048 (0.241)	0.031	0.001	-0.024	42
A5, B3B1	-0.018 (0.014)	-0.965** (0.438)	0.403	0.163	0.129	27
Panel B: Regression of Average Post-Merger Industry-Adjusted ROE on Average Pre-Merger Industry-Adjusted ROE						
A1A2, B3B1	-0.023** (0.009)	0.874*** (0.209)	0.464	0.215	0.203	66
A1A3, B3B1	-0.028*** (0.008)	0.713 (0.189)***	0.471	0.222	0.207	52

$AdjROE_{Ai}$ denotes the industry-adjusted ROE of the combined firm in the ith year following the acquisition.$AdjROE_{A1Ai}$ denotes the average industry-adjusted ROE of the combined firm from the first to the ith year following the acquisition. $AdjROE_{B1B3}$ denotes the average industry-adjusted ROE of the combined firm from the third to the first year prior to the acquisition.

Table 7: Domestic versus Cross-Border M&A Deals

Panel A: Acquirers' versus Targets' Industry-Adjusted Pre-Merger ROE

	Domestic M&A Deals					Cross-Border M&A Deals				
	Mean ROE		Wilcoxon Test			Mean ROE		Wilcoxon Test		
N. of years	Acquirer	Target	Acquirer vs Target			Acquirer	Target	Acquirer vs Target		
before the deal	%	%	N	%+	Z	%	%	N	%+	Z
B5	2.50	1.69	37	70.3	3.55***	2.45	0.76	41	48.8	0.32
B4	1.57	-1.95	41	56.1	3.55***	1.83	4.49	50	56.0	0.44
B3	1.32	0.18	56	60.7	2.59***	2.33	4.03	63	47.6	0.49
B2	1.51	-0.48	71	52.6	2.11**	0.85	2.62	79	37.2	1.71*
B1	2.63	-0.66	84	54.8	2.71***	-0.01	1.14	85	44.7	1.26

Panel B: Post-Merger versus Pre-Merger Industry-Adjusted ROE

	Domestic M&A Deals					Cross-Border M&A Deals				
N. of years	Mean ROE		Wilcoxon Test			Mean ROE		Wilcoxon Test		
before the deal	N	ROE (%)	N	Change in ROE (%)	%+ (Z)	N	%	N	Change in ROE (%)	%+ (Z)
B3B1	53	0.31				99	0.52			
A1	50	-1.61	27	-2.19	44.4 (1.18)	273	-0.77	69	0.06	0.79
A2	38	-1.04	22	-2.21	54.5. (0.47)	281	-1.84	64	-2.27	26.6 2.88***
A3	36	-0.27	19	-1.42	52.6 (0.44)	265	-1.28	56	-1.82	32.1 2.87***
A4	31	-1.37	14	-2.29	42.9 (0.22)	231	-1.06	45	-1.43	26.7 2.53**
A5	25	5.36	11	1.29	54.5 (0.62)	206	-2.10	34	-3.83	20.6 3.22***
A1A2	88	-0.60	22	-2.47	40.9 (1.45)	302	-1.05	72	-0.98	37.5 1.90*
A1A3	74	-0.59	19	-1.19	57.9 (0.73)	314	-1.07	73	-1.14	38.4 1.90*
A1A5	45	+0.05	21	1.15	72.7 (1.16)	336	-1.35	73	-1.86	28.8 3.00***

In this table, in the interest of concision, ROE refers to mean industry-adjusted Return on Equity, where equity is measured at the beginning of the year. In the same spirit, Change in ROE refers to the difference between the mean industry-adjusted Return on Equity in some year following the acquisition and the mean industry-adjusted Return on Equity in the 3 years before the acquisition.

Table 8: Comparison of net margin and asset turnover before and after the deal

Panel A: Acquirers' Pre-Merger Performance

	NBM							BAT						
N. of years	NBM		Adjusted NBM		Wilcoxon Test			BAT		Adjusted BAT		Wilcoxon Test		
before the deal	Median (%)	N	Median (%)	N	%+	%-	Z	Median (%)	N	Median (%)	N	%+	%-	Z
B5	15.1	493	0.00	453	47.2	40.4	2.01**	2.18	404	0.04	375	51.7	48.3	0.18
B4	15.9	557	0.00	504	49.0	38.3	3.15***	2.17	452	0.02	407	50.4	49.6	1.00
B3	17.0	649	0.00	578	45.8	42.4	2.40**	2.17	521	0.04	461	53.4	46.6	1.43
B2	17.2	720	0.00	645	48.7	41.1	3.28***	2.20	592	0.12	505	56.4	43.6	0.41
B1	18.0	746	0.00	667	46.3	41.4	3.15***	2.27	642	0.15	533	55.5	44.5	0.02

Panel B: Targets' Pre-Merger Performance

	NBM							BAT						
N. of years	NBM		Adjusted NBM		Wilcoxon Test			BAT		Adjusted BAT		Wilcoxon Test		
before the deal	Median (%)	N	Median (%)	N	%+	%-	Z	Median (%)	N	Median (%)	N	%+	%-	Z
B5	14.9	177	-1.96	134	39.6	56.7	2.50**	2.02	134	-0.11	97	47.4	52.6	1.18
B4	16.0	212	-0.30	164	42.7	50.0	1.58	1.97	160	-0.05	119	45.4	54.6	2.09**
B3	16.9	256	-0.57	206	39.3	53.9	1.35	2.13	183	-0.15	140	43.6	56.4	2.75***
B2	17.2	286	0.00	236	41.1	51.3	1.75*	2.06	217	-0.19	168	45.2	54.8	3.22***
B1	18.5	300	0.77	251	40.2	54.2	2.40**	2.07	235	-0.12	180	47.2	52.8	2.65***

Panel C: Post-Merger versus Pre-Merger Industry-Adjusted Performance

Pre-Merger					Post-Merger					Post versus Pre Wilcoxon Tesrs				
Year	NBM Median (%)	N	BAT Median (%)	N	Year	NBM Median (%)	N	BAT Median (%)	N	NBM %+ (%-)	NBM Z	BAT %+ (%-)	BAT Z	N NBM N BAT
B2B1	-0.05	189	0.01	149	A1A2	-0.11	119	-0.04	97	53.3 (40.0)	0.69	34.1 (39.0)	0.94	105 82
B3B1	-0.36	194	0.01	147	A1A3	0.00	120	-0.02	97	50.9 (39.6)	0.07	31.3 (46.3)	1.48	106 80
B5B1	-0.36	194	0.04	141	A1A5	-0.08	121	-0.09	89	50.0 (43.4)	0.03	21.9 (38.4)	1.83*	106 73

NBM = Net Income / Net Revenue. BAT = Net Revenue / [Total Assets + Off Balance Sheet Assets (beginning of the year)]. % +: % of positive cases under the Wilcoxon test. % -: % of negative cases under the Wilcoxon test. ***, **, * statistical significance at 1%, 5% and 10%. N: number of observations.

Table 9: Comparison of ratios of personnel and other administrative expenses over revenue before and after the deal

Panel A: Acquirers' Pre-Merger Performance

N. of years before the deal	PEX							OAE						
	PEX		Adjusted PEX		Wilcoxon Test			OAE		Adjusted OAE		Wilcoxon Test		
	Median (%)	N	Median (%)	N	%+	%-	Z	Median (%)	N	Median (%)	N	%+	%-	Z
B5	14.1	485	-1.47	444	25.9	63.3	8.97***	8.36	465	-0.25	426	30.0	56.1	6.37***
B4	14.6	549	-1.31	497	23.3	63.0	9.36***	8.48	526	-0.36	476	28.6	56.3	6.26***
B3	14.8	638	-1.46	567	23.3	63.3	10.1***	8.60	610	-0.31	542	27.7	55.4	6.69***
B2	15.6	704	-1.26	630	25.9	61.9	10.2***	9.32	674	-0.21	603	31.5	52.9	6.30***
B1	15.9	730	-1.18	651	24.1	60.8	10.2***	9.63	694	-0.20	620	30.0	54.8	6.47***

Panel B: Targets' Pre-Merger Performance

N. of years before the deal	PEX							OAE						
	PEX		Adjusted PEX		Wilcoxon Test			OAE		Adjusted OAE		Wilcoxon Test		
	Median (%)	N	Median (%)	N	%+	%-	Z	Median (%)	N	Median (%)	N	%+	%-	Z
B5	14.7	173	-0.90	130	36.2	57.7	2.74***	8.75	147	-0.05	114	40.4	51.8	1.86*
B4	15.6	202	-0.49	155	34.8	56.1	1.81*	9.85	167	0.00	133	47.4	46.6	0.61
B3	15.4	241	-0.49	193	34.7	54.9	2.28**	9.60	195	-0.07	162	42.0	50.6	1.30
B2	15.9	275	-0.47	225	37.8	53.8	1.54	9.90	215	0.00	181	43.1	50.3	0.72
B1	16.4	292	-0.34	243	36.6	52.3	0.93	10.50	217	0.00	185	45.9	49.2	0.46

Panel C: Post-Merger versus Pre-Merger Industry-Adjusted Performance

Pre-Merger					Post-Merger					Post versus Pre Wilcoxon Tesrs				
N. of years before the deal	PEX Median (%)	N	OAE Median (%)	N	Years	PEX Median (%)	N	OAE Median (%)	N	PEX %+ (%-)	PEX Z	OAE %+ (%-)	OAE Z	N PEX N OAE
B2B1	-1.68	176	-0.39	145	A1A2	-1.15	110	-0.07	89	54.7 (45.3)	1.86*	58.2 (41.8)	2.00**	95 79
B3B1	-1.69	180	-0.51	148	A1A3	-1.07	111	-0.01	90	57.3 (40.6)	2.40**	61.3 (37.5)	2.18**	96 80
B5B1	-1.92	183	-0.70	150	A1A5	-1.28	112	0.00	91	62.5. (36.5)	2.96***	62.5. (36.3)	2.70***	96 80

PEX = Personnel Expense / Revenue. OAE = Other Administrative Expense / Revenue. % +: % of positive cases under the Wilcoxon test. % -: % of negative cases under the Wilcoxon test. ***, **, * statistical significance at 1%, 5% and 10%. N: number of observations.

Table 10: Comparison of cash-flow returns before and after the deal

Panel A: Acquirers' Pre-Merger CFR

Year	Acquirer		Acquirer Industry-Adjusted				
	Mean CFR (%)	N	Mean CFR (%)	N	% +	% -	Z Score
B5	27.1	316	4.83	292	69.2	29.5	7.28***
B4	24.7	360	6.13	332	67.8	30.4	6.90***
B3	23.5	418	4.84	382	63.6	35.9	5.62***
B2	23.1	484	4.27	433	60.7	37.4	4.89***
B1	21.2	513	1.46	467	53.3	45.4	2.04**
B5B1	26.8	561	6.86	517	64.3	35.7	6.70***
B3B1	24.2	551	4.98	507	62.8	37.2	4.73***
B2B1	22.7	540	3.29	494	55.8	43.8	3.85***

Panel B: Targets' Pre-Merger CFR

Year	Target		Target Industry-Adjusted				
	Mean CFR (%)	N	Mean CFR (%)	N	% +	% -	Z Score
B5	27.3	63	-2.56	52	55.8	44.2	0.62
B4	25.8	79	-2.99	65	63.1	36.9	1.08
B3	24.5	92	2.64	77	50.6	45.5	0.48
B2	20.1	112	-1.51	98	45.9	53.1	0.20
B1	18.6	113	-1.43	100	53.0	47.0	0.32
B5B1	21.6	57	-5.14	45	53.3	46.7	0.80
B3B1	18.6	84	-3.36	68	47.1	52.9	1.23
B2B1	18.2	101	-3.47	86	46.5	53.5	1.32

Panel C: Acquirers' versus Targets' Pre-Merger CFR

Year	Mean Industry Adjusted CFR (%)		Acquirer versus Target (Wilcoxon Test)			
	Acquirer	Target	N	%+	%-	Z Score
B5	4.83	-2.56	30	30.0	46.7	0.09
B4	6.13	-2.99	38	44.7	28.9	1.64
B3	4.84	2.64	42	42.9	32.7	1.12
B2	4.27	-1.51	73	47.9	34.2	2.42**
B1	1.46	-1.43	72	48.6	29.2	2.37**
B5B1	6.86	0.36	85	43.5	38.8	1.61
B3B1	4.98	0.30	85	45.9	36.5	1.55
B2B1	3.29	-0.58	85	50.0	30.5	2.35**

Panel D: Post-Merger versus Pre-Merger CFR

Year	Mean Industry Adjusted CFR		Change in Mean-Industry Adjusted CFR		Wilcoxon Test		
	N	(%)	N	(%)	%+	%-	Z Score
B3B1	82	1.12					
A1	453	-4.34	63	-13.14	30.2	69.8	3.21***
A2	453	-2.67	53	-8.45	18.9	81.1	3.35***
A3	427	-3.07	48	-10.15	25.0	75.0	3.97***
A4	383	-5.46	40	-16.85	20.0	80.0	4.44***
A5	343	-4.86	27	-17.96	7.4	92.6	4.01***
A1A2	509	-5.11	67	-14.82	23.9	76.1	4.18***
A1A3	531	-4.60	67	-13.37	16.4	83.6	5.14***
A1A5	562	-5.20	67	-13.95	13.4	86.6	5.29***

CFR = (Net Revenue – Personnel Expense – Other Administrative Expense)/Market Value (beginning of the year). % +: % of positive cases under the Wilcoxon test. % -: % of negative cases under the Wilcoxon test. ***, **, * statistical significance at 1%, 5% and 10%. N: number of observations.

Table 11: Adjusted cost and profit efficiency (M&A banks and control sample of non-M&A banks) by year

Year	Cost Efficiency (M&A banks)	Cost Efficiency (control sample)	Adjusted Cost Efficiency	Profit efficiency (M&A banks)	Profit efficiency (control sample)	Adjusted Profit efficiency
2005	.82032	.79306	.02915*	.76389	.72321	.04067**
2004	.81477	.80533	.00927	.79554	.73537	.06017***
2003	.80557	.78707	.01850**	.79047	.73329	.05718***
2002	.79174	.80390	-.01216	.78895	.70961	.07934***
2001	.79654	.80368	.00910	.77040	.70384	.08056***
2000	.80622	.82037	-.01414**	.77840	.72924	.04915***
1999	.80031	.80093	-.00062	.80246	.73295	.06950***
1998	.79734	.80619	-.00885	.79270	.72584	.06686***
1997	.79391	.79770	-.00379	.80412	.74373	.06041***
1996	.79367	.77490	.01877**	.78867	.74148	.04718***
1995	.78690	.76774	.01917**	.77878	.72919	.04958***
1994	.77718	.75837	.01881*	.77592	.72414	.05179***
1993	.74617	.69564	.05052***	.76062	.69850	.06212***
1992	.72573	.71039	.01534	.74890	.71006	.03884***
1991	.70968	.78817	-.07849***	.76635	.68591	.08044***
Average	.78884	.78482	.00402*	.78391	.72439	.05953***

Table 12: Adjusted cost and profit efficiency (M&A banks and control sample of non-M&A banks) by country

Country	Number of banks	Cost Efficiency (M&A banks)	Cost Efficiency (control sample)	Adjusted Cost Efficiency	Profit efficiency (M&A banks)	Profit efficiency (control sample)	Adjusted Profit efficiency
Argentina		0.8426	0.8209	0.0217*	0.6740	0.6650	0.0090
Australia		0.8776	0.8316	0.0460***	0.7248	0.6858	0.0397
Austria		0.8165	0.7848	0.0316***	0.8475	0.7795	0.0780***
Belgium		0.7962	0.8502	-0.0540***	0.8214	0.6597	0.1617***
Brazil		0.8489	0.7673	0.0815***	0.3906	0.4732	-0.0826***
Canada		0.8350	0.8238	0.0113	0.7742	0.7383	0.0359***
Chile		0.7988	0.7699	0.0288*	0.7852	0.7562	0.0290**
Colombia		0.7837	0.8129	-0.0292	0.5815	0.7139	-0.1324***
Denmark		0.7910	0.8261	-0.0351***	0.7915	0.7660	0.0255***
Finland		0.5493	0.8061	-0.2567***	0.8199	0.7482	0.0717***
France		0.7367	0.7827	-0.0460***	0.7323	0.7063	0.0260***
Germany		0.7487	0.6618	0.0870***	0.8292	0.7660	0.0632***
Greece		0.8185	0.8024	0.0162*	0.8038	0.7630	0.0408***
Hungary		0.7445	0.9226	-0.1781***	0.7756	0.6126	0.1631***
Iceland		0.8490	0.8019	0.0470**	0.6915	0.7046	-0.0131
India		0.8956	0.8221	0.0735**	0.8017	0.7457	0.0560***
Ireland		0.7984	0.8582	-0.0598***	0.8505	0.7884	0.0621***
Italy		0.8401	0.8297	0.0104**	0.7864	0.7449	0.0416***
Lebanon		0.5084	0.4153	0.0931**	0.8665	0.8429	0.0236
Luxembourg		0.6393	0.8181	-0.1288***	0.8462	0.6081	0.2383***
Mexico		0.6451	0.7526	-0.1075*	0.5323	0.4449	0.0874
Morocco		0.7320	0.6189	0.1131***	0.8896	0.8560	0.0336***
Netherlands		0.8138	0.7523	0.0615***	0.7908	0.7700	0.0208
Norway		0.8142	0.8378	-0.0236**	0.7988	0.6992	0.0996***
Poland		0.8420	0.8132	0.0288**	0.7304	0.7107	0.0197
Portugal		0.7473	0.6874	0.0600***	0.8386	0.7671	0.0715***
South Africa		0.8281	0.7433	0.0849***	0.4989	0.6559	-0.1570***
South Korea		0.7900	0.7904	-0.0005	0.8566	0.7590	0.0914***
Spain		0.8068	0.7946	0.0122*	0.8276	0.7585	0.0691***
Sweden		0.8773	0.6466	0.2307***	0.8230	0.4439	0.3790***
Switzerland		0.7704	0.7791	-0.0086	0.8204	0.7914	0.0290***
Thailand		0.7176	0.7055	0.0120	0.8924	0.8018	0.0906***
Turkey		0.8717	0.8089	0.0628***	0.5942	0.5973	-0.0031
UK		0.7863	0.7765	0.0098	0.7869	0.6836	0.1033***
US		0.8853	0.7656	0.1197***	0.7251	0.6090	0.1161
Venezuela		0.8642	0.7959	0.0683***	0.5552	0.6705	-0.1153***

Table 13: Comparison of adjusted values of efficiency prior to the M&A deal

N. of years before the deal	N. obs	Cost efficiency Mean (Std. Dev)	Cost efficiency % +ve cases (Z-test)	Profit efficiency Mean (Std. Dev)	Profit efficiency % +ve cases (Z-test)
Panel A. Acquirer. Industry-adjusted values for cost efficiency and profit efficiency before the deal (adjustment: mean by year and country)					
B1	694	.0145 (.1200)	57%- (-4.25)°°°	.0739 (.1062)	83% (-17.38)°°°
B2	661	.0214 (.1218)	59% (-5.16)°°°	.0722 (.1061)	85% (-16.68)°°°
B3	586	.0285 (.1422)	58% (-4.58)°°°	.0761 (.1117)	85% (-16.03)°°°
B4	510	.0264 (.1355)	58% (-4.51)°°°	.0794 (.1104)	88% (-15.88)°°°
B5	435	.0203 (.1343)	53% (-3.27)°°°	.0724 (.1053)	85% (-13.96)°°°
B6	378	.0229 (.1341)	56% (-3.16)°°°	.0822 (.0933)	91% (-14.78)°°°
Panel B. Target. Industry-adjusted values for cost efficiency and profit efficiency before the deal (adjustment: mean by year and country)					
B1	264	.0026 (.1313)	56% (-1.949)°°	.0535 (.1208)	76% (-7.746)°°°
B2	251	-.0014 (.1374)	57% (-1.764)°	.0596 (.1160)	78% (-8.220)°°°
B3	211	.0113 (.1458)	59% (-2.737)°°°	.0658 (.1177)	81% (-8190)°°°
B4	181	.0119 (.1416)	59% (-2.289)°°	.0727 (.1338)	78% (-7.669)°°°
B5	160	.0195 (.1565)	67% (-3.169)°°°	.0708 (.1439)	79% (-6.854)°°°
B6	130	.0212 (.1285)	64% (-2.594)°°°	.0657 (.1327)	83% (-6.422)°°°
Panel C. Acquirer versus Target. Industry-adjusted values for cost efficiency and profit efficiency before the deal (adjustment: mean by year and country)					
B1	196	.0093 (.1625)	45% (-.561)	.0019 (.1443)	47% (.647)
B2	188	.0179 (.1710)	45% (-1.052)	.0038 (.1436)	44% (-.652)
B3	157	.0088 (.1798)	43% (-.132)	.0049 (.1538)	42% (-.629)
B4	123	.0122 (.1807)	45% (-.494)	-.0019 (.1667)	45% (-.303)
B5	100	.0080 (.1839)	42% (-.283)	.0036 (.1562)	42% (-.175)
B6	89	-.0025 (.1717)	48% (-.290)	.0133 (.1452)	41% (-.040)

% of positive cases under the Wilcoxon test. °°°, °°, ° Z-test respectively statistically significant at 1%, 5% and 10%. Total number of deals: 647. Number of domestic deals: 345. Number of cross-border deals: 302.

Table 14: Comparison of X-efficiency before and after the deal

Panel A. Post values of the combined bank vs. Pre values of the merging banks. Adjusted for cost and profit efficiency (adjustment: mean by year and country)

No of years after the deal	Cost efficiency		Cost efficiency		Profit efficiency		Profit efficiency	
	Base year: B6B1		Base year: B3B1		Base year: B6B1		Base year: B3B1	
	Mean (Std. Dev)	% negative cases (Z-test)	Mean (Std. Dev)	% negative cases (Z-test)	Mean (Std. Dev)	% positive cases (Z-test)	Mean (Std. Dev)	% positive cases (Z-test)
A1	0.0308***	60%	0.0302***	64%	-0.0117*	53%	-0.0057	52%
n. deals: 160	(0.082)	(-4.177)°°°	(0.079)	(-4.519)°°°	(0.084)	(-1.603)°	(0.081)	(-0.829)
A2	0.0366***	71%	0.0358***	72%	-0.0187**	52%	-0.0127*	46%
n. deals: 136	(0.074)	(-5.467)°°°	(0.073)	(-5.629)°°°	(0.087)	(-1.616)°	(0.082)	(0.419)
A3	0.0375***	65%	0.0364***	69%	-0.0155**	52%	-0.0092*	44%
n. deals: 121	(0.079)	(-5.053)°°°	(0.077)	(-5.308)°°°	(0.085)	(-1.380)	(0.079)	(-0.317)
A4	0.0397***	73%	0.0387***	74%	-0.0225**	54%	-0.0155*	46%
n. deals: 104	(0.083)	(-4.887)°°°	(0.080)	(-5.034)°°°	(0.088)	(-2.276)°°	(0.082)	(-1.211)
A5	0.0407***	65%	0.0386***	72%	-0.0424**	65%	-0.0340**	61%
n. deals: 77	(0.093)	(-3.465)°°°	(0.091)	(-3.614)°°°	(0.124)	(-3.064)°°°	(0.121)	(-2.459)°°
A6	0.0510***	80%	0.0436***	75%	-0.0533***	73%	-0.0444***	73%
n. deals: 49	(0.104)	(-3.576)°°°	(0.106)	(-3.057)°°°	(0.094)	(-3.566)°°°	(0.087)	(-3.344)°°°
Mean (A1A3)			0.0380	0.0734			-0.0073	0.0805
Mean (A1A6)	0.0400	0.0746			-0.0170	0.0861		

Panel B. Domestic M&A. Post values of the combined bank vs. Pre values of the merging banks. Adjusted for cost and profit efficiency (adjustment: mean by year and country)

No of years After the deal	Cost efficiency		Cost efficiency		Profit efficiency		Profit efficiency	
	Base year: B6B1		Base year: B3B1		Base year: B6B1		Base year: B3B1	
	Mean (Std. Dev)	%negative cases (Z-test)	Mean (Std. Dev)	% negative cases (Z-test)	Mean (Std. Dev)	% positive cases (Z-test)	Mean (Std. Dev)	% positive cases (Z-test)
A1	0.0384***	57%	0.0387***	62%	-0.0055	54%	-0.0022	50%
n. deals: 87	(0.094)	(-2.963)°°°	(0.090)	(-3.318)°°°	(0.081)	(-0.601)	(0.081)	(-0.76)
A2	0.0450***	70%	0.0441***	70%	-0.0068	44%	-0.0048	37%
n. deals: 70	(0.076)	(-4.322)°°°	(0.073)	(-4.427)°°°	(0.077)	(-0.243)	(0.074)	(-0.688)
A3	0.0461***	70%	0.0444***	73%	-0.0017	44%	0.0001	38%
n. deals: 64	(0.073)	(-4.588)°°°	(0.070)	(-4.628)°°°	(0.072)	(-0.187)	(0.068)	(-0.983)
A4	0.0460***	76%	0.0432***	75%	-0.0137	49%	-0.0106	42%
n. deals: 55	(0.078)	(-4.223)°°°	(0.075)	(-4.198)°°°	(0.075)	(-1.089)	(0.068)	(-0.369)
A5	0.0449***	76%	0.0397***	76%	-0.0397*	59%	-0.0333	59%
n. deals: 41	(0.088)	(-3.285)°°°	(0.085)	(-3.065)°°°	(0.148)	(-1.432)	(0.145)	(-1.160)
A6	0.0544**	86%	0.0463**	82%	-0.0521***	68%	-0.0452***	68%
n. deals: 28	(0.106)	(-3.006)°°°	(0.104)	(-2.983)°°°	(0.084)	(-2.788)°°°	(0.075)	(-2.801)°°°

Panel C. Cross-border M&A. Post values of the combined bank vs. Pre values of the merging banks. Adjusted for cost and profit efficiency (adjustment: mean by year and country)

Number of years After the deal	Cost efficiency		Cost efficiency		Profit efficiency		Profit efficiency	
	Base year: B6B1		Base year: B3B1		Base year: B6B1		Base year: B3B1	
	Mean (Std. Dev)	% negative cases (Z-test)	Mean (Std. Dev)	% negative cases (Z-test)	Mean (Std. Dev)	% positive cases (Z-test)	Mean (Std. Dev)	% positive cases (Z-test)
A1	0.0217***	64%	0.0199***	65%	-0.0190*	52%	-0.0099	54%
n. deals: 73	(0.065)	(-2.966)°°°	(0.063)	(-3.143)°°°	(0.088)	(-1.685)°	(0.081)	(-1.038)
A2	0.0276***	71%	0.0269***	74%	-0.0313***	59%	-0.0213*	55%
n. deals: 66	(0.072)	(-3.440)°°°	(0.072)	(-3.683)°°°	(0.095)	(-2.399)°°	(0.089)	(-1.650)°
A3	0.0278**	58%	0.0273**	64%	-0.0311**	61%	-0.0199*	52%
n. deals: 57	(0.085)	(-2.411)°°	(0.083)	-2.847)°°°	(0.096)	(-2.054)°°	(0.089)	(-1.224)
A4	0.0327**	69%	0.0336***	73%	-0.0323**	59%	-0.0212	50%
n. deals: 49	(0.089)	(2.591)°	(0.087)	(-2.903)°°°	(0.101)	(-2.084)°°	(0.095)	(-1.272)
A5	0.0359**	53%	0.0374**	69%	-0.0455***	72%	-0.0349**	63%
n. deals: 36	(0.100)	(-1.650)°	(0.099)	(-2.047)°°	(0.090)	(-2.765)°°°	(0.086)	(-2.260)°°
A6	0.0465*	71%	0.0397	65%	-0.0549**	81%	-0.0433*	80%
n. deals: 21	(0.104)	(-1.929)°°	(0.110)	(-1.456)	(0.108)	(-2.416)°°	(0.103)	(-2.016)°°

Base year are weighted averages of the performance measure in the years prior to the M&A of the target and acquiring banks. ***, **, * T-test respectively statistically significant at 1%, 5% and 10%. °°°, °°, ° Z-test respectively statistically significant at 1%, 5% and 10%. Total number of deals: 647. Number of domestic deals: 345. Number of cross-border deals: 302.

Table 15: X-efficiency before and after the deal: M&A impact and trend

Panel A: M&A sample (post vs. 3 years pre- deal)						**Panel B: M&A sample (post vs. 6 years pre- deal)**					
	α	β	R	R^2	$AdjR^2$		α	β	R	R^2	$AdjR^2$
Cost efficiency											
A1, B3B1	0.029*** (0.006)	0.796*** (0.062)	0.715	0.512	0.509	A1, B6B1	0.029*** (0.006)	0.761*** (0.063)	0.691	0.478	0.474
A2, B3B1	0.033*** (0.006)	0.689*** (0.057)	0.726	0.527	0.523	A2, B6B1	0.033*** (0.006)	0.670*** (0.056)	0.715	0.512	0.508
A3, B3B1	0.031*** (0.006)	0.558*** (0.063)	0.630	0.397	0.392	A3, B6B1	0.032*** (0.006)	0.527*** (0.063)	0.608	0.370	0.365
A4, B3B1	0.031*** (0.007)	0.554*** (0.071)	0.616	0.389	0.373	A4, B6B1	0.031*** (0.007)	0.528*** (0.071)	0.595	0.354	0.347
A5, B3B1	0.027*** (0.008)	0.462*** (0.075)	0.583	0.340	0.331	A5, B6B1	0.027*** (0.008)	0.440*** (0.075)	0.561	0.314	0.305
A6, B3B1	0.020* (0.012)	0.349*** (0.099)	0.463	0.214	0.197	A6, B6B1	0.023** (0.012)	0.354*** (0.097)	0.471	0.222	0.205
A1A3, B3B1	0.036*** (0.006)	0.777*** (0.057)	0.735	0.541	0.538	A1A6, B6B1	0.038*** (0.006)	0.746*** (0.056)	0.724	0.524	0.521
Profit efficiency											
A1, B3B1	0.001 (0..8)	0.887*** (0.067)	0.729	0.531	0.528	A1, B6B1	-0.001 (0.008)	0.855*** (0.069)	0.701	0.492	0.488
A2, B3B1	-0.003 (0.009)	0.874*** (0.074)	0.716	0.512	0.508	A2, B6B1	-0.004 (0.010)	0.813*** (0.077)	0.673	0.453	0.448
A3, B3B1	0.005 (0.009)	0.818*** (0.083)	0.674	0.454	0.449	A3, B6B1	0.007 (0.010)	0.725*** (0.082)	0.628	0.395	0.390
A4, B3B1	-0.012 (0.011)	0.952*** (0.952)	0.696	0.484	0.479	A4, B6B1	-0.008 (0.012)	0.826*** (0.098)	0.641	0.411	0.406
A5, B3B1	-0.012 (0.019)	0.743*** (0.160)	0.475	0.226	0.215	A5, B6B1	-0.010 (0.020)	0.662*** (0.151)	0.450	0.203	0.192
A6, B3B1	-0.024 (0.030)	0.751*** (0.190)	0.504	0.254	0.238	A6, B6B1	-0.014 (0.020)	0.571*** (0.164)	0.453	0.206	0.189
A1A3, B3B1	0.007 (0.007)	0.774*** (0.064)	0.691	0.477	0.474	A1A6, B6B1	0.004 (0.008)	0.693*** (0.067)	0.633	0.401	0.397

Panel C: Domestic M&A sample (post vs. 6 years pre- deal)						**Panel D: Cross-border M&A sample (post vs. 6 years pre- deal)**					
Cost efficiency											
	α	β	R	R^2	$AdjR^2$		α	β	R	R^2	$AdjR^2$
A1, B3B1	0.033*** (0.010)	0.780*** (0.107)	0.622	0.386	0.379	A1, B6B1	0.024*** (0.007)	0.757*** (0.070)	0.791	0.626	0.620
A2, B3B1	0.032*** (0.009)	0.600*** (0.089)	0.633	0.400	0.392	A2, B6B1	0.032*** (0.008)	0.727*** (0.077)	0.763	0.582	0.576
A3, B3B1	0.034*** (0.008)	0.542*** (0.090)	0.607	0.368	0.358	A3, B6B1	0.030*** (0.009)	0.521*** (0.093)	0.604	0.365	0.354
A4, B3B1	0.025*** (0.009)	0.458*** (0.099)	0.538	0.289	0.276	A4, B6B1	0.034*** (0.011)	0.566*** (0.107)	0.610	0.372	0.359
A5, B3B1	0.011 (0.012)	0.359*** (0.114)	0.450	0.203	0.182	A5, B6B1	0.042*** (0.013)	0.431*** (0.108)	0.563	0.317	0.297
A6, B3B1	0.005 (0.018)	0.267* (0.150)	0.329	0.109	0.074	A6, B6B1	0.039** (0.016)	0.369** (0.130)	0.545	0.297	0.259
Profit efficiency											
A1, B3B1	0.026*** (0.009)	0.427*** (0.097)	0.431	0.186	0.176	A1, B6B1	-0.029** (0.013)	1.107*** (0.092)	0.819	0.670	0.666
A2, B3B1	0.036*** (0.011)	0.358*** (0.110)	0.367	0.135	0.122	A2, B6B1	-0.032** (0.015)	1.008*** (0.103)	0.774	0.600	0.594
A3, B3B1	0.035*** (0.011)	0.436*** (0.113)	0.441	0.194	0.181	A3, B6B1	-0.020 (0.018)	0.891*** (0.11)	0.709	0.503	0.494
A4, B3B1	0.024** (0.012)	0.454*** (0.121)	0.459	0.211	0.196	A4, B6B1	-0.040** (0.021)	1.071*** (0.147)	0.729	0.531	0.521
A5, B3B1	-0.007 (0.032)	0.544** (0.304)	0.275	0.076	0.052	A5, B6B1	-0.011 (0.022)	0.712*** (0.143)	0.648	0.420	0.403
A6, B3B1	-0.009 (0.021)	0.485 (0.184	0.459	0.211	0.180	A6, B6B1	-0.021 (0.039)	0.676** (0.307)	0.450	0.203	0.161

Post values of the combined bank vs. Pre values of the merging banks. Adjusted values for cost and profit efficiency (adjustment: mean by year and country).

Table 16: Descriptive statistics of institutional, deal- specific and bank-specific determinants of the change in X-efficiency

	N. obs.	Minimum	Maximum	Mean	Std. Deviation
T_Freedom from Government	312	0.11	0.99	.4923	.1804
T_Regulatory quality	291	-.01	0.02	.0095	.0042
A_Freedom from Government	703	0.06	0.86	.3938	.1179
A_ Regulatory quality	631	.02	1.94	.0107	.0032
Payment method (=1 if Cash only)	970	.00	1.00	.5515	.4976
Deal Period: 2000-2005	970	.00	1.00	.4701	.4994
Deal Period: 1994-1999	970	.00	1.00	.5299	.4994
Deal Period: 1991-1993	970	.00	1.00	.1309	.3375
Cross border dummy (=1 if cross border)	970	.00	1.00	.8557	.3516
C_big	708	.00	1.00	.3319	.4712
C_medium	708	.00	1.00	.3362	.4727
A_big	786	.00	1.00	.3282	.4699
A_medium	786	.00	1.00	.3384	.4735
T_medium	303	.00	1.00	.3333	.4722
T_small	271	.00	1.00	.2435	.4300
C_ Traditional banking	708	.06	.90	.5269	.1322
A_Traditional banking	786	.02	.89	.5132	.1252
T_ Traditional banking	303	.06	.96	.5461	.1743
C_ Riskiness	636	.00	3.41	.0591	.1729
A_Riskiness	717	.00	3.41	.0569	.1965
T_ Riskiness	266	.00	1.05	.0899	.1444

Freedom from government (http://www.heritage.org/research/features/index/) is defined to include all government expenditures- including consumption and transfers - and state-owned enterprises. Regulatory quality (www.worldbank.org), the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. Traditional banking = Loans/Total assets; Riskiness = Stand. Dev ROE; Big = Fist terzile (ln (Total assets)); Medium = Second terzile (ln (Total assets)); Small = Third terzile (ln (Total assets)).

Table 17: Determinants of changes in X-efficiency prior and after M&A

	Change in Profit efficiency		Change in Cost efficiency	
Independent Variables:	Par	T-stat	Par	T-stat
Intercept	0.56	0.785	0.078	1.141
T_Freedom from Government	0.139**	2.413	0.061	1.448
T_Regulatory quality	4.629*	1.705	-0.213	-0.107
A_Freedom from Government	-0.343***	-3.722	-0.132*	1.946
A_ Regulatory quality	-7.212**	2.418	3.622*	1.651
Payment method dummy (=1 if Cash only)	-0.27*	-1.670	-0.006	-0.513
Deal Period: 2000-2005	0.009	0.434	-0.026*	-1.659
Deal Period: 1994-1999	-0.049***	-2.863	-0.026**	-2.028
Cross border dummy (=1 if cross border)	0.001	0.083	-0.020*	-1.625
C_big	0.069*	1.718	0.032	1.087
C_medium	0.028	0.139	0.026	1.278
A_big	-0.091**	-2.570	-0.018	-0.691
A_medium	-0.41	-1.400	-0.013	-0.627
T_medium	-0.072***	-3.910	-0.024*	-1.745
T_small	-0.016	-0.769	-0.020	-1.287
C_Traditional banking	0.529***	4.915	0.037	0.465
A_Traditional banking	-0.548***	-4.719	-0.119	-1.394
T_ Traditional banking	0.038	0.787	-0.007	-0.207
C_Riskinesst	0.999***	3.785	0.609***	3.135
A_Riskiness	0.549***	3.372	0.345***	2.880
T_Riskiness_pre	0.236***	3.170	0.043	0.785
N. of obs.	96		96	
R^2	0.651		0.416	

Cross-border Bank Acquisitions: Is there a Performance Effect?

Ricardo Correa*
Federal Reserve Board

November 8, 2007

Abstract

This paper uses a unique database that includes deal and bank balance sheet information for 220 cross-border acquisitions between 1994 and 2003, to analyze the characteristics and performance effects of international takeovers on target banks. A discrete choice estimation shows that banks are more likely to get acquired in a cross-border deal if they are large, bad performers, in a small country, and when the banking sector is concentrated. Post-acquisition performance for target banks does not improve in the first two years relative to domestically-owned financial institutions. This result is explained by a decrease in the banks' net interest margin in developed countries and an increase in overhead costs in emerging economies.

JEL Codes: F21, F23, G21, G34.

Keywords: Mergers and Acquisitions, Performance, International Banking.

* I thank Juan J. Cruces and seminar participants at the International Finance Workshop at the Federal Reserve Board and at the LACEA-LAMES annual meeting in Bogota, Colombia. The views in this paper are solely the responsibility of the author and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System. Address for correspondence: Ricardo.Correa@frb.gov.

