SEACEN

Statistical Methods for IRB Models

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Agenda

- Type of IRB models
- Approaches to Model Development
- Statistical methods for Development of Probability of Default (PD) Models
- Statistical methods for Development of Exposure at Default (EAD) models
- Statistical methods for Development of Loss Given Default (LGD) models
- Statistical methods for Validation of IRB models
- Challenges in Development and Validation of IRB models
- Maybank Background

Type of IRB Models

- Foundation versus Advanced approach
- Probability of Default (PD) Models
- Exposure at Default (EAD) Models
- Loss Given Default (LGD) Models

Type of IRB Models

Different approaches for credit risk

Increased sophistication

Advanced Internal Ratings Based Approach

- Risk weights based on internally determined PD, LGD, EAD parameters

RWA = f (PD, LGD, EAD, M)

Foundation Internal Ratings Based Approach

- Risk weights based on internally determined PD but regulator prescribed LGD, EAD and Maturity
- FIRB not applicable to Retail

RWA = f (PD, LGD, EAD, M)

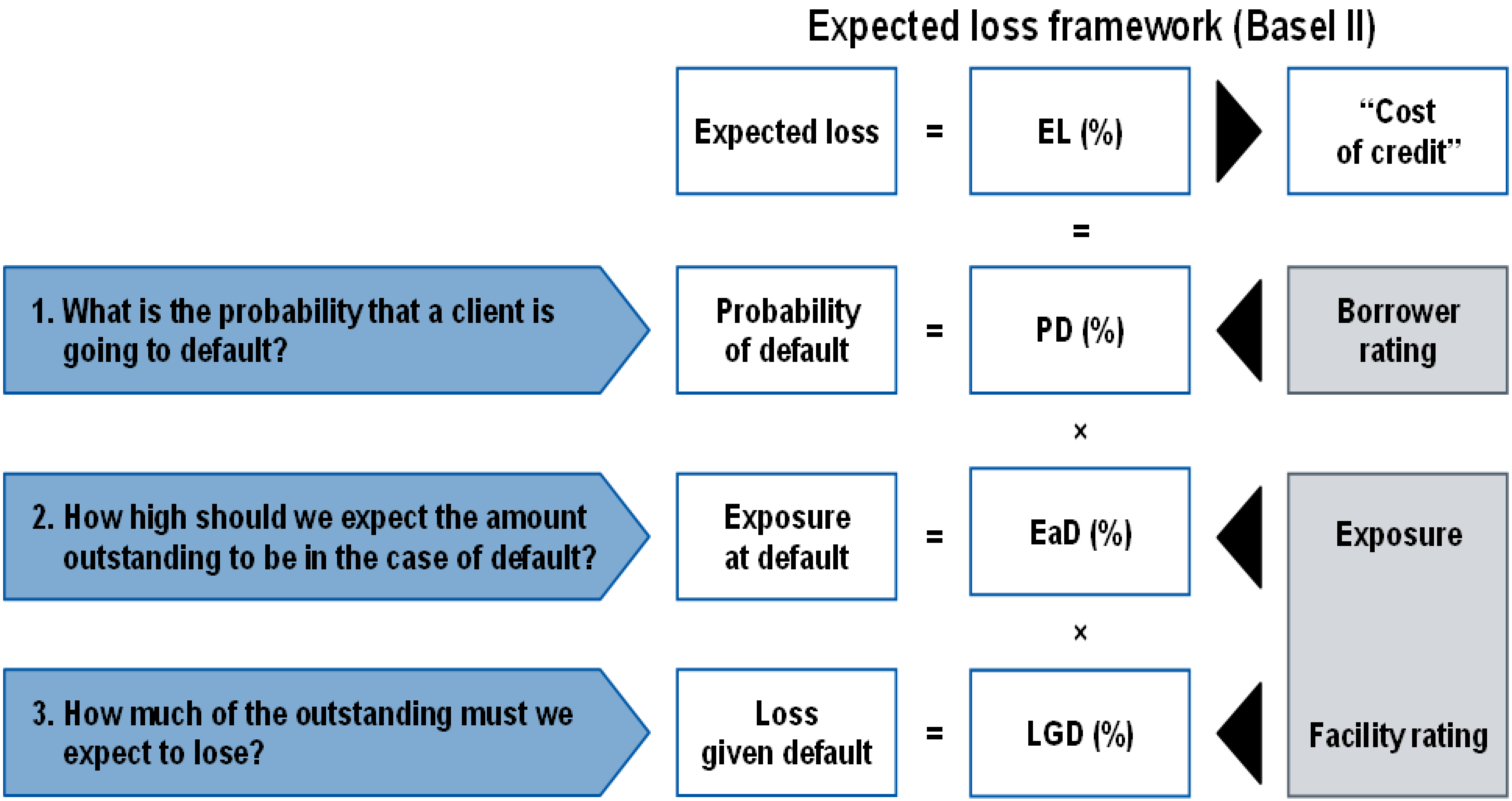
Standardized Approach

- “Slot” Methodology
- More categories of risk weights are available but they are still prescribed by regulators

RWA = Exposure x Risk Weight

Increasing risk sensitive capital requirements

Basel II Expected Loss Framework



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Types of Model varies from pure judgment to “simulation based”