1. Introduction

For the last 15 years the international financial system has experienced significant changes that have reshaped its structure and exposure to global shocks. An important issue in this trend has been the increasing presence of foreign banks in developed and emerging countries. The existing literature has associated financial liberalization with an increase in growth (Levine, 2005), stability (Crystal *et al*., 2001), and better credit allocation (Giannetti and Ongena, 2005) in emerging economies. It has also become one of the main policy recommendations from multilateral organizations.[1]

This paper uses a unique cross-border Mergers and Acquisitions (M&As) database to answer four questions: Which factors influence cross-border acquisitions? Do these type of acquisitions improve the target's performance? Is there any post-acquisition difference in performance for targets in developed and emerging economies? Is it influenced by host-country or home-country characteristics?

The determinants of cross-border acquisitions are evaluated using 220 deals that took place between 1994 and 2003. A discrete choice model is estimated to test the factors that increase the probability of an international takeover. This study finds that the target's bank size, pre-acquisition profitability, and the level of concentration in the host country's banking sector are significant determinants of cross-border deals. For emerging economies, regulatory restrictions decrease the probability of bank acquisitions by Multinational Banks (MNBs).

The effects of bank acquisitions have been studied in developed economies and cross-border deals in Europe. The evidence shows limited performance improvements in the post-acquisitions period. In contrast, foreign banks in emerging economies are found to be better performers than their domestic counterpart.[2] This paper focuses on the first two years after a cross-border acquisition to test if foreign acquirers are able to increase

[1] See Mishkin (2001) and Tschoegl (2004) for a discussion on the benefits and costs of foreign bank entry as a policy to prevent financial crises.
[2] Micco *et al*. (2006) show evidence on performance indicators divided by type of ownership.

the target's efficiency in the short run in emerging economies.

Post-acquisition changes in performance are tested using a sub-sample of 102 deals with information for at least two years before and after the cross-border deal. A difference-in-difference analysis is used to control for economy-wide and country specific effects. Banking indices by country serve as the counterfactual to the targets' profitability measures. I find that acquired banks perform worse, or at the same level of the country-specific indices after a takeover. This is explained by a decline in net interest margins. Loan loss provisions decrease, partially compensating the negative effect of the deal.

A comparison of deals in developed and emerging economies shows similar results in terms of the targets' performance. The change in *Overhead* costs is the only measure that is statistically different when comparing emerging and developed countries. Median expenditures in non-interests and personnel costs decline in the latter countries while the opposite is the case in the former. This result shows the difficulties in improving efficiency in different institutional, economic, and cultural environments.[3]

Finally, I test for diseconomies in managing foreign subsidiaries due to differences in language, legal origin and geographical distance. Targets perform better if the home country of the acquirer and the host country share the same language. This factor is particularly relevant in determining post-acquisition *Overhead* costs in developed and emerging economies. In contrast, difference in neither legal origin nor distance appears to affect performance negatively in the post-acquisition period.

The rest of the paper is organized as follows. Section 2 reviews the literature on cross-border acquisitions and their impact on bank performance. Section 3 describes the empirical methodology used to answer the questions posed in this study. Section 4 describes the data and sample selection criteria. Section 5 presents the main results.

[3] Demirgüc-Kunt *et al*. (2004) do a cross-country comparison of the link between regulation and national institutions and bank overhead costs and interest margins.

Finally, Section 6 concludes.

2. Motivation and Related Literature

The literature on cross-border acquisitions has approached the subject from different perspectives. A first set of studies analyzes the determinants of this type of deals. The motivation for cross-border consolidation ranges from the "follow-your-customer" hypothesis (Miller and Parkhe, 1998, Esperanca and Gulamhussen, 2001) to differences in efficiency between acquirers and target banks (Berger *et al*., 2000). Some studies have explained these deals using arguments from the Foreign Direct Investment (FDI) literature (Goldberg, 2004) and New Trade Theory (Berger *et al*., 2004) literature. Cross-border acquisitions have been relatively scarce compared to their domestic counterpart. Buch and DeLong (2004) attribute this phenomenon to information costs and regulatory restrictions. Using a sample of OECD countries, Focarelli and Pozzolo (2005) find that it is more likely for MNBs to enter countries "where the expected economic growth is higher", banking sector concentration is lower and the regulatory environment is less stringent.[4]

This paper expands the literature reviewed above by analyzing both the determinants of financial FDI at the country level, and also focusing on the target specific characteristics that motivate cross-border acquisitions. The framework used in this study is similar to the approaches followed in Focarelli *et al*. (2002) for Italian banks and Hannan and Rhoades (1987) for U.S. institutions.

Another body of research discusses the effect of M&As on stock prices and operating performance. Piloff and Santomero (1998) and Calomiris and Karceski (2000) review the findings in this literature for U.S. institutions.[5] The effects of M&As on stock market value are negligible for most of the deals analyzed in these studies. There is a

[4] For a theoretical explanation of banking M&A's, see Milbourn *et al*. (1999).
[5] These authors argue that there are several shortcomings in the empirical methods used in these performance studies, and recommend more M&A case-study analysis.

transfer of wealth from the acquirer to the target shareholders mostly explained by high premiums paid on these transactions. The lack of comparable stock price information internationally, outside of Europe, has limited the amount of studies using the event methodology to analyze performance effects after cross-border M&As.[6] Amihud *et al*. (2003) focus on acquirers involved in international acquisitions and find that there is no reduction in risk for those banks that diversify by acquiring financial institutions abroad. Moreover, the cumulative abnormal returns for the acquirers in these transactions are negative and significant.

Other studies use accounting data to asses the effect of M&As on operating performance. Chamberlain (1998) analyzes a sample of deals that took place in the U.S. in the eighties and finds that these transactions did not yield any operating efficiencies. This result is consistent with similar evidence that shows no improvements in Return on Assets (ROA) or growth in operating income in the same time period (Linder and Crane (1992)). There are few studies that show positive changes in performance after a deal, for instance, Cornett and Tehranian (1992) find an increase in the post-acquisition Return on Equity (ROE) and operating cash flow.

Vander Vennet (2002) analyzes a sample of European cross-border deals and finds an increase in profit efficiency for the target bank on the first year after an acquisition. Nevertheless, the same improvements do not show in the cost efficiency and ROA measures. These mixed results are the only comprehensive evidence on cross-border deals and their impact on target performance. The current paper uses the same operating performance methodology but expands the sample of deals to include targets in developed and emerging economies.

The literature reviewed in this section shows mixed effects in terms of the impact of M&As on banks in developed economies. Alternatively, some empirical studies find that foreign bank presence benefits emerging economies. In countries with MNBs, the

---

[6] See Cybo-Ottone and Murgia (2000) and Beitel and Schierek (2001) for evidence on the performance effect in European M&As.

domestic banking sector is more efficient (Claessens *et al*., 2001, Bayraktar and Wang, 2004), stable (Crystal *et al*., 2001), capital allocation improves (Giannetti and Ongena, 2005), and economic growth is enhanced (Levine, 2001). By expanding the sample of deals to emerging countries, this study attempts to test if cross-border acquisitions increase bank performance in less developed economies.

3. Empirical Methodology

3.1. Determinants of Cross-Border Acquisitions

This section describes the methodology used to test the first question addressed by this study. Following Vander-Vennet (2002) and Focarelli *et al*. (2002), I use a probit-model to estimate the characteristics of banks that have been involved in cross-border acquisitions in comparison to those that were not part of any deal during the sample period. The dependent variable is a binary choice variable equal to one, the year a bank is the target in a takeover where the acquirer is a foreign financial institution. The model to estimate is given by:

$$\Pr(Y_{ijt} = 1) = \Phi\left(X_{it-1}, Z_{jt-1}, M_{jt-1}\right) \tag{1}$$

where Y_{ijt} equals one when bank i in country j gets acquired in year t by a foreign bank and zero otherwise. Φ is the standard cumulative normal probability distribution; X_{it-1} is a vector of bank-specific variables; Z_{jt-1} represents a vector of country characteristics, including macroeconomic aggregates and financial indicators; M_{jt-1} is a vector of variables that describe the regulatory environment and concentration level in the banking sector by country.

All explanatory variables enter in the regression with one lag. This specification assumes that buyers take the decision to acquire a target using information available to them at the end of the year before the acquisition takes place. The coefficients on the regressors included in this model indicate the change in the probit score in terms of standard deviations, following a one-unit increase in the predictors. To establish the relevant characteristics determining cross-border deals, I test the significance and magnitude of these coefficients.

Following Focarelli and Pozzolo (2000), four sets of variables are included in these estimations. The first group of variables consists of *ex ante* measures of bank profitability, size, capital, and lending activity. The second set draws from the literature on the determinants of growth, and includes real GDP, inflation and GDP *per capita* growth. The third group includes variables that proxy for regulatory restrictions and bank concentration.[7] These proxies measure the degree of bank competition in the host country and implicit limitations to bank entry. Finally, the last set of variables measure the degree of financial development in the host country, proxied by the value of stock market and private and public bond market capitalization to GDP.

3.2. Performance Effect

The second question outlined in this paper analyzes the change in performance for target banks after a cross-border acquisition. In order to measure this change, this paper has to determine what performance would have been if the acquisition had not taken place. This study draws on Cornett *et al*. (2005) and measures the counterfactual of the target's performance with a country-specific bank index. Then, the effect of the deal is calculated by subtracting this benchmark from the acquired-bank performance indicators, and comparing this measure between the before and after acquisition period. This estimation technique controls for possible differences in accounting methods across countries, regulatory environments and country specific-economic activity.

The empirical methodology in this section follows Chamberlain (1998). The target's performance is assumed to be given by:

---

[7] Bank Concentration is measured as the share of the three largest banks by country and year.

$$r_{\tau i} = \mu_z + c_{\tau i} + \eta_{\tau i} \tag{2}$$

where $r_{\tau i}$ represents the performance proxy for target i at event time τ; μ_z is a constant treatment effect; $c_{\tau i}$ is an unobserved target control effect; and $\eta_{\tau i}$ represents a target specific error term.

The control effect ($c_{\tau i}$) is measured with error using the country (j) specific industry index. This measure is defined as:

$$\mathrm{c}_{\tau \mathrm{j}} = c_{\tau i} + \varepsilon_{\tau j} \tag{3}$$

It is assumed that $\eta_{\tau i}$ and $\varepsilon_{\tau j}$ are mutually and cross-sectionally independent, but could be correlated over time. Then, by subtracting (3) from (2) I obtain:

$$r_{\tau i} - \mathrm{c}_{\tau \mathrm{j}} = \mu_z + \eta_{\tau i} - \varepsilon_{\tau \mathrm{j}} = \widehat{\mu}_{\tau i} \tag{4}$$

With this expression I can compute the pre-acquisition ($\widehat{\mu}_{bi}$) and post-acquisition ($\widehat{\mu}_{ai}$) relative performance measures by averaging all $\widehat{\mu}_{\tau i}$ in each period. These measures will proxy for the treatment effect μ_z with an error that is independent across observations. Using the sample distributions of $\widehat{\mu}_{bi}$ and $\widehat{\mu}_{ai}$, I test for changes in the target's relative performance (ρ) after an acquisition. By subtracting $\widehat{\mu}_{bi}$ from $\widehat{\mu}_{ai}$, ρ plus an error term (ν_i) are obtained:

$$\widehat{\mu}_{ai} - \widehat{\mu}_{bi} = \rho + \nu_i = \widehat{\rho}_i \tag{5}$$

The Sign Test and $\widehat{\rho}_i$ are used to examine the null hypothesis that the number of positive and negative relative differences are equal.[8] In other words, this method tests if

[8] The Sign Test is used instead of the t-test because the sample distributions of the relative (differenced

cross-border acquisitions had an effect on the acquired banks' performance. The only requirement for the Sign Test is that each ν_i has to come from a continuous median zero distribution.

Bank performance is measured using three accounting ratios: Return on Average Assets (*ROA*), Return on Average Equity (*ROE*) and the *Cost to Income Ratio*.[9] In addition, I analyze the post-acquisition change in four revenue and cost components: *Net Interest Margin*, *Non-Interest Income*, *Overhead* and *Loan Loss Provision*.[10]

An additional test divides the sample between targets located in emerging and developed economies. Following Barth *et al*. (2001) a bank is defined as being located in a developed country, if GDP *per capita* in the host-country is above 10,000 dollars (1995 U.S. dollars). Then, performance and other income indicators are compared using the Sign Test, Wilcoxon Test and the Median Test.

3.3. Performance, Economic Integration and Information Costs

The third set of tests deal with the effect of economic integration and information costs on the target's performance after a cross-border acquisition takes place. Buch and DeLong (2004) find that information costs and regulation decrease the amount of cross-border M&A activity.[11] The following empirical specification includes these factors to measure their effect on post-acquisition bank profitability:

$$y_{ijt} = \alpha_0 + \alpha_1 Yr0 + \alpha_2 Yr12 + \alpha_1 Yr3^+ + X_{jh}\beta' + Z_{jt}\gamma' + \upsilon_i + \eta_j + \varepsilon_{ijt} \qquad (6)$$

---

with respect to the country index) accounting ratios are skewed. This would make the use of parametric techniques inappropriate. See Section 5.

[9] The *Cost to Income Ratio* is defined as *Overhead* costs divided by *Net Interest Revenue* and Non-interest Income.

[10] These variables are all divided by *Average Assets*. This measure is calculated by averaging *Assets* using *t* and *t-1* information.

[11] Berger *et al*. (2004) use similar variables to analyze exports and imports of financial Foreign Direct Investment (FDI) across countries.

where y_{ijt} is the performance proxy for year t, country j, and deal i. This variable is a transformation of the original balance sheet ratios into percentile ranks in the distribution of all non-acquired banks by country.[12] This method makes it possible to control for changes in the distribution of the relevant variables over time, as well as comparing the target banks to their relevant peer group. *Yr0*, *Yr12* and *Yr3*$^+$ are indicator variables equal to 1 for event year 0, 1 and 2, and 3 or more respectively; X_{jh} is a vector of bilateral variables representing information costs and the level of integration between the host country j and the home country h; Z_{jt} is a vector of macroeconomic aggregates and bank competition variables; η_j and υ_i are host-country and target fixed effects, respectively.

As discussed by Berger and DeYoung (2001), there are diseconomies in managing subsidiaries that are located at longer distance relative to their parent's bank location. The same argument applies to other dimensions of distance like the difference in language and legal systems across countries. Vector X controls for these factors as it includes a dummy indicating if the country of the acquirer and target share the same principal language (*Same Language*); another indicator variable equals one if both countries have similar legal systems (*Same Legal*).[13] *Log distance* measures the geographical distance between the host country and home country of the acquirer; *Same Region* is a dummy variable equaling one if the target and acquirer are located in the same region.[14] In addition, following Berger *et al*. (2004) I include an index of comparative size (*Similar GDP*) and another index measuring comparative economic development (*Similar GDP PC*) between the home and host countries.[15] These indices range from 0 to 1, with a value of 1 indicating that both countries have the same size or the same GDP *per capita*. These set of variables will measure the effect of economic integration and information cost on the target bank's performance.

[12] Berger (1998) and Focarelli *et al.* (2002) use the same transformation.

[13] There are five legal origin categories: British, French, Socialist, German and Scandinavian.

[14] See Appendix 1 for a definition of these regions by country.

[15] Similar GDP and Similar GDP PC are equal to $1-\left[abs\left(X_j - X_h\right)\right]/\max\left(X_j, X_h\right)$, where X is defined as GDP in the former case and GDP *per capita* in the latter.

4. Data Description

To estimate the models defined in the previous section, I construct a sample of banks involved in cross-border deals between 1994 and 2003. For this purpose, two databases are matched: the first one includes bank financial data and the second has information on cross-border M&As. Data on banks' financial statements is collected from the Bankscope database maintained by Bureau van Dijk. This dataset contains annual statements for listed and unlisted banks in 179 countries starting at the beginning of the nineties. For M&A information, I use the Zephyr database from Bureau van Dijk, the SDC Platinum database from Thompson Financial Securities Data, and individual bank web pages.

In addition to bank information, data at the country level is also included in the estimations. Macroeconomic and financial aggregates are from the World Development Indicators (WDI) database published by the World Bank. The Banking Freedom index is constructed by the Heritage Foundations.[16] Institutional variables are taken from La Porta *et al.* (2002), and bilateral data were compiled by Rose and Spiegel (2004).

The next two sub-sections describe the sample selection process for banks included in the estimations described in sub-sections 3.1 and 3.2. In addition, the last sub-section outlines the construction of the control indices used in the performance estimations.

4.1 Sample Selection

Two data samples were constructed to estimate the regressions described in the previous section. The first one includes all financial institutions classified as Commercial Banks in Bankscope between 1994 and 2004 (3564).[17] Table 1 shows the distribution of banks across countries. A large percentage of the sample is represented by financial institutions

[16] The Banking Freedom Index was renamed the Finance Freedom Index by the Heritage Foundation in 2007. It has values between 0 and 100. Countries with higher values for this index have less stringent financial regulations.

[17] This paper focuses on Commercial Banks due to their central role in retail banking in emerging economies. In addition, some Bank Holding Companies are included due to their similarities to Commercial Banks, especially in countries different from the U.S. I use unconsolidated financial statements when available (codes U1 and U2 in Bankscope).

from the United States (25.3%), Germany (5.1%) and France (4.9%). Amongst emerging economies, Brazil (2.6%), Argentina (1.9%) and Panama (1.7%) have the largest shares.[18] The second sample is limited to a group of banks acquired in cross-border transactions.

To construct the first sample, the Bankscope dataset is matched to an M&A database, which is comprised of information for all cross-border acquisitions between 1994 and 2003.[19] This paper requires two conditions for a deal to be defined as a cross-border acquisition: first, the transaction has to give the acquiring bank a majority stake (more than 50%) in the target bank, provided that it previously held either no shares or a minority stockholding in the target. Additionally, the headquarters of the target bank has to be located in a country different from the home-country of the ultimate parent of the acquirer. The result is 328 deals matched to Bankscope.

The next step is to exclude all bank-year observations that are defined as outliers in terms of their income and balance sheet components.[20] This restriction reduces the number of deals to 220 as shown in Table 1. One third of the deals involve targets in the United States, France, Germany, Brazil, Argentina and Poland. Panel A in Table 2 shows that 174 of these targets were acquired by Western European institutions. The preferred destinations of these acquirers are Western and Eastern European countries (56 and 55, respectively), closely followed by Latin American (40) targets.

Table 3 displays summary statistics for this sample. Acquired and non-acquired banks are similar in terms of their level of equity as shown in Panels A and B, but the median size, defined as Real Assets, is larger for the former group. The three performance measures for non-acquired banks, *ROA*, *ROE* and the *Cost to Income Ratio*, have larger medians in the first two cases and lower in the last case, relative to the target

[18] Panama is an international financial center.

[19] Deals where the same target is acquired more than once are excluded.

[20] Bank-year observations are excluded if *Equity* to *Total Assets*, *Non-interest Income* or *Net Loans to Total Assets* are less than 0. I also exclude observations with *Net Interest Margins* below -2.5 or above 28; *ROA* less than -10 or more than 12; *ROE* less than -100; *Cost to Income Ratios* below 0 or above 244; *Non-interest Expenses to Average Assets* above 100.

banks. These statistics show that the median acquired bank performed less efficiently than its non-acquired counterpart during this sample period.

For the performance estimations described in Section 3.2., the sample is restricted to deals with at least two years of information before the cross-border acquisition and two years after. This creates a sample of 102 deals shown in the last two columns of Table 1. A significant share of targets is located in Germany (7.8%), Belgium (5.9%), Brazil (5.9%), Poland (6.9%), and the United States (5.9%). The share of Argentinean (1%) banks in this sample decreases relative to the full set of deals in this country, due to missing and outlier observations attributed to the banking crises in 2001. Panel B in Table 2 shows that most of the acquirers are based in Western European countries (84). These financial institutions are mostly involved in deals within the region (33) or in Eastern European (25) and Latin American (17) countries.

Figure 1 shows the number of all matched deals by year and those used in the performance estimations. Most of the deals are clustered around the last years of the nineties. Data restrictions for the performance estimations reduce the sample of deals considerably.

To estimate the regressions in Section 3.3., the restriction of information for two years before and two years after the deal are relaxed to one year before and one year after. This increases the sample to 132 cross-border deals for the period between 1994 and 2003.

4.2 Control Indices

As it was described in Section 3.2., to calculate the change in performance before and after a cross-border acquisition, I have to control for overall changes in banking activity at the country level. This study uses the methodology from Cornett and Tehranian (1992) and Linder and Crane (1992), and calculates banking industry indices for each country in the sample.

The selection of banks included in these indices, starts with the sample of non-acquired banks described in the previous sub-section. First, countries with less than five banks wit non-missing information in any year between 1994 and 2004 are excluded. Then, with this sample of banks, averages for the relevant performance and income statement variables are computed. These indices by country and variable are used as the counterfactual to the target banks' profitability measures.

In Section 3.3., y_{ijt} was defined as a percentile rank transformation of the performance ratios. The peer group used to calculate these ranks is the same sample of banks used to compute the industry indices by country.

5. Results

5.1. Determinants of Cross-Border Acquisitions

Table 4 shows the results of the probit estimation described in equation (1). Columns (1) through (3) include bank, country and banking market characteristics as regressors. These columns differ in the performance proxy used in the estimations. The coefficients for *ROA* and *ROE* are negative, and positive and significant for the *Cost to Income Ratio* at the 1% level. This suggests that there is a higher probability for *ex ante* poorly performing banks of being acquired in a cross-border deal. In addition, larger banks are more likely to be targets, especially if they are located in smaller countries. This is supported by the coefficients on *Log Assets* and *Log GDP*, respectively. Finally, *Concentration* has a positive and significant coefficient, with a similar level across the three columns.

The results on the performance variables could be explained as in Vander Vennet (2002) by efficiency motivations. MNBs are more likely to acquire *ex ante* poor performers with above average size in small countries with concentrated banking sectors. Better technology, geographical diversification and management skills are factors that may induce MNBs to acquire targets of considerable importance in local market where they could exert some market power and turn around the profitability ratios. The concentration result differs from the evidence found in Focarelli and Pozzolo (2005), who find that this variable has a negative effect on cross-border bank entry using a sample of OECD countries.

Columns (3) through (6) include three additional proxies for financial development. Missing observations reduces de number of countries and deals covered from 80 to 34 and from 214 to 125, respectively. The coefficients on performance is still significant, and with the same sign as in previous estimations. The coefficient on *Market Cap. to GDP* enters with a negative and significant sign in the regressions. A more developed stock market competes with the banking sector in the allocation of resources. This reduces market power and makes entry less attractive for international banks.[21]

In Table 5 the model described in Section 3.1. is estimated separately for acquisitions in emerging and developed economies. Columns (1) through (3) show the results for the former group. As in Table 4, the coefficients for the three performance proxies, bank size, and concentration are significant. In addition, the *Banking Freedom Index* enters with a positive coefficient that is significant in the estimations including *ROA* and *ROE*. These results suggest that MNBs are attracted to poor performing large banks in concentrated banking markets with less stringent regulatory environments. Columns (4) through (6) display the same estimations restricting the sample to developed economies. In this case, performance and concentration have significant coefficients. As opposed to emerging countries' estimations, *Log GDP per capita* has a negative and significant coefficient. This signals that acquisitions primarily take place in smaller countries within this group.

5.2. Performance Effect

This section displays the results for the difference-in-difference estimations described in Section 3.2. Tables 6 through 8 provide distributional characteristics on the acquired

---

[21] For a discussion on market-based and bank-based economies see Demirgüç-Kunt and Levine (2001).

banks (*Targets*), control country-indices (*Industry*) and on the differences between these two measures (*Targ-Ind*). The columns headings in Tables 7 and 8 indicate pre-acquisition (Before), acquisition-year (Yr0), post-acquisition (After) and changes (Change) in the performance and income statement items of target banks. The Sign Test statistically evaluates the null hypothesis of a median equal to zero for *Targ-Ind* in each one of this event stages.

Table 6 shows summary statistics for the sample of 102 deals in the two pre-acquisition years and compares them to the country-industry indices. Targets in this sample are smaller than controls as measured by median real assets, and have a lower *Equity to Total Assets* ratio. Only the latter difference is significant (at the 1% level) as shown by the Sign Test. In terms of the level of net loans in the balance sheet, the null hypothesis of a zero median for the differences in ratios between target and industry indices can not be rejected.

Table 7 compares the three performance proxies, *ROA*, *ROE* and *Cost to Income Ratio*, for targets and controls before and after the acquisitions. In particular, the null hypothesis of no changes in performance is evaluated by testing the *Targ-Ind* median in the *Change* column.[22] Although the *Return on Assets* and *Return on Equity* are lower for acquired banks after a cross-border deal, I can not reject the null hypothesis of a zero median relative change. In contrast, the median *Cost to Income Ratio* is 8.07 percentage points higher in the post-acquisition period for targets while the industry index decreases by 0.15. The median adjusted change in the *Cost to Income Ratio* is 9.1 percentage points higher, and the Sign Test rejects the null hypothesis of an equal share in positive and negative values for this measure. In total, 64% of targets experience an increase in their costs relative to interest and non-interest income.

Table 8 reports the main earning components in the banks' income statement. Excluding *Overhead* costs and *Non- Interest Income*, the targets' have similar indicators

---

[22] Estimations using matched pair controls instead of industry indices yield similar results.

relative to controls in the pre-acquisition period. After the deal takes place, *Net Interest Margins* are lower for targets, but the median net change is not significantly different from zero. These results are consistent with more competition in the local banking sector after MNB acquisitions, or a reduction in prices and fees implemented to gain market share.[23]

The items representing bank costs, like median *Overhead* expenditures, have a slight increase for targets in the post-acquisition period, but its median relative change is not different from zero. These findings show that in the short run there are few gains in terms of cost efficiency for this sample of cross-border deals. In contrast, the result on *Loan Loss Provisions* shows that there is a significant decline in this accounting measure for the target banks. The fraction of negative net changes is 36%, which in turn implies that the median is significantly different from zero. This is caused by a decrease in lending in the post-acquisition period.

These tests confirm the findings in Vander Vennet (2002) for a sample of European M&As, in which there is no positive performance effect in the short term after a cross-border acquisition. Profitability is affected by a reduction in interest income, and by a lack of cost-efficiency gains. This pattern is also found in Chamberlain (1998) for U.S. mergers during the eighties, but it contrasts with the positive performance results described in Cornett *et al*. (2005) for U.S. banking M&As in the nineties.

Table 9 divides the sample between targets located in developed and emerging economies. Column (1) shows that the number of deals is evenly divided across these two groups. The three performance measures deteriorate in the post-acquisition period, but only the change in the *Cost to Income Ratio* is significant. The proxies for revenues decrease for developed countries, but these figures are not significantly different from the median observed for target banks located in emerging countries. In contrast, the Median

[23] Bayraktar and Wang (2004) show that there is a decrease in *Net Interest Margins*, *Non-interest Income* and profitability as foreign banks increase their share in the local banking sector. This is true for countries that liberalized the stock market first. See also Demirgüç-Kunt and Huizinga (1999) for cross-country evidence on net interest margins and profitability.

test shows that changes in *Overhead* costs are significantly different at the 11% level amongst the targets in the two sets of countries. For emerging economies there is a median relative increase of 0.59, while for targets in developed countries this ratio decreases by 0.10. This result shows that cost efficiencies are harder to realize in emerging countries in the short run. Finally, like in the full sample case, there is a decrease in *Loan Loss Provisions* without differences based on the host country's level of development. This is explained by a reduction in the loan portfolio for targets located in emerging economies, but this is not observed in the data for banks in developed countries. The latter effect could be attributed to earnings management (Scholes *et al*., 1990) or the use of better techniques in loan monitoring and screening.

To summarize, dividing the target banks by the host country's level of development provides the same aggregate results. The only noticeable difference is a change in *Overhead* expenditures. It appears that cost reductions are more difficult to implement in emerging markets.

5.3. Performance, Economic Integration and Information Costs

Tables 10 and 11 show the results for the regression outlined in equation (6). This section tests the presence of diseconomies associated with operating subsidiaries after being acquired in a cross-border deal. The dependent variable is measured in terms of percentile ranks relative to the relevant peer group defined in Section 4.2. An *x* percentile rank indicates that the target bank ranks above *x* percent of the peer group banks in terms of performance, revenue or income for a particular year. The sample used in these estimations includes deals with at least one pre-acquisition and one post-acquisition year of data.

In Table 10A the dependent variables are the *ROA*, *ROE* and the *Cost to Income Ratio*. Three sets of variables are included as regressors: event dummies for the year of the deal (*Yr0*), one and two years after (*Yr12*) and three or more years after ($Yr3^+$); country pair characteristics reflecting similarities between the host and home countries;

and host country market and macroeconomic characteristics. The coefficients on the event time indicator variables are negative in almost all cases in the three columns. These results confirm the findings in the last sub-section, namely, that there is a negative effect on the target's performance in the short run triggered by a cross-border acquisition.

In Table 10B the deals are divided by the host country's level of development. Columns (1) through (3) estimate the model using deals where the acquired bank is located in a developed economy. In contrast to the estimations including all deals, performance increases in the post-acquisition period for this sub-sample of targets. This result is significant for the *ROE* after the second post-acquisition year. As expected, the coefficients for *Same Language* and *Similar GDP* are positive. Alternatively, the coefficients for *Same Legal* and *Similar GDP PC* are negative and significant. This result implies that differences in legal systems and GDP *per capita* do not act as barriers when managing subsidiaries abroad.

The results for emerging economies shown in Columns (4) through (6) are in line with the aggregate estimations displayed in Table 10A. The coefficients on the event time indicators are all negative but only significant in the *Cost to Income Ratio* estimation. Country pair characteristics do not enter the regressions with significant coefficients although language, legal and comparative economic size have the right signs in most of the cases.

Lastly, Tables 11A and 11B use the same estimating equation to determine the factors that influence revenue and cost items for targets. For all estimations but *Non-interest Income* and *Net Interest Margins* in developed countries, the coefficient on the time-event dummies are negative. Acquired banks have higher *Net Interest Margins* if the host and home countries are similar in terms of GDP *per capita*, especially when the host is located in an emerging country (Column (4), Table 11B). *Overhead* costs are lower in the post-acquisitions period if the countries share the same language or are located in the same region. The opposite result is true if they share the same legal origin. These results are influenced by deals within the EU. In emerging economies bank concentration reduces the incentive for target to decrease these costs as shown in Table 11B, Column (5). Finally, the results on *Non-interest Income* are very different for emerging and developed economies. For the former group, having the same language increases the percentile rank of targets after an acquisition, while the opposite applies to the latter set of countries.

These results show significant information costs associated with the language used in the host and home countries, especially when measuring *Overhead* costs and *Non-interest Income* after an acquisition. On the other hand, difference in legal origin and geographical distance do not affect post-acquisition performance.

6. Conclusions

This paper uses a unique database on cross-border acquisitions to examine the determinants of international takeovers and their impact on the performance of target banks. The results show that banks are more likely to get acquired in a cross-border deal if they are large, bad performers, when the host economy is growing and when the banking sector concentration is high. Nevertheless, post-acquisitions performance does not improve in the first two years after the acquisition. This is caused by a decrease in *Net Interest Margins* and an increase in *Overhead* costs in targets located in emerging economies. The absence of net performance gains is linked to diseconomies in managing international subsidiaries, in particular differences in language between the host and home-country.

The effect of M&As has been studied in developed economies or using cross-border deals in Europe. Evidence from emerging economies is mostly limited to acquisitions in Eastern European countries or to static analysis of efficiency. The current paper shows dynamic evidence on performance and expands the sample of transactions to 220 in 58 different countries. Moreover, using the same database, it analyzes both the determinants of cross-border deals, as well as its impact on post-acquisition efficiency.

Foreign bank entry liberalization has been recommended as a policy designed to increase stability in the domestic banking sector and prevent financial crises. In addition, foreign bank presence has been linked to growth and better allocation of resources in emerging markets. The results shown in this paper do not challenge these findings, but indicate that bank performance benefits are not observed in the short run.

There are three extensions to further develop the questions outlined in this paper. The addition of new data points in the last three years to the database should help increase the number of deals with sufficient information to be included in the estimations. This provides a larger dataset and a longer post-acquisition period to test the changes in performance. Another extension would be to create a database of stock prices for target banks located in emerging economies to conduct event studies on the effect of cross-border acquisitions. These results would complement the findings in the current paper. Finally, it would be important to produce a series of case-studies for targets in emerging economies to understand why foreign bank acquisitions have a limited effect on bank performance in the short run.

References

Amihud, Yakov, Gayle L. DeLong, and Anthony Saunders. 2003. The Effects of Cross-Border Bank Mergers on Bank Risk and Value. *Journal of International Money and Finance*, 21, 857-877.

Barth, James R., Gerard Caprio, Jr., and Ross Levine. 2000. Banking systems around the Globe: Do Regulation and Ownership affect performance and stability? *World Bank Working Paper No. 2325*.

Bayraktar, Nihal, and Yan Wang. 2004. Foreign Bank Entry, Performance of Domestic Banks, and Sequence of Financial Liberalization. *World Bank Policy Research Working Paper No. 3416*.

Beitel, Patrick, and Dirk Schiereck. 2001. Value Creation at the Ongoing Consolidation of the European Banking Markets. *IMA Working Paper No. 05/01*.

Berger, Allen N. 1998. The Efficiency Effects of Bank Mergers and Acquisition: A Preliminary Look at the 1990s Data. *In Yakov Amihud and Geoffrey Miller eds. Bank Mergers and Acquisitions, Kluwer Academic Publishers, Boston*, 79-111.

Berger, Allen N., Claudia M. Buch, Gayle L. DeLong, and Robert DeYoung. 2004. Exporting Financial Institutions Management via Foreign Direct Investment Mergers and Acquisitions. *Journal of International Money and Finance*, 22(3), 333-366.

Berger, Allen N., and Robert DeYoung. 2001. The Effects of Geographic Expansion on Bank Efficiency. *Journal of Financial Services Research*, 19, 163-184.

Berger, Allen N., Robert DeYoung, Hesna Genay, and Gregory F. Udell . 2000. Globalization of Financial Institutions: Evidence from Cross-Border Banking Performance. *Brookings-Wharton Papers on Financial Services*, 23-120

Buch, Claudia M., and Gayle L. DeLong. 2004. Cross-Border Bank Mergers: What Lures the Rare Animal? *Journal of Banking and Finance***,** 28(9), 2077-2102.

Calomiris, Charles W., and Jason Karceski. 2000. Is the Bank Merger Wave of the 90s Efficient? *In Steven Kaplan ed. Mergers and Productivity, National Bureau of Economic Research, University of Chicago Press*, 93-161.

Chamberlain, Sandra L. 1998. The Effect of Bank Ownership Changes on Subsidiary-Level Earnings. *In Yakov Amihud and Geoffrey Miller eds. Bank Mergers and Acquisitions, Kluwer Academic Publishers, Boston*, 132-172.

Claessens, Stijn, Asli Demirgüç-Kunt, and Harry Huizinga. 2001. How Does Foreign Entry Affect the Domestic Banking Market? *Journal of Banking and Finance*, 25 (5), 891-911.

Clarke, George R., Robert Cull, and Maria Soledad Martinez Peria. 2001. Does Foreign Bank Penetration Reduce Access to Credit in Developing Countries? Evidence from Asking Borrowers. *Policy Research Working Paper 2716, World Bank*.

Cornett, Marcia M., and Hassan Tehranian. 1992. Changes in corporate performance associated with bank performance. *Journal of Financial Economics*, 31, 211-234.

Cornett, Marcia M., Jamie John McNutt, and Hassan Tehranian. 2005. Performance Changes Around Bank Mergers: Revenue Enhancements Versus Cost Reductions. Unpublished manuscript.

Crystal, Jennifer S., B. Gerard Dages, and Linda S. Goldberg. 2001. Does foreign ownership contribute to sounder banks? The Latin American experience. *In R. Litan, P. Masson, and M. Pomerleano eds. Open Doors: Foreign Participation in Emerging Financial Systems, Brookings Press*, 217-66.

Cybo-Ottone, Alberto, and Maurizio Murgia. 2000. Mergers and shareholder wealth in European banking. *Journal of Banking and Finance*, 24, 831-859.

Demirgüç-Kunt, Asli, and Harry Huizinga. 1999. Determinants of Commercial Bank Interest Margins and Profitability: Some International Evidence. *World Bank Economic Review*, 13(2), 379-408.

Demirgüç-Kunt, Asli, and Ross Levine. 2001. Bank-Based and Market-Based Financial

Systems: Cross-Country Comparisons. *In Asli Demirguc-Kunt and Ross Levine eds. Financial Structure and Economic Growth: A Cross-Country Comparison of Banks, Markets, and Development, MIT Press, Cambridge, MA*.

Demirgüç-Kunt, Asli, Luc Laeven, and Ross Levine. 2004. Regulations, market structure, institutions, and the cost of financial intermediation. *Proceedings, Federal Reserve Bank of Cleveland*, 593-626.

Esperanca, José P., and Mohamed A. Gulamhussen. 2001. (Re)Testing the 'follow the customer' hypothesis in multinational bank expansion. *Journal of Multinational Financial Management*, 11, 281-293.

Focarelli, Dario, and Alberto Pozzolo. 2000. The determinants of cross-border shareholding: An analysis with bank-level data from OECD countries. *Banca d'Italia Temi di Discussione del Sevizio Studi*, n. 381.

Focarelli, Dario, and Alberto Pozzolo. 2005. Where Do Banks Expand Abroad? An Empirical Analysis. *Journal of Business*, 78(6), 2435-63.

Focarelli, Dario, Fabio Panetta, and Carmelo Salleo. 2002. Why Do Banks Merge? *Journal of Money Credit and Banking*, 34(4), 1047-66.

Giannetti, Mariassunta, and Steven Ongena. 2005. Financial integration and entrepreneurial activity - evidence from foreign bank entry in emerging markets. *Working Paper Series 498, European Central Bank*.

Goldberg, Linda S. 2004. Financial-Sector FDI and Host Countries: New and Old Lessons. *NBER working paper # 10441*.

Hannan, Timothy H., and Stephen A. Rhoades. 1987. Acquisition Targets and Motives: The Case of the Banking Industry. *The Review of Economics and Statistics*, 69(1), 67-74.

La Porta, Rafael, Florencio Lopez-De-Silanes, and Andrei Shleifer. 2002. Government Ownership of Banks. *Journal of Finance*, 57(1), 265-301.

Levine, Ross. 2001. International Financial Liberalization and Economic Growth. *Review* *of International Economics*, 9(4), 684-698.

Levine, Ross. 2005. Finance and Growth: Theory and Evidence. *In Philippe Aghion and Steven Durlauf, eds. Handbook of Economic Growth*, Elsevier Science, The Netherlands.

Linder, Jane C., and Dwight B. Crane. 1992. Bank mergers: integration and profitability. *Journal of Financial Service Research*, 7, 35-55.

Micco, Alejandro, Ugo Panizza, and Monica Yañez. 2006. Bank Ownership and Performance Does Politics Matter? *P.O.L.I.S. department's Working Papers 62*.

Milbourn, Todd T., Arnoud W. A. Boot, and Anjan V. Thakor. 1999. Megamergers and expanded scope: Theories of bank size and activity diversity. *Journal of Banking and Fin ance*, 23(2-4), 195-214.

Miller, Stewart R. and Arvind Parkhe. 1998. Patterns in the Expansion of US Banks' Foreign Operations. Journal of International Business Studies, 29(2), 359-90.

Mishkin, Frederic S. 2001. Financial Policies and the Prevention of Financial Crises in Emerging Market Countries. *NBER Working Paper # W8087*.

Peek, Joe, Eric S. Rosengren, and Faith Kasirye. 1999. The poor performance of foreign bank subsidiaries: Were the problems acquired or created? *Journal of Banking and Finance*, 23(2-4), 579-604.

Piloff, Steven J., and Anthony M. Santomero. 1998. The value effects of bank mergers and acquisitions. *In Yakov Amihud and Geoffrey Miller eds. Bank Mergers and Acquisitions, Kluwer Academic Publishers, Boston*, 59-78.

Rose, Andrew K., and Mark M. Spiegel. 2004. A Gravity Model of Sovereign Lending: Trade, Default and Credit. *IMF Staff papers No. 51*, 50-63.

Scholes, Myron, G. Peter Wilson, and Mark A. Wolfson. 1990. Tax Planning, regulatory capital planning and financial reporting strategy for commercial banks. The Review of Financial Studies, 3, 625-50.

Tschoegl, Adrian E. 2004. Financial Crises and the Presence of Foreign Banks. *International Finance 0405016, Economics Working Paper Archive EconWPA*.

Vander Vennet, Rudi. 2002. Cross-border mergers in European banking and bank efficiency. *In Herrmann H. and Lipsey R. eds. Foreign direct investment in the real and financial sector of industrial countries, Springer Verlag*, 295-315.

Appendix 1: Countries and Regions

Country	***Region***	***Country***	***Region***
Albania	Eastern Europe	Republic of Korea	East Asia
Argentina	Latin America	Latvia	Eastern Europe
Australia	Oceania	Lebanon	Middle East
Austria	Western Europe	Lithuania	Eastern Europe
Barbados	Latin America	Luxembourg	Western Europe
Belarus	Eastern Europe	Macau	East Asia
Belgium	Western Europe	Macedonia (Fyrom)	Eastern Europe
Bolivia	Latin America	Malaysia	East Asia
Bosnia-Herzegovina	Eastern Europe	Mexico	Latin America
Brazil	Latin America	Mongolia	East Asia
Bulgaria	Eastern Europe	Morocco	Africa
Cameroon	Africa	Netherlands	Western Europe
Canada	US and Canada	New Zealand	Oceania
Cape Verde	Africa	Nicaragua	Latin America
Chad	Africa	Nigeria	Africa
Chile	Latin America	Norway	Western Europe
Colombia	Latin America	Pakistan	East Asia
Croatia	Eastern Europe	Panama	Latin America
Czech Republic	Eastern Europe	Paraguay	Latin America
Denmark	Western Europe	Peru	Latin America
Dominican Republic	Latin America	Philippines	East Asia
Ecuador	Latin America	Poland	Eastern Europe
Egypt	Africa	Portugal	Western Europe
El Salvador	Latin America	Romania	Eastern Europe
Estonia	Eastern Europe	Russian Federation	Eastern Europe
Finland	Western Europe	Saudi Arabia	Middle East
France	Western Europe	Slovakia	Eastern Europe
Germany	Western Europe	Slovenia	Eastern Europe
Ghana	Africa	South Africa	Africa
Greece	Western Europe	Spain	Western Europe
Guatemala	Latin America	Sweden	Western Europe
Honduras	Latin America	Switzerland	Western Europe
Hong Kong	East Asia	Thailand	East Asia
Hungary	Eastern Europe	Tunisia	Africa
India	East Asia	Turkey	Western Europe
Indonesia	East Asia	Uganda	Africa
Ireland	Western Europe	Ukraine	Eastern Europe
Israel	Middle East	United Kingdom	Western Europe
Italy	Western Europe	Uruguay	Latin America
Jamaica	Latin America	United States	US and Canada
Japan	East Asia	Venezuela	Latin America
Kenya	Africa	Western Samoa	Oceania

Table 1: Banks and Deals by Country

Deal data is from Zephyr, SDC and the banks' webpages. Bank data is from Bankscope. The deals' sample period ranges between 1994 and 2003. Bank balance sheet and income statement information covers the 1994-2004 period.

	Total Banks		*Total Deals*		*Performance Deals*	
	Banks	*Percentage*	*Deals*	*Percentage*	*Deals*	*Percentage*
Albania	5	0.1%	0	0.0%	0	0.0%
Argentina	66	1.9%	11	5.0%	1	1.0%
Australia	25	0.7%	1	0.5%	1	1.0%
Austria	47	1.3%	3	1.4%	2	2.0%
Belarus	9	0.3%	1	0.5%	0	0.0%
Belgium	35	1.0%	7	3.2%	6	5.9%
Bolivia	11	0.3%	2	0.9%	1	1.0%
Bosnia-Herzegovina	15	0.4%	2	0.9%	1	1.0%
Brazil	94	2.6%	12	5.5%	6	5.9%
Bulgaria	22	0.6%	5	2.3%	3	2.9%
Cameroon	4	0.1%	1	0.5%	0	0.0%
Canada	47	1.3%	2	0.9%	0	0.0%
Cape Verde	2	0.1%	0	0.0%	0	0.0%
Chad	3	0.1%	0	0.0%	0	0.0%
Chile	24	0.7%	4	1.8%	2	2.0%
Colombia	23	0.6%	2	0.9%	2	2.0%
Croatia	32	0.9%	4	1.8%	2	2.0%
Czech Republic	17	0.5%	7	3.2%	2	2.0%
Denmark	53	1.5%	3	1.4%	2	2.0%
Dominican Republic	24	0.7%	1	0.5%	0	0.0%
Ecuador	23	0.6%	0	0.0%	0	0.0%
Egypt	28	0.8%	4	1.8%	2	2.0%
El Salvador	7	0.2%	1	0.5%	0	0.0%
Estonia	5	0.1%	3	1.4%	0	0.0%
Finland	5	0.1%	1	0.5%	0	0.0%
France	173	4.9%	12	5.5%	6	5.9%
Germany	182	5.1%	12	5.5%	8	7.8%
Ghana	10	0.3%	1	0.5%	0	0.0%
Greece	10	0.3%	0	0.0%	0	0.0%
Guatemala	27	0.8%	0	0.0%	0	0.0%
Honduras	14	0.4%	0	0.0%	0	0.0%
Hong Kong	14	0.4%	0	0.0%	0	0.0%
Hungary	27	0.8%	4	1.8%	1	1.0%
India	58	1.6%	0	0.0%	0	0.0%
Indonesia	49	1.4%	4	1.8%	2	2.0%
Ireland	15	0.4%	0	0.0%	0	0.0%
Israel	14	0.4%	0	0.0%	0	0.0%
Italy	110	3.1%	1	0.5%	1	1.0%
Jamaica	6	0.2%	1	0.5%	0	0.0%
Japan	133	3.7%	0	0.0%	0	0.0%
Kenya	23	0.6%	0	0.0%	0	0.0%
Republic of Korea	13	0.4%	0	0.0%	0	0.0%
Latvia	19	0.5%	7	3.2%	1	1.0%
Lebanon	43	1.2%	1	0.5%	0	0.0%
Lithuania	10	0.3%	6	2.7%	0	0.0%
Luxembourg	102	2.9%	4	1.8%	2	2.0%
Macau	5	0.1%	1	0.5%	1	1.0%
Macedonia (Fyrom)	10	0.3%	2	0.9%	1	1.0%
Malaysia	26	0.7%	0	0.0%	0	0.0%
Mexico	36	1.0%	6	2.7%	3	2.9%
Mongolia	3	0.1%	0	0.0%	0	0.0%
Morocco	7	0.2%	1	0.5%	1	1.0%
Netherlands	21	0.6%	2	0.9%	2	2.0%

Table 1 (cont.): Banks and Deals by Country

Deal data is from Zephyr, SDC and the banks' webpages. Bank data is from Bankscope. The deals' sample period ranges between 1994 and 2003. Bank balance sheet and income statement information covers the 1994-2004 period.

	Total Banks		*Total Deals*		*Performance Deals*	
	Banks	*Percentage*	*Deals*	*Percentage*	*Deals*	*Percentage*
New Zealand	8	0.2%	0	0.0%	0	0.0%
Nicaragua	8	0.2%	1	0.5%	1	1.0%
Nigeria	46	1.3%	0	0.0%	0	0.0%
Norway	12	0.3%	3	1.4%	2	2.0%
Pakistan	19	0.5%	0	0.0%	1	1.0%
Panama	59	1.7%	3	1.4%	0	0.0%
Paraguay	18	0.5%	1	0.5%	0	0.0%
Peru	16	0.4%	3	1.4%	1	1.0%
Philippines	22	0.6%	1	0.5%	1	1.0%
Poland	39	1.1%	11	5.0%	7	6.9%
Portugal	21	0.6%	1	0.5%	0	0.0%
Romania	14	0.4%	4	1.8%	2	2.0%
Russian Federation	80	2.2%	0	0.0%	0	0.0%
Saudi Arabia	8	0.2%	0	0.0%	0	0.0%
Slovakia	12	0.3%	7	3.2%	4	3.9%
Slovenia	17	0.5%	3	1.4%	3	2.9%
South Africa	32	0.9%	0	0.0%	0	0.0%
Spain	74	2.1%	7	3.2%	3	2.9%
Sweden	9	0.3%	0	0.0%	0	0.0%
Switzerland	157	4.4%	8	3.6%	3	2.9%
Thailand	7	0.2%	1	0.5%	1	1.0%
Tunisia	15	0.4%	1	0.5%	1	1.0%
Turkey	10	0.3%	0	0.0%	0	0.0%
Uganda	12	0.3%	1	0.5%	0	0.0%
Ukraine	29	0.8%	0	0.0%	0	0.0%
United Kingdom	63	1.8%	2	0.9%	1	1.0%
Uruguay	31	0.9%	2	0.9%	1	1.0%
United States	900	25.3%	12	5.5%	6	5.9%
Venezuela	37	1.0%	5	2.3%	2	2.0%
Western Samoa	3	0.1%	1	0.5%	0	0.0%
Total	3564		220		102	

Table 2: Deals by Region

Deal data is from Zephyr, SDC and the banks' webpages. The deals' sample period ranges between 1994 and 2003. See Appendix 1 for a description of the countries included in each region.

Panel A: All Deals

		Acquirer								
		Latin America	*Eastern Europe*	*East Asia*	*Western Europe*	*US and Canada*	*Oceania*	*Africa*	*Middle East*	*Total*
	Latin America	7	0	0	40	7	0	0	1	55
T	*Eastern Europe*	0	8	1	55	2	0	0	0	66
a	*East Asia*	0	0	3	3	1	0	0	0	7
r	*Western Europe*	1	3	0	56	5	0	0	1	66
g	*US and Canada*	1	0	1	10	2	0	0	0	14
e	*Oceania*	0	0	0	1	0	1	0	0	2
t	*Africa*	0	0	0	9	0	0	0	0	9
	Middle East	0	0	0	0	0	0	0	1	1
	Total	9	11	5	174	17	1	0	3	220

Panel B: Performance Deals

		Acquirer								
		Latin America	*Eastern Europe*	*East Asia*	*Western Europe*	*US and Canada*	*Oceania*	*Africa*	*Middle East*	*Total*
	Latin America	0	0	0	17	2	0	0	1	20
T	*Eastern Europe*	0	1	0	25	1	0	0	0	27
a	*East Asia*	0	0	2	2	1	1	0	0	6
r	*Western Europe*	1	3	0	33	0	0	0	1	38
g	*US and Canada*	1	0	1	2	2	0	0	0	6
e	*Oceania*	0	0	0	1	0	0	0	0	1
t	*Africa*	0	0	0	4	0	0	0	0	4
	Middle East	0	0	0	0	0	0	0	0	0
	Total	2	4	3	84	6	1	0	2	102

Table 3: Summary Statistics

Bank Balance Sheet and Income Statement data is from Bankscope. The sample period is 1994 to 2004. The variable *Real Assets* is defined in terms of millions of 2000 U.S. dollars. The rest of the variables are defined in terms of percentage points.

Panel A: Acquired Banks

	Obs.	Mean	Median	Std. Dev.	Min.	Max.
Real Assets	1576	6356.5	1075.2	15617.6	5.3	150291.8
Equity to Avg. Assets	1578	12.22	9.28	10.8	1.0	95.2
ROA	1578	1.02	0.84	2.0	-8.8	11.8
ROE	1577	9.09	9.34	18.5	-96.9	135.4
Cost to Income Ratio	1578	71.80	67.55	27.6	3.4	232.4
Net Loans to Avg. Assets	1577	48.37	49.56	20.7	0.0	98.8
Net Interest Margins	1578	4.82	3.80	3.9	-1.8	27.8
Non-Interest Inc. to Avg. Ass.	1578	2.73	1.86	3.3	0.0	54.6

Panel B: Non-Acquired Banks

	Obs.	Mean	Median	Std. Dev.	Min.	Max.
Real Assets	37016	10375.6	756.6	51370.6	0.0	1352996.0
Equity to Avg. Assets	37747	12.74	8.86	13.6	0.0	100.0
ROA	37760	1.21	0.97	1.8	-10.0	12.0
ROE	37707	11.64	10.65	20.0	-100.0	928.0
Cost to Income Ratio	37760	63.73	62.38	24.4	0.0	244.0
Net Loans to Avg. Assets	37398	51.17	54.80	22.9	0.0	100.0
Net Interest Margins	37760	4.29	3.61	3.5	-2.3	28.0
Non-Interest Inc. to Avg. Ass.	37760	2.54	1.33	4.2	0.0	92.5

Table 4: Determinants of Cross-Border Acquisitions

The empirical model in equation (1) has been estimated using a probit specification. The dependent variable equals one if a bank is acquired by a foreign institution in year *t* and zero otherwise. The model is explained in Section 3.1.; the sample is defined in Section 4.1. The model is estimated for the 1994-2004 period. Columns (1) through (6) differ in the performance proxy included. In Columns (1) and (3) profitability is measured by the Return on Average Assets (*ROA*). Columns (2) and (5) include the Return on Average Equity (*ROE*). In Columns (3) and (6) performance is defined as the *Cost to Income Ratio*. Columns (4) to (6) include Financial Development proxies in addition to the variables included in the first three columns.

	ROA	***ROE***	***Cost to Income Ratio***	***ROA***	***ROE***	***Cost to Income Ratio***
	(1)	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***
Performance	-0.0463**	-0.0060***	0.0056***	-0.0619***	-0.0070***	0.0059***
	[0.0184]	[0.0020]	[0.0011]	[0.0186]	[0.0017]	[0.0014]
Log Assets	0.0630***	0.0638***	0.0766***	0.0418	0.0407	0.0544**
	[0.0177]	[0.0179]	[0.0182]	[0.0264]	[0.0268]	[0.0264]
Equity to Assets	0.0019	0.0001	0.0019	-0.001	-0.0026	-0.0015
	[0.0024]	[0.0025]	[0.0026]	[0.0033]	[0.0032]	[0.0034]
Net Loans to Assets	0	-0.0001	0.001	0.0002	0	0.0013
	[0.0016]	[0.0016]	[0.0014]	[0.0020]	[0.0020]	[0.0017]
Non-Interest Income to Assets	0.0047	0.0038	0.0015	0.0166***	0.0134**	0.0114*
	[0.0051]	[0.0047]	[0.0050]	[0.0060]	[0.0054]	[0.0063]
Log GDP	-0.1030***	-0.1055***	-0.1103***	-0.0826	-0.0816	-0.0937*
	[0.0200]	[0.0199]	[0.0187]	[0.0552]	[0.0562]	[0.0536]
GDP Per Capita Growth	0.0005	0.0009	0.0006	-0.0023	-0.0022	-0.0031
	[0.0069]	[0.0073]	[0.0077]	[0.0034]	[0.0034]	[0.0032]
Inflation	-0.0006	-0.0006	-0.0005	-0.0088	-0.009	-0.0103*
	[0.0014]	[0.0014]	[0.0017]	[0.0061]	[0.0061]	[0.0056]
Banking Freedom Index	-0.0024	-0.0022	-0.002	0.0022	0.0023	0.0024
	[0.0023]	[0.0023]	[0.0023]	[0.0033]	[0.0033]	[0.0033]
Concentration	0.4811**	0.4717**	0.4467**	0.3052	0.3049	0.2673
	[0.1970]	[0.1981]	[0.1916]	[0.2309]	[0.2355]	[0.2382]
Market Cap. to GDP				-0.0016**	-0.0016**	-0.0015**
				[0.0006]	[0.0006]	[0.0006]
Priv. Bond Mkt. Cap. to GDP				-0.1918	-0.1949	-0.1681
				[0.1512]	[0.1512]	[0.1333]
Pub. Bond Mkt. Cap. to GDP				-0.31	-0.324	-0.3256
				[0.3192]	[0.3253]	[0.3108]
Observations	26235	26206	26235	17348	17336	17348
Countries	80	80	80	34	34	34
LR chi2	80.48	94.75	143.3	132.8	141.6	155.2
Pseudo R^2	0.049	0.0519	0.0606	0.0621	0.0645	0.0742

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Determinants of Cross-Border Acquisitions - Emerging vs. Developed Economies

The empirical model in equation (1) has been estimated using a probit specification. The dependent variable equals one if a bank is acquired by a foreign institution in year *t* and zero otherwise. The model is explained in Section 3.1.; the sample is defined in Section 4.1. The model is estimated for the 1994-2004 period. Columns (1) through (6) differ in the performance proxy included. In Columns (1) and (3) profitability is measured by the Return on Average Assets (*ROA*). Columns (2) and (5) include the Return on Average Equity (*ROE*). In Columns (3) and (6) performance is defined as the *Cost to Income Ratio*. Columns (4) to (6) include Financial Development proxies in addition to the variables included in the first three columns. A country is defined as an Emerging Economy if its real GDP *per capita* is below US$10,000 in 2000 prices. Developed Economies are defined as the complement to this group.

	Emerging Economies			*Developed Economies*		
	ROA	*ROE*	*Cost to Income Ratio*	*ROA*	*ROE*	*Cost to Income Ratio*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Performance	-0.0435**	-0.0054**	0.0057***	-0.0503	-0.0062**	0.0046***
	[0.0212]	[0.0023]	[0.0014]	[0.0374]	[0.0026]	[0.0014]
Log Assets	0.1259***	0.1260***	0.1431***	0.0102	0.0106	0.0192
	[0.0264]	[0.0267]	[0.0273]	[0.0278]	[0.0287]	[0.0263]
Equity to Assets	0.0027	0.0009	0.0031	0.0012	-0.0005	0.0011
	[0.0027]	[0.0027]	[0.0027]	[0.0043]	[0.0043]	[0.0045]
Net Loans to Assets	-0.0017	-0.0019	-0.0004	0	-0.0001	0.0007
	[0.0021]	[0.0021]	[0.0019]	[0.0022]	[0.0023]	[0.0019]
Non-Interest Inc. to Assets	-0.0002	-0.001	-0.0016	0.0095	0.0072	0.0033
	[0.0081]	[0.0082]	[0.0082]	[0.0085]	[0.0057]	[0.0061]
Log GDP	-0.0625	-0.0663	-0.0755*	-0.0535***	-0.0556***	-0.0633***
	[0.0438]	[0.0437]	[0.0407]	[0.0164]	[0.0169]	[0.0151]
GDP Per Capita Growth	0.0145	0.0152	0.0157	-0.0039	-0.0038	-0.0044
	[0.0134]	[0.0133]	[0.0130]	[0.0038]	[0.0039]	[0.0039]
Inflation	-0.0013	-0.0012	-0.0015	0.0031	0.0068	0
	[0.0032]	[0.0031]	[0.0038]	[0.0386]	[0.0388]	[0.0386]
Banking Freedom Index	0.0050*	0.0048*	0.0046	-0.0045*	-0.004	-0.0041
	[0.0029]	[0.0029]	[0.0029]	[0.0025]	[0.0026]	[0.0025]
Concentration	0.8784***	0.8518**	0.8648***	0.5018***	0.4977***	0.4486***
	[0.3337]	[0.3339]	[0.3347]	[0.1266]	[0.1290]	[0.1325]
Observations	9012	8986	9012	17223	17220	17223
Countries	56	56	56	25	25	25
LR chi2	64.15	68.15	90.04	143.6	148.2	155.2
Pseudo R2	0.0491	0.0517	0.0616	0.033	0.0344	0.0401

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Ex-Ante Target and Bank Indices Characteristics

Bank Balance Sheet and Income Statement data is from Bankscope. The sample period is between 1994 and 2003. The variable *Real Assets* is defined in terms of millions of 2000 U.S. dollars. The rest of the variables are defined in terms of percentage points. Frac>0 is the fraction of deals with positive *Targ-Ind* values. The Sign Test statistically evaluates the null hypothesis of a median equal to zero for *Targ-Ind* in each event stage. t(mean) tests the null hypothesis that mean *Targ-Ind* is equal to zero.

		Total Assets (Millions 1995 $US)	*Equity to Total Assets*	*Net Loans to Average Assets*	*Net Loans to Customer Funds*
Targets	Mean	7956.9	11.33	48.17	62.53
	Std. Dev.	20232.2	8.86	21.52	31.85
	Median	1121.9	8.86	50.11	62.42
Industry	Mean	5050.7	13.40	47.25	65.69
	Std. Dev.	5232.5	5.10	12.99	18.48
	Median	2785.4	11.83	47.61	64.42
Targ-Ind	Mean	2906.2	-2.08	0.93	-3.17
	Std. Dev.	19630.9	8.18	18.80	29.99
	Q1	-4147.0	-6.80	-11.91	-26.79
	Median	-450.5	-2.98	2.45	-2.69
	Q3	2873.6	0.10	13.13	12.69
	Frac>0	0.44	0.25	0.56	0.44
	Sign Test[+]	0.28	0.00	0.28	0.28
	t(mean)	1.50	-2.57	0.50	-1.07

[+] P-Value

Table 7: Difference-in-Difference Analysis - Performance

The variables of interest are *Return on Assets*, *Return on Equity* and the *Cost to Income Ratio*. The difference-in-difference methodology is explained in Section 3.2.; variables are defined in Section 4. The sample includes 102 deals with at least to pre and post-acquisition years. Rows display summary statistics for acquired banks (*Targets*), control country-indices (Industry) and differences between these two measures (*Targ-Ind*). The column headings indicate pre-acquisition (*Before*), acquisition-year (*Yr0*), post-acquisition (*After*) and changes (*Change*) in the dependent variable. Construction of the control-country indices is explained in Section 4.2. Frac>0 is the fraction of deals with positive *Targ-Ind* values. The Sign Test statistically evaluates the null hypothesis of a median equal to zero for *Targ-Ind* in each event stage. t(mean) tests the null hypothesis that mean *Targ-Ind* is equal to zero.

		Return on Assets (%)				Return on Equity (%)				Cost to Income Ratio (%)			
		Before	Yr0	After	Change	Before	Yr0	After	Change	Before	Yr0	After	Change
Targets	Mean	1.03	0.48	0.73	-0.31	6.67	3.44	6.12	-0.54	67.87	76.51	77.53	9.65
	Std. Dev.	1.71	2.35	2.10	2.26	22.33	24.31	21.24	30.85	24.11	36.33	30.26	30.56
	Median	0.99	0.61	0.67	-0.35	9.15	8.52	7.91	-1.53	63.54	68.74	71.63	8.07
Industry	Mean	1.12	1.07	0.99	-0.13	8.96	9.38	9.38	0.43	66.52	65.83	67.15	0.64
	Std. Dev.	0.83	0.95	0.79	0.78	8.94	17.51	9.43	10.47	9.51	9.27	8.76	9.71
	Median	1.05	1.02	0.95	-0.03	8.62	9.81	9.97	0.09	67.39	65.20	67.60	-0.15
Targ-Ind	Mean	-0.09	-0.59	-0.26	-0.17	-2.29	-5.95	-3.26	-0.97	1.36	10.67	10.37	9.02
	Std. Dev.	1.51	2.29	1.86	2.08	21.87	23.21	19.35	28.29	24.08	35.23	29.08	29.73
	Median	-0.10	-0.26	-0.18	-0.11	0.57	-1.47	-2.07	-1.18	-2.35	3.35	4.27	9.08
	Frac>0	0.43	0.52	0.44	0.46	0.53	0.54	0.46	0.44	0.44	0.74	0.59	0.64
	Sign Test+	0.20	0.01	0.28	0.49	0.62	0.03	0.49	0.28	0.28	0.26	0.09	0.01
	t(mean)	-0.60	-2.52	-1.43	-0.84	-1.06	-2.90	-1.70	-0.35	0.57	3.20	3.60	3.06

+ P-Value

Table 8: Difference-in-Difference Analysis – Income Statement Components

The variables of interest are *Net Interest Margin to Average Assets*, *Non-Interest Income to Average Assets*, *Overhead costs to Average Assets* and *Loan Loss Provisions to Average Assets*. The difference-in-difference methodology is explained in Section 3.2.; variables are defined in Section 4. The sample includes 102 deals with at least to pre and post-acquisition years. Rows display summary statistics for acquired banks (*Targets*), control country-indices (Industry) and differences between these two measures (*Targ-Ind*). The column headings indicate pre-acquisition (*Before*), acquisition-year (*Yr0*), post-acquisition (*After*) and changes (*Change*) in the dependent variable. Construction of the control-country indices is explained in Section 4.2. Frac>0 is the fraction of deals with positive *Targ-Ind* values. The Sign Test statistically evaluates the null hypothesis of a median equal to zero for *Targ-Ind* in each event stage. t(mean) tests the null hypothesis that mean *Targ-Ind* is equal to zero.

		Net Interest Margin to Avg. Assets (%)				***Non-Interest Income to Avg. Assets (%)***			
		Before	***Yr0***	***After***	***Change***	***Before***	***Yr0***	***After***	***Change***
Targets	Mean	4.05	3.74	3.38	-0.67	2.50	2.28	2.25	-0.25
	Std. Dev.	3.04	2.78	2.32	2.01	2.75	2.11	1.83	2.26
	Median	3.34	3.13	3.00	-0.37	1.83	1.59	1.57	-0.03
Industry	Mean	4.06	3.92	3.75	-0.31	2.54	2.53	2.46	-0.07
	Std. Dev.	2.23	2.33	2.17	0.91	1.85	1.55	1.56	1.36
	Median	3.60	3.22	3.30	-0.15	2.09	2.00	2.03	-0.03
Targ-Ind	Mean	-0.02	-0.19	-0.38	-0.36	-0.04	-0.25	-0.21	-0.17
	Std. Dev.	2.02	1.86	1.54	1.76	1.92	1.86	1.81	1.89
	Median	-0.17	-0.32	-0.48	-0.10	-0.31	-0.54	-0.36	-0.09
	Frac>0	0.46	0.58	0.33	0.44	0.41	0.56	0.38	0.49
	Sign Test+	0.49	0.14	0.00	0.28	0.09	0.08	0.02	0.92
	t(mean)	-0.08	-1.03	-2.46	-2.07	-0.20	0.27	-1.18	-0.93

		Overhead to Avg. Assets (%)				***Loan Loss Prov. to Avg. Assets (%)***			
		Before	***Yr0***	***After***	***Change***	***Before***	***Yr0***	***After***	***Change***
Targets	Mean	4.12	4.26	4.10	-0.02	1.11	1.01	0.61	-0.50
	Std. Dev.	2.70	2.55	2.37	2.07	1.86	1.66	1.25	2.20
	Median	3.54	3.64	3.52	0.07	0.52	0.37	0.27	-0.11
Industry	Mean	4.30	4.17	4.14	-0.16	0.74	0.80	0.75	0.01
	Std. Dev.	2.18	2.12	2.16	1.18	0.57	0.68	0.61	0.51
	Median	3.81	3.68	3.41	-0.09	0.63	0.63	0.62	0.00
Targ-Ind	Mean	-0.18	0.09	-0.03	0.14	0.38	0.20	-0.13	-0.51
	Std. Dev.	2.47	1.96	1.99	2.22	1.63	1.44	1.00	1.97
	Median	-0.57	-0.09	-0.04	0.06	-0.01	-0.06	-0.24	-0.11
	Frac>0	0.36	0.65	0.48	0.52	0.49	0.63	0.29	0.36
	Sign Test+	0.01	0.80	0.77	0.77	0.92	0.55	0.00	0.01
	t(mean)	-0.72	1.26	-0.16	0.66	2.33	2.43	-1.35	-2.61

+ P-Value

Table 9: Difference-in-Difference Analysis - Emerging vs. Developed Economies

The variables of interest are defined as difference-in-difference using the country-indices as controls. The methodology is explained in Section 3.2.; variables are defined in Section 4. The sample includes 102 deals with at least two pre and post-acquisition years. A country is defined as being developed if GDP *per capita* is above US$10,000 in 2000 prices. The Sign Test statistically evaluates the null hypothesis of a median equal to zero for the difference-in-difference measure. Frac>0 is the fraction of deals with positive *Targ-Ind* values. The Wilcoxon Test evaluates the hypothesis that two independent samples (i.e., unmatched data) are from populations with the same distribution. The Median Test evaluates the null hypothesis that the samples of developed and emerging country deals were drawn from populations with the same median.

		Change in Relative Performance							
		Deals (1)	Mean (2)	Std Dev (3)	Median (4)	Frac>0 (5)	Sign Test + (6)	Wilcoxon (7)	Median (8)
Return on Assets (%)	Developed	48	-0.17	1.24	-0.08	0.46	0.67	-0.27	0.00
	Emerging	54	-0.18	2.62	-0.11	0.46	0.68		
Return on Equity (%)	Developed	48	-1.83	19.61	-0.95	0.46	0.67	-0.31	0.00
	Emerging	54	-0.21	34.39	-1.18	0.43	0.34		
Cost to Income Ratio (%)	Developed	48	12.32	26.81	7.06	0.65	0.06*	-0.44	0.16
	Emerging	54	6.08	32.08	9.74	0.63	0.08*		
Profits Before Taxes and Provisions (%)	Developed	48	-0.20	1.71	-0.24	0.40	0.47	0.04	0.00
	Emerging	54	-0.18	2.86	-0.28	0.43	0.68		
Net Interest Margin (%)	Developed	48	-0.07	0.87	-0.13	0.35	0.06*	-0.17	0.63
	Emerging	54	-0.62	2.25	0.14	0.52	0.89		
Non-Interest Income (%)	Developed	48	-0.23	1.32	-0.13	0.44	0.47	0.72	0.63
	Emerging	54	-0.13	2.30	0.19	0.54	0.68		
Overhead Costs (%)	Developed	48	0.27	1.45	-0.10	0.44	0.47	0.72	2.52
	Emerging	54	0.04	2.75	0.59	0.59	0.22		
Loan Loss Provisions (%)	Developed	48	-0.38	1.06	-0.11	0.29	0.01***	0.13	0.00
	Emerging	54	-0.63	2.53	-0.10	0.43	0.34		

* significant at 10%; ** significant at 5%; *** significant at 1%

+ P-Value

Table 10A: Performance, Economic Integration and Information Costs

The dependent variable is a percentile rank transformation of the performance measure. The models are explained in Section 3.3.; variables are defined in Section 4. The models are estimated for the 1994-2004 period. Three sets of variables are included as regressors: event dummies for the year of the deal (Yr0), one and two years after (Yr12) and three or more years after (Yr3+); country pair characteristics reflecting similarities between the host and home countries; and host country market and macroeconomic characteristics. The regressions include deal and country fixed effects.

	ROA	*ROE*	*Cost to Income Ratio*
	(1)	*(2)*	*(3)*
Yr0	-0.132	-0.007	-0.152
	[0.106]	[0.111]	[0.104]
Yr12	-0.073	0.048	-0.144
	[0.106]	[0.111]	[0.104]
Yr3+	-0.066	0.042	-0.13
	[0.106]	[0.111]	[0.103]
Same Language	0.059	0.109**	0.148***
	[0.041]	[0.043]	[0.042]
Same Legal	-0.073*	-0.117***	-0.152***
	[0.040]	[0.041]	[0.039]
Similar GDP PC	-0.128	-0.126	-0.129
	[0.092]	[0.094]	[0.092]
Similar GDP	0.075	0.124*	0.115**
	[0.064]	[0.068]	[0.055]
Log Distance	0.013	-0.001	0.022
	[0.016]	[0.017]	[0.017]
Same Region	0.035	0.022	0.07
	[0.067]	[0.072]	[0.069]
Concentration	-0.029	0.016	-0.076
	[0.111]	[0.109]	[0.098]
GDP Growth	0.004	0.001	0.004
	[0.003]	[0.003]	[0.003]
Inflation	0.01	0.017***	0.005
	[0.006]	[0.006]	[0.008]
Observations	1196	1178	1191
R-squared	0.45	0.46	0.51

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10B: Performance, Economic Integration and Information Costs – Emerging vs. Developed Economies

The dependent variable is a percentile rank transformation of the performance measure. The models are explained in Section 3.3.; variables are defined in Section 4. The models are estimated for the 1994-2004 period. A country is defined as being developed if GDP *per capita* is above US$10,000 in 2000 prices. Three sets of variables are included as regressors: event dummies for the year of the deal (Yr0), one and two years after (Yr12) and three or more years after (Yr3+); country pair characteristics reflecting similarities between the host and home countries; and host country market and macroeconomic characteristics. The regressions include deal and country fixed effects.

	Developed Economies			*Emerging Economies*		
	ROA	*ROE*	*Cost to Income Ratio*	*ROA*	*ROE*	*Cost to Income Ratio*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Yr0	0.262	0.279	0.018	-0.235	-0.119	-0.344**
	[0.187]	[0.182]	[0.150]	[0.188]	[0.200]	[0.167]
Yr12	0.269	0.277	0.005	-0.146	-0.027	-0.317*
	[0.188]	[0.185]	[0.150]	[0.189]	[0.200]	[0.166]
Yr3+	0.28	0.303*	0.036	-0.164	-0.077	-0.320*
	[0.186]	[0.184]	[0.149]	[0.192]	[0.202]	[0.168]
Same Language	0.082	0.101*	0.173***	0.02	0.104	0.119
	[0.056]	[0.052]	[0.044]	[0.063]	[0.071]	[0.074]
Same Legal	-0.185***	-0.252***	-0.177***	0.072	0.041	-0.102
	[0.051]	[0.049]	[0.042]	[0.061]	[0.069]	[0.069]
Similar GDP PC	-0.348***	-0.314**	-0.340***	-0.059	-0.06	-0.116
	[0.133]	[0.123]	[0.103]	[0.167]	[0.176]	[0.171]
Similar GDP	0.254***	0.219**	0.273***	-0.073	0.035	0.038
	[0.092]	[0.088]	[0.066]	[0.087]	[0.101]	[0.088]
Log Distance	-0.031	-0.027	0.009	0.008	-0.017	0.014
	[0.030]	[0.029]	[0.025]	[0.021]	[0.023]	[0.024]
Same Region	-0.054	0.034	0.024	0.012	-0.131	-0.105
	[0.096]	[0.094]	[0.078]	[0.141]	[0.176]	[0.169]
Concentration	0.202	0.141	-0.086	-0.089	-0.015	-0.115
	[0.178]	[0.189]	[0.174]	[0.138]	[0.135]	[0.122]
GDP Growth	-0.002	0	0.012	0.005*	0.001	0.003
	[0.010]	[0.009]	[0.009]	[0.003]	[0.003]	[0.003]
Inflation	0.54	0.564	-0.501	0.010*	0.016***	0.005
	[1.760]	[1.645]	[1.421]	[0.006]	[0.006]	[0.008]
Observations	495	495	495	701	683	696
R-squared	0.54	0.56	0.64	0.41	0.41	0.43

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 11A: Costs, Revenue, Economic Integration and Information Costs

The dependent variable is a percentile rank transformation of the income statement ratios. The models are explained in Section 3.3.; variables are defined in Section 4. The models are estimated for the 1994-2004 period. Three sets of variables are included as regressors: event dummies for the year of the deal (Yr0), one and two years after (Yr12) and three or more years after (Yr3+); country pair characteristics reflecting similarities between the host and home countries; and host country market and macroeconomic characteristics. The regressions include deal and country fixed effects.

	Net Interest Margins (1)	*Overhead Costs (2)*	*Non-Interest Income (3)*
Yr0	-0.142*	-0.133	-0.079
	[0.085]	[0.082]	[0.093]
Yr12	-0.149*	-0.143*	-0.055
	[0.085]	[0.083]	[0.091]
Yr3+	-0.123	-0.127	-0.112
	[0.087]	[0.082]	[0.092]
Same Language	-0.053	0.108***	-0.011
	[0.033]	[0.031]	[0.030]
Same Legal	0.01	-0.059**	0.021
	[0.032]	[0.030]	[0.031]
Similar GDP PC	0.099	-0.155**	-0.068
	[0.067]	[0.069]	[0.065]
Similar GDP	-0.002	0.031	0.017
	[0.047]	[0.044]	[0.045]
Log Distance	0.029**	0.016	0.002
	[0.013]	[0.013]	[0.015]
Same Region	-0.032	0.151***	-0.035
	[0.050]	[0.050]	[0.046]
Concentration	0.147	-0.141*	0.098
	[0.096]	[0.082]	[0.093]
GDP Growth	0.006**	0.004*	0.002
	[0.002]	[0.002]	[0.003]
Inflation	0.01	-0.008	-0.011*
	[0.006]	[0.008]	[0.006]
Observations	1196	1189	1195
R-squared	0.64	0.63	0.52

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

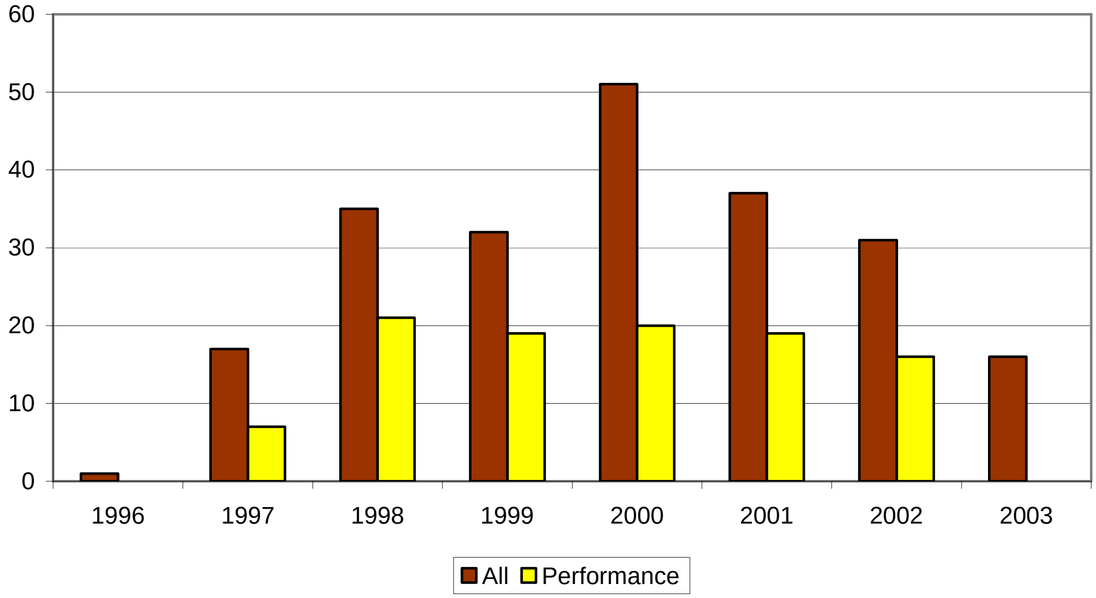
Table 11B: Costs, Revenue, Economic Integration and Information Costs – Emerging vs. Developed Economies

The dependent variable is a percentile rank transformation of the income statement ratios. The models are explained in Section 3.3.; variables are defined in Section 4. The models are estimated for the 1994-2004 period. A country is defined as being developed if GDP *per capita* is above US$10,000 in 2000 prices. Three sets of variables are included as regressors: event dummies for the year of the deal (Yr0), one and two years after (Yr12) and three or more years after (Yr3+); country pair characteristics reflecting similarities between the host and home countries; and host country market and macroeconomic characteristics. The regressions include deal and country fixed effects.

	Developed Economies			Emerging Economies		
	Net Interest Margins (1)	Overhead Costs (2)	Non-Interest Income (3)	Net Interest Margins (4)	Overhead Costs (5)	Non-Interest Income (6)
Yr0	0.148	-0.14	0.167	-0.135	-0.141	-0.005
	[0.105]	[0.118]	[0.106]	[0.176]	[0.147]	[0.150]
Yr12	0.139	-0.168	0.191*	-0.139	-0.134	0.015
	[0.108]	[0.119]	[0.109]	[0.177]	[0.147]	[0.147]
Yr3+	0.155	-0.155	0.115	-0.111	-0.126	-0.017
	[0.115]	[0.117]	[0.110]	[0.178]	[0.148]	[0.150]
Same Language	-0.061	0.105***	-0.090***	-0.051	0.121**	0.08
	[0.037]	[0.029]	[0.033]	[0.054]	[0.061]	[0.054]
Same Legal	0.01	-0.047*	0.046	-0.013	-0.068	-0.018
	[0.034]	[0.028]	[0.035]	[0.056]	[0.058]	[0.057]
Similar GDP PC	0.097	-0.286***	0.012	0.325**	-0.153	-0.107
	[0.070]	[0.067]	[0.081]	[0.158]	[0.134]	[0.143]
Similar GDP	0.068	0.027	-0.042	-0.114	0.069	0.045
	[0.063]	[0.042]	[0.051]	[0.071]	[0.075]	[0.074]
Log Distance	-0.014	0.014	-0.039**	0.046**	0.005	0.007
	[0.016]	[0.019]	[0.017]	[0.018]	[0.019]	[0.022]
Same Region	-0.082	0.103*	-0.140***	-0.011	0.048	0.106
	[0.055]	[0.058]	[0.052]	[0.118]	[0.128]	[0.087]
Concentration	0.199	-0.053	-0.043	0.149	-0.194*	0.189
	[0.140]	[0.108]	[0.140]	[0.124]	[0.108]	[0.123]
GDP Growth	0.004	-0.002	-0.003	0.006**	0.004*	0.003
	[0.006]	[0.006]	[0.008]	[0.002]	[0.002]	[0.003]
Inflation	2.680***	-0.759	2.502**	0.01	-0.008	-0.013**
	[0.966]	[0.861]	[1.186]	[0.006]	[0.008]	[0.006]
Observations	495	495	495	701	694	700
R-squared	0.83	0.79	0.72	0.49	0.53	0.41

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Figure 1: Deals by Year



International Diversification Gains and Home Bias in Banking

July 2007

Alicia García-Herrero[1] and Francisco Vázquez[2]

Abstract

This paper assembles a bank-level dataset covering the operations of 38 international banks from eight industrial countries and their subsidiaries overseas during 1995–2004, and studies the extent of diversification gains from their local operations abroad. The paper finds that international banks with a larger share of assets allocated to foreign subsidiaries, particularly to those located in emerging market countries, are able to attain higher risk-adjusted returns. These gains are somewhat reduced—but by no means depleted—when international banks concentrate their subsidiaries in specific geographical regions. The paper also finds a substantial home bias in the international allocation of bank assets, relative to the results of a mean-variance portfolio optimization model. Overall, international diversification gains in banking appear to be substantial, albeit largely unexploited by current bank expansion strategies. These results suggest that bank capital charges for international risk exposures under the first pillar of Basel II may be excessively penalizing, as they are based only on the idiosyncratic risk of recipient countries. Accordingly, international diversification gains may be considered in the second pillar of Basel II.

JEL Classification [G11, G21, E44, F40]

Keywords: International Banking, Home Bias, Portfolio Diversification, Basel II.

[1] Bank for International Settlements. alicia.garcia-herrero@bis.org.
[2] International Monetary Fund. fvazquez@imf.org.

The views expressed in this article are those of the authors' and not necessarily those of the institutions they are affiliated with. Excellent assistance in data collection was provided by Enrique Martínez Casillas and Kalin Tintchev. The authors wish to thank, without implicating, Nicolás Amoroso, Sergio Gavilá, Hans Genber, Robert McCauley, Pedro Rodríguez, Rafael Romeu, Daniel Santabárbara and Miguel Segoviano for comments. We also thank participants at several seminars where the paper was presented (IMF, Hong Kong Institute of Monetary Research, Bank of Korea, and Monetary Authority of Singapore).

I. INTRODUCTION

Financial globalization since the mid-1990s has been characterized by a massive expansion of bank activities overseas. Following banking sector liberalization in emerging market countries and a large increase in cross-border merger and acquisitions worldwide, the foreign claims of BIS-reporting banks (which include both local and cross-border claims), doubled from 1.3 trillion dollars in 1990 to 2.7 trillion dollars in 2006.

To the extent that business cycles are imperfectly correlated across countries, a bank with broad global exposures—particularly in its lending portfolio—should, in principle, be better able to diversify away country-specific risks.[1] International diversification in banking, however, is barely understood, as shown by the fact that it was neglected by the single factor model under Basel II.

Following the pioneering work of Markovitz (1952, 1959) on portfolio optimization, and subsequent extensions to the international context by Grubel (1968), Levy and Sarnat (1970), and Lessard (1973), a large body of literature in finance has studied the effects of international diversification in securities portfolios. Not surprisingly, since portfolio diversification depends on the correlations between return distributions of individual securities, which tend to be lower between- than within-countries, the gains from international diversification have been found to be large. However, there is also robust evidence that international diversification gains have not been fully exploited by investors due to the so-called "home bias"—or an excessive investment in domestic securities relative to the efficient portfolios.[2]

A parallel literature addressing the benefits of geographical diversification in banking is only incipient. A few studies have focused on the benefits of diversification between regions in individual countries (local geographical diversification), yielding inconclusive results. Using data for Italian banks during 1993-1999, Acharya, Hasan, and Saunders (2002) found that local geographical diversification did not necessarily improve the risk-return trade-off of banks. For the U.S., Morgan and Samolyk (2003) found that broader geographical presence of banks within the U.S. has not been associated with higher returns or lower risk. These findings suggest that the benefits of local geographical diversification may be limited, which is likely due to the strong co-movement of economic variables within individual countries.

[1] While separation theorems in finance imply that banks operating in a frictionless world should focus exclusively on profit maximization leaving portfolio diversification to their shareholders, the existence of prudential regulations, taxes, bankruptcy costs, and informational asymmetries, justify an active management of risks by banks (see for, example, Diamond, 1988).

[2] The evidence indicates that unexploited diversification gains between industrial countries' securities have been decreasing over time.

As regards international geographical diversification, Griffith-Jones, Segoviano, and Spratt, 2002, showed that business cycles tend to be more synchronized between industrial countries than between emerging market countries. They also showed that the synchronization of economic activity between these two groups of countries was generally low. On that basis, and the fact that banks carry a considerable degree of country-specific risks in their lending portfolios, they argued that the benefits of international diversification in banking could potentially be large.

Our paper assesses the extent of diversification gains generated by the operations of international banks overseas. It assembles a bank-level dataset covering the operations of 38 international banks incorporated in eight industrial countries and their subsidiaries overseas during 1995-2004. Linking each international bank with its subsidiaries, and classifying the latter by their location, the paper finds that larger asset allocation to foreign subsidiaries improves the risk-adjusted returns of the consolidated financial group. The paper also finds that these gains are partially eroded by the concentration of foreign subsidiaries in specific geographical regions implied by the observed patterns of international bank expansion. All in all, and even after controlling for concentration risk, our results show much broader international diversification gains than those obtained by Hayden, Porath and Westernhagen (2006). This may reflect the fact that their study is based on bank-level data for the population of German banks, which includes many institutions with little or no exposure to foreign risks,

We also find that the actual allocation of international bank assets across borders displays a substantial home bias, using the mean-variance portfolio model as a normative benchmark,. This finding is qualitatively consistent with Buch, Discroll, and Ostrgaard (2005), who also apply the mean-variance portfolio model to study international diversification gains in banking. Their work, however, uses aggregate data on cross-border claims of banks in four industrial countries during 1995-1999, and is therefore not well suited to address portfolio effects at the level of individual banks. In contrast, by exploiting information from the financial statements of international banks and their subsidiaries overseas, we obtain profitability measures and portfolio diversification effects at the bank level, which is the relevant unit of analysis.

The rest of the paper is as follows. Section 2 provides an overview of the data, discusses stylized facts on the international allocation of bank assets and compares the behavior of bank returns across groups of countries. Section 3 uses regression analysis to assess the effects of foreign subsidiaries' operations on the risk-adjusted returns of international banks. Section 4 uses the mean-variance portfolio model as a benchmark to assess the optimality of the observed allocation of international bank assets overseas. Section 5 concludes.

II. Data and Stylized Facts

In this paper, we try to assess the potential geographical diversification gains of banks which are already pursuing an internationalization strategy. We measure international geographical diversification in terms of the assets held by subsidiaries abroad, relative to those maintained by their parent banks in their home countries. This comparison is based on unconsolidated financial data to avoid double counting of assets. There are, obviously, other means for a bank to achieve geographical internationalization, including cross-border operations and foreign branching, but data do not allow to disentangle these two types of operations from the regular parent banks' businesses in their home countries.[3] Furthermore, foreign transactions in the trading book or off-balance sheet can also serve diversification purposes, but information is not publicly available at the bank level.[4] Such data constraints introduce a potential bias. As shall be explained in the next section, we tackle this in the paper with a novel strategy.

The sample used in the paper entails bank-level data for the 38 largest international banks incorporated in the G-7 (Canada, France, Germany, Italy, Japan, U.K., U.S.) and Spain. Data were gathered from Bankscope, at the yearly frequency, for the period 1995–2004. For each parent bank, we obtained unconsolidated financial statements to capture their profitability on a stand-alone basis, as well as consolidated financial statements to measure the overall profitability of their financial group. In addition, we gathered the unconsolidated financial statements of 399 subsidiaries overseas of the sampled international banks.

The nationality of parent banks is based on their country of incorporation, regardless of the nationality of its shareholders, which marches the regulatory criteria of home and host supervisors under the Basel Accord. Foreign subsidiaries are restricted to those with at least 50 percent ownership by their parent banks. We also crosscheck Bankscope ownership information with the Zephyr dataset on mergers and acquisitions to track the time evolution of bank subsidiaries overseas.

Summary information on the distribution of international bank assets and subsidiaries across regions is presented in Table 1. The 38 parent banks maintained only a few more subsidiaries in industrial countries than in emerging ones over the sampled period (209 observations versus 190), but the share of assets allocated to subsidiaries in industrial countries are much larger. On average, the typical international bank maintained 82.4 percent of its assets at home during the sampled period, against 12.6 percent in subsidiaries located in other industrial countries and a mere 5 percent in subsidiaries operating in emerging countries. While this distribution varies widely across countries, there are some common characteristics. Parent banks have a significant share of their assets in their home countries and in subsidiaries located in other industrial countries. In fact, with the exceptions of British and Spanish banks, the average share of assets in emerging market countries tends to be very

[3] In fact, when available, cross-border operations include intra-group lending. Branches, in turn, do not have their own balance sheets.

[4] Still, some bank subsidiaries also have their own branches. In those cases, international branches would correctly be treated as operations abroad.

small, below 2 percent in most cases.[5] At the same time, international bank expansion into emerging market countries displays strong regional patterns that seem to reflect historic and cultural ties. For example, Spanish and Canadian banks tend to concentrate in Latin America, French banks in Africa and the Middle East, German and Italian banks in Eastern European countries, and British and Japanese banks focus in emerging Asia.

We now move to a few stylized facts on the a-priori of our empirical exercise. First, we expect that banks would benefit from international geographical diversification as long as the major systemic factors behind bank profitability (for example, GDP growth, interest rates, and other macroeconomic conditions) turn out to be less correlated between their home and host countries and, in particular, between industrial and emerging market countries. A second a-priori is that the concentration of bank exposures in specific emerging regions would limit such diversification gains.

Regarding international diversification, we build upon Griffith-Jones, Segoviano, and Sprat, 2002, comparing the correlations of selected macroeconomic variables across groups of countries. In particular, we examine the correlations of GDP growth, money market rates (expressed in US$), and long-term government bond yields. We restrict the exercise to the set of home and host countries associated with the banks in our sample, classifying them in industrial versus emerging, and further splitting the later by geographical regions. This partition reflects the presumption that the synchronization of macroeconomic conditions would tend to be higher within industrial countries. It also reflects the idea that macroeconomic conditions may be more synchronized within geographical regions (for example, within Latin America) due to similar economic fundamentals and exposure to common risk factors.

To test these conjectures, we compute the pair-wise correlations for each macroeconomic variable, and compare the cumulative distribution frequencies (CDF) of these correlations by country groups. The results for GDP growth are presented in Figure 2. The graph in the upper-left corner compares the CDF of the correlations industrial-industrial against industrial-emerging. Since the former is always below, it provides strong evidence in support of our first a-priori. In turn, the graph in the upper-middle position shows that economic activity between industrial countries is more synchronized than between emerging market countries. The other three graphs provide a richer partition of the sampled countries by geographical regions, showing that the co-movement of economic activity tends to be relatively more synchronized within regions, which is consistent with our second a-priori. Parallel exercises comparing the correlations of money market rates, and long-term yields on government bonds between countries, yielded similar results (not shown).

As an additional reference, Table 2 displays summary statistics of the correlations of the three macroeconomic variables by country groups, plus the correlations of a composite

[5] The sample of British banks is heavily influenced by the large presence of HSBC in Asia.

series, based on their first principal component. Overall, the lower correlations obtained for the industrial-emerging pairs provides a very rough support for our first a-priori, namely, that banks exposed to emerging countries should be in a better position to diversify away country-specific risks. Furthermore, the results also show that these diversification gains tend to be more limited within specific geographic regions. However, while these results are suggestive, the fact that there are many other factors affecting bank profitability obviously call for a more specific analysis, which we undertake in the next section.

We now explore for differences in the risk-return results attained by parent banks in their countries of incorporation, vis-à-vis those of their subsidiaries overseas, splitting the later by their location. We measure returns by the after-tax return on assets (ROA), and risk by its standard deviation, using data from unconsolidated financial statements to measure the profitability of the institutions involved on a stand-alone basis.[6] As before, the population of subsidiaries was divided in two groups, separating those located in industrial from those in emerging market countries, on the conjecture that the latter may tend to be more profitable on average, but also riskier.

The results in the upper panel are based on the pooled dataset, that is, they refer to the entire distribution of yearly returns obtained by individual institutions. Not surprisingly, the figures show a clear trade-off between return and risk. Subsidiaries located in emerging countries seem to be more profitable on average but also substantially riskier, as shown by the standard deviation of their ROA (6.3 percent), which is roughly two-times higher than the standard deviation attained by parent in their home countries (2.9 percent). This result is partly driven by several episodes of economic and financial crisis in emerging market countries during the sampled period. On the other hand, the profitability attained by parent banks in their home countries roughly compares to the profitability of their subsidiaries in other industrial countries.

The results obtained from the pooled dataset, however, are very crude, because the observations are not independent within banks (and possibly not even within countries) as implied. To present a more refined picture, we compute a second set of summary statistics using a two-stage approach. First, we obtain the average return and risk for each bank over the entire period (i.e., treating subsidiaries overseas as individual entities), and compute the risk-normalized returns for each bank. Then, we compute summary statistics of the resulting figures, grouping banks by their location (i.e., home, other industrial, and emerging market countries). The results, presented in the lower panel, are similar to those discussed above in qualitative terms. The average returns of parent banks at home (1.4 percent are lower than the returns obtained by their foreign subsidiaries in emerging market countries (2.1 percent), but also significantly less volatile (1.0 percent at home versus 2.8 percent in emerging market

[6] An alternative profitability measure based on the after-tax return on equity (ROE) would provide a closer indication of shareholders' return, but has the drawback of being potentially affected by cross-country differences in the treatment of net worth and other accounting definitions.

countries. Interestingly, the risk-normalized returns obtained by parent banks in their home countries dominate those obtained by their foreign subsidiaries, particularly those located in emerging countries. This result, however, does not imply a negative contribution of foreign subsidiaries to the performance of the consolidated portfolio of international banks, since the later depends on the entire correlations of profit distributions. This will be investigated below.

III. BANK INTERNATIONALIZATION AND RISK-NORMALIZED RETURNS

In this section, we explore empirically whether major international banking groups benefit from international geographical diversification. To give the most accurate answer possible within data limitations (we can only measure geographical diversification in terms of subsidiaries' assets relative to the those of their parent banks), we pursue the following strategy.

We first conduct a baseline exercise, estimating the contribution of foreign subsidiaries' assets to the risk-return performance of the consolidated banking group. As discussed below, this approach introduces a potential omitted variable bias to the results due, since consolidated profits mix the operations of international banks in their home countries (which include cross-border transactions and other foreign risk exposures originated from home), with the operations of their subsidiaries overseas, but we are not able to directly observe the size of the foreign risk exposures originated from home. To correct for this, we carry out a parallel exercise after filtering-out the profits originated from the operations of international banks in their home countries. For such control, we take the difference in risk-adjusted profitability between the consolidated and unconsolidated financial statements of parent banks, exploiting variations in their information contents.

For the baseline exercise we consider the following specification:

$$sharpe_{i,t} = \alpha_0 share^H_{i,t} + \alpha_1 share^I_{i,t} + \alpha_2 share^E_{i,t} + \beta_1 H^I_{i,t} + \beta_2 H^E_{i,t} + macro^{'}_{c,t}\delta + \varepsilon_{i,t} \tag{1}$$

Where the dependent variable, $sharpe_{i,t}$, is a measure of the risk-adjusted profitability obtained by the consolidated group of international bank i, during year t. The series are computed by dividing the yearly consolidated ROA over its standard deviation, using data from the consolidated financial statements of each parent bank. Thus, they reflect the entire operations of parent banks in their home countries and those of their subsidiaries overseas. The index i goes from 1 to 38 (i.e., the number of international banks in the sample), and the time dimension is unbalanced, during the period 1995-2004.

The target explanatory variables are the relative allocation of bank assets in three regions: their home countries, $share_{i,t}^H$, their subsidiaries located in other industrial countries $share_{i,t}^I$, and their subsidiaries in emerging economies $share_{i,t}^E$. The asset shares are computed using data from the unconsolidated financial statements to avoid double counting. Since these three variables add-up to one, the regression does not include a constant term. Under this specification, the coefficients associated with the regional distribution of assets provide a way to assess whether international banks with larger exposure overseas obtain any significantly different risk-adjusted returns, on average, during the sample period. In particular, we want to individually test whether $\alpha_1 \geq \alpha_0$, and $\alpha_2 \geq \alpha_0$.

To the extent that the shares of assets abroad are a choice variable for international banks, they bring in potential endogeneity. Arguably, a subsidiary with higher (observed or prospective) profitability would tend to receive a larger capital allocation, growing faster in terms of assets and ending up with a larger relative size. This may introduce a bias toward finding beneficial effects of international diversification (i.e., banks with larger assets abroad having better risk-adjusted returns).[7] We deal with this issue by using lagged values of the asset shares as instruments in the regressions. A look at the data, however, indicates that this problem may not be serious, as the share of bank assets in a particular subsidiary is fairly stable between two consecutive years.

In addition, as mentioned before, there is a potential omitted variable bias originating from our inability to disentangle the cross-border exposures of parent banks from their regular operations in their home countries, since the former also provide exposure to foreign risks and therefore potential diversification gains. The direction of this bias would depend on whether local operations abroad and cross-border operations are substitutes or complements. Under the plausible assumption that local and cross-border operations were substitutes, the results would be biased against finding international diversification gains. This is because international diversification achieved by banks with relatively small local operations abroad (and more heavily reliant on cross-border operations) will be wrongly attributed to their activities at home. On the other hand, if local and cross-border operations were complements, the results would be biased in the other direction, overestimating the diversification gains of local operations abroad. Below, we propose a strategy to overcome this problem.

Going back to the specification, the regression includes two Herfindhal indexes measuring the concentration of the assets of each international bank within industrial and emerging countries, as a way to capture the effect of international diversification *within* country groups. These are computed as:

$$H_{i,t}^{G} = \sum_{j \in G} s_{i,j,t}^{2} \qquad \text{for } i=1,2,\ldots,38 \tag{2}$$

Where H^{G}_{i} indicates the Herfindhal index of parent bank i in country group G (either industrial or emerging), and $s_{i,j}$ is the average share of assets of parent bank i in host country j in year t. The Herfindhal indexes vary in the interval (0, 1], with a larger value indicating a

[7] Notice however that this possibility also applies in the opposite, so the direction of the bias is unclear. That is, a bank with better business prospects at home could end up with a lower share of assets in foreign subsidiaries, biasing the coefficients in the opposite direction.

less diversified portfolio (i.e., a higher concentration within industrial or emerging market countries). The shares are computed relative to the assets of the corresponding bank in each group of countries. Thus, a Herfindhal equal to one indicates that the international bank operates in just one country in that particular group. The hypothesis that international diversification brings positive benefits in terms of the risk-return achieved by international banks is consistent with negative coefficients associated with the concentration indexes.

The regressions also include a vector of macroeconomic controls, $macro_{c,t}$, which are intended to isolate the influence of macroeconomic conditions in the home countries of the international banks on their overall performance. In our preferred specification, the vector contains money market rates expressed in US$, and GDP growth. These variables vary along the time dimension and are common to international banks incorporated in the same home country, denoted by index c. The vector also contains a set of home-country dummies to control for time-invariant differences in the average profitability of international banks across their countries of incorporation.

The regressions, computed with robust standard errors, and presented in Table 4. The specification in the first column does not include any controls, other than home-country dummies, and thus provides an exploratory comparison of the risk-adjusted returns across international banks with varying levels of exposures overseas. On average, after adjusting for differences in risk-adjusted profitability between home countries, the sampled international banks obtained an overall risk-adjusted ROA of 3.942 during the sampled period. International banks with larger allocation of assets overseas obtained substantially higher risk-normalized returns. In particular, the coefficient associated with the share of assets in emerging market countries (9.408) is significantly larger than the coefficient associated with the share of assets at home, as indicated by the probability values of the tests of coefficient equality presented at the bottom. In terms of the magnitude, international banking groups with an additional 1 percent of their assets allocated to subsidiaries in emerging market countries obtained an average increase in their risk-adjusted returns of 5.466 basis points (i.e., 9.408–3.942). There is also evidence that international banks with a larger share of assets in subsidiaries located in industrial countries were able to obtain better risk-adjusted returns.

These results remain valid after the inclusion of the macroeconomic controls, as shown in the second column. They are consistent with the notion that subsidiaries overseas allow international banks to diversify risk (i.e., to increase their risk-adjusted return) and point to an important underinvestment in emerging countries, at least from the pure risk-return perspective. These two tests, however, are not well suited to compare profitability across parent banks with different international diversification profiles, as they ignore differences in the actual patterns of international asset allocation. For example, two banks with the same share of assets in industrial countries are treated similarly in these tests, regardless of the number of countries involved (and the same applies to bank exposures to emerging market countries).

To explore the effects of international diversification on risk-adjusted profitability, the previous regressions were estimated again, after adding the indexes of asset concentration within country groups. The results are presented in the third row of Table 4. Adding information on the international concentration of bank operations to the set of explanatory variables increases the point estimates of the coefficients associated with the asset shares in emerging market countries. Consistent with this, the coefficients of the Herfindhal indexes are negative, indicating that the regional concentration of the operations of international banks has been detrimental to their risk-adjusted profitability. The marginal effect of regional concentration is particularly severe for international bank operations in emerging market countries, as the associated coefficient (–1.461) is three times larger that its counterpart in industrial countries (–0.446). This probably reflects the higher volatility of economic conditions in emerging countries, and also the clustering of crisis episodes due to exposure to common risk factors and international contagion. To some extent, however, this has been compensated by the fact that international bank operations in emerging market countries have been relatively less concentrated. During the sampled period, the Herfindhal index in emerging market countries averaged 0.40, against with 0.61 for industrial countries. Using these values, the average change in risk-adjusted ROA originated by the regional concentration of bank activities overseas is –0.59 for emerging economies and –0.27 for industrial countries.

We now explore the consequences of international diversification in a more specific way. In particular, we want to assess whether the erosion in risk-adjusted profitability originates from specific geographic regions. This conjecture builds from the strong regional patterns of international bank expansion, and the fact that macroeconomic conditions tend to move in tandem within geographical regions. To test this, we split the sample of emerging economies in four regions denoted by R: Asia, Africa and the Middle East, Eastern Europe, and Latin America. Based on this partition, we linearly decompose the Herfindhal index of each parent bank in emerging economies, $H^E{}_i$, in its regional parts using:

$$H_{i,t}^{E} = \sum_{R\in E} w_{i,R,t}^{2} H_{i,R,t} \qquad \text{for } i=1,2,...,38 \qquad (3)$$

which indicates that the Herfindhal index in emerging economies for a given parent bank equals the sum of the Herfindhal indexes of its component geographical regions, $H_{i,t.R}$, weighted by their squared asset shares, $w_{i,t,R}$.

Using this, we re-estimate the regression after replacing the Herfindhal index in emerging economies by its weighted components. All the previous results on the coefficients of the asset shares in the three regions hold, as shown in the fourth column of Table 4, so they do not merit further comments. The coefficients of the disaggregated concentration indexes show some differences in the marginal costs of geographical concentration across regions, with the lower effects obtained in Eastern Europe. Combining these coefficients with the average values of the regional Herfindhal indexes, which are presented in Table 5, confirms that regional concentration has been relatively less detrimental to international banks with operations in Eastern Europe. For example, the average drop in risk adjusted profitability for asset concentration in Eastern Europe is –0.806 (–2.304×0.35), compared with –0.743 in Latin America and –0.666 in Asia.

The results obtained so far could be challenged on two grounds. First, as discussed above, our inability to disentangle the cross-border operations of international banks from their regular operations in their home countries, creates a potential source of bias. Besides, since the regressions do not include bank-level controls, the results could be also driven by other omitted variables at the bank-level. For example, differences in business strategies across banks could have an impact on their profitability, influencing at the same time the nature of their international exposures in a systematic way. Unfortunately, typical controls used in the banking literature (i.e., size, capitalization, or liquidity) offer little help to tackle these issues, as they convey no information of the characteristics of bank businesses.

To tackle these issues, we exploit differences in the information content of the consolidated and unconsolidated financial statements of parent banks, providing a closer assessment of the contribution of foreign subsidiaries to risk-adjusted profitability, while controlling at the same time for other bank specificities. In particular, we exploit the fact that unconsolidated financial statements convey information on the activities of parent banks in their home countries, plus their cross-border activities (including cross-border lending to their subsidiaries and other financial institutions), and other exposures to foreign risk originated from home. On the other hand, the consolidated financial statements of parent banks include the above plus those of their subsidiaries, netting out intra-group transactions. Since both consolidation levels refer to the same institution, taking the difference between consolidated and unconsolidated data isolates the contribution of foreign subsidiaries to the risk-return profile of parent banks. Notably, this also removes unwarranted cross-sectional differences between parent banks, including time-varying unobservable variables such as risk appetite and business strategies.

To implement this idea, we compute the risk-adjusted ROA for each parent bank using both consolidated and unconsolidated data, and obtain the difference between the two (consolidated minus unconsolidated). A positive value of the resulting metric indicates a positive contribution of foreign subsidiaries to the risk-return profile of their parent banks. A practical drawback of this approach is the decrease in sample size, since there are parent banks for which we do not have parallel information at the two consolidated levels. This includes all U.S. and Canadian banks.

To illustrate the resulting data, Figure 3 plots the difference in risk-adjusted ROA of each parent bank against the average share of their assets in the three groups of countries: (i) home (at the bottom), (ii) other industrial countries (upper-left), and (iii) emerging economies (upper-right). Surprisingly, the graphs show that the average risk adjusted-return obtained by parent banks on a stand-alone basis is not consistently below the risk adjusted-return obtained at the consolidated level (as should be expected by the effects of diversification), since roughly half of the differences in risk-adjusted ROA are negative. At the same time, there is strong evidence that higher international exposure is positively correlated with risk-adjusted returns, which is consistent with the previous results.

A more formal test of the relationship between the difference in risk-adjusted ROA and the international exposure of parent banks was obtained by running a set of regressions similar to those reported previously, but after excluding the country fixed effects and the macro-controls (since these are removed by differencing, together with other bank-level idiosyncrasies). The results are presented in Table 6. Due to incomplete data at the two consolidation levels for some parent banks, the sample size drops to 23 international banks and a total of 120 observations.

Overall, the results indicate that foreign subsidiaries had a positive contribution to the risk-adjusted returns of their parent banks. The coefficient of the share of assets at home is close to zero and not statistically significant, implying that, on average, the risk-adjusted returns obtained by parent banks on their consolidated operations are no different from those obtained on *a solo* basis. On the other hand, parent banks with a larger share of their assets abroad, particularly in emerging market countries, have been able to attain higher risk-adjusted returns. These results are roughly unchanged after the inclusion of the Herfindhal indexes. While the signs of the coefficients associated with the Herfindhal indexes are consistent with those reported previously, their standard errors are too large, a result possibly due to the drop in sample size.

Summarizing, there is strong evidence that a larger allocation of bank assets to subsidiaries overseas has contributed to increase the risk-adjusted returns of international banks, albeit regional concentration has reduced such gains. However, the tests conducted so far are largely silent with respect to the optimality of the observed international asset allocation. The next section studies this issue in more detail using a portfolio approach as a normative framework to study international diversification in banking.

IV. A PORTFOLIO APPROACH

Following Markovitz (1952), the return and risk of a portfolio of n assets can be decomposed into the contributions of its individual components. Let r denote the $n\times1$ vector of expected returns of individual assets, w the $n\times1$ vector of their corresponding weights in the portfolio, and Σ the $n\times n$ variance-covariance matrix of asset returns in the portfolio. The expected return and variance of the portfolio are given by $\mu = w'r$, and $\sigma^2 = w'\Sigma w$, respectively. Applying quadratic programming techniques to this setup, it is possible to obtain the vector of nonnegative weights that minimize the variance required to attain a given return, and obtain a set of efficient portfolios in the risk-return space.

This framework appears suitable to analyze international diversification in the banking context, treating the subsidiaries of international banks in each country as individual assets in a global portfolio. But the application of this idea to the case at hand requires some modifications. In the context of portfolio theory, individual securities are treated as perfect substitutes, which is an unlikely assumption for the case of foreign subsidiaries of international banks. In fact, launching banking operations in a foreign country is costly from the economic and managerial perspectives and entails multiple frictions—generated by legal, cultural, and historic differences between countries—. These costs and frictions are likely to differ across international banks depending, for example, on their country of origin and other bank-specific characteristics. On the other hand, for a given international bank, the costs of internal capital relocation between its *existing* subsidiaries overseas are likely to be significantly lower, making the substitutability assumption more plausible. Therefore, we restrict the exercise to assessing the optimality of the observed asset allocation within the *observed* set of foreign subsidiaries for each international bank. This means that banking groups are not allowed to open subsidiaries in new countries but only to transfer assets within existing ones. While this clearly reduces potential gains from diversification, it also accounts better for sunk costs in closing and opening new bank affiliates. It also helps us control for regulatory restrictions to foreign entry, which could affect the ability of a bank to operate in a specific country.

Applied in this context, portfolio theory provides a tool to assess the contributions of specific bank subsidiaries (or a subset of them) to the overall risk-return performance of international banks. It also provides a benchmark to assess the optimality of the observed global asset allocation of international banks. Unfortunately, studying the diversification of bank portfolios at the level of individual countries poses some practical limitations. As the collection of foreign subsidiaries (and host countries) of each international bank evolves over time, the yearly coverage of portfolio components tends to be uneven, affecting our ability to compute the variances and covariances of the returns obtained at the level of individual countries. To circumvent this problem, we work at the level of country groups, splitting the operations of each international bank in three groups G, as we did before (G={home, other industrial countries, emerging market countries}).

In particular, let $\pi_{i,c,t}$ denote the unconsolidated after-tax profits obtained by international bank i (or its subsidiaries) in country c during year t, and $A_{i,c,t}$ denote the corresponding unconsolidated assets.[8] We calculate the return on assets $r_{i,G,t}$ obtained by international bank i in country group G as:

[8] Unconsolidated figures provide a closer (albeit imperfect) measure of the profitability of individual business units, since each bank is treated as an independent entity. Admittedly, this may also introduce noise in the aggregation of profits at the group level, as it ignores the effects of mutually canceling transactions between parent banks and their subsidiaries. However, this problem may not be critical, since there are no obvious reasons to believe that this noise is systematic.

$$r_{i,G,t} = \frac{\sum_{c \in G} \pi_{i,c,t}}{\sum_{c \in G} A_{i,c,t}} \tag{4}$$

Using this, we compute the first two moments of the return distributions obtained by each international bank in the three groups of countries (i.e., we compute the 3×1 vector of expected returns r_i and the 3×3 associated variance-covariance matrix Σ_i), plus the corresponding vector of asset shares w_i. We then estimate the set of efficient mean-variance portfolios for each international bank, by solving (bank indexes are omitted for brevity):

$$\min_{w \geq 0} \sigma = w'\Sigma w \qquad \text{s.t.} \qquad w'r \geq \mu \tag{5}$$

For varying values of target portfolio returns μ. The efficient frontier of each international bank is the set of points in the risk-return space $\{\sigma^*(\mu), \mu\}$, where $\sigma^*(\mu)$ is the solution to (5).

This provides a benchmark to assess the optimality of the observed allocation of international bank assets. Since all the portfolios along the frontier are efficient, choosing a particular combination would require a measure of the risk appetite of international banks, or the return of a risk-free asset. We use an alternative criteria, selecting a point consistent with the observed ROA. More precisely, we select an efficient portfolio with a return equal to (or slightly higher than) the observed ROA.[9] We then measure the optimality of international bank portfolios using the horizontal distance between the observed risk-return attained by each international bank (σ_0, μ_0) and its frontier, $d=\sigma_0 - \sigma^*(\mu_0)$. Therefore, the resulting metric reflects the reduction in risk associated with an efficient *relocation* of international bank assets within its *existing* subsidiaries. Finally, we compute the efficient asset allocation and the implied Sharpe ratios, comparing them with the observed values for each international bank.

It is important to emphasize that this approach understates the potential gains of international diversification for two reasons. First, restricting the analysis to diversification within the observed network of foreign subsidiaries for each international bank, neglects potential diversification gains from operating in a different and potentially broader set of countries. Second, the aggregation of bank operations by groups of countries prevents us from assessing the potential diversification gains of alternative asset allocations within county groups. Thus, for example, the sub-portfolio in emerging market countries reflects the diversification achieved by the observed asset allocation in these countries, neglecting potential diversification gains associated with an alternative relocation of assets within this group.

[9] In most cases, the ROA of the selected efficient allocation is larger than the ROA of the actual portfolio due to approximation, as the frontier is based on a grid of 20 points.

These two effects operate in the same direction, introducing an unambiguous and potentially large underestimation of the diversification gains of cross-border operations.

Summary results are presented in Table 7, comparing the actual asset allocation of international banks worldwide and their associated risk-returns, against the alternative, risk-minimizing portfolios. The reported figures are unweighted averages of the results obtained for individual banks, classified by their countries of incorporation, so they convey information on the profile of the typical international banks. As discussed previously, sampled banks maintained an average 82.4 percent of their assets at home, 12.6 percent in subsidiaries located in other industrial countries and 5 percent in subsidiaries located in emerging countries. In contrast, the optimal allocation matching the observed returns implies an average of 60.1 percent of assets at home, 28.9 percent in other industrial countries, and 11.0 percent in emerging markets. This home bias holds qualitatively for all the countries studied, except for the U.K. and Spain. The later probably reflects the robust economic performance in Spain during the period, combined with large volatility in Latin America, including financial crises in Brazil (1999), Argentina (2001), and Uruguay (2002).

The results also indicate that international diversification gains are large and unexploited. In particular, under the observed asset allocation, international banks obtained an average ROA of 1.1 percent over the entire period, with a standard deviation of 0.7 percent. In contrast, the risk-minimizing allocation for a ROA of 1.5 percent entails a 30 percent reduction in volatility. This result is significant from the financial stability perspective, entailing potentially large reductions in economic and regulatory capital that could be taken into account in the prudential framework.

To further explore the sources of these international diversification gains, we examine the vectors of expected returns in the three groups of countries for each international bank, and their corresponding variance-covariance matrices. Table 8 presents the values for the typical international bank, computed by taking unweighted averages across the entire sample. The figures indicate that the expected returns at home are roughly in line with the expected returns of subsidiaries located in other industrial countries, but substantially lower than average returns in emerging economies. The volatilities of the returns at home and in other industrial countries are also similar, but roughly four-times smaller than the volatility of returns in emerging economies. The diversification gains from the operations of subsidiaries abroad, including in emerging economies, originate from the extremely low return covariances.

V. CONCLUDING REMARKS

This paper provides evidence that international diversification gains in banking, through the opening up of subsidiaries, are large and not entirely exploited. Our results show robust systematic differences in the risk-return performance of international banks in their home countries vis-à-vis their subsidiaries overseas, indicating that the later are more profitable, on average, but also riskier, particularly in emerging market countries. Larger systematic risks abroad, however, do not prevent the generation of international diversification gains, stemming from the generally low correlations of returns between-countries. The fact that banking activities in emerging market countries tend to be concentrated in some of the regions has eroded somewhat the gains from international diversification but has by no means depleted them.

Using the mean-variance portfolio model as a benchmark, the results show a substantial home bias in the international allocation of bank assets. Notably, these results come from a test that substantially underestimates the gains from international diversification, as it is restricted to diversification gains *within* the observed set of subsidiaries of each international bank. This implies that—notwithstanding the current regional concentration for emerging economies—the potential gains are sizable.

These finding have two important sets of policy implications. The first one concerns bank regulation. Risk weighting in the single factor model under the first pillar of Basel II does not take into account geographical diversification gains. If they exist and are large—as this paper proposes—the resulting capital charges may be unwarranted, reducing bank incentives to increase their international exposures. This, however, could usefully be taken up by Basel II's second pillar. In fact, the home supervisors of international banks may want to consider the entire contribution of foreign exposures to the overall risk performance of bank assets, which depends on return correlations. This would help reduce home bias in international banking, with positive consequences for the risk-adjusted profitability for international banks and for the financing of growth in host countries, particularly emerging economies.

There are a number of issues to take into account regarding these results. First, our dataset deals with bank internationalization through subsidiaries, but we lack information on branches and cross-border loans. Such comprehensive data would allow us to draw firmer conclusions on the issues but it is unfortunately not available. One possible venue for future research might be case studies for which cross-border bank lending is available. Second, due to data limitations, the assessment of the optimality of the observed allocation of bank assets is based on diversification gains between country groups, and not at the level of individual countries. Future research on this topic, based on more complete bank-level data, will likely find even larger estimates of unexploited benefits.

VI. References

Acharya, V.V., I. Hasan, and A. Saunders (2002). "The Effects of Focus and Diversification on Bank Risk and Return: Evidence from Individual Bank Loan Portfolios." CEPR Working Paper No. 3252.

Buch, C., J. Driscoll, and C. Ostergaard (2005). "Cross-Border Diversification in Bank Asset Portfolios." European Central Bank Working Paper No. 429, January.

Diamond, D., 1984, "Financial Intermediation and Delegated Monitoring," Review of Economic Studies, 393–414.

Griffith-Jones, S., M. Segoviano, and S. Spratt (2002). "Basel II and Developing Countries: Diversification and Portfolio Effects." Working Paper, The London School of Economics.

Hayden, E., D. Porath, and N. von Westernhagen, 2006, "Does Diversification Improve the Performance of Germsn banks? Evidence from Individual Bank Portfolios," Oesterreichische Nationalbank Working Paper No. 110.

Grubel, H. (1968) "Internationally Diversified Portfolios: Welfare gains and Capital Flows." The American Economic Review, Vol. 58, 1299-1314.

Lessard, D. (1973) "International Portfolio Diversification: A Multivariate Analysis for a Group of Latin American Countries." Journal of Finance (June), 619-633.

Levy, H. and M. Sarnat (1970) "International Diversification Gains of Investment Portfolios." The American Economic Review, Vol. 60, No. 4, 668-675.

Markowitz, H. (1952). "Portfolio Selection." Journal of Finance 7, 77-91.

Markowitz, H. (1959). Portfolio Selection: Efficient Diversification of investments. John Wiley, New York.

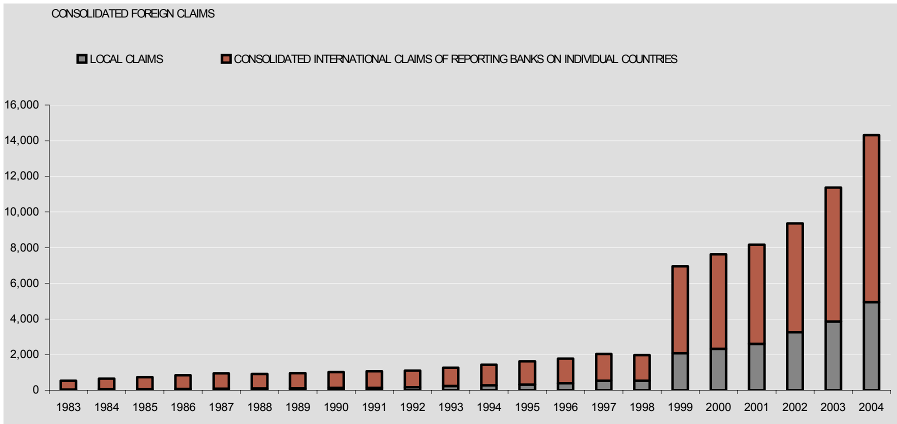
Morgan, D. and K. Samolik. "Geographic Diversification in Banking and its Implications for Bank Portfolio Choice and Performance." Working Paper, Federal Reserve Bank of New York.

Stiroh, K. (2005). "Bank Risk and revenue Diversification: An Assessment Using Equity Returns." Working Paper, Federal Reserve Bank of New York.

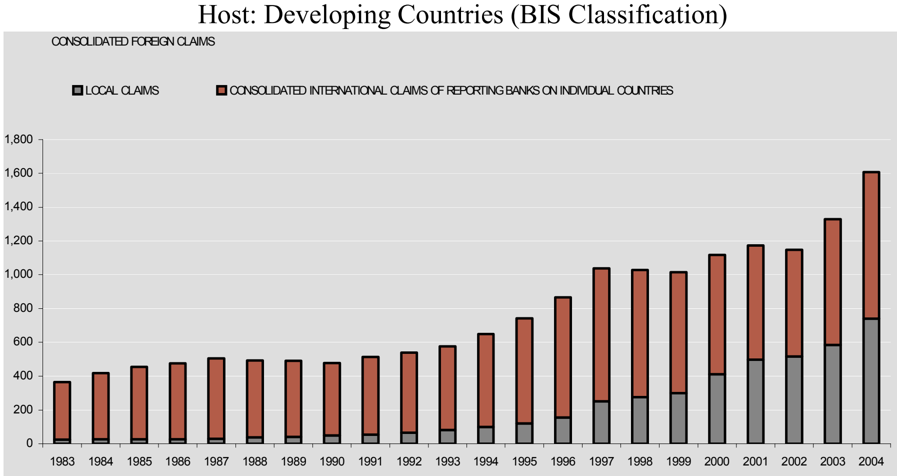
Figure 1. Evolution of Local and Cross-Border Claims of BIS-Reporting Banks, 1983–2004

In Billion US$ 1/

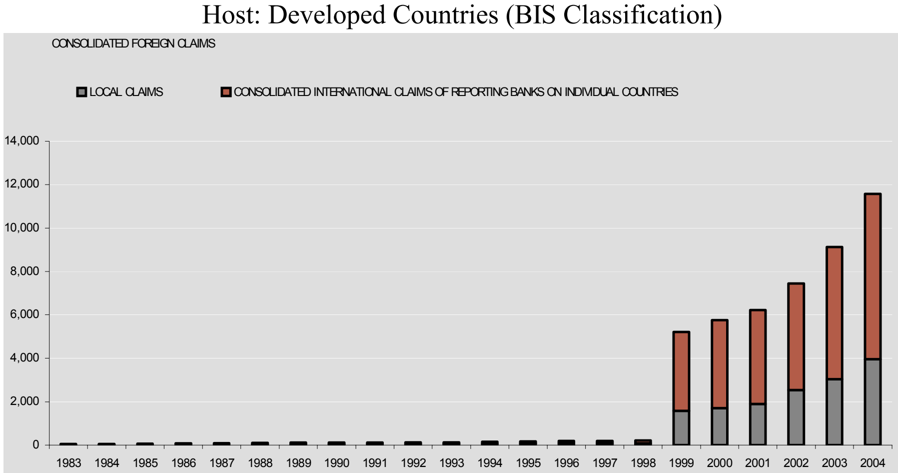
Host: All Countries



Host: Developing Countries (BIS Classification)



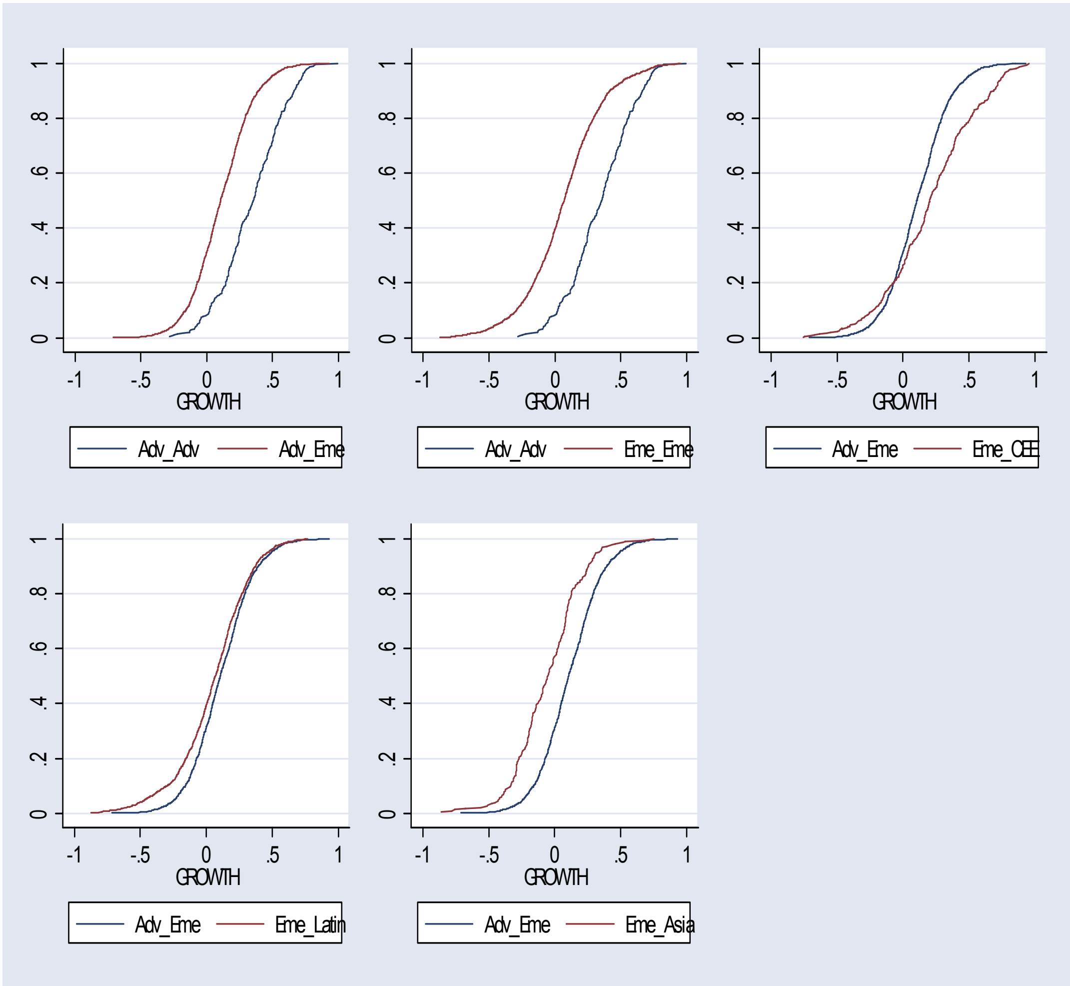
Host: Developed Countries (BIS Classification)



Source: Bank of International Settlements.
1/ There is a break in the series in 1999 due to a change in definitions.

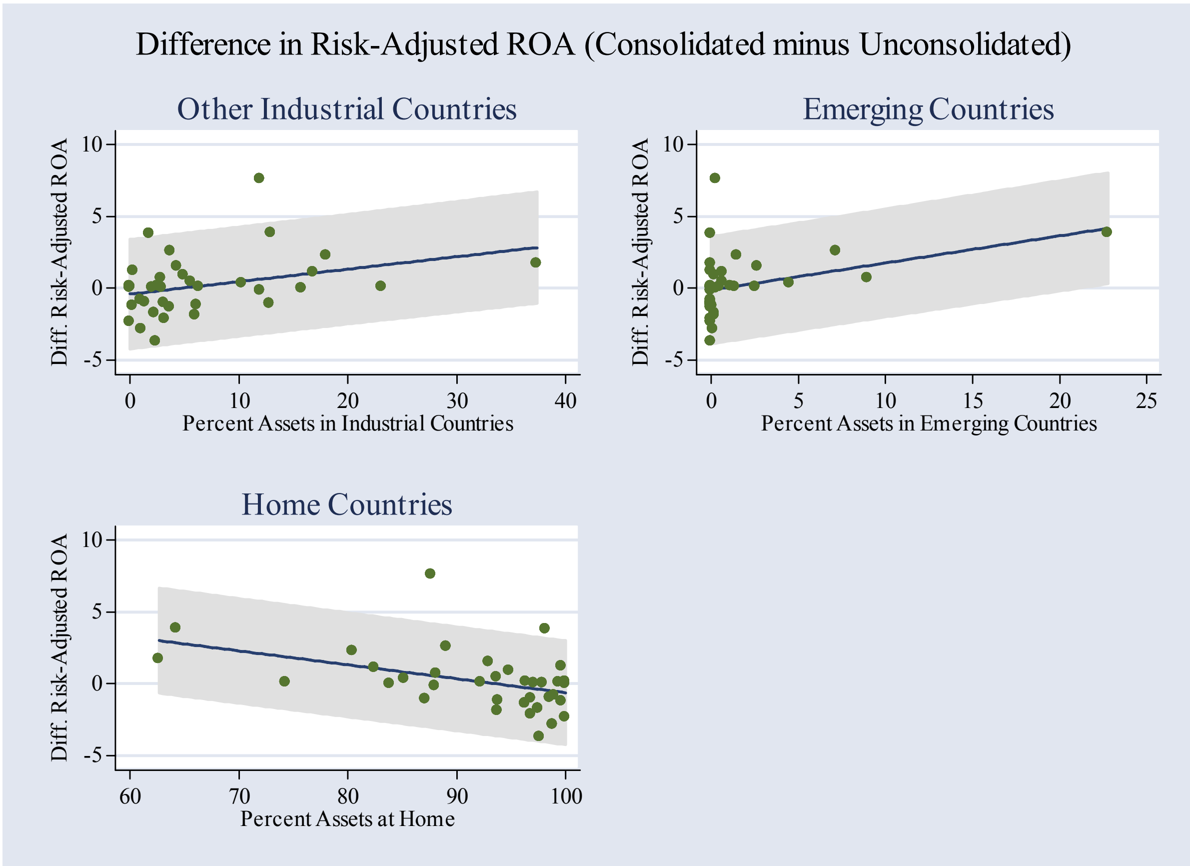
Figure 2. Cumulative Frequencies of GDP Growth Correlations

By Groups of Countries



This figure compares the cumulative distribution frequencies of GDP growth by groups of countries.

Figure 3. Risk-Adjusted Profitability and International Exposure of Parent Banks



For each international bank, the difference in risk-adjusted profitability was computed as the risk-adjusted profits obtained from consolidated financial statements minus those obtained from the unconsolidated financial statements. This figure plots the difference in the risk-adjusted ROA obtained by each international bank against their asset allocation in three groups of countries: their home countries, other industrial countries, and emerging economies. The lines show the fitted values of a linear regression and two standard deviation bands are depicted by the shaded areas.

Table 1. Regional Distribution of Bank Subsidiaries Overseas

	Country of incorporation of parent banks								
	Canada	France	Germany	Italy	Japan	Spain	U.K.	U.S.	Total
Number of institutions									
Number of mother banks	5	4	5	5	7	2	4	6	38
Number of subsidiaries	27	70	67	30	38	33	61	73	399
In Industrial Economies	15	33	40	19	26	12	35	29	209
In Emerging Economies	12	37	27	11	12	21	26	44	190
Africa and Middle East	.	17	.	.	.	.	12	6	35
Asia	3	6	3	.	9	.	7	12	40
Eastern Europe	.	10	23	9	1	.	2	7	52
Latin America	9	4	1	2	2	21	5	19	63
Regional distribution of assets (unweighted averages, in percent)									
Home Country	92.1	93.9	78.6	90.4	78.3	67.7	50.4	93.7	82.4
Subsidiaries Overseas	7.8	6.1	21.4	9.5	21.7	32.2	49.5	6.2	17.6
In Industrial Economies	7.2	5.1	20.6	7.7	20.3	11.9	23.1	4.6	12.6
In Emerging Economies	0.6	1.0	0.8	1.8	1.4	20.3	26.4	1.6	5.0
Africa and Middle East	.	0.5	.	.	.	.	3.9	0.2	0.5
Asia	0.1	0.1	0.1	.	1.1	.	20.6	0.6	2.5
Eastern Europe	.	0.3	0.7	1.6	.	.	.	0.1	0.4
Latin America	0.5	0.1	.	0.2	0.3	20.3	1.9	0.7	1.6

The upper panel of this table presents the distribution of bank subsidiaries overseas, classified by their location and the country of incorporation of their parent banks. Two subsidiaries sharing a parent bank and located in the same country are counted separately. The lower panel presents the unweighted average distribution of international bank assets, grouped by their countries of incorporation.

Table 2. Summary Statistics of Correlations of Selected Macroeconomic Variables Between Groups of Countries

	Mean	Min.	Max.	No. Obs.
GDP Growth				
Industrial vs. Industrial	0.413	-0.247	0.997	210
Industrial vs. Emerging	0.126	-0.603	0.929	1386
Emerging vs. Emerging	0.066	-0.872	0.957	2145
Industrial vs. Africa & Middle East	0.085	-0.517	0.694	462
Industrial vs. Asia	0.120	-0.495	0.542	189
Industrial vs. Eastern Europe	0.171	-0.603	0.929	315
Industrial vs. Latin America	0.139	-0.462	0.630	420
Government Bond Yields				
Industrial vs. Industrial	0.725	-0.282	0.997	134
Industrial vs. Emerging	0.255	-1.000	1.000	189
Emerging vs. Emerging	0.247	-1.000	1.000	69
Industrial vs. Africa & Middle East	.	.	.	0
Industrial vs. Asia	0.136	-0.723	1.000	82
Industrial vs. Eastern Europe	0.856	-1.000	1.000	43
Industrial vs. Latin America	0.004	-0.824	0.945	64
Money Market Rates in US$				
Industrial vs. Industrial	0.597	-0.244	1.000	103
Industrial vs. Emerging	0.113	-1.000	1.000	447
Emerging vs. Emerging	0.243	-1.000	1.000	463
Industrial vs. Africa & Middle East	-0.071	-1.000	0.998	135
Industrial vs. Asia	0.105	-0.929	0.959	86
Industrial vs. Eastern Europe	0.213	-1.000	1.000	112
Industrial vs. Latin America	0.240	-0.861	1.000	114
First Principal Component				
Industrial vs. Industrial	1.085	-0.770	2.513	87
Industrial vs. Emerging	-0.711	-3.457	2.637	101
Emerging vs. Emerging	-0.755	-2.580	1.782	30
Industrial vs. Africa & Middle East	.	.	.	0
Industrial vs. Asia	-1.118	-3.457	0.739	53
Industrial vs. Eastern Europe	0.446	-2.359	2.637	22
Industrial vs. Latin America	-0.859	-2.558	0.659	26

This table displays summary statistics of the correlations of selected macroeconomic variables between country pairs. The results are presented by groups of countries, splitting them in industrial versus emerging market countries, and further splitting the later by geographical regions. Correlations with the same country are excluded from the computations.

Table 3. Summary Statistics of Returns and Risk by Country Groups
(In Percent)

	Mean	St. Dv.	Min.	Max.	No. Obs.
Pooled Data					
Home	1.2	2.9	-8.7	26.5	229
Industrial	1.2	3.6	-19.5	48.9	1123
Emerging	1.8	6.3	-41.2	68.6	930
Averaging by Banks					
Home country					
Return	1.4	2.5	-1.2	10.1	38
Risk	1.0	1.8	0.0	9.3	38
Risk-Normalized Return	4.4	6.7	-0.3	35.7	38
Industrial countries					
Return	1.2	2.9	-7.2	24.6	209
Risk	1.2	2.3	0.0	15.4	207
Risk-Normalized Return	3.1	9.3	-1.3	126.7	207
Emerging countries					
Return	2.1	6.3	-25.6	58.6	190
Risk	2.8	5.5	0.0	51.0	190
Risk-Normalized Return	2.6	7.0	-68.9	34.4	190

The upper panel of this table presents summary statistics of the yearly ROA obtained by individual credit institutions in three groups of countries. The statistics are based on the pooled dataset, treating institutions at each point in time as individual observations. The lower panel presents the average return, risk, and risk-normalized returns obtained by credit institutions in three groups of countries. Return is given by the ROA and risk by its standard deviation. The statistics are based on a two-stage approach. First we compute the average return, risk, and risk-normalized return for each credit institution. Second, we average across credit institutions located in each group of countries.

Table 4. The Effect of Bank Internationalization on Risk-Adjusted Profitability
Dependent Variable is Risk-Normalized ROA

	[1]	[2]	[3]	[4]
	ROA/StDv	ROA/StDv	ROA/StDv	ROA/StDv
Percent assets in home country (coef_1)	3.942	3.880	4.929	4.966
	[0.445]***	[0.830]***	[0.930]***	[0.917]***
Percent assets in industrial (coef_2)	8.577	8.519	8.032	8.828
	[2.104]***	[2.205]***	[2.189]***	[2.231]***
Percent assets in emerging (coef_3)	9.408	9.426	11.990	11.301
	[2.177]***	[2.238]***	[2.425]***	[2.696]***
GDP Growth		0.113	0.106	0.117
		[0.124]	[0.120]	[0.117]
Money Market Rate in US$		-0.087	-0.093	-0.115
		[0.121]	[0.115]	[0.112]
Herfindhal index in industrial			-0.446	-0.275
			[0.508]	[0.505]
Herfindhal index in emerging			-1.461	
			[0.444]***	
Herfindhal Africa and Middle East				-2.304
				[1.124]**
Herfindhal Asia				-1.479
				[0.575]**
Herfindhal Eastern Europe				-0.102
				[0.445]
Herfindhal Latin America				-2.478
				[0.647]***
Observations	236	236	236	236
R-squared	0.83	0.84	0.84	0.85
coef_1=coef_2				
F-Stat	5.03	4.98	2.16	3.14
Prob > F =	0.03	0.03	0.14	0.08
coef_1=coef_3				
F-Stat	6.27	6.51	8.55	5.85
Prob > F =	0.01	0.01	0.00	0.02

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

This table presents the results of regressions of the risk-normalized ROA obtained by parent banks, on their asset shares in three groups of countries: (i) home, (ii) other industrial countries, and (iii) emerging economies. The regressions include a set of home-country macroeconomic controls, home-country fixed effects, and Herfindhal indexes of asset concentration in specific regions. F-tests of coefficient equality and their p-values are displayed at the bottom.

Table 5. Average Herfindhal Indexes by Groups of Countries

	Industrial Countries	Emerging Market Countries: Total Emerging	Africa and the Middle East	Asia	Eastern Europe	Latin America
Canada	0.69	0.50	.	0.59	.	0.21
France	0.54	0.25	0.34	0.32	0.64	0.38
Germany	0.47	0.33	.	0.34	0.43	0.20
Italy	0.69	0.45	.	.	0.30	0.16
Japan	0.71	0.47	.	0.56	0.07	0.19
Spain	0.58	0.38	.	.	.	0.38
U.K.	0.70	0.44	0.51	0.44	0.27	0.37
U.S.	0.54	0.39	0.21	0.44	0.16	0.51
Average	0.61	0.40	0.35	0.45	0.31	0.30

This table summarizes the average Herfindhal indexes of the concentration of assets in subsidiaries overseas for the sampled international banks.

Table 6. The Effect of Bank Internationalization on Risk-Adjusted Profitability
Dependent Variable is the Difference in Risk-Normalized ROA
(Consolidated minus Unconsolidated)

	[1] Diff. in Risk-Normalized ROA	[2] Diff. in Risk-Normalized ROA	[3] Diff. in Risk-Normalized ROA
Percent assets in home country (coef_1)	-0.345	0.406	0.610
	[0.289]	[0.496]	[0.554]
Percent assets in industrial (coef_2)	4.191	4.328	4.343
	[1.785]**	[1.724]**	[1.807]**
Percent assets in emerging (coef_3)	3.753	4.918	5.876
	[1.059]***	[0.972]***	[1.268]***
Herfindhal index within industrial		-0.802	-0.823
		[0.645]	[0.685]
Herfindhal index within emerging		-0.320	
		[0.489]	
Herfindhal Africa and Middle East			-5.116
			[2.458]**
Herfindhal Asia			-1.192
			[1.035]
Herfindhal Eastern Europe			-0.259
			[0.546]
Herfindhal Latin America			-0.008
			[0.772]
Observations	120	119	119
R-squared	0.25	0.32	0.35
coef_1=coef_2			
F-Stat	5.10	3.80	3.23
Prob > F =	0.026	0.054	0.075
coef_1=coef_3			
F-Stat	17.67	28.41	19.63
Prob > F =	0.000	0.000	0.000

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

The dependent variable is the difference of the risk-normalized ROA obtained by international banks on a consolidated basis, minus the risk-normalized ROA obtained on a solo basis. The target variables are the share of assets of each international bank in three country groups: (i) their home country, (ii) other industrial countries, and (iii) emerging economies. F-tests of coefficient equality and their p-values are displayed at the bottom.

Table 7. Comparison Between Observed and Optimal Portfolios Allocations by Country of Incorporation of International Banks
(In percent)

	Return	Risk	Sharpe	Asset Allocation Percent of Assets in: Home	Industrial	Emerging
Observed Portfolios (Period Average)						
Average	1.1	0.7	1.7	82.4	12.6	5.0
Canada	0.7	0.2	3.9	92.1	7.2	0.7
Germany	0.3	0.4	0.9	78.6	20.6	0.9
Spain	0.8	0.2	4.5	67.7	11.9	20.3
France	0.4	0.1	3.7	93.9	5.1	1.0
U.K.	5.1	2.2	2.3	50.4	23.9	26.5
Italy	0.5	0.7	0.7	90.4	7.7	1.9
Japan	0.7	1.3	0.6	78.3	20.3	1.3
U.S.	1.1	0.2	4.5	93.7	4.7	1.6
Optimal Portfolios (Frontier)						
Average	1.5	0.5	3.1	60.1	28.9	11.0
Canada	2.1	0.2	8.6	72.2	23.5	4.3
Germany	0.5	0.3	2.0	46.3	46.7	7.1
Spain	0.8	0.1	10.2	77.7	17.2	5.2
France	0.5	0.1	6.2	79.9	17.0	3.0
U.K.	5.2	2.4	2.2	52.9	17.1	29.9
Italy	0.9	0.3	3.1	44.5	36.9	18.6
Japan	1.1	0.4	3.0	41.4	44.7	14.0
U.S.	1.1	0.2	4.9	79.2	15.6	5.2
Deviation (Optimal-Observed)						
Average	0.4	-0.2	1.5	-22.3	16.2	6.0
Canada	1.4	0.1	4.7	-19.8	16.2	3.6
Germany	0.2	-0.1	1.1	-32.3	26.1	6.2
Spain	0.0	-0.1	5.7	9.9	5.2	-15.2
France	0.1	0.0	2.6	-14.0	11.9	2.0
U.K.	0.1	0.2	-0.1	2.6	-6.8	3.4
Italy	0.4	-0.4	2.4	-45.9	29.2	16.7
Japan	0.4	-0.9	2.5	-37.0	24.3	12.6
U.S.	0.0	0.0	0.5	-14.6	10.9	3.6

This table presents a comparison of the observed allocation of assets by international banks and their implied risk-returns, against an optimal, risk-minimizing allocation, that renders similar returns. The results are disaggregated by the countries of incorporation of international banks. All figures are unweighted averages.

Table 8. Returns and Variance-Covariance Matrix of the Typical International Bank

	Home	Industrial	Emerging
Variances-Covariances			
Home	3.58	0.20	0.45
Industrial	0.20	2.85	0.27
Emerging	0.45	0.27	12.17
Returns	1.32	0.78	3.30
Weights	82.4	12.6	5.0

This table shows the average variance-covariance matrix of yearly returns of international banks in three groups of countries: (i) home, (ii) other industrial countries, and (iii) emerging countries. The table also displays the average returns and the observed asset allocation in these three groups of countries. All figures are unweighted averages.

CONSOLIDATION IN THE US CREDIT UNION SECTOR:

DETERMINANTS OF FAILURE AND ACQUISITION

John Goddard[a]
Bangor Business School
University of Wales, Bangor

Donal McKillop[b]
School of Management and Economics
Queen's University of Belfast

John O.S. Wilson[c]
School of Management
University of St Andrews

Abstract

We examine the determinants of disappearance through liquidation or acquisition for US credit unions during the period 2001-06. The hazard of disappearance is inversely related to both asset size and profitability, and positively related to liquidity. Growth-constrained credit unions are less attractive acquisition targets, but are more likely to fail. Credit unions with low capitalization and those with relatively small loans portfolios are attractive as acquisition targets. We report unique empirical evidence of a link between technological capability and the hazard of disappearance. The absence of an internet banking capability rendered a credit union more vulnerable to acquisition, but did not affect the probability of failure.

Keywords: Credit unions, consolidation, acquisition, failure, technology

JEL: G21

a Bangor Business School, University of Wales, Bangor, Gwynedd, LL57 2DG, UK. Tel: +44 1248 383221. Fax: +44 1248 383228. Email: j.goddard@bangor.ac.uk

b School of Management and Economics, Queen's University Belfast, BT7 1NN, Northern Ireland, UK. Tel + 44 289 0973646. Email: dg.mckillop@qub.ac.uk

c School of Management, University of St Andrews, The Gateway, North Haugh, St Andrews, Fife, KY16 9SS, UK. Tel: +44 1334 462803. Fax: +44 1334 462812. Email: jsw7@st-and.ac.uk

CONSOLIDATION IN THE US CREDIT UNION SECTOR: DETERMINANTS OF FAILURE AND ACQUISITION

1. INTRODUCTION

In recent years, technological change and deregulation have fundamentally transformed the financial services industry. Technology improvements in data collection, storage and processing capabilities have occurred, and costs of product development and service delivery have declined. Financial institutions are now able to trade more freely in their local markets, and often beyond. Consequently, they have also increased the range of products and services to customers. Increased competition from a myriad of financial institutions has led to an increased emphasis on efficiency and profitability.

Many financial institutions have responded to the changing competitive environment by expanding, either through internally generated growth, or through merger and acquisition. Growth has enabled banks to realize scale and scope economies, reduce labor and other variable costs, and reduce or eliminate operational inefficiencies. Many financial institutions have sought to diversify their revenue sources. As net interest margins have been subjected to increasing competitive pressure, resulting, generally, in a depression of earnings streams relative to costs, many financial institutions have focused on achieving growth from other, non-interest income sources. Consolidation via acquisition and merger has contributed significantly to a reduction in the number of financial institutions in many countries (Nolle, 1995; Berger et al., 1995; Berger et al., 1999; Amel et al., 2004; Jones and Critchfield, 2005; Goddard et al., 2007a). "(T)he extraordinary advance in communications and data processing technology over the last two decades is the single most powerful underlying force... driving the merger wave" (Broaddus, 1998, p5).

In many countries, the credit union sector (in common with the banking and insurance sectors) has also experienced a wave of consolidation. However, with relatively few exceptions (Fried et al., 1999; Ralston et al., 2001; Worthington, 2004), this increase in merger activity has remained unexplained. In this study, we seek to fill this gap by examining the determinants of merger activity for the US credit union sector. Most previous studies of merger activity in financial services have neglected the role of technology. An important contribution of this paper is the incorporation of technology variables into a model of the determinants of the probability of acquisition or failure for financial institutions.

The rest of this paper is structured as follows. Section 2 outlines the structure of the US credit union sector. Section 3 reviews the theoretical and empirical literature on corporate failure, merger, and technology adoption, with particular emphasis on the financial services industry. Section 4 describes the data set, and develops an empirical model for the determinants of credit union acquisition or failure. Section 5 presents the results of the empirical analysis. Finally, Section 6 summarizes and concludes.

2. THE US CREDIT UNION SECTOR

Credit unions are not-for-profit financial cooperatives. Each credit union is governed by its members, who elect from within the membership unpaid volunteer officers and directors. Voting is on a one-member-one-vote basis, regardless of the size of each member's financial stake. At the end of 2006 there were 8,372 credit unions in the US, with a membership of 87 million and total assets of $710 billion. In recent years the asset and membership base of US credit unions has grown, but the number of credit unions has declined through consolidation. As credit unions have become larger and more sophisticated, there has been a gradual shift away from using volunteers for day-to-day operational needs and towards salaried employees. Credit unions serve a membership defined theoretically by a common bond (Goddard et al, 2002). The common bond might restrict membership to members of a local community, employees of a particular firm, or individuals with some other organizational affiliation (such as a church).[1]

[1] According to the American Bankers Association (2004), the 1998 Credit Union Membership Access Act resulted in erosion of the importance of the common bond, with federal credit unions permitted to add select employee groups (SEGs) to their fields of membership. In certain circumstances, a credit union's existing common bond designation may make it difficult, or inappropriate, to add SEGs. Some credit unions have converted from occupational to community common bonds with the objective of expanding their membership.

Growth in membership has also been accompanied by product diversification, particularly in the case of the larger credit unions (Goddard et al., 2007b). Many credit unions provide an array of retail financial services similar to those of banks and savings and loan associations. In addition, credit unions may also offer interest-bearing business checking accounts and commercial loans, agricultural loans and venture capital loans. Credit unions may also deal in investment products such as bankers' acceptances, cash forward agreements and reverse purchase transactions. These product offerings have further blurred the lines of demarcation between credit unions and mainstream financial services providers (Tokle and Tokle, 2000; Feinburg, 2001; Feinburg and Rahman, 2001; Hannan, 2003; Schmid, 2005).

Recently technological change has impacted heavily on the structure, operations and economics of the financial services industry. Information technology (IT) alters the ways in which customers can access services, mainly through automated distribution channels such as the internet, phone-based and other banking access channels. IT can also yield cost savings associated with the management of information (collection, storage, processing and transmission), and by substituting paper-based and labour-intensive procedures with automated processes[2] (Hernandez and Nieto, 2007; DeYoung et al., 2007).

3. CORPORATE FAILURE, MERGER AND TECHNOLOGICAL ADOPTION

In this section, we provide a selective review of academic literature on the determinants of corporate failure, the motives for merger and acquisition, and the adoption and diffusion of new technology. In

---

[2] Technological change in financial services can be classified under four main headings: Customer Facing Technologies; Business Management Technologies; Core Processing Technologies; and Support and Integration Technologies. Customer Facing Technologies include Automated Teller Machines (ATM), Electronic Funds Transfer at the Point of Sale (EFTPOS), Telephone Banking, Call Centres, Internet Banking, e-commerce and e-card business and Customer Relationship Management Systems (CRM). Business Management Technologies include Data Warehousing, Data Mining, Middleware, Credit and Risk systems. Core Processing Technologies include Cheque Processing, Statement Issuance, Interest and Charging Systems. Support and Integration Technologies include General Ledgers, Human Resources Systems, Finance Systems and Technology Support Systems.

each case, we focus primarily on literature that is relevant to financial services, and provide a few key citations from the broader industrial organization literature.

3.1 Corporate Failure

Academic research on the determinants of corporate survival or failure extends back to the 1960s. Beaver (1967) used a univariate model to assess the differences between surviving and non-surviving firms. Subsequently, multivariate models have been used to assess the usefulness of liquidity, profitability, risk and financial structure as predictors of survival or failure. Both discriminant analysis and discrete choice regression models have been employed (Altman, 1968, 1993; Ohlson, 1980; Shumway, 2001).

Several studies have examined the role of bank-specific, regulatory and regional economic conditions as determinants of bank failure (Sinkey, 1975; Demirguc-Kunt, 1989; Gajewski, 1989; Thomson, 1991; Wheelock and Wilson, 1995, 2000; Cole and Gunther, 1995, 1998; Kolari et al., 2002; Nuxoll, 2003; Nuxoll et al., 2003; King et al, 2005; and Lanine and Vander Vennet, 2006). Estrella et al (2000) find that capital ratios are useful predictors of US bank failure. Leverage ratios, which capture operational risk, interest rate risk and reputation risk, are better predictors of failure over short time periods than the more sophisticated risk-based capital ratios, which focus primarily on credit risk. An unadjusted capital to gross revenue measure, suggested by Shepheard-Walwyn and Litterman (1998), performs reasonably well in predicting bank failure. DeYoung (2003) notes that around 25% of US banks that were newly chartered during the 1980s have failed subsequently.

The rather limited evidence on credit union failure suggests that young, small and poorly capitalized credit unions are most likely to fail (Kharadia and Collins, 1981; GAO, 1991; Wilcox, 2005). Poor macroeconomic conditions also increased the probability of failure. In terms of the overall riskiness of credit unions relative to banks, the losses imposed on insurance funds appear to be lower for credit unions. For example, the (per dollar of insured deposit) losses over the period 1971-2004 for the Bank Insurance Fund (BIF) of the Federal Deposit Insurance Corporation (FDIC) and the

National Credit Union Share Insurance Fund (NCUSIF) were 0.073% and 0.018%, respectively (Wilcox, 2005).

3.2 Merger

Corporate finance theory summarises the motives for merger activity in any industry under the general headings of synergy, hubris and agency (Collins, 2003; Copeland and Weston, 2005). Synergy, the most common justification given by senior management for merger proposals, refers to the increased market power of the merged entity, and to the potential for cost savings. Cost savings may be realized through the exploitation of scale economies, vertical integration, or the adoption of more efficient production or organizational technology. Savings may be realized through the elimination of overlapping costs, by combining head office and various back office functions or branch networks. Scope economies, realized through the cross-selling of products and services, as in deals involving banks and insurance companies, may also be available. Mergers may allow the exploitation of certain accounting advantages, such as under-utilized tax shields. Another possible cost saving derives from the removal of inefficient management at the target institution.

The hubris hypothesis suggests that managers make mistakes in evaluating target firms, and overestimate the potential for synergy (Roll, 1986). Consequently, bidding firms tend to pay too much for the target. Finally, according to the agency hypothesis, acquiring managers deliberately overpay for their targets, because they benefit personally, even if the stock price and shareholder wealth is adversely affected. There may be greater prestige associated with managing a larger organization; promotion opportunities may be better; or merger may divert attention and allow senior managers to avoid dismissal if their institution has been performing poorly.[3]

[3] Gorton et al. (2006) develop a hybrid theory that combines managerial motives and a regime shift. They argue that managers benefit personally from operating the firm, and therefore have an incentive to keep the firm independent. However, if a regime shift increases the importance of economies of scale, managers find themselves under pressure to increase firm size, either for defensive or for strategic positioning reasons, leading to what is termed an eat-or-be-eaten scenario. "Our models show that in industries with economies of scale, firm size becomes the driving force for merger dynamics. Often this leads to profitable acquisitions. However, if a firm becomes very large and its manager's private benefits are high, it may engage in unprofitable defensive acquisition. (Gorton et al., 2006, p4).

Empirical evidence on the motives for bank merger tends to confirm the importance of the synergy motive (Zhang, 1995; Grabowski et al., 1995; Rhoades, 1998; Wheelock and Wilson, 2000, 2004; Focarelli et al., 2002).[4] Banks with low earnings, low capital-to-assets ratios, high local market share, or which operate in urban areas, are more likely to be acquired (Hannan and Rhoades, 1987; Amel and Rhoades, 1989; Moore, 1997; Hadlock et al., 1999; Hannan and Piloff, 2006).

Studies of the impact of bank mergers examine either pre- and post-merger cost efficiency, or stock price reactions to merger announcements. Rhoades (1986) finds no difference between the performance of US banks that were acquired and those that were not, but using bank merger case studies, Rhoades (1998) finds some evidence of cost savings. Spindt and Tarhan (1992) find that the profitability of many merged banks improved in the years after merger. However, the view that realized post-merger cost efficiency gains are quite limited is prevalent in the empirical literature (Berger and Humphrey, 1992; Rhoades, 1993; Peristiani, 1997; DeYoung, 1997). This evidence is confirmed by analysts' estimates of projected cost savings associated with mergers (Houston et al., 2001). Recent empirical evidence suggests that information spillovers from previous mergers, and learning-by-doing within banks, have led to improved post-merger returns (DeLong and DeYoung, 2007).

Shaffer (1992) and Molyneux et al. (1996) evaluate the impact of mergers by calculating potential cost savings arising from hypothetical, simulated mergers, using cost functions estimated from real data. The majority of simulated mergers lead to increases in costs. Some studies that focus on profit efficiency report post-merger benefits (Akhavein et al., 1997; Berger, 1998). Cornett et al. (2006) report that geographically focused mergers provide both revenue enhancements and cost savings, while Park and Pennacchi (2007) report that mergers involving large multimarket banks tend to enhance competition in loans markets, but damage competition in deposit markets.

Overall, the empirical evidence on bank mergers suggests there is often little improvement in the efficiency or performance of the merged entity. This suggests that the hubris and agency motives

[4] Some non-bank studies also report evidence in support of the hubris and agency hypotheses (Berkovitch and Narayanan, 1998; Rossi and Volpin, 2004). Cross-country merger studies suggest that differences in accounting standard and shareholder protection are significant drivers of shareholder activities (Rossi and Volpin, 2004; Buch and DeLong, 2004; and Pozzolo and Focarelli, 2007).

for merger may be relevant; or that synergy derives more from enhanced market power than from cost savings. These explanations are not mutually exclusive: increased market power might be reflected in senior mangers directing a larger proportion of revenues towards executive salaries or fringe benefits; or large banks might choose to adopt risk-averse strategies, as the 'quiet-life' hypothesis (Hicks, 1935; Berger and Hannan, 1998). This could explain why increased market power resulting from merger is not reflected in increased profitability or shareholder value.

Evidence on the motives for credit union mergers is limited, but three studies are noteworthy. Fried et al. (1999) finds that in the US, acquiring credit unions benefit more when they and the target credit union have different levels of profitability, different numbers of select employee groups, and when one of them has a community charter. This implies that the acquired credit union can exploit the complementarities offered by the merger. On average, members of acquiring credit unions experienced no deterioration in service provision post-merger, while members of acquired credit unions experienced improvements of at least three years' duration.

For Australian credit union mergers, Ralston et al. (2001) find mixed evidence of post-merger gains and losses in technical and scale efficiency. The highest gains were found where pre-merger efficiency scores were low for both partners. This is inconsistent with the notion that efficiency gains are realized by transferring assets from inefficient managers to efficient managers. Mergers do not appear to generate efficiency gains greater than those that non-merging credit unions are able to achieve through internal growth. Finally, in a study of the determinants of merger for Australian credit unions, Worthington (2004) finds that asset size and quality, managerial efficiency; earnings and liquidity are all significant drivers of merger activity.

3.3 Technology adoption and diffusion

Technological change might provide the impetus for industry consolidation. Mergers take place when managers respond to technological or regulatory shocks, which change the industry's cost and demand conditions (Gort, 1969; Mitchell and Mulherin, 1996). In the case of major technology shocks such as the IT revolution of the late-20th century, a merger wave can spread across many industries simultaneously. At the same time, merger activity might serve as an important vehicle for the diffusion of new technology (Mansfield, 1961, 1969; Damanpour, 1991, 1992). Mergers play a role in the diffusion process by speeding up the transmission of new information, and spreading the risks associated with new technologies over larger volumes of output.[5]

In banking, several studies have examined patterns of adoption of innovations, including: Auto Teller Machines (Hannan and McDowell, 1984; 1986; Saloner and Shepard, 1995); Automated Clearinghouse Settlement Systems (Gowrisankaran and Stavins, 2004); credit scoring technologies (Akhavein et al., 2005); and Real Time Gross Settlement Systems (Bech and Hobijn, 2006). Furst et al. (2002) use multivariate logit regressions to identify factors driving the adoption of internet banking. Banks that incurred high fixed costs relative to net operating revenues, were members of a bank holding company, or were located in an urban area, were more likely adopters. Courchane et al. (2002) examine the decision to invest in internet banking using a two-stage real options framework. Bank size, industry concentration and bank location were significant determinants of the probability of adoption. Nickerson and Sullivan (2004) suggest banks are more likely to adopt internet banking where uncertainty over the level of demand is low. Sullivan and Wang (2005) find that the adoption of internet banking was slower in US states where average income is low, where there is a scarcity of internet access, where financial institutions are older, and where average bank size is smaller. Fuentes et al. (2006) find that banks are more likely to adopt transactional internet banking when competition is intense, and when rival banks have already adopted.

[5] Smythe (2001) examines mergers in US manufacturing industries between 1895-1904 using a Schumpeterian framework. The turn-of-the-century merger movement was " ... the consequence of an aggressive, unremitting technological competition that concurrently swept across a wide swathe of American industries in the wake of the technological innovations clustered at the end of the nineteenth century. Because the implementation of these innovations required significant capital investments, and because the outcome of the competitive process was highly uncertain, firms' incentives to cooperate with their rivals were increased at the same time that sustaining such cooperation at arms length was made impossible. The only way of realizing the benefits of cooperation, therefore, was by internalizing it through horizontal mergers. Once realized, the cooperation helped facilitate the capital investments necessary to implement the new technologies" (Smythe, 2001, p254).

4. DATA AND MODEL SPECIFICATION

4.1 Data and sample selection

In this section, we describe the data that are used below to estimate hazard functions for US credit union disappearances through acquisition or failure. We also discuss the selection of covariates for the hazard functions. The credit union balance sheet and income statement data are compiled from the '5300 Call Reports' published by the National Credit Union Association (NCUA). Semi-annual data are available for the period June 2001 to June 2006, providing a maximum of 11 time-series observations on each credit union.

The covariates of the hazard functions control for asset size, market penetration, age, profitability, liquidity, risk, asset mix, asset quality, managerial efficiency and technological capability. In addition, we include controls for the charter and common bond characteristics of each credit union, distinguishing between state and federally chartered credit unions, and between single and multiple common bond credit unions.

The complete list of covariate definitions is as follows:

Size:	LASSET = natural logarithm of total assets
Market penetration:	MEMPOT = actual members / potential members
Age:	LAGE = natural logarithm of (current year – year of formation)
Profitability:	ROA (return on assets) = net income / total assets
Liquidity:	LIQ = (cash on hand + cash on deposit + cash equivalents) / total assets
Capital adequacy:	CAPASS (capital-to-assets ratio) = net worth / total assets
Asset mix:	LOANASS = total loans / total assets
Asset quality:	NONPER = non-performing loans / total loans
Efficiency:	NINTASS = non-interest expenses / total assets
Technological capability:	
	TECH1 = 0-1 dummy identifying credit unions with an informational website

	TECH2 = 0-1 dummy identifying credit unions with an interactive website
	TECH3 = 0-1 dummy identifying credit unions with a transactional website
Charter type:	FED = 0-1 dummy identifying federally chartered credit unions
Common bond:	MULT = 0-1 dummy identifying multiple common bond credit unions

For credit unions that disappeared, NCUA provide a three-way classification by mode of disappearance, as follows: (i) acquisition; (ii) liquidation; and (iii) purchase and assumption (P&A) orders. Acquisition refers to the case where the acquiring credit union absorbs all of the assets and liabilities of the acquired credit union. Under the terms of the Federal Credit Union Act (section 120 and section 207), NCUA can place a credit union into liquidation, if it deems the credit union to be bankrupt or insolvent. NCUA can also place a solvent credit union into involuntary liquidation for violation of the terms its charter or breach of NCUA regulations. P&A is similar to acquisition, except it takes place after a credit union has entered liquidation, usually because the credit union is financially unsound. The purchasing credit union acquires specified assets and liabilities, with the rest covered by the insurance fund (NCUSIF).[6]

For June 2001, NCUA report data for 10,269 credit unions. We eliminated from the sample a number of credit unions for which data on any variable were missing for one or more subsequent six-monthly time periods up to and including June 2006, and the credit union concerned was not reported as either acquired, liquidated or subject to a P&A order within the same period. We also eliminated from the sample any credit union that reported an extreme or unbelievable value for any of the variables for any six-monthly period. We also eliminated a small number of credit unions for which the year of formation was not reported. Trimming the sample in this way resulted in the loss of exactly 700 credit unions (6.8% of the total that are reported for June 2001). The final sample comprises 9,569 credit unions that were live in June 2001 and reported complete and believable data either up to the recorded date of disappearance, or up to and including June 2006 in the case of non-

[6] The NCUA delegates responsibility for managing liquidation or P&A to the Asset Management and Assistance Centre (AMAC), which manages the repayment of insured deposits (shares), sale of loans, liquidation of assets and cancellation of charters.

disappearing credit unions. Of the 9,569 sample credit unions that were live in June 2001, 7,949 survived until December 2006 and 1,620 disappeared between June 2001 and December 2006.

In addition to the three modes of disappearances described above, NCUA provides a coding for each disappearing credit union according to the reported reason for disappearance. Table 1 provides a two-way classification of the 1,620 sample credit unions that disappeared, by mode of disappearance (acquisition, liquidation or P&A), and by reported reason for disappearance. For a very large majority of the sample credit unions that disappeared (96.9% of all disappearances), the mode of disappearance is acquisition. By comparison, the proportions of disappearances through liquidation (2.3%) and through P&A (0.8%) are very small. This suggests that it may be difficult to identify separate hazard functions for disappearance through merger, liquidation and P&A. Nevertheless, despite the small numbers in the latter two categories, in Section 5 we report a competing risks model in which these two categories are combined, and separate hazard functions are estimated for disappearance due to merger, and disappearance due to either liquidation or P&A.

The classification according to the reported reason for disappearance produces a more balanced subdivision. In Section 5 we also report an alternative competing risks model based on the reported reasons for disappearance, which are grouped into three broad categories: (i) financial or managerial difficulties (21.5% of all disappearances); (ii) expansion (27.5%); and (iii) reorganization and restructuring (51.0%).

4.2 Choice of hazard function covariates

In the rest of Section 4, we discuss the theoretical basis for the selection of covariates for the hazard functions for credit union disappearances, and we comment on the sample summary statistics for each of the covariates. The summary statistics are reported in Tables 2 to 5. Table 2 reports sample means, standard deviations and correlation coefficients for the time-varying covariates of the hazard function model, excluding the technology covariates. In calculating these summary statistics, the semi-annual observations on each sample credit union from the period June 2001 to June 2006 (inclusive) are pooled. Accordingly, each sample credit union contributes up to 11 observations to the summary statistics. Table 3 reports summary statistics for the non-time-varying covariates. These statistics are reported separately for all sample credit unions, and for the credit unions that disappeared. Table 4 reports sample mean values for the time-varying covariates in each semi-annual period, calculated using the data for all surviving credit unions in each period. Table 5 reports the sample mean values for the time-varying covariates for credit unions that disappeared, calculated using only the data from the last-reported observation on each disappearing credit union.

The relationship between asset size and performance is widely documented in the theoretical and empirical banking literature. Economies of scale in screening, lending and monitoring may render large financial institutions better able to judge cost and demand conditions. Accordingly, it seems likely that smaller credit unions are at greater risk of disappearance than larger ones, and we expect a negative coefficient on LASSET in the hazard functions. Table 4 indicates that the average asset size of the sample credit unions increased steadily throughout the sample period, while Table 5 indicates that the credit unions that disappeared were much smaller on average than those that survived.

Age might be correlated with a number of unobservable managerial characteristics that could impact on the probability of disappearance, but we have no specific prior concerning the sign of the coefficient on LAGE. Table 3 suggests there was little difference between the age profile of the sample as a whole, and that of the credit unions that disappeared.

The market penetration measure shows the number of actual members of the credit union as a proportion of the potential membership determined by the terms of the credit union's charter. High market penetration indicates that a credit union has already captured most of its potential membership, and further growth under the credit union's present common bond designation may be constrained. In this case, absorption into another credit union with a broader common bond designation through acquisition might eliminate this growth constraint, and we would expect a positive coefficient on MEMPOT in the hazard function. Alternatively, a growth-constrained credit union might represent an unattractive target to a potential acquirer, in which case a negative coefficient might be expected. At the start of the sample period, credit unions that disappeared had slightly higher average values of MEMPOT than the sample as a whole (Tables 4 and 5). This difference appears to have narrowed over the course of the sample period.

It seems likely that credit unions with poor profitability are more likely to disappear than those with high profitability; therefore we expect a negative coefficient on ROA in the hazard function. In fact, the average ROA of disappearing credit unions immediately before they disappeared was always negative, and considerably lower than the average ROA of the sample as a whole. A highly liquid credit union might be at greater risk of being acquired than an illiquid one, because high liquidity makes it an attractive target for a cash-strapped acquirer, or because it may be forgoing an investment return on the assets concerned. Therefore we expect a positive coefficient on LIQ. According to the summary statistics, the average LIQ of the disappearing credit unions is higher than the average for the sample as a whole.

In common with other financial institutions, credit unions are subject to capital requirements.[7] We might expect either a positive or a negative relationship between CAPASS and the probability of acquisition. A positive relationship might be expected if a credit union holds excess capital because it has limited opportunities for growth. This would make a highly capitalized credit union an attractive target to a growth-oriented acquirer. Alternatively, an acquirer might be poorly capitalized, and seeking to improve its capitalization by acquiring a well-capitalized credit union. The summary statistics indicate that for 10 of the 11 semi-annual periods, the average value of CAPASS is slightly higher for the credit unions that disappeared than for the sample as a whole.

Conversely, a negative relationship between CAPASS and the hazard of disappearance might be expected if the acquired credit union's high capitalization is a proxy for efficiency, suggesting limited scope for further efficiency gains following a merger. According to Hannan and Piloff (2006), acquirers might prefer a high level of leverage because this enables them to maximize post-merger performance gains relative to the cost of achieving those gains. For any given asset size, the purchase

[7] Credit unions cannot raise capital as easily as other financial institutions, because they cannot issue equity. However, the tax-exempt status of any capital the credit union raises internally through retained earnings represents a form of subsidy to shareholders. This has been justified as beneficial for tackling financial exclusion, on the grounds that credit unions serve low-income clients; but a 2001 Federal Reserve survey of consumer finance suggested that credit unions do not actually serve a higher proportion of such clients than other financial institutions. Consequently it has been suggested that credit unions should be taxed on the same basis as banks (Chimura Economics and Analytics, 2004; Tatom, 2005). Recently, US Congress has asked the NCUA to collect data to identify the types of services provided to members, the income distribution of members, and levels of executive compensation and benefits to board members (US Government Accountability Office, 2005; NCUA, 2006).

price is likely to be lower if the target credit union is poorly capitalized. Therefore a less capitalized target offers the acquirer the prospect of achieving a given performance gain for a lower investment.

Because loans are typically less liquid and more risky than other assets, a credit union with a high loans-to-assets ratio might be at greater risk of failure. In this case, we would expect a positive coefficient on LOANASS in the hazard function. Alternatively, credit unions with relatively small loans portfolios might be vulnerable as targets for acquirers who may believe they can earn a higher return by increasing the size of the loans portfolio. The summary statistics indicate that average values of LOANASS are generally lower for the disappearing credit unions than for the sample as a whole.

A high ratio of non-performing loans to total loans should be a relevant indicator of potential insolvency; therefore we expect a positive coefficient on NONPER. The average values of NONPER are higher for the disappearing credit unions than for the sample as a whole. Completing the list of company accounts covariates, the ratio of non-interest expenses to total assets is employed as a crude measure of cost efficiency. On the grounds that inefficient credit unions are likely to be more vulnerable to failure or acquisition, we would expect a positive coefficient on NINTASS. However, the average values of NINTASS are generally lower for the disappearing credit unions than for the sample as a whole (although the difference does not appear large relative to the random variation in NINTASS for the disappearing credit unions).

The increasing penetration in recent years of internet technology into all aspects of commercial activity provides opportunities for studying the interactions between technology adoption and diffusion, and other strategic decisions of commercial organizations, including merger and acquisition in the present case. Our prior is that a credit union that is backward in the adoption of internet technology might be at greater risk of acquisition by an institution whose managers have the requisite technological capability, and might be able to earn a higher return on assets than the backward credit union's current managers.

We identify three indicators of internet technology adoption, dependent on the existence and capabilities of the credit union's website. At the first (lowest) level, an informational website displays general information on interest rates, and contract details. At the second (intermediate) level, an interactive website also allows members to request information on share and loan balances, and to request statements. It also accepts applications for membership, loans or share accounts. Finally, at the third (highest) level, a transactional website also allows members to complete transactions such as paying bills, make loan payments or deposits, and transfer funds between accounts. In accordance with the preceding discussion, we expect negative coefficients on the dummy variables TECH1, TECH2 and TECH3 in the hazard function. The summary statistics indicate that credit unions that disappeared were much less likely to have developed websites by the time of disappearance than the sample as a whole (Tables 4 and 5).

Finally, only those individuals who fall within a credit union's common bond (field of membership) can use the credit union's services. Both state governments and the federal government charter credit unions.[8] In the hazard functions, the dummy variable MULT distinguishes between single and multiple common bond credit unions, and the dummy variable FED does the same for state chartered and federally chartered credit unions. The summary statistics suggest that a relatively high proportion of the disappearing credit unions were single common bond, but the proportions of disappearances that were state chartered and federally chartered were similar to those for the sample as a whole.

5. ESTIMATION METHOD AND RESULTS

5.1 Estimation method

The estimation of hazard functions for the disappearance of US credit unions through acquisition or failure is based on the method used by Wheelock and Wilson (2000) to model the determinants of failure and acquisition for US banks. The empirical model for the hazard of disappearance is based on the Cox (1972) proportional hazard model with time-varying covariates. In several of the estimations that are reported below, we model probabilities for the disappearance of credit unions, treating all disappearances as identical events and ignoring the mode and reported

[8] The laws governing state-chartered credit unions' common bond limits and powers tend to be more liberal than the corresponding federal laws. State chartered credit unions may therefore assume more risk or adopt more aggressive portfolio management techniques. However, state chartered credit unions are unable to branch across state lines, and are therefore subject to a significant constraint on their growth.

reason for disappearance. In other estimations, we model separate probabilities using a competing risks model. In the latter, the alternative modes of disappearance or reported reasons for disappearance are treated as independent events, and the observations on a credit union that disappeared through one event are treated as right-censored in the estimations of the hazard for disappearance through any of the other events.

The hazard function expressing the probability that credit union i disappears through event k between time t and time t+1, conditional on a vector of covariates specific to credit union i at time t that influence the probability of event k, denoted $x_{i,k}(t)$, is modelled as follows:

$$\lambda_{k,i}(t \mid x_{k,i}(t), \beta_k) = \bar{\lambda}_k(t)\exp(x_{k,i}(t)'\beta_k)$$

$\bar{\lambda}_k(t)$ denotes the baseline hazard, and β_k is a vector of coefficients to be estimated. The time-index t is measured in calendar time elapsed since the first observation, for June 2001. Since all sample credit unions were in existence in June 2001, calendar time and duration until disappearance are equivalent for all observations in the data set. We let R_t denote the set of credit unions that are in existence at time t and at risk of disappearance between t and t+1, and we let $D_{k,t}$ denote the set of $d_{k,t}$ credit unions that disappear through event k between time t and time t+1. The contribution to the partial likelihood function of credit union i, which disappears through event k between t and t+1, is:

$$\exp(x_{k,i}(t)'\beta_k) / \sum_{j\in R_t} \exp(x_{k,j}(t)'\beta_k)$$

We note that $\bar{\lambda}_k(t)$ drops out when the partial likelihood function is formed. Therefore $\bar{\lambda}_k(t)$ is not parameterized explicitly, and the proportional hazards model is described as semi-parametric. The log-partial likelihood function is:

$$\ln[L(\beta_k)] = \sum_{t=1}^{T}[\sum_{i\in D_{k,t}} x_{k,i}(t)'\beta_k - d_{k,t}\ln\{\sum_{j\in R_t}\exp(x_{k,j}(t)'\beta_k)\}]$$

All estimations are carried out using the survival analysis routines available in *Stata* 9.

5.2 Hazard function estimation results

Table 6 reports the hazard function estimation results. In Equation I, the hazard is for disappearance due to either merger, liquidation or purchase and assumption (P&A). Equations II and III comprise a competing risks model, in which separate hazards are estimated for disappearance due to merger (Equation II) and liquidation or P&A (Equation III). Equations IV to VI comprise an alternative competing risks model, in which disappearances due to either merger, liquidation or P&A are subdivided according to the reported reason for disappearance. As noted in Section 4, the reported reasons for disappearance are: financial or managerial difficulties; expansion; and reorganization or restructuring. Equations VII to VIII repeat the estimation in Equation I, using only the data for state and federally chartered credit unions, respectively. Finally, Equations IX and X repeat the estimation in Equation I, using only the data for single and multiple common bond credit unions, respectively.

The anticipated inverse relationship between asset size and the hazard of disappearance is evident in all of the hazard function estimations reported in Table 6. The coefficients on LASSET are negative and strongly significant coefficients in all 10 equations. Therefore subdivision of the sample by mode of disappearance, by reported reason for disappearance, or by charter or common bond, does not appear to affect this strong underlying relationship between size and the hazard of disappearance.

The coefficient on MEMPOT is negative and significant in Equation I, indicating that the closer is the credit union's membership to its maximum, the less likely is the credit union to disappear. This does not support the hypothesis that acquisition is used as a means for eliminating a constraint on growth, but it is consistent with the hypothesis that acquiring credit unions prefer targets with higher growth potential. Further evidence in support of this interpretation is found in Equations II, III and V. The coefficient on MEMPOT in Equation II (hazard of disappearance due to acquisition) is negative and significant, but the coefficient in Equation III (liquidation or P&A) is positive and significant (at the 10% level). In other words, credit unions that are growth-constrained are less likely to be attractive acquisition targets, but are more likely to disappear due to liquidation or P&A. The negative coefficient on MEMPOT in Equation V (disappearance for reasons associated with expansion) is large in absolute terms and highly significant. Credit unions that are growth-constrained naturally make less attractive targets when expansion is the motive for acquisition.

The coefficient on LAGE in Equation I is positive and significant, suggesting that older credit unions are at greater risk of disappearance. This pattern is repeated in most of the other estimations, although not all of these coefficients are significant.

The anticipated inverse relationship between profitability and the hazard of disappearance is evident throughout Table 6. The coefficients on ROA are negative and strongly significant coefficients in all except Equation III (hazard of disappearance due to liquidation or P&A). The insignificant coefficient in the latter case may perhaps reflect the relatively small number of disappearances in this estimation. In general, and as is also the case with the size covariate, subdivision of the sample does not seem to affect this strong underlying relationship between profitability and the hazard of disappearance. Similarly, a positive relationship between liquidity and the hazard of disappearance is evident throughout Table 6, with only one insignificant coefficient reported, in Equation III. These results are consistent with the hypotheses that highly liquid credit unions tend to make attractive targets, perhaps because they generally fail to realize an adequate return on their assets. We note that Table 2 reports a negative correlation between ROA and LIQ.

The coefficients on CAPASS are negative and significant in all equations except Equation III (hazard of disappearance due to liquidation or P&A), where the coefficient is positive and significant. These results lend support to the explanations for a negative relationship between CAPASS and the hazard of acquisition advanced by Hannan and Piloff (2006): namely, that high capitalization is a proxy for efficiency, and is indicative of limited scope for post-merger efficiency gains; or low capitalization reduces the purchase price and increases the attractiveness of the target. On the other hand, highly capitalized credit unions appear to be at greater risk of disappearance due to liquidation or P&A.

Most of the estimated coefficients on NONPER reported in Table 6 are insignificant, and there is a mix of positively and negatively signs. This seems surprising, because Tables 4 and 5 suggest the proportion of non-performing loans was consistently higher for the disappearing credit unions than for the sample as a whole. The explanation may lie in Table 2, which reports relatively high correlation coefficients between NONPER and several other covariates (ROA, LIQ, CAPASS and LOANASS in particular). After controlling for the effects of these other factors on the hazard of disappearance, any apparent effect from NONPER drops out in most cases. One exception is VII (hazard of any disappearance for any reason, state chartered credit unions only), in which the coefficient on NONPER is positive and significant as anticipated.

The coefficients on LOANASS are predominantly negative and significant, with the exception of the coefficient in Equation IV (disappearance for reasons associated with financial or managerial difficulties), for which the coefficient is positive but insignificant. In general, the estimation results are consistent with the hypothesis that credit unions with relatively small loans portfolios are vulnerable as targets to acquirers who may anticipate earning a higher return on assets.

The coefficient on NINTASS in Equation I is positive and significant. This seems consistent with the interpretation of the ratio of non-interest expenses to assets as a managerial inefficiency measure, and the hypothesis that inefficient credit unions are more vulnerable to acquisition or failure. Although no such pattern is apparent in the sample averages reported in Tables 4 and 5, the pattern becomes apparent in the multivariate model after controlling for other covariates. However, only 3 of the 9 corresponding coefficients in Equations II to X are also positive and significant, so any such effect does not appear to be particularly robust.

The coefficients on the internet banking covariates TECH1-TECH3 in Equation I are negative and significant. The absolute values of these coefficients are consistent with the hypothesis advanced in Section 4: credit unions with no website are at the highest risk of disappearance, followed by those with informational, interactive and transactional websites respectively, in the anticipated order. The corresponding coefficients are insignificant in Equation III (disappearance due to liquidation or P&A). In all of the other equations, the coefficients on TECH3 are significant, as are many of the coefficients on TECH1 and TECH2. Equation II in particular lends support to the hypothesis that the absence of an internet banking capability renders a credit union more vulnerable to acquisition, presumably by acquiring managers who have the technological capability and perceive that they can earn a higher return from the target credit union's assets. According to Equation III, however, the absence of an internet banking capability did not significantly increase the hazard of disappearance through liquidation or P&A.

Finally, the coefficient on FED in Equation I suggests that after allowing for the other controls, the hazard of disappearance was higher for state chartered than for federally chartered credit unions. The same pattern is evident in some but not all of the other estimations. In general the coefficients on MULT suggest there was little difference in the hazard between single and multiple common bond credit unions. Therefore the higher proportion of disappearances among single common bond credit unions shown in Table 3 seems to be explained by the other covariates, and drops out of the multivariate model. In general, the individual estimations for state and federally chartered credit unions, and for single and multiple common bond credit unions, reported in Table 6 as Equations VII to X, are quite similar to Equation I. The determinants of the hazard of disappearance do not appear to vary greatly by charter type or by common bond type.

6. CONCLUSION

In recent years, the US credit union sector has undergone a wave of consolidation. With a few exceptions, however, this increase in merger activity has remained largely unexplained in the academic literature. In this study we have sought to fill this gap, by examining the determinants of disappearance through liquidation or acquisition for US credit unions. Most previous studies of merger activity in financial services have largely neglected the role of technology. An important contribution of this paper has been the incorporation of technology variables into a model of the determinants of the probability of acquisition or failure for financial institutions.

In common with several other financial services sector merger or failure studies, we have found evidence of a strong inverse relationship between asset size and the hazard of credit union disappearance. Credit unions that are growth-constrained are less likely to be attractive acquisition targets, but are more likely to disappear through liquidation or P&A (purchase and assumption). Older credit unions are at slightly greater risk of disappearance, although the empirical link between age and the hazard of disappearance is not particularly strong or robust.

There is a strong inverse relationship between profitability and the hazard of disappearance. The average ROA of credit unions that disappeared for the six-monthly period immediately preceding disappearance was always negative. Highly liquid credit unions appear to be attractive acquisition targets, perhaps because of the accessibility of their assets in liquid form, or perhaps because they have a tendency not to realize an adequate return on their assets.

Credit unions with low capitalization are at greater risk of disappearance. This could be because poorly capitalized credit unions have been inefficiently managed, and offer acquirers scope for introducing efficiency gains. Alternatively, it could be that low capitalization reduces the purchase price and therefore increases the attractiveness of the target to the acquirer. Highly capitalized credit unions appear to be at greater risk of failure through liquidation or P&A.

Although the credit unions that disappeared had a higher proportion of non-performing loans, the share of non-performing loans in the loans portfolio does not appear to be an important factor in determining the hazard of disappearance, after controlling for other factors such as profitability and liquidity. Credit unions with relatively small loans portfolios appear to be attractive targets for acquirers who may believe they can earn an improved return in such cases. Using the ratio of non-interest expenses to assets as a crude managerial efficiency measure, there is some evidence that inefficient credit unions are more vulnerable to acquisition or failure, although this relationship does not appear to be particularly strong or robust.

Finally, this paper has presented what we believe to be unique empirical evidence of a link between technological capability and the hazard of disappearance through acquisition in financial services. During the period 2001-06, when there was sustained growth in the uptake of internet technology, credit unions with no website were at the highest risk of disappearance, followed by those with informational, interactive and transactional websites. In other words, the risk of disappearance decreased as the level of website sophistication and capability increased. We therefore find support for the hypothesis that the absence of an internet banking capability renders a credit union more vulnerable to acquisition, presumably by acquiring managers who have the technological capability and perceive that they can earn a higher return from the target credit union's assets.

References

Akhavein, J.D., Berger, A.N. and Humphrey, D.B. (1997) The effects of mega mergers on efficiency and prices: Evidence from a bank profit function, *Review of Industrial Organization*, 12, 95-139.

Akhavein, J., Frame, S. and White, L.J. (2005) The diffusion of financial innovation: An examination of the adoption of small business credit scoring by large banking organizations, *Journal of Business*, 78, 577-596.

American Bankers Association (2004) Submission by the American Bankers Association to the Ways and Means Committee of the US House of Representatives, Washington D.C.

Altman, E. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, 23, 589-609.

Altman, E. (1993). *Corporate financial distress and bankruptcy: A complete guide to predicting and avoiding distress and profiting from bankruptcy*, 2nd Ed. New York: John Wiley.

Altunbas Y., Molyneux P. and J. Thornton (1997) Big bank mergers in Europe: An analysis of cost implications, *Economica*, 64, 317-329.

Amel, D. and Rhoades, S. (1989) Empirical evidence on the motives for bank mergers, *Eastern Economic Journal*, 15, 17-27.

Amel, D., Barnes, C., Panetta, F. and Salleo, C. (2004) Consolidation and efficiency in the financial sector: A review of the international evidence, *Journal of Banking and Finance*, 28, 2493-2519.

Beaver, W. (1967). Financial ratios as predictors of failure, *Journal of Accounting Research* (supplement) 4, 71-111.

Bech, M.L. and Hobijn, B. (2006) Technology diffusion in central banking, *Feral Reserve Bank of New York Staff Reports*, No. 260, September 2006.

Berger, A.N., (1998) The efficiency effects of bank mergers and acquisition: A preliminary look at the 1990s data. In: Y. Amihud and G. Miller (eds.), *Bank Mergers and Acquisitions*, Kluwer Academic Publishers.

Berger, A.N. and Hannan, T.H. (1998) The efficiency cost of market power in the banking industry: A test of the quite life and related hypotheses, *Review of Economics and Statistics*, 80, 454-465.

Berger, A. and Humphrey, D. (1992) Mega mergers in banking and the use of cost efficiency as an antitrust defense, *Antitrsut* Bulletin, 37, 541-600.

Berger, A., Demsetz, R. and Strahan, P. (1999) The consolidation of the financial services industry: Causes, consequences and implications for the future, *Journal of Banking and Finance*, 23, 135-194

Berger, A.N., Kashyap, A.K. and Scalise, J.M. (1995) The transformation of the US banking industry: What a long strange trip it's been, *Brookings Papers on Economic Activity*, 2, 54-219.

Berkovitch, E. and Narayanan, M.P. (1998) Motives for takeovers: An empirical investigation, *Journal of Financial Economics*, 48, 347-362

Broaddus, J.A. (1998) The bank merger wave: causes and consequences, *Federal Reserve Bank of Richmond Economic Quarterly*, 84/3, 1-11.

Buch, C.M., De Long, G., (2004) Cross-border bank mergers: What lures the rare animal? *Journal of Banking and Finance*, 28, 2077-2102.

Cole, R.A. and Gunther, J.W. (1995) Separating the likelihood and timing of bank failure, *Journal of Banking and Finance*, 19, 1073-89.

Cole, R.A. and Gunther, J.W. (1998) Predicting bank failures: A comparison of on- and off-site monitoring systems, *Journal of Financial Services Research*, 13, 103-117.

Collins, G. (2003) The Economic Case for Mergers: Old, New, Borrowed, and Blue, *Journal of Economic Issues*, 37, 987-1009.

Copeland, T.E., Weston, J.F. and Shastri, K. (2005), *Financial Theory and Corporate Policy*, 4th ed., Englewood Cliffs, New Jersey: Prentice Hall.

Cornett, M.M., McNutt, J.J. and Tehranian, H. (2006) Performance changes around bank mergers: Revenue enhancements versus cost reductions, *Journal of Money, Credit and Banking*, 38, 1013-1051.

Cox, D.R. (1972) Regression models and life tables, *Journal of the Royal Statistical Society Series B*, 34, 187-220.

Courchane, M., Nickerson, D. and Sullivan, R. (2002) Investment in Internet banking as a real option: Theory and tests, *Journal of Multinational Financial Management*, 12, 347-363.

Damanpour, F. (1991) Organizational innovations: A meta analysis of the determinants and moderators, *Academy of Management Journal*, 34, 555-590.

Damanpour, F. (1992) Organizational size and innovation, *Organization* Studies, 13, 375-402.

DeLong, G. and DeYoung, R. (2007) Learning by observing: information spillovers in the execution and valuation of commercial bank M&As, *Journal of Finance*, 62, 181-217.

DeYoung, R., (1997) Bank mergers, X-efficiency, and the market for corporate control, *Managerial Finance*, 23, 32-47

DeYoung, R. (2003) The failure of new entrants in commercial banking markets: A split population duration analysis, *Review of Financial Economics*, 12, 7-33.

DeYoung, R., Lang, W. and Nolle, D. (2007) How the internet affects the output and performance of community banks, *Journal of Banking and* Finance, 31, 1033-1060.

Demirguc-Kunt, A. (1989) Deposit institution failures: A review of empirical literature, *Federal Reserve Bank of Cleveland Economic Review*, 25, 4, 2-18.

Estrella, A., Park, S. and Peristiani, S. (2000) Capital ratios as predictors of bank failure, *Federal Reserve Bank of New York Economic Policy Review*, July, 33-52.

Feinberg, R.M. (2001) The competitive role of credit unions in small local financial services markets, *Review of Economics and Statistics*, 83, 560-563.

Feinberg, R.M., and Ataur Rahman, A.F.M. (2001) A causality test of the relationship between bank and credit union lending rates in local markets, *Economics Letters*, 71, 271-275.

Focarelli, D., Panetta, F. and Salleo, C. (2002) Why do banks merge? *Journal of Money, Credit and Banking*, 34, 1047-1066..

Fried, H.O., Lovell, C.A.K. and Yaisawarng, S. (1999) The impact of mergers on credit union service provision, *Journal of Banking and Finance*, 23, 237-386.

Fuentes, R., Hernandez-Murillo, R. and Llobet, G. (2006) Strategic on-line banking adoption, *Federal Reserve Bank of St Louis* Working Paper.

Furst, K., Lang, W.W. and Nolle, D.E. (2002) Internet banking, *Journal of Financial Services Research*, 22, 95-117.

Gajewski, G.R. (1989) Assessing the risk of bank failure. In: *Proceedings from conference on Bank Structure and Competition*. Chicago: Federal Reserve Bank of Chicago.

Goddard, J., McKillop, D., Wilson, J.O.S. (2002) The growth of US credit unions, *Journal of Banking and Finance*, 22, 2327-2356

Goddard, J., Molyneux, P., Wilson, J.O.S. and Tavakoli, M. (2007a) European banking: An overview, *Journal of Banking and Finance*, 31, 1911-1935.

Goddard, J., McKillop, D.G., and Wilson, J.O.S. (2007b) The diversification and performance of US credit unions, *University of St Andrews Working Paper.*

Gort, M. (1969) An economic disturbance theory of mergers, *Quarterly Journal of Economics*, 83, 624-642.

Gorton, G., Kahl, M. and Rosen, R. (2006) Eat or be eaten: A theory of mergers and firm size, *Federal Reserve Bank of Chicago Working Paper*, WP2006-14.

Gowrisankavan, G. and Stavins, J. (2004) Network externalities and technology adoption, *Rand Journal of Economics*, 35, 260-276.

Grabowski, R., Mathur, I. and N.Rangan (1995) The role of takeovers in increasing efficiency, *Managerial and Decision Economics*, 16, 211-223

Hadlock, C., Houston, J. and Ryngaert, M. (1999) The role of managerial incentives in bank acquisitions, *Journal of Banking and* Finance, 23, 221-249.

Hannan, T.H. (2003) The impact of credit unions on the rates offered for retail deposits by banks and thrift institutions, *Board of Governors of the Federal Reserve System Working Paper 2003-6.*

Hannan, T. and McDowell, J.M. (1984) The determinants of technology adoption: The case of the banking firm, *Rand Journal of Economics*, 15, 328-335.

Hannan, T. and McDowell, J.M. (1986) Rival precedence and the dynamics of technology adoption: An empirical analysis, *Economica*, 54, 155-171.

Hannan, T.H. and Pilloff, S.J. (2006) Acquisition targets and motives in the banking industry, *Finance and Economics Discussion Series*, 2006-40. Federal Reserve Board.

Hannan, T.H. and Rhoades, S. (1987) Acquisition targets and motives: The case of the banking industry, *Review of Economics and Statistics*, 69, 67-74.

Hernando, I. and Nieto, M. (2007) Is the internet delivery channel changing banks' performance? *Journal of Banking and Finance*, 31, 1083-1099.

Hicks, J.R. (1935) Annual survey of economic theory: The theory of monopoly, *Econometrica*, 3, 1-20.

Houston, J.F., James, C.M. and Ryngaert, M.D. (2001) Where do merger gains come from? Bank mergers from the perspective on insiders and outsiders, *Journal of Financial Economics*, 60, 285-331.

Jones, K.D. and Critchfield, T. (2005) Consolidation in the US banking industry: Is the 'long, strange trip' about to end? *FDIC Banking Review*, 17, 31-61.

Kharadia, V.C. and Collins, R.A. (1981) Forecasting credit union failures, *Journal of Economics and Business*, 33, 147-152.

King, T.B., Nuxoll, D.A., and Yeager, T.J. (2005) Are the causes of bank distress changing? Can researcher keep up? *FDIC Center for Financial Research Working Paper*, Number, 2005-03.

Kolari, J., Glennon, D., Shin, H. and Caputo, M. (2002) Predicting large US bank failures, *Journal of Economics and Business*, 54, 361-387.

Lanine, G. and Vander Vennet, R. (2006) Failure prediction in the Russian bank sector with logit and trait recognition models, *Expert Systems with Applications*, 30, 463-478.

Mansfield, E. (1961) Technical change and the rate of imitation, *Econometrica*, 29, 741-766

Mansfield, E. (1969) Industrial research and development: Characteristics, costs and diffusion results *American Economic Review*, 59, 65-79.

Mitchell, M.L and Mulherin, J.H. (1996) The impact of industry shocks on takeover and restructuring activity, *Journal of Financial Economics*, 41, 193-229.

Moore, R.R. (1997) Bank acquisition determinants: Implications for small business credit, *Federal Reserve Bank of Dallas,* April.

National Credit Union Administration (2006) Measuring service to members, *NCUA Letter to Credit Unions*, Number 06-FCU-02. NCUA.

Nickerson, D. and Sullivan, R.J. (2003) Financial innovation, strategic real options and endogenous competition: Theory and tests, *Journal of Multinational Financial Management*, 12, 347-363.

Nolle, D.E. (1995) Banking industry consolidation: past changes and implications for the future, *Economic and Policy Analysis Working Paper 95-1.* Office of the Comptroller of Currency.

Nuxoll, D.A. (2003) The contribution of economic data to bank failure models, *FDIC Center for Financial Research Working Paper* 2003-03.

Nuxoll, D.A., O'Keefe, J. and Samolyk, K. (2003) Do local economic data improve off-site models that monitor bank performance? *FDIC Banking Review*, 15, 39-53.

Ohlson, J.A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, 18, 109-131.

Park, K. and Pennacchi, G. (2007) Harming depositors and helping borrowers: The disparate impact of bank consolidation, *Federal Reserve Bank of Cleveland*, Discussion Paper, 2007-04.

Peristiani, S. (1997) Do mergers improve the X-efficiency and scale efficiency of US banks? Evidence from the 1980s, *Journal of Money Credit Banking*, 29, 326–337.

Pozzolo, F. and Focarelli, D. (2007) Cross-border M&As in the financial sector. Is banking different from insurance? *Bank of Italy Working Paper.*

Ralston, D., Wright, A., and Garden, K. (2001) Can mergers ensure the survival of credit unions in third millennium, *Journal of Banking and Finance*, 25, 2277-2304.

Rhoades, S.A. (1986) The operating performance of acquired firms in banking before and after acquisition, *Staff Study Number 149.* US Federal Reserve Board.

Rhoades, S.A. (1998). The efficiency effects of bank mergers: An overview of case studies of nine mergers, *Journal of Banking and Finance*, 22, 273-291

Roll, R. (1986) The hubris hypothesis of corporate takeovers, *Journal of Business*, 59, 197-216.

Rossi, S., and Volpin, P. (2004) Cross-country determinants of mergers and acquisitions, *Journal of Financial Economics*, 74, 277-304.

Saloner, G. and Shepard, A. (1995) Adoption of technologies with network effects: An empirical examination of the adoption of Automated Teller Machines, *Rand Journal of Economics*, 26, 479-501.

Schmid, F. (2006) When for-profits and not-for profits compete: Theory and empirical evidence from retail banking. *Managerial Finance* 31, 50-71.

Shaffer, S. (1992) Potential merger synergies among large commercial banks, *Working Paper*, Federal Reserve Bank of Philadelphia, October.

Shepheard-Walwyn, T. and Litterman, R. (1998) Building a coherent risk measurement and capital optimisation model for financial firms, *Federal Reserve Bank of New York Economic Policy Review*, 4, 171-182.

Shumway, T. (2001) Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business*, 74, 101-124.

Sinkey, J.F. (1975) A multivariate statistical analysis of the characteristics of problem banks, *Journal of Finance*, 30, 21-26.

Smythe, D.J. (2001) The great merger movement and the diffusion of electric power utilization in American manufacturing, 1899-1909, *Eastern Economic Journal*, 27, 253-266.

Spindt, P.A. and Tarhan.V. (1992) *Are there synergies in bank mergers?* Working Paper, Tulane University: New Orleans.

Sullivan, R. and Wang, Z. (2005) Internet banking: An exploration in technology diffusion and impact, *Payments System Research Department*, Federal Reserve Bank of Kansas City, Working Paper 05-05.

Tatom, J.A. (2005) Competitive advantage: A study of the federal tax exemption for credit unions, US Tax Foundation.

Thomson, J.B. (1991) Predicting bank failures in the 1990s, *Federal Reserve Bank of Cleveland Economic Review*, 1st Quarter, 9-20.

Tokle, R.J. and Tokle, J.G. (2000) The influence of credit union and savings and loan competition on bank deposit rates in Idaho and Montana, *Review of Industrial Organization*, 17, 427-439.

US General Accounting Office (1991) Credit unions: Reforms for future soundness, Washington D.C: Government Accountability Office.

US Government Accountability Office (2005) *Financial institutions: Issues regarding the tax exempt status of credit unions*, *GAO-06-220T.* Washington DC: Government Accountability Office.

Wheelock, D.C. and Wilson, P.W. (1995) Explaining bank failure: Deposit insurance, regulation and efficiency, *Review of Economics and Statistics*, 77, 689-700.

Wheelock, D.C. and Wilson, P.W. (2000). Why do banks disappear? The determinants of US bank failures and acquisitions, *Review of Economics and Statistics*, 82, 127-138.

Wheelock, D.C. and Wilson, P.W. (2004). Consolidation in US banking: Which banks engage in mergers? *Review of Financial Economics*, 13, 7-39.

Wilcox, J.A. (2005) Credit union failures and insurance losses: 1971-2004, *Federal Reserve Bank of San Francisco Economic Letter, Number 2005-20, August 19 2005*.

Worthington, A.C. (2004) Determinants of merger and acquisition activity in Australian cooperative deposit taking institutions, *Journal of Business Research*, 57, 47-57.

Zhang, W. (1995) Wealth effects of US bank takeovers, *Applied Financial Econom*ics, 5, 329-336.

Table 1 Classification of sample credit unions that disappeared, June 2001 to December 2006

Stated reason for disappearance	Mode of disappearance			
	Acquisition	Liquidation	P&A	Total
1. Financial or managerial difficulties				
Lack of sponsor support	53	10	2	65
Loss/declining membership	48	13	0	61
Poor management	15	2	1	18
Poor financial condition	120	3	5	128
Lack of growth	32	5	0	37
Inability to obtain officials	36	4	0	40
2. Expansion				
Expanded services	445	0	0	445
3. Reorganization or restructuring				
Conversion to or merger with FCU	417	0	0	417
Conversion to or merger with FISCU	388	0	0	388
P&A with FCU	2	0	2	4
P&A with FISCU	1	0	3	4
Conversion to or merger with NFICU	9	0	0	9
Corporate restructuring	4	0	0	4
Total	1570	37	13	1620

Table 2 Summary statistics: Time-varying covariates

	Mean	St. Dev.	Correlation coefficients						
			ASSET	MEMPOT	ROA	LIQ	CAPASS	LOANASS	NONPER
ASSET	64.9	333.3	-	-	-	-	-	-	-
MEMPOT	.4671	.2703	-.0569	-	-	-	-	-	-
ROA	.00289	.01177	.0284	-.0045	-	-	-	-	-
LIQ	.1516	.1384	-.0916	.0823	-.0599	-	-	-	-
CAPASS	.1366	.0613	-.0879	.1902	.0462	.1388	-	-	-
LOANASS	.5745	.1799	.0678	-.1475	.0453	-.3039	-.2086	-	-
NONPER	.0235	.0480	-.0660	.0507	-.1214	.2341	.1736	-.1676	-
NINTASS	.00393	.00616	.0521	-.2049	.2411	-.0203	-.1375	.1592	-.0586

Table 3 Summary statistics: Non-time-varying covariates

	All sample credit unions	Disappearing credit unions
Distribution by charter type		
State charter	.3881	.4019
Federal charter	.6119	.5981
Distribution by common bond type		
Single common bond	.5016	.6025
Multiple common bond	.4984	.3975
Distribution by year of formation		
- 1930	.0202	.0111
1931-1940	.2031	.1562
1941-1950	.1128	.1136
1951-1960	.3307	.3364
1961-1970	.1896	.2093
1971-1980	.1038	.1333
1981-	.0400	.0401

Table 4 Mean values of time-varying covariates by observation: All sample credit unions

	Number	ASSET	MEMPOT	ROA	LIQ	CAPASS	LOANASS	NONPER	NINTASS	TECH0	TECH1	TECH2	TECH3
Jun-01	9569	47.2	.5171	.00387	.1552	.1396	.6179	.0226	.00363	.5887	.1691	.0609	.1813
Dec-01	9415	50.3	.5105	.00283	.1582	.1378	.6005	.0244	.00364	.5584	.1727	.0574	.2116
Jun-02	9254	55.0	.5021	.00270	.1637	.1319	.5682	.0227	.00329	.5289	.1683	.0500	.2529
Dec-02	9131	58.0	.4940	.00323	.1566	.1348	.5701	.0250	.00380	.5010	.1656	.0449	.2885
Jun-03	8976	63.4	.4859	.00314	.1885	.1307	.5381	.0243	.00364	.4719	.1614	.0412	.3254
Dec-03	8818	65.8	.4751	.00213	.1637	.1333	.5525	.0250	.00390	.4520	.1558	.0388	.3534
Jun-04	8676	69.7	.4659	.00278	.1567	.1325	.5452	.0228	.00383	.4310	.1453	.0393	.3844
Dec-04	8497	72.6	.4542	.00227	.1412	.1363	.5638	.0236	.00427	.4085	.1424	.0377	.4114
Jun-05	8363	76.3	.4459	.00303	.1315	.1379	.5680	.0224	.00425	.3866	.1360	.0379	.4396
Dec-05	8208	79.1	.4382	.00220	.1206	.1434	.5954	.0239	.00468	.3701	.1156	.0385	.4758
Jun-06	8077	82.8	.4309	.00345	.1232	.1454	.5973	.0209	.00448	.3509	.1070	.0366	.5055

Note:
TECH0 is the proportion of sample credit unions with no website. TECH1 is the proportion with an informational website only. TECH2 is the proportion with an interactive website. TECH3 is the proportion with a transactional website.

Table 5 Mean values of time-varying covariates by observation: Sample credit unions that disappeared during the subsequent six-month period

	Number	ASSET	MEMPOT	ROA	LIQ	CAPASS	LOANASS	NONPER	NINTASS	TECH0	TECH1	TECH2	TECH3
Jun-01	154	11.7	.5386	-.00559	.1975	.1603	.5782	.0446	.00267	.8182	.0909	.0195	.0714
Dec-01	161	5.4	.5545	-.01277	.2179	.1492	.5530	.0564	.00270	.8509	.0683	.0124	.0683
Jun-02	123	7.3	.5547	-.00565	.2543	.1425	.5419	.0408	.00238	.8130	.0732	.0407	.0732
Dec-02	155	10.6	.5085	-.00797	.2369	.1449	.5111	.0614	.00346	.7742	.1226	.0387	.0645
Jun-03	158	9.4	.5002	-.01203	.2978	.1441	.4710	.0624	.00274	.7911	.1076	.0380	.0633
Dec-03	142	9.5	.5101	-.01052	.2317	.1392	.5014	.0594	.00256	.7465	.1338	.0211	.0986
Jun-04	179	6.8	.4954	-.00475	.2711	.1488	.4671	.0504	.00434	.7430	.0894	.0223	.1453
Dec-04	134	8.3	.4505	-.01065	.2210	.1420	.5767	.0454	.00324	.7239	.1418	.0299	.1045
Jun-05	155	12.4	.4401	-.00860	.2273	.1372	.5146	.0428	.00295	.6774	.0839	.0194	.2194
Dec-05	131	9.4	.4994	-.01466	.1937	.1504	.5408	.0531	.00442	.5802	.1679	.0382	.2137
Jun-06	128	32.0	.4412	-.01744	.1946	.1536	.5165	.0354	.00192	.6406	.0938	.0313	.2344

Note:
TECH0 is the proportion of sample credit unions that disappeared during the subsequent six-month period with no website. TECH1 is the proportion with an informational website only. TECH2 is the proportion with an interactive website. TECH3 is the proportion with a transactional website.

Table 6 Hazard function estimation results

Equation	I	II	III	IV	V	VI	VII	VIII	IX	X
Sample	All	All	All	All	All	All	State	Federal	Single	Multiple
Mode of disappearance	All	Merger	Liq/P&A	All	All	All	All	All	All	All
Reason for disappearance+	1,2,3	1,2,3	1,2,3	1	2	3	1,2,3	1,2,3	1,2,3	1,2,3
LASSET	-.3092***	-.2932***	-.5651***	-.4391***	-.2343***	-.2845***	-.3652***	-.2858***	-.2695***	-.4365***
	(-15.93)	(-14.82)	(-6.28)	(-10.84)	(-6.02)	(-10.57)	-(11.43)	(-11.25)	(-11.10)	(-11.91)
MEMPOT	-.2813***	-.2979***	.9521*	.0157	-.6101***	-.2031	-.4684***	-.2367*	-.1580	-.4666***
	(-2.85)	(-2.97)	(1.82)	(0.07)	(-3.25)	(-1.47)	(-3.02)	(-1.83)	(-1.24)	(-2.94)
LAGE	.2555***	.2739***	-.1645	.3297**	.1750	.2635***	.1497	.3192***	.2394***	.3792***
	(3.60)	(3.77)	(-0.47)	(2.06)	(1.26)	(2.70)	(1.48)	(3.27)	(2.65)	(3.29)
ROA	-8.7800***	-9.2656***	-1.3353	-6.1376***	-9.9713***	-9.6242***	-10.102***	-8.7613***	-8.0965***	-9.7649***
	(-20.89)	(-21.83)	(-0.92)	(-7.20)	(-11.85)	(-16.31)	(-12.50)	(-15.32)	(-14.96)	(-11.53)
LIQ	.9771***	.9635***	.8493	.9822***	1.1915***	.8964***	.5918**	1.1302***	.8526***	1.4419***
	(6.53)	(6.25)	(1.40)	(3.31)	(3.90)	(4.25)	(2.43)	(5.99)	(4.79)	(5.24)
CAPASS	-2.9156***	-3.7413***	4.3956***	-.4849	-3.0019***	-4.4420***	-3.4102***	-2.3642***	-1.9259***	-6.4859***
	(-8.44)	(-10.25)	(6.43)	(-0.83)	(-3.86)	(-8.75)	(-4.96)	(-5.44)	(-4.72)	(-7.63)
NONPER	-.0288	-.0499	.6756	.6091	-2.1786***	.3790	1.8717***	-.7268*	-.0353	.7304
	(-0.10)	(-0.16)	(0.92)	(1.25)	(-2.69)	(0.89)	(3.59)	(-1.86)	(-0.10)	(1.05)
LOANASS	-.3382**	-.2786**	-2.2155***	.1519	-.6444**	-.4086**	-.4331*	-.2642	-.3468**	-.7396***
	(-2.45)	(-1.98)	(-2.84)	(0.53)	(-2.42)	(-2.09)	(-1.93)	(-1.49)	(-2.03)	(-3.01)
NINTASS	6.0106**	4.6696	-.3347	8.4463***	5.2734	2.9020	18.118***	2.0651	3.2041	12.764***
	(2.13)	(1.56)	(-0.12)	(3.10)	(0.97)	(0.61)	(3.63)	(0.48)	(0.76)	(3.56)
TECH1	-.3383***	-.3715***	.2624	-.5015**	.0059	-.5080***	-.2015	-.4167***	-.3479***	-.2216*
	(-3.82)	(-4.15)	(0.41)	(-2.27)	(0.04)	(-4.01)	(-1.40)	(-3.70)	(-2.73)	(-1.77)
TECH2	-.3797**	-.4417***	.9663	-.8675*	-.0686	-.5282**	.0843	-.8031***	-.3688	-.2313
	(-2.37)	(-2.72)	(0.92)	(-1.69)	(-0.26)	(-2.34)	(0.39)	(-3.27)	(-1.50)	(-1.08)
TECH3	-.6760***	-.7370***	-.2761	-.8361***	-.3794**	-.9662***	-.4779***	-.8040***	-.7096***	-.4413***
	(-6.91)	(-7.46)	(-0.26)	(-3.33)	(-2.27)	(-6.53)	(-3.14)	(-6.18)	(-4.80)	(-3.14)
FED	-.1989***	-.1903***	-.5219*	.1531	-.0292	-.4287***	-	-	-.2335***	-.0900
	(-3.83)	(-3.61)	(-1.65)	(1.28)	(-0.29)	(-5.99)			(-3.41)	(-1.10)
MULT	.0944*	.0929*	-.3114	-.1160	.0539	.1938**	.0161	.1423*	-	-
	(1.72)	(1.67)	(-0.73)	(-0.90)	(0.52)	(2.56)	(0.20)	(1.89)		
Observations	96984	96984	96984	96984	96984	96984	37429	59555	47756	49228
Credit unions	9569	9569	9569	9569	9569	9569	3714	5855	4800	4769
Disappearances	1620	1570	50	349	445	826	651	969	976	644

Note:
+ Stated reasons for disappearance (see also Table 1) are: 1. Financial or managerial difficulties; 2. Expansion; 3. Reorganization or restructuring
*** Estimated coefficient significantly different from zero, two-tail test, 1% significance level. ** As above, 5% significance level. * As above, 10% significance level.

Bank Mergers and the Dynamics of Deposit Interest Rates

Ben R. Craig* and Valeriya Dinger°

This version: November 2007

Summary: Despite extensive research interest in the last decade, the banking literature has not reached a consensus on the impact of bank mergers on deposit rates. In particular, results on the dynamics of deposit rates surrounding bank mergers vary substantially across different studies. In this paper, we aim for a comprehensive empirical analysis of a bank merger's impact on deposit rate dynamics. We base the analysis on a unique dataset comprising deposit rates of 624 US banks with a monthly frequency for the time period 1997-2006. These data are matched with individual bank and local market characteristics and the complete list of bank mergers in the US. The data allow us to track the dynamics of bank mergers while controlling for the rigidity of the deposit rates and for a range of merger, bank and local market features. An innovation of our work is the introduction of an econometric approach of estimating the change of the deposit rates given their rigidity.

Key words: deposit rate dynamics, bank mergers, deposit rate rigidity

JEL: G21, L11

We thank participants of the Federal Reserve Bank of Cleveland Research Seminar, the University of Bonn Macro-Workshop and the Pro-Banker Symposium 2007 in Maastricht for useful comments on earlier versions of the paper. Dinger gratefully acknowledges financial support by the Deutsche Forschungsgemeinschaft (Research Grant DI 1426/1). This research reflects the views of the authors and not necessarily the views of the Deutsche Bundesbank, the Federal Reserve Bank of Cleveland, or the Board of Governors of the Federal Reserve Bank.

* Federal Reserve Bank of Cleveland and Deutsche Bundesbank

° Corresponding author. University of Bonn, Lennestr. 37, 53113 Bonn, Germany, Tel: +49 228 734029, Fax: +49 228 737953, e-mail: valeriya.dinger@uni-bonn.de

1. Introduction

Bank mergers affect bank competition by altering the market structure in affected local bank markets and the size and geographical scope of the merging banks. The wide-spread bank consolidation in the US has been met with a growing literature on the impact of bank mergers on bank competition. A substantial portion of this literature concentrates on the impact of bank mergers on bank loan and deposit rates.

The empirical research on the topic concentrates on two reciprocal hypotheses. The "efficiency hypothesis" states that the merged bank might reach economies of scale and other efficiency gains and transfer these to the customers in the form of more beneficial interest rates. The opposite, "structure-conduct-performance hypothesis", states that the merged bank may exploit its increased market power and impose disadvantageous interest rates. Berger and Hannan (1989) find empirical support for the "structure-conduct-performance hypothesis" by showing that high market concentration results in lower deposit rates. Hannan and Prager (1998) explicitly concentrate on bank mergers as a determinant of local bank market concentration and study the dynamics of deposit rates in the first year after bank mergers. They are able to document a negative impact of mergers on deposit rates. On the other hand, Focarelli and Panetta (2003) argue that the analysis of merger effects should embrace a longer time period after the merger since efficiency gains need more time to materialize. They are able to find support for the efficiency hypothesis by showing that in the long-run merging banks offer higher deposit rates than their rivals.

The contradicting results of these previous studies motivate us to revisit the topic. We present a comprehensive analysis of the impact of bank mergers on deposit rate dynamics. We base our analysis on a unique dataset comprising monthly deposit rates data of 624 banks in the period 1997-2006. The deposit rate data are matched with bank and market characteristics and a complete list of bank mergers from 1988 to 2005.

Our detailed dataset allows us to address two important lacunae of the existing literature. First, the empirical literature on deposit rate dynamics around bank mergers has so far ignored the rigidity of deposit rates. As documented in earlier studies (Hannan and Berger, 1991; and Neumark and Sharpe, 1992) deposit rates adjust sluggishly to changes in the market interest rates. Deposit rate rigidity is relevant for the analysis of the changes of deposit rates around bank mergers because for a dominating number of observations no immediate change in the deposit rates is observed. In addition to a possibly slow adjustment to the change in market structure, which must be modelled with a dynamic model, the data present the additional problem of rigidity: that is for the vast majority of observations, the price is the same as for the period before. In econometric terms this censoring presents large potential problems. It has long been well known that in the presence of censoring, OLS regression results can be inconsistent and biased (see a standard text such as Wooldridge, 2002). We incorporate the rigidity of deposit rates in the empirical analysis by explicitly integrating the censoring process into the empirical estimation. Our focus is on modelling bank pricing behaviour by accounting for both the probability of a deposit rate change and the de facto change of the deposit rates in a joint framework. The design is to estimate bank merger's impact on the deposit rate setting mechanism.

Second, previous research on the impact of bank mergers has mostly concentrated on in-market mergers. We argue that the distinction between in- and out-of-market mergers is not clear cut since modern bank mergers might be classified as both in- and out-of-market depending on the perspective of the different local markets. We include all bank mergers (without ex ante imposing restrictions on the type of merger) together with a range of controls for the characteristics of the mergers. Thus, we are able to assess the impact of a wide range of bank mergers and how this impact may be modified by various features of the merger (bank size growth, market share growth, or rise in the number of markets). In other words, we estimate whether bank mergers exert negative impacts on depositors and if that is the case, which particular features of the merger reinforce the negative impact.

The rest of the paper is organized as follows. Section 2 presents a review of the existing literature. Section 3 illustrates the data. Section 4 presents replications of earlier research approaches using our new dataset. Section 5 presents our empirical approach and its results. Section 6 draws the concluding remarks.

2. Literature

Our study aims to contribute to a broad empirical literature on the pricing effects of mergers. Whereas studies exist on the impact of company mergers in various industries[1], due to better data availability most of the research has concentrated on the banking industry.

As mentioned in the introduction, most of the literature on the impact of bank mergers has concentrated on testing the validity of two hypotheses, the "efficiency hypothesis" and its opposite, the "structure-conduct-performance hypothesis". The paper by Berger and Hannan (1989) which emphasizes the structure-conduct-performance hypothesis, is a static study of the relationship between local banking market concentration and deposit rates. Here, the authors find that more concentrated deposit markets are characterized by lower deposit rates[2]. The later work by Hannan and Prager (1998) focuses on bank mergers as a determinant of bank market concentration. The authors explore the dynamics of the deposit rate changes[3] and

[1] In a study that has inspired the early research on the effect of mergers in banking Kim and Singal (1993) find out that airline merger have resulted in higher airfares. On the contrary, Connor, Feldman, Dowd and Radcliff (1997) find out that hospital mergers have resulted in more beneficial consumer prices.

[2] Corvoisier and Gropp (2002) replicate Berger and Hannan's (1989) analysis on a sample of EU banks.

[3] Kahn et al (2004) study the dynamics of loan rates in a similar framework.

find that after a substantial in-market merger, the merging banks significantly decrease their deposit rates which they explain by an increase in market power.

The paper by Focarelli and Panetta (2003) which supports the efficiency view argues that previous studies have only examined the very short post-merger period[4]. They consider a longer time period. They posit that the effect of market power materializes instantaneously where efficiency gains need more time to materialize[5]. They present a more comprehensive study incorporating long-run post-merger dynamics and controlling for bank size and asset risk (bad loans/total asset) on the bank level and for market concentration on the local market level. In this study efficiency gains prevail. Whereas merging banks tend to decrease deposit rates in the transition period (up to three years after the merger) in the long-run deposit rates of merged banks go up and beyond those of rival banks.

The studies mentioned above focus mostly on in-market mergers, occasionally using out-of-market mergers as a control for mergers which do not increase market power. A newer strand of the literature suggests that although out-of-market mergers do not directly affect the distribution of market shares, they can significantly impact bank pricing behavior. The theoretical foundation, as given by the models of Barros (1999) and Park and Pennacchi (2005), is based on the assumption that multimarket banks (which are a result of out-of-market mergers) have access to more diverse sources of financing, whereas single-market banks depend largely on retail deposits[6]. As a result they argue that out-of-market mergers result in lower deposit rates. Park and Pennacchi (2005)[7] and Hannan and Prager (2006)

---

[4] Sapienza (2002) studies loan rate dynamics in a similar framework.

[5] Berger, Sounders, Scalise and Udell (1998) and Calomiris and Karceski (2000) argue that the "gestation" period needed to restructure a merged bank is three years.

[6] The structure of bank liabilities has been the subject also of a growing literature on market discipline. It has argued that banks may not refinance in the wholesale market because wholesale exposures are not insured and create incentives for the lenders to monitor. Therefore, banks which are perceived as riskier may prefer to refinance mostly with insured retail deposits (Billett, et el, 1998).

[7] Park and Pennacchi (2005) use bank size as a proxy for geographical scope.

present empirical tests of this hypothesis, and both find that multimarket banks offer lower deposit rates than their single-market rivals. Using a separate dataset and estimation approach Rosen (2003), however, finds different results. He argues that growing banks tend to offer higher interest rates on deposits, and moreover, a market with more and larger multimarket banks generally sees higher deposit rates at all banks.

The literature on multimarket banking is closely related to the strand in the banking literature which concentrates on the interaction between bank size and the way banks compete. In a seminal paper Stein (1992) argues that large and small banks process information differently and that is why they compete differently in the loan market. Park and Pennacchi (2005) extend this argument and argue that bank size is also important for deposit market competition.

The literature on multimarket banks is also related to an industrial organisation literature focusing on multiple contacts between firms as a factor facilitating collusion. Edwards (1955) points to the fact that when firms meet in numerous markets they may have higher incentives to collude because retaliation by the rivals may follow on numerous markets. This relation is known as the "linked oligopoly" hypothesis. Mester (1987) provides an empirical test of this hypothesis. She finds out that, contrary to expectations, multiple market contacts lead to more competitive pricing, especially in concentrated markets.

Obviously, these are contradictory results. One potential reason for the deviating results is that researchers have used different datasets. However, results might also be biased because of the fragmentary treatment of deposit rate dynamics (in particular the time series structure of the deposit rates has been ignored). Moreover, all existing studies include only a fraction of the past mergers in the analysis. We add to the literature by performing a comprehensive analysis which addresses both the dynamics of the deposit rates and the features of a broad range of the mergers with a single dataset which controls for pre- and post-merger characteristics of the local markets.

3. Data

We base the empirical estimation on a unique dataset based on the full list of bank mergers in the US in the time period 1988-2005 from the *Supervisory Master File of Bank Mergers and Acquisitions*. For each bank we construct a list of its six most recent mergers. We match this data with *Bankrate Monitor's* deposit rates of 624 US banks operating in 164 local markets (a total of 1738 bank-market groups) for the period starting from September 19, 1997 and ending on July 21, 2006. Radecki (1998) presents evidence that multimarket banks tend to offer uniform rates across local markets. However, we observe banks which offer different rates in different local markets in our sample. Therefore, we prefer to keep the bank-market as observation unit. By doing this we can control for both bank and local market characteristics in the analysis.

Bankrate Monitor's deposit rate data have weekly frequency. Using the weekly deposit rate changes as a proxy for deposit rate setting after a merger however contains a lot of noise. Therefore, as in Kahn et al (2005) we base our tests on rate changes computed over 4-week intervals. Our sample encompasses a total of 461 weeks which allows us to construct a time series of 115 4-week intervals, which we refer to as "month" although they do no correspond to calendar months. This approach also allows the comparison of our results with those of Hannan and Prager (1998).

Bankrate Monitor reports cover a comprehensive set of deposit products (checking accounts, money market deposit accounts and certificates of deposits with a maturity of three months to up to five years). In this paper we concentrate on checking account and money market deposit account (MMDA) rates only. We exclude the rates on certificates of deposit because they are investment products with a relatively high minimum denomination and we expect them to react less to changes in local deposit market conditions[8].

In addition, we enrich the dataset with a broad range of control variables on the individual bank level with quarterly frequency from the *Quarterly Reports of Conditions and Income* (*call reports*). We also include control variables on the local market level. The source of the local market controls is the *Summary of Deposits*. These data are only available at an annual frequency.

4. Mergers and deposit rate dynamics: a simple empirical framework

As pointed out in Section 2 previous studies have reached contradicting results on the impact of bank mergers on deposit rates. Results may differ because of different estimation approaches but also because researchers have employed different data sources. So, Hannan and Prager (1998), for example, employ data from US bank mergers, whereas Focarelli and Panetta (2003) base their analysis on Italian data. In order to illustrate how sensitive the empirical results are to the changes of the model specification we start the empirical analysis by replicating Hannan and Prager's and Focarelli and Panetta's estimation approaches with our dataset.

Our first exercise is to replicate Hannan and Prager's (1998) estimation approach. For the sake of comparability, we concentrate on substantial in-market mergers only[9]. As in Hannan and Prager (1998) we estimate the following empirical model:

$$\ln deprate_{ijt} - \ln deprate_{ijt-1} = \alpha_0 + \alpha_1 merger\_dummies_{i,t} + \xi_{i,j,t} \qquad (1)$$

[8] Hannan and Prager (1998) find no significant impact of bank mergers on certificate of deposit rates

[9] As in Hannan and Prager (1998) we concentrate on substantial in-market mergers defined as mergers which led to a rise in local market's HHI of at least 100 basis points.

The dependant variable, $\ln deprate_{ijt} - \ln deprate_{ijt-1}$, is the change in the log of the deposit rate (checking account rates and money market deposit account rates) between t-1 and t. The $merger\_dummies_{i,t}$ are a vector of dummy variables measuring the time to the latest merger of bank i. We adopt four time dummies here: 26 to 13 weeks pre-merger, 12 to 1 week pre-merger, 0 to 12 weeks post-merger and 13 to 52 weeks post-merger. The dummies take the value of 1 if a bank has experienced a merger within this time window and zero otherwise[10].

Table 1: Short-term effects of in-market bank mergers

	ckecking account rate	money market deposit account rate
26 to 13 weeks pre-merger	**-0.018**	**-0.020**
	0.012	0.013
12 to 1 week pre-merger	**0.026** **	**0.026** *
	0.013	0.014
0 to 12 weeks post-merger	**0.009**	**-0.017** **
	0.007	-0.008
13 to 52 weeks post-merger	**-0.012** ***	**-0.009** **
	0.003	0.004
constant	**0.000** ***	**0.007**
	0.001	0.002

Note: Coefficients in bold, standard errors below coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively

As illustrated in Table 1 for both the checking account and the MMDA rates we are able to qualitatively replicate the results of Hannan and Prager (1998). The time dummies for *0 to 12 weeks post-merger* and *13 to 52 weeks post-merger* enter the money market deposit account regressions with negative statistically significant coefficients. In the case of checking account rate only the *13 to 52 weeks post-merger* dummy is significant. These results confirm the negative short-term effect of in-market mergers[11] on deposit rates and can be interpreted is evidence for the structure-conduct-performance hypothesis.

[10] Our approach is slightly different for Hannan and Prager's here. They adopt a dummy variable for each of the -12/+12 months around the merger.

[11] In these regression specifications we follow Hannan and Prager (1998) and do not control for any features of the bank ort he local market

Here the change of deposit rates around a merger is studied without controlling for changes in the reference interest rates (T-Bill rate or Fed funds rate), which are important determinants of deposit rates. We control for the rates by adopting the more comprehensive approach suggested by Focarelli and Panetta (2003). Focarelli and Panetta (2003) examine the level of deposit rates relative to the reference rate around the merger rather than just the simple change of deposit rates. Focarelli and Panetta also expand the analyzed time period after the merger and include a few controls on the bank and local market level. The estimated model in this case is:

$$relative\_rate_{i,j,t} = \gamma_0 + \gamma_1 merger\_dummies_{i,t} + \gamma_2 Controls + \nu_{i,j,t} \qquad (2)$$

As in Focarelli and Panetta (2003) our dependant variable $relative\_rate_{i,j,t}$ in Table 2 is the difference between the deposit rate (checking account rate or MMDA rate) and the fed funds rate. The time distance to the merger is measured by a set of five dummies (for the first, second, third, fourth and fifth year after the merger). Controls for bank characteristics are bank size (log of total assets) and bank size squared. On the local market level we control for market concentration using the Herfindahl Index (HHI) and average per capita income in the local market (in log form).

Our results suggest that if we do not control for bank and market features, bank mergers have a positive short- and mid-term effect on deposit rates. The long-term effect (5 and more years after the merger) is, however, negative. Nevertheless, the magnitude of the coefficients suggests that the short-term positive impact outweighs the negative effect and the total impact is still positive.

Once we control for bank size, HHI and local market's average income the negative long-term effect disappears, and we are able to document that mergers are associated with a rise in deposit rates. The control variables enter the regression with coefficients of the expected sign, given a Focarelli and Panetta world. So, larger banks offer lower deposit rates, but the negative effect of bank size is exhausted at a certain threshold. The Herfindahl Index (HHI) has a negative and statistically significant coefficient suggesting that banks offer lower deposit rates in more concentrated local markets.

Table 2: Short and long-term effect of bank mergers

	checking account rate		money market deposit account rate	
	(1)	(2)	(3)	(4)
1st year after the merger	**1.321** ***	**1.002** ***	**1.028** ***	**0.807** ***
	0.033	0.060	0.031	0.061
2nd year after the merger	**0.687** ***	**0.914** ***	**0.435** ***	**0.778** ***
	0.032	0.065	0.031	0.067
3rd year after the merger	**0.165** ***	**0.943** ***	**-0.004**	**0.863** ***
	0.037	0.079	0.035	0.081
4th year after the merger	**0.283** ***	**0.715** ***	**0.116** ***	**0.692** ***
	0.041	0.086	0.039	0.087
5th and more years after the merger	**-0.067** *	**0.123**	**-0.221** ***	**0.028**
	0.041	0.088	0.039	0.091
size		**-1.058** ***		**-0.746** **
		0.395		0.362
size squared		**0.037** ***		**0.026** **
		0.012		0.011
HHI		**-6.604** ***		**-4.212** ***
		0.542		0.528
income		**-0.176** **		**-0.128** **
		0.076		0.062
constant	**-3.882** ***	**7.854** **	**-3.275** ***	**5.202** *
	0.032	3.380	0.030	3.052

Note: Dependant variable is the difference between the deposit rate (money market rate or checking account rate) and the fed funds rate. Coefficients in bold, standard errors below coefficients. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

The results of this exercise substantially differ from those of the Hannan and Prager's (1998) approach. They can be interpreted as evidence on the efficiency hypothesis. Our results, however, differ from Focarrelli and Panetta's results, in that we do not document a negative short-term (that is in the first two years after the merger) impact on deposit rates. A comparison of the results illustrates that even when the same dataset is employed, empirical results change substantially when we expand the time window around the merger and the set of control variables. This conclusion leads us to track the dynamics of deposit rate changes in a more comprehensive framework.

5. Bank mergers and the dynamics of deposit interest rates: an extended empirical analysis

The empirical tests presented in Section 4 do not consider the censoring issue arising from the rigidity of the deposit rates. When we replicate Hannan and Prager's (1998) approach we estimate a regression where the dependent variable is the monthly change of deposit rates. In our sample this variable is equal to 0 in about 90% of the observations[12]. The observed values of the dependent variable are severely censored. As a result of the censoring OLS estimates can be biased and inconsistent[13].

In this section we present an estimation methodology which accounts for the censoring and thus incorporates deposit rate rigidity. We employ the following baseline empirical model:

$$\ln deprate_{ijt} - \ln deprate_{ijt-1} = \beta_0 + \beta_1 merger\_splines_{it} + \beta_2 Controls_{it} + \beta_3 Controls_{jt} + \beta_4 \Delta fedfund_t + \varepsilon_{ijt} \quad (3)$$

where $deprate_{ijt}$ is the deposit rate (checking account rate or money market deposit account rate) offered by bank i in market j in "month" t, $merger\_splines_{it}$ is a vector of splines for different time distances from the merger. $Controls_{it}$ and $Controls_{jt}$ are vectors of control variables on the individual bank level and the local market respectively. $\Delta fedfund$ is a vector of the change in the fed funds rate during the periods: (t-1,t), (t-2, t-1) and (t-3, t-2).

Our model, therefore, estimates how the process of adjustment—of bank deposit rates to changes in the reference rate during the current and previous periods—is modified by bank mergers and the characteristics of the bank and the local bank market. Thus, when we discuss

---

[12] We will present more detailed evidence on the rigidity of deposit rates in the next subsection.

[13] Although less obvious the censoring problem is also present in Focarelli and Pannetta's (2003) framework, where the difference between the deposit and the fed funds rate is used as a dependent variable. Again since deposit rates change very infrequently, the changes of the dependent variable are only driven by changes in the fed funds rate.

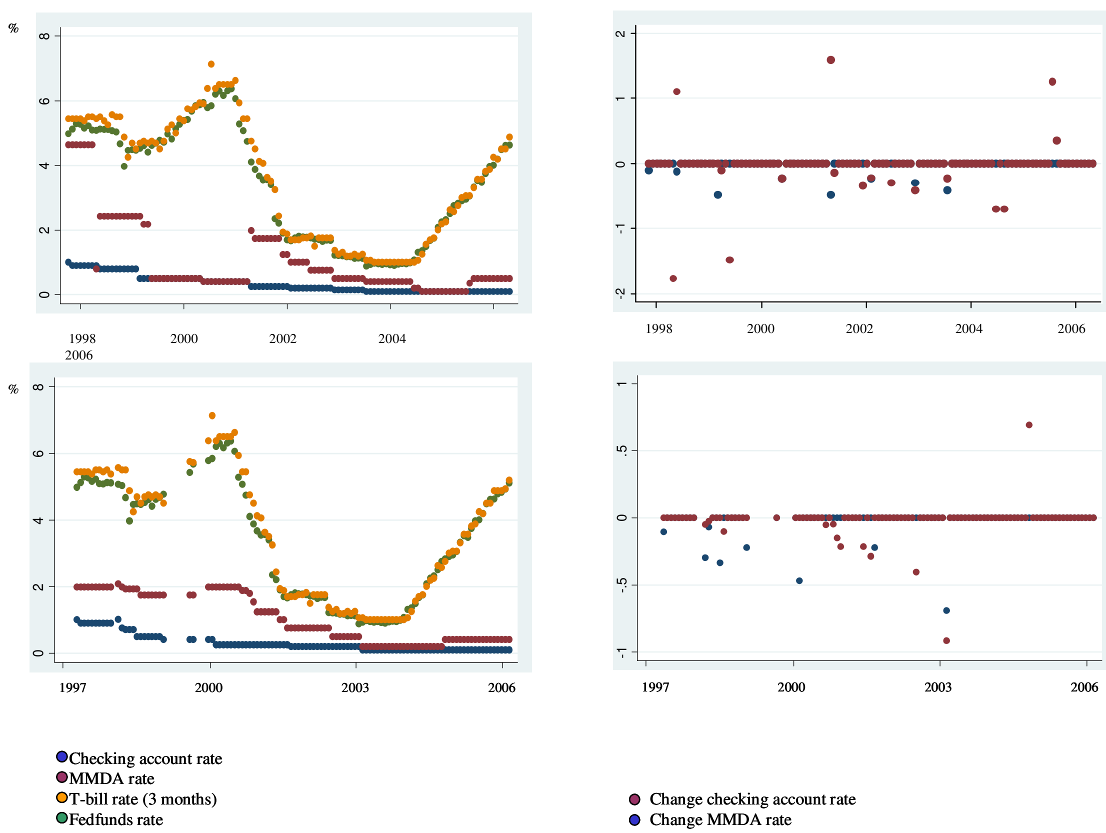
a negative/positive impact of a merger on the deposit rates, we mean the impact of the merger on this process.

Dependent Variable

Evidence on the rigidity of retail deposit rates

Our dependent variable $\ln deprate_{ijt} - \ln deprate_{ijt-1}$ represents the monthly change of the log of bank deposit rates[14].

Figure 1: Two examples of bank retail deposit rates



Source: Bankrate Monitor, Inc

Figure 1 shows cases illustrating the infrequent changes of bank deposit rates. The left hand panels of the figure present two examples of checking account rates and money market

[14] As robust checks we rerun the regressions using the difference of the deposit rate levels. Results do not change qualitatively. We report the change in log results in order to facilitate comparison with Hannan and Prager's results.

account rates together with the fed funds and the 3-month T-bill rate. The right hand panels present the changes of the log of the checking account rates and money market account rates for the same bank/market and time period. The graphs illustrate that deposit rates change very infrequently. As suggested by Berger and Hannan (1991) and Neumarke and Sharpe (1992) they react particularly sluggishly to upward changes in the wholesale interest rates. Table 3 presents a summary of the frequencies of interest rate changes in our sample. The two examples plotted in Figure 1 represent the usual pattern of infrequent deposit rate changes. On average checking account rates stay unchanged in 90% of the months, whereas money market account rates do not change in more than 84% of the months.

Table 3: Frequency of positive and negative monthly deposit rate changes

	fed funds rate	checking account rate	money market deposit account rate
positive change	45%	2%	5%
negative change	38%	8%	11%
no change	16%	90%	84%

Estimation technique

As a benchmark we first estimate the model by standard OLS. We then proceed with modelling the rigidity of the deposit rates to estimate the impact of bank mergers on deposit rates by a "trigger model" with fixed costs of the price (deposit rate) adjustment constructed in the tradition of the "Ss" literature. We assume that an underlying latent variable, itself a function of measured time series characteristics, must reach a positive or a negative trigger point before it can change the deposit rate in either direction.

The desired deposit rate, in the absence of a fixed cost of deposit rate adjustment is P^*. The pooling model gives the following system

$$\Delta P^*_{i,t} = X_{i,t}\beta + u_{1i,t}, \qquad (4)$$

where $X_{i,t}$ denotes the vector of explanatory variables and $u_{1i,t}$ is the error term.

We then observe the following classic Ss model, where $\Delta P_{i,t}$ denotes the observed deposit rate change:

$$\Delta P_{i,t} = \Delta P_{i,t}^*, \text{ if } \Delta P_{i,t}^* + u_{2i,t} > c_u$$

$$\Delta P_{i,t} = \Delta P_{i,t}^*, \text{ if } \Delta P_{i,t}^* + u_{2i,t} < c_l \tag{5}$$

$$\Delta P_{i,t} = 0, \text{ otherwise.}$$

Here the parameters, $c_l < 0 < c_u$, represent the trigger points of the Ss rule, and are estimated from the data. The term, $u_{2i,t}$ represents the error. It is straightforward to show that if $u_{1i,t}$ ~ $N(0,\sigma_1)$ and $u_{2i,t}$ ~ $N(0,\sigma_2)$, then

$$E(\Delta P_{i,t} | X_{i,t}, \Delta P_{i,t} \neq 0) = A_l E(\Delta P_{i,t} | X_{i,t}, \Delta P_{i,t} < 0) + A_l E(\Delta P_{i,t} | X_{i,t}, \Delta P_{i,t} > 0) \qquad (6),$$

where

$$E(\Delta P_{i,t} / X_{i,t}, \Delta P_{i,t} < 0) = X_{i,t}\beta + \sigma \frac{\phi(v_l)}{\Phi(v_l)}$$

$$E(\Delta P_{i,t} / X_{i,t}, \Delta P_{i,t} > 0) = X_{i,t}\beta + \sigma \frac{\phi(v_u)}{\Phi(v_u)}$$

$$v_l = \frac{c_l - X_{i,t}\beta}{\sigma} \tag{7}$$

$$v_u = \frac{-c_u + X_{i,t}\beta}{\sigma}$$

$$\sigma = \sqrt{\sigma_1^2 + \sigma_2^2}$$

$$A_l = \frac{\Phi(v_l)}{\Phi(v_u) + \Phi(v_l)}$$

$$A_u = 1 - A_l.$$

and where ϕ, Φ, are the standard normal density and cumulative normal density functions, respectively.

The likelihood functions for the system described above are well defined, but maximum likelihood estimation procedures rarely converged because of the large numbers of parameters combined with the huge number of observations. However, the form of the expectation above suggests a simple three stage procedure that we adopt when coding the estimator.

In the first step we estimate $v_l = \dfrac{c_l - X_{i,t}\beta}{\sigma}$ and $v_u = \dfrac{-c_u + X_{i,t}\beta}{\sigma}$ using two separate probits on whether or not we observe price increases or decreases and compute

$$\hat{\lambda}(v_l, v_u) = A_l(\hat{v}_l, \hat{v}_u)\frac{\phi(\hat{v}_l)}{\Phi(\hat{v}_l)} + A_u(\hat{v}_l, \hat{v}_u)\frac{\phi(\hat{v}_u)}{\Phi(\hat{v}_u)} \tag{8}$$

The intuition behind λ is that it represents the expectation due to the censoring process. By including an estimated value of λ as a right hand variable, we ensure that the unobserved error term has an expectation that approaches zero in large samples, giving us consistent estimates of our parameters of interest, β.

These parameters, β, are estimated in the second step, using simple GLS on

$$E(\Delta P_{i,t} / X_{i,t}, \Delta P_{i,t} \neq 0) = X_{i,t}\beta + \sigma\hat{\lambda}(v_l, v_u) \tag{9}$$

where, again, λ is included as a regressor in the estimation of $\Delta P_{i,t}$ to correct for the censoring bias.

Of course the standard errors for the estimated parameters must be estimated in a way that accounts for the fact that an included regressor, $\lambda(v_l, v_u)$, is estimated in the first stage. The methods we use are standard in the literature.

Finally, the trigger parameters, c_l and c_u, can be estimated in a third stage, using simple probits on $v_l = \frac{c_l - X_{i,t}\beta}{\sigma}$ and $v_u = \frac{-c_u + X_{i,t}\beta}{\sigma}$. Because each stage of the procedure represents an M-estimate, in the sense of Huber, standard errors can be estimated from the stacked system in fairly standard ways, described in Wooldridge (2002).

The empirical approach described above gives us a consistent estimate of the impact of mergers on deposit rates while accounting for interest rate rigidity. The estimates illustrate how mergers affect the bank pricing setting and in particular how the reaction of a bank to a change in the reference rate is modified by a merger.

Explanatory variables

Variables measuring merger's impact across time

When defining the bank merger impact on deposit rates we concentrate on two major issues, the evolution of the effect of a bank merger over time; and the question of the number mergers back in time that should be considered (numerous banks acquire multiple targets within a very short period). By concentrating exclusively on the last merger, we might omit important information about the evolution of bank merger effects.

To consider the evolution of a merger effect, we account for a period from a year before the merger date[15] to ten years after the merger. We approximate the development of deposit rates around the merger by linear spline interpolation, the simplest form of spline interpolation. It is equivalent to piecewise linear interpolation, where the function to be modeled is divided into a fixed number of subintervals, and within each of the subintervals the function is linearly approximated. Nonlinearity can, therefore, be modeled by different slopes of the linear

[15] The merger date is the date when the target bank loses its charter.

functions across the subintervals. The end points of the linearly approximated subintervals are known as “knots”.

Algebraically, each spline is a linear function constructed as:

$$\frac{x_{i+1}-x}{x_{i+1}-x_i}\alpha_i+\frac{x-x_i}{x_{i+1}-x_i}\alpha_{i+1}, \qquad \text{when } x\in(x_i,x_{i+1}],$$

$$\text{and} \qquad 0, \text{ otherwise} \qquad (10)$$

and where x is the value of the explanatory variable (the time distance to the merger, in our case). The values x_i denote the “knots” of the spline, and the coefficients, α_i, are estimated from the data. In our case we approximate the impact of a merger on the change of the deposit rates by dividing the time period around the merger into several subperiods. We fix the knots, x_i, at 6 months before the merger date, at the merger date, 6 months, one year, 1 1/2 year, 2 years, 3 years and 4 years after the merger. Through the splines we model the potential nonlinearity of the dependence between deposit rate changes and time after the merger.

To our knowledge previous research on the impact of mergers on bank rates has only used dummies for different time windows around the merger. A disadvantage of the dummies is that they are a step-wise and discontinuous approximation of the merger effect across time. Linear splines give a more precise approximation by modeling the effect of mergers as a set of continuous linear functions[16].

With regard to the history of a number of mergers experienced by the bank, we proceed as follows: to keep the model parsimonious, we define the splines for the time distance from the latest merger only. For previous mergers we define a set of dummy variables *merger*$_i$ which takes the value of one if the bank has had at least i mergers and zero, otherwise. Our dataset

[16] As a robustness check, we reran our regressions with dummies instead of splines; results did not change qualitatively; statistical significance of the splines results was, however, higher.

contains up to 6 mergers of a bank. The variables *merger*$_4$, *merger*$_5$, and *merger*$_6$ entered all regression specifications with statistically insignificant coefficients[17], we therefore, dropped them from the analysis. We interpret the insignificance of the dummies for earlier mergers as a result of the fact that banks which have merged three times during our sample horizon tend to have merged numerous times and so are all similar in this regard.

Variables controlling for the type of merger

In our study we include the full sample of bank mergers in the period 1988-2005. We do not divide mergers into in-market and out-of-market groups, because we think that this distinction is not clear cut. Most of the mergers in the US during the last few years are mergers between banks which are already operating in multiple markets. From one local market's point of view, a merger might appear as an in-market merger (if the local market is part of the overlapping geographical range of the two merging banks). In contrast, from the point of view of a local market, which has been operated by only one of the merging banks, the merger appears as a market extension (out-of-market) merger. Based on these considerations, we include all mergers in the analysis together with a range of merger characteristics as controls.

The existing literature has so far emphasized three important features of bank mergers, which might influence the pricing behavior of the merged bank. We include these three key merger features in the identification of the merger impact. The first one is the change in market share. When two banks operating in the same market merge, their joint market share allows them to exercise market power and offer lower deposit rates. We control for this effect by including in the regressions the change of market share (CMS) caused by the merger. We do not have precise data on the change of market share directly related to the merger for each of the affected local markets. We have instead to approximate this change by the change of market

[17] We interpret the insignificant impact of 4th to 6th latest mergers as a result of the fact that of the banks which have merged at least trice in our sample, most have merged up to 6 times.

share realized in the year of the merger. That is, if a bank has merged in a year T we approximate the change of market share caused by the merger as the difference between this bank's market share in T and T-1[18].

In order to estimate how the effect of the change of market share evolves in the time after the merger we also introduce a cross-product of CMS and the time after the merger (CMS**time after merger*=CMS*ln(1+ weeks after the merger)).

A second key aspect of mergers that has been emphasized in the literature is the change of bank size. By merging, banks grow in size. As a result, they might materialize efficiencies of scale. On the other hand, as pointed out by Park and Pennacchi (2005), larger banks have access to more diversified sources of refinancing and might therefore, keep deposit rates low. To estimate the impact of *target size* we include the volume of total assets of the target bank[19] (normalized to the acquirer's total assets) in the regression. The cross-product of the *target size* and the time after the merger (target size* ln(1+ weeks after the merger)) is also included in the regression.

Finally, as suggested by the linked oligopoly hypothesis, the number of markets where a bank is active might also significantly impact its pricing behavior. In order to estimate the effect of the market extension dimension of the mergers we include the *change of number of local markets* (CNM) divided by the number of markets prior to the merger as a regressor. We have again to approximate the CNM by the difference between a bank's number of markets in year T and year T-1. Again, we also include the cross-product of the CNM variable and the time after the merger (CNM* ln(1+ weeks after the merger)) as a regressor.

---

[18] The Summary of Deposits publish market shares as of June 30; therefore we define the year in this case as the period July, 1 to June, 30.

[19] The *Supervisory Master File of Bank Mergers and Acquisitions* provides data for the target banks' ID. Given these we match the acquirer banks' data with the target banks' data from the Call Report.

Control variables

In addition to the merger related variables and the variables measuring the change of the fed funds rate we include a number of control variables in the regression. On the individual bank level these are bank size (measured by the log of total assets), bank size squared and share of deposits to total assets (lagged with one year in order to avoid simultaneity). On the local market level we control for market concentration (as measured by the Herfindahl index) and per capita income (in log form).

Empirical results

The results of the baseline OLS estimations of the changes of the checking account rates and the money market deposit account rates are illustrated in Table 4 and 5, respectively. Those of the estimations of the "trigger" model are presented in Table 6 and 7.

A comparison of the OLS with the "trigger" model results indicates that both the economic and the statistical effect of mergers are stronger when we control for the rigidity of the deposit rates. The higher statistical significance can be explained by the fact that the "trigger" model ignores the noise introduced by the "no change" observations. The lower economic significance is a direct effect of the censoring bias which is present in the OLS estimation. In the following discussion we will concentrate on the unbiased "trigger" model results.

The empirical results in regard with the change of the checking account rate point to a negative impact of mergers. Whereas the pre-merger effect is insignificant in all checking account rate regression specifications, the immediate effect of the merger is negative and statistically significant. Moreover, the merger continues to exert a negative impact on the deposit rates up until the beginning of the third year after the merger. Only during the third year we can identify a positive impact of the merger on deposit rates changes, but this positive impact is offset by the negative effect during the following years.

Table 4: Mergers and checking account rate dynamics: OLS estimates

	(1)	(2)	(3)	(4)	(5)
spline-.5	**-0.001**	**0.000**	**-0.001**	**-0.001**	**0.000**
	0.006	0.006	0.006	0.006	0.006
spline0	**0.023** ***	**0.023**	**0.023**	**0.023** ***	**0.023** ***
	0.004	0.004	0.004	0.004	0.004
spline+.5	**0.003**	**0.001**	**0.003**	**0.003**	**0.002**
	0.004	0.004	0.004	0.004	0.004
spline+1	**0.006**	**0.004**	**0.006**	**0.006**	**0.004**
	0.004	0.004	0.004	0.004	0.004
spline+1 1/2	**-0.011** ***	**-0.014** ***	**-0.011** ***	**-0.011** **	**-0.013** ***
	0.004	0.005	0.004	0.005	0.005
spline+2	**-0.007** *	**-0.011** ***	**-0.007** *	**-0.007** *	**-0.010** **
	0.004	0.004	0.004	0.004	0.004
spline+3	**0.002**	**-0.002**	**0.002**	**0.002**	**-0.001**
	0.004	0.004	0.004	0.004	0.004
spline+4	**-0.012** ***	**-0.018** ***	**-0.013** ***	**-0.012** ***	**-0.017** ***
	0.003	0.003	0.003	0.003	0.004
target' size		**-0.006**			**-0.005**
		0.005			0.005
TS*time after merger		**0.005**			**0.006**
		0.002			0.002
change market share (CMS)			**-0.023**		**-0.013**
			0.031		0.031
CMS*time after merger			**0.005**		**-0.001**
			0.009		0.009
change number of markets (CNM)				**-0.002**	**-0.001**
				0.002	0.002
CNM*time after merger				**0.000**	**-0.001**
				0.001	0.001
merger2	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**
	0.003	0.003	0.003	0.003	0.003
merger3	**-0.003**	**-0.002**	**-0.003**	**-0.004**	**-0.002**
	0.003	0.003	0.003	0.003	0.003
change fed fundsrate (t;t-1)	**0.022** ***	**0.022** ***	**0.022** ***	**0.022** ***	**0.022** ***
	0.002	0.002	0.002	0.002	0.002
change fed fundsrate (t-1;t-2)	**0.052** ***	**0.052** ***	**0.052** ***	**0.052** ***	**0.052** ***
	0.002	0.002	0.002	0.002	0.002
change fed fundsrate (t-2;t-3)	**0.031** ***	**0.032** ***	**0.031** ***	**0.031** ***	**0.032** ***
	0.002	0.002	0.002	0.002	0.002
bank size	**-0.016** ***	**-0.013** **	**-0.017** ***	**-0.018** ***	**-0.014** **
	0.005	0.005	0.005	0.005	0.005
bank size squared	**0.001** ***	**0.000** ***	**0.001** ***	**0.001** ***	**0.000** ***
	0.000	0.000	0.000	0.000	0.000
deposits to assets	**0.001**	**-0.001**	**0.000**	**0.000**	**-0.001**
	0.014	0.014	0.014	0.014	0.014
market share	**-0.006**	**-0.008**	**-0.006**	**-0.006**	**-0.008**
	0.007	0.007	0.008	0.007	0.008
HHI	**-0.005**	**-0.005**	**-0.006**	**-0.006**	**-0.005**
	0.011	0.011	0.011	0.011	0.011
income	**0.004** **	**0.004** **	**0.004** **	**0.004** **	**0.004** **
	0.002	0.002	0.002	0.002	0.002
constant	**0.096** **	**0.074** *	**0.099** **	**0.106** **	**0.075** *
	0.044	0.046	0.044	0.045	0.047
number of observations	41440	41440	41440	41440	41440
R-squared	0.0194	0.0195	0.0194	0.0197	0.0198

Note: Dependant variable is the money market account rate with weekly frequency. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively

Table 5: Mergers and money market deposit account rate dynamics: OLS estimates

	(1)	(2)	(3)	(4)	(5)
spline-.5	**-0.005**	**-0.005**	**-0.005**	**-0.005**	**-0.005**
	0.007	0.007	0.007	0.007	0.007
spline0	**-0.003**	**-0.002**	**-0.003**	**-0.003**	**-0.002**
	0.005	0.005	0.005	0.005	0.005
spline+.5	**-0.007**	**-0.008**	**-0.007**	**-0.007**	**-0.007**
	0.005	0.005	0.005	0.005	0.005
spline+1	**0.027** ***	**0.026** ***	**0.027** ***	**0.027** ***	**0.027** ***
	0.005	0.005	0.005	0.005	0.005
spline+1 1/2	**-0.002**	**-0.003**	**-0.002**	**-0.002**	**-0.003**
	0.005	0.005	0.005	0.005	0.005
spline+2	**-0.017** ***	**-0.018** ***	**-0.017** ***	**-0.017** ***	**-0.018** ***
	0.004	0.005	0.004	0.005	0.005
spline+3	**0.007**	**0.006**	**0.007**	**0.007**	**0.006**
	0.004	0.004	0.004	0.004	0.004
spline+4	**-0.023** ***	**-0.025** ***	**-0.023** ***	**-0.023** ***	**-0.025** ***
	0.003	0.004	0.003	0.004	0.004
target' size		**0.006**			**0.007**
		0.005			0.006
TS*time after merger		**0.001**			**0.002**
		0.002			0.002
change market share (CMS)			**-0.001**		**-0.006**
			0.034		0.035
CMS*time after merger			**-0.002**		**-0.003**
			0.010		0.010
change number of markets (CNM)				**0.000**	**-0.001**
				0.002	0.002
CNM*time after merger				**0.000**	**0.000**
				0.001	0.001
merger2	**0.000**	**-0.002**	**0.000**	**0.000**	**-0.001**
	0.003	0.003	0.003	0.003	0.003
merger3	**-0.001**	**0.001**	**-0.001**	**-0.001**	**0.000**
	0.003	0.003	0.003	0.003	0.003
change fed fundsrate (t;t-1)	**0.021** ***	**0.021** ***	**0.021** ***	**0.021** ***	**0.021** ***
	0.003	0.003	0.003	0.003	0.003
change fed fundsrate (t-1;t-2)	**0.073** ***	**0.073** ***	**0.073** ***	**0.073** ***	**0.073** ***
	0.003	0.003	0.003	0.003	0.003
change fed fundsrate (t-2;t-3)	**0.035** ***	**0.035** ***	**0.035** ***	**0.035** ***	**0.035** ***
	0.003	0.003	0.003	0.003	0.003
bank size	**-0.001**	**0.002**	**-0.001**	**-0.001**	**0.003**
	0.006	0.006	0.006	0.006	0.006
bank size squared	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
	0.000	0.000	0.000	0.000	0.000
deposits to assets	**0.070** ***	**0.070** ***	**0.070** ***	**0.070** ***	**0.071** ***
	0.016	0.016	0.016	0.016	0.016
market share	**0.014** *	**0.012**	**0.014** *	**0.014** *	**0.012**
	0.008	0.008	0.008	0.008	0.008
HHI	**0.000**	**0.001**	**0.000**	**0.000**	**0.001**
	0.012	0.012	0.012	0.012	0.012
income	**0.004** **	**0.004** **	**0.004** **	**0.004** **	**0.004** **
	0.002	0.002	0.002	0.002	0.002
constant	**-0.026**	**-0.054**	**-0.027**	**-0.024**	**-0.056**
	0.050	0.052	0.050	0.050	0.053
number of observations	39861	39861	39861	39861	39861
R-squared	0.0261	0.0262	0.0261	0.0261	0.0262

Note: Dependant variable is the money market account rate with weekly frequency. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively

Table 6: Mergers and checking account rate dynamics: results of the "trigger" model

	(1)	(2)	(3)	(4)	(5)
spline-.5	**-0.058**	**-0.054**	**-0.059**	**-0.056**	**-0.056**
	0.057	0.056	0.057	0.057	0.057
spline0	**-0.102** **	**-0.110** **	**-0.095** **	**-0.104** **	**-0.102** **
	0.046	0.046	0.047	0.046	0.046
spline+.5	**-0.090** **	**-0.109** **	**-0.090** **	**-0.096** **	**-0.107** **
	0.044	0.045	0.044	0.045	0.045
spline+1	**-0.021**	**-0.030**	**-0.022**	**-0.027**	**-0.033**
	0.039	0.039	0.039	0.039	0.039
spline+1 1/2	**-0.102** **	**-0.128** ***	**-0.106** **	**-0.098** **	**-0.121** ***
	0.044	0.044	0.044	0.045	0.045
spline+2	**-0.092** **	**-0.115** ***	**-0.098** **	**-0.093** **	**-0.115** ***
	0.041	0.042	0.041	0.042	0.043
spline+3	**0.096** ***	**0.072** **	**0.088** **	**0.095** ***	**0.068** *
	0.035	0.035	0.035	0.035	0.035
spline+4	**-0.056** **	**-0.096** ***	**-0.064** **	**-0.057** *	**-0.096** ***
	0.028	0.031	0.029	0.030	0.032
target' size		**-0.034**			**-0.016**
		0.030			0.032
TS*time after merger		**0.043** ***			**0.040** ***
		0.013			0.014
change market share (CMS)			**-0.408** **		**-0.378** *
			0.195		0.193
CMS*time after merger			**0.143** **		**0.103** *
			0.061		0.060
change number of markets (CNM)				**-0.021** *	**-0.017**
				0.012	0.013
CNM*time after merger				**0.002**	**0.000**
				0.005	0.005
merger2	**-0.028**	**-0.026**	**-0.023**	**-0.022**	**-0.019**
	0.021	0.022	0.021	0.021	0.022
merger3	**-0.017**	**-0.014**	**-0.019**	**-0.021**	**-0.018**
	0.019	0.020	0.019	0.020	0.020
change fed fundsrate (t;t-1)	**-0.015**	**-0.013**	**-0.014**	**-0.017**	**-0.014**
	0.016	0.015	0.016	0.016	0.015
change fed fundsrate (t-1;t-2)	**0.103** ***	**0.104** ***	**0.103** ***	**0.101** ***	**0.103** ***
	0.013	0.013	0.013	0.013	0.013
change fed fundsrate (t-2;t-3)	**0.059** ***	**0.061** ***	**0.059** ***	**0.056** ***	**0.058** ***
	0.015	0.015	0.015	0.015	0.015
bank size	**-0.096** **	**-0.087** **	**-0.105** **	**-0.114** ***	**-0.103** **
	0.043	0.043	0.044	0.045	0.044
bank size squared	**0.003** **	**0.003** **	**0.003** **	**0.003** ***	**0.003** **
	0.001	0.001	0.001	0.001	0.001
deposits to assets	**0.354** ***	**0.350** ***	**0.341** ***	**0.351** ***	**0.338** ***
	0.112	0.112	0.112	0.112	0.113
market share	**0.057**	**0.053**	**0.039**	**0.064**	**0.043**
	0.061	0.061	0.062	0.061	0.062
HHI	**-0.226** **	**-0.229** **	**-0.222** **	**-0.241** ***	**-0.235** ***
	0.091	0.091	0.091	0.091	0.091
income	**0.020**	**0.020**	**0.021**	**0.019**	**0.019**
	0.014	0.014	0.014	0.014	0.014
lambda	**-0.374** ***	**-0.379** ***	**-0.367** ***	**-0.380** ***	**-0.377** ***
	0.034	0.034	0.034	0.034	0.034
constant	**0.949** **	**0.886** **	**1.013** ***	**1.111** ***	**1.015** ***
	0.384	0.384	0.390	0.396	0.392
number of observations	41440	41440	41440	41440	41440
censored regression observations	4360	4360	4360	4360	4360
R-squared	0.09	0.09	0.09	0.09	0.09

Note: Dependant variable is the money market account rate with weekly frequency. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively

Table 7: Mergers and money market deposit account rate dynamics: results of the "trigger" model

	(1)	(2)	(3)	(4)	(5)
spline-.5	**-0.017**	**-0.017**	**-0.017**	**-0.015**	**-0.016**
	0.023	0.023	0.023	0.023	0.023
spline0	**0.032**	**0.031**	**0.032**	**0.031**	**0.033**
	0.021	0.021	0.021	0.021	0.021
spline+.5	**-0.113** ***	**-0.113** ***	**-0.113** ***	**-0.117** ***	**-0.116** ***
	0.034	0.034	0.034	0.034	0.034
spline+1	**0.108** ***	**0.101** ***	**0.108** ***	**0.105** ***	**0.099** ***
	0.037	0.037	0.037	0.037	0.038
spline+1 1/2	**0.022**	**0.023**	**0.022**	**0.018**	**0.021**
	0.029	0.030	0.029	0.029	0.030
spline+2	**-0.102** ***	**-0.102** ***	**-0.101** ***	**-0.105** ***	**-0.105** ***
	0.025	0.028	0.025	0.026	0.029
spline+3	**0.092** ***	**0.087** ***	**0.093** ***	**0.089** **	**0.086** **
	0.035	0.033	0.035	0.035	0.033
spline+4	**-0.076** ***	**-0.082** ***	**-0.075** ***	**-0.081** ***	**-0.084** ***
	0.020	0.023	0.020	0.021	0.024
target' size		**0.007**			**0.018**
		0.021			0.024
TS*time after merger		**0.006**			**0.004**
		0.010			0.010
change market share (CMS)			**0.100**		**0.085**
			0.157		0.157
CMS*time after merger			**-0.029**		**-0.029**
			0.047		0.047
change number of markets (CNM)				**-0.011** *	**-0.015** *
				0.007	0.008
CNM*time after merger				**0.002**	**0.003**
				0.003	0.003
merger2	**-0.017**	**-0.019**	**-0.018**	**-0.014**	**-0.018**
	0.015	0.015	0.014	0.015	0.015
merger3	**-0.022** *	**-0.020**	**-0.022** *	**-0.023** *	**-0.020**
	0.013	0.013	0.013	0.013	0.013
change fed fundsrate (t;t-1)	**-0.027** **	**-0.026** **	**-0.027** **	**-0.027** **	**-0.027** **
	0.012	0.012	0.012	0.012	0.012
change fed fundsrate (t-1;t-2)	**0.080** ***	**0.081** ***	**0.080** ***	**0.080** ***	**0.080** ***
	0.010	0.010	0.010	0.010	0.010
change fed fundsrate (t-2;t-3)	**0.016**	**0.017**	**0.016**	**0.015**	**0.016**
	0.010	0.010	0.010	0.010	0.010
bank size	**0.082** ***	**0.088** ***	**0.084** ***	**0.074** **	**0.082** ***
	0.028	0.029	0.028	0.029	0.030
bank size squared	**-0.002** ***	**-0.003** ***	**-0.002** ***	**-0.002** **	**-0.002** ***
	0.001	0.001	0.001	0.001	0.001
deposits to assets	**0.375** ***	**0.375** ***	**0.378** ***	**0.365** ***	**0.370** ***
	0.069	0.069	0.069	0.069	0.070
market share	**0.045**	**0.045**	**0.048**	**0.047**	**0.047**
	0.043	0.043	0.044	0.043	0.044
HHI	**-0.061**	**-0.059**	**-0.060**	**-0.065**	**-0.062**
	0.070	0.070	0.071	0.070	0.071
income	**0.013**	**0.013**	**0.013**	**0.012**	**0.013**
	0.010	0.010	0.010	0.010	0.010
lambda	**-0.221** ***	**-0.218** ***	**-0.221** ***	**-0.223** ***	**-0.220** ***
	0.019	0.019	0.019	0.018	0.019
constant	**-0.717** ***	**-0.774** ***	**-0.738** ***	**-0.653** ***	**-0.727** ***
	0.238	0.246	0.239	0.247	0.249
number of observations	39861	39861	39861	39861	39861
censored regression observations	6893	6893	6893	6893	6893
R-squared	0.07	0.07	0.07	0.07	0.07

Note: Dependant variable is the checking account rate with weekly frequency. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively

Among the merger features only the change of market share (CMS) has both statistically and economically significant impact. Substantial in-market mergers have stronger negative effect on checking account rates in the affected market. This negative effect is, as expected, decreasing with the time after the merger. This result is consistent with Hannan and Prager's (1998) results, which also document a negative impact of substantial in-market mergers on deposit rates. The effect of target size is statistically insignificant. The effect of the change of the number of markets (CNM) is negative but statistically only marginally significant. We, therefore, find limited support of the hypothesis that the expansion of the geographical scope negatively affects checking account rates (once bank size has been controlled for), especially mergers that increase in market share significantly.

The statistically insignificant coefficients of the *merger2* and *merger3* variables indicate that earlier mergers do not have a significant impact on checking account rates. The change of the fed funds rate during the current month also has no significant impact on the change of the checking account rates. The change of checking account rates is determined instead by the changes of the fed funds rate in the previous two months. These results show that checking account rates adjust to fed fund rate changes only with a substantial delay. The coefficients of the change of fed funds rate variables also suggest that the pass-through is incomplete[20].

Bank size enters the checking account rate regressions with negative significant coefficients indicating that larger banks tend to offer lower deposit rates. This result is consistent with results of previous studies (Park and Pennacchi, 2005). The ratio of deposits to total assets has a significant positive impact on checking account rates: if retail deposits are the primary source of financing of a bank, it will be more likely to increase the deposit rates. Market share and local market average population income are not significant, but the local market

[20] Grop et al (2007) find evidence on incomplete and delayed adjustment of deposit rates offered by European banks.

concentration (measured by the Hyrfindahl index HHI) enters the regression with the expected negative significant coefficient.

When we turn from checking account rates to money market deposit account rates we cannot document a persistent positive or negative impact of mergers. MMDA rates significantly decrease about six months after the merger but recover again in about a year after the merger, they drop again about two years after the merger and significantly increase during the third year. In the following years the effect is negative. We interpret this dynamic path of the MMDA rate changes as a result of the post-merger integration of the pricing policies of the merging banks. It is unlikely that this pattern is caused by a systematic abuse of market power.

Among the merger features only the change in the number of markets enters the regression with a statistically significant coefficient. The sign of this coefficient is negative and points to a negative impact of geographical expansion on MMDA rates. Target's size and the change in the market share have no significant impact on MMDA rates.

A comparison between the checking account and MMDA rate results shows that mergers mainly affect the checking account rates. Our interpretation of this result is that because of the high switching costs monopoly rents can more easily be extracted from checking account customers. Instead of this, MMDAs are an investment product with low switching costs, so that MMDA customers can easily switch to a competitor, if their current bank offers relatively low MMDA rates.

Moreover, the coefficients of the control variables suggest that local market characteristics are irrelevant for MMDA rates. These results suggest that competition on the MMDA market is not geographically limited to the metropolitan statistical area (MSA). Previous research has already argued that the traditional definition of the bank local market limited to the MSA may not be valid nowadays, because telecommunication allows customers to access more distantly located banks (Edelstein and Morgan, 2006). Our results show indeed that MMDA rates are generally decoupled from local market conditions. Checking account rates, on the contrary, still strongly depend on local market concentration and on the changes in the distribution of market shares.

Another interesting difference between MMDA and checking account rates is their dependence on bank size. Whereas larger bank tend to keep checking account rates low they are more likely to increase their money market account rates. It may be that larger banks are associated with more sophisticated customers, who can take advantage of the increased competition offered in the larger geographical markets.

6. Conclusion

This research project is motivated by the contradicting results of previous studies examining the impact of mergers on deposit rates. By replicating previous studies on our new comprehensive deposit rate dataset we are able to show that empirical results are very sensitive to the treatment of the time span around a merger and the choice of control variables. This observation encourages us to revisit the topic of the deposit rate dynamics around bank mergers. For this purpose we employ deposit rate data with monthly frequency. The high frequency data allows a better treatment of the deposit rate dynamics. However, it makes necessary an estimation methodology accounting for the rigidity of deposit rates.

When accounting for deposit rate rigidity we are able to document a significant negative impact of mergers on checking account rates. In particular, in-market merger which substantially increase the market share of the merging bank tend to cause a substantial drop their checking account rates. On the other hand, MMDA rates are not consistently aggravated after bank mergers. Moreover, once we control for bank size, we cannot document a negative impact of out-of-market mergers on deposit rates. Our results are not inconsistent with results of earlier studies which find support for the structure-conduct-performance hypothesis (Berger and Hannan, 1989 and Hannan and Prager, 1998). They do, however, contradict with Focarelli and Panetta (2003) results since we are not able to find any positive long-term effects of the mergers on both types of deposit rates.

A major contribution of our analysis is the uncovered importance of the deposit rate dynamics. A more comprehensive analysis of the time series structure of the deposit rate and its reaction to wholesale rate changes is a scheduled extension of this research project.

References:

Barros, Pita P. (1999): Multimarket competition in Banking, with an example from the Portuguese market, *International Journal of Industrial Organization* Vol. **17:** 335–352

Berger, Allan N. and Timothy H. Hannan (1989): The Price-Concentration Relationship in Banking. *The Review of Economics and Statistics*, Vol. 71: 291-299.

Berger, Allan N. and Timothy H. Hannan (1991): The Rigidity of Prices: Evidence from the Banking Industry. *The American Economic Review*, Vol. 81: 938-945

Berger, Allan N., Saunders, Anthony, Scalise, Joseph M. and Gregory F. Udell (1998): 'The Effects of Bank Mergers and Acquisitions on Small Business Lending. *Journal of Financial Economics,* Vol. 50: 187-229.

Billet, M. T., Jon A. Garfinkel and Edward S. O'Neal (1998): The cost of market versus regulatory discipline in banking. Journal of Financial Economics, Vol. 48: 333 - 358

Calomiris, Charles W. and Jason Karceski (2000): Is the Bank Merger Wave of the 1990's Efficient? *Mergers and Productivity, ed. by S. N. Kaplan.Chicago: The University of Chicago Press*: 93-161.

Connor, Robert, Feldman, Roger, Dowd, Bryan and Tiffany Radcliff (1997): Which Types of Hopsital Mergers Save Consumers Money? *Health Affairs*, Vol. 16: 62-72

Corvoisier, Sandrine and Reint Gropp (2002): Bank Concentration and Retail Interest Rates. *Journal of Banking and Finance,* Vol. 26: 2155–2189

Edelstein, Paul and Donald P. Morgan (2006): Local or State? Evidence on Bank Market Size Using Branch Prices, *Economic Policy Review*, Vol. 12: 15-25

Focarelli, Dario and Fabio Panetta (2003): Are Mergers Beneficial to Consumers? Evidence from the Italian Market for Bank Deposits. *American Economic Review*, Vol. 93 : 1152-1172

Hannan, Timothy H. and Robin A. Prager (1998): Do substantial horizontal mergers generate significant price effects? Evidence from the banking industry. *Journal of Industrial Economics*, Vol. 46: 433-452

Hannan, Timothy H. and Robin A. Prager (2004): The competitive implications of multimarket bank branching, *Journal of Banking and Finance*, Vol. 28: 1889-1914

Hannan, Timothy H. and Robin A. Prager (2006): Multimarket bank pricing: An empirical investigation of deposit interest rates, *Journal of Economics and Business*, Vol. 58(3): 256-272

Kahn, Charles, Pennacchi, George and Ben Sopranzetti. (2005): Bank Consolidation and Consumer Loan Rates, *Journal of Business*, Vol. 78: 99-133

Mester, Loretta (1987): Multiple Market Contact between Savings and Loans. *Journal of Money, Credit, and Banking,* Vol. 19: 538-549.

Mester, Loretta and Anthony Saunders (1995): When does the prime rate change. *Journal of Banking and Finance,* Vol. 19: 743–64.

Neumark, David and Steven A. Sharpe (1992): Market Structure and the Nature of Price Rigidities: Evidence from the Market for Consumer Deposits. *Quarterly Journal of Economics*, Vol. 107: 657-680.

Park, Kwangwoo and George Pennachi (forthcoming): Harming Depositors and Helping Borrowers: The Disparate Impact of Bank Consolidation, *Review of Financial Studies*

Radecki, Lawrence (1998): The Expanding Geographic Reach of Retail Banking Markets, *Economic Policy Review* (Federal Reserve Bank of New York), Vol. 4

Sapienza, Paola (2002): The Effects of Banking Mergers on Loan Contracts. *Journal of Finance*, Vol. 57: 329-368

Wooldridge, Jeffrey (2002): Econometric Analysis of Cross-Section and Panel Data, *MIT Press, Cambridge*