Credit Risk Modeling Methodologies

I — **Pure judgment**

- Potentially inconsistent within and across segments
- No reliable link to expected loss
- Possibly accurate for rank ordering credits within a single segment

II — **Template**

- Structuring of process for judgment-based rating, creating more consistency within segment
- Flexibility for non-standard credits
- May create a ‘score’, but weighting and score assignment are completely judgmental

III — **“Statistical scorecard”**

- Consistent process and evaluation of risk within and across segments
- All or majority or scorecard is built statistically
- Ultimate decision still with credit-qualified officer
- Can be calibrated to Probability of Default (PD)

IV — **“Pure model”**

- Intervention for exception only
- Typically works solely based on objective information
- Can be statistically calibrated to Probability of Default (PD)

V — **“Simulation based” rating model**

- Cash flow simulation tailored to product/facility structure
- Strong statistical basis, but requires credit expert user input

Portfolio Type

Mid Market

Specialized Lending

Corporate

Specialized Lending

Financial Institutions
Holding Companies

Small business
“Micro” small business
Retail Segmentation

Model Development Process

Data Preparation

- Sample defining
- Determination of observation window
- Definition of risk parameter eg: Definition of Default

Model Design

- Type and scope of the model
- Statistical model versus judgmental model

Variable Selection and Initial Model

- Univariate analysis
- Multivariate analysis
- Short-listing of variables
- Initial model
  - Logistic Regression
  - Discriminant analysis
  - Slotting methodology
- Model Calibration
  - Long run default frequency
  - Long run average EAD
  - Downturn LGD

Model Performance Test

- Model power test
- Model refinement
- Hold-out-sample validation
  - "Out-of-sample" model test
  - "Out-of-time" model test

Final Model

- Independent model validation
  - "Out-of-sample" model validation
  - "Out-of-time" model validation

Segmentation Model Development Process

1	2	3	4	5	6	7	8
Defining the sample	**Pooling of delinquent accounts**	**Existing scorecard validation**	**Single factor analysis**	**Multi factor analysis**	**Performance testing**	**Calibration**	**Seasoning overlay**
▪ Define the sample on which the model will be developed upon	▪ Test whether delinquent accounts should form separate pools ▪ Default rates substantially higher and are reasonably homogenous; additional segmentation dimensions don't add predictive power	▪ Test the existing scorecards ability of predicting default ▪ Output determines if scorecard should be used for segmentation	▪ Identify potential set of factors in addition to existing scorecards that may be predictive of default ▪ Determine relationship between single factors and default	▪ Regression analysis to determine the optimal weights of factors in the model ▪ Output includes several model options for discussion	▪ Conduct stability tests for each of models across different cohorts	▪ Calibration of model score to PD and rating grade ▪ Test and confirm accuracy of model, adjusting model parameters where necessary	▪ Credit portfolios season as they go through the first few years and this effect must be incorporated

Statistical Methods for PD Model Development

- Univariate and Multivariate analysis
- Logistic Regression
- Calibration
- Estimating Long Run Default Frequency

Univariate analysis – single factor analysis

Range of Factors

Selection criteria

Predictive
- Is the (in sample) predictive power acceptable?
- Does the factor add information not contained in other factors?

Robust
- Is the factor stable and reliable over time?

Intuitive
- Does the factor make sense?
- Does the factor fit with the banks Experience?

Practical
- Is the factor readily and regularly available ?
- Is the factor easy and cheap to collect / calculate?

Accepted
- Is the factor accepted by both credit and business experts?

Short-listed factors

Multivariate analysis – multifactor analysis

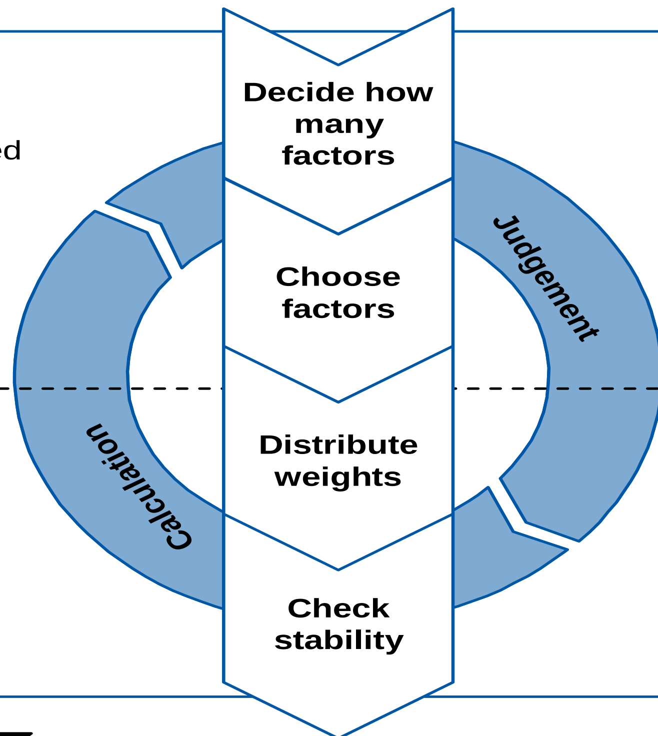
Shortlist of factors

Multi-factor analysis

Statistical calculation

1 Score transformed data processed in SAS to determine statistical optimal selection of factors and weights

4 SAS used to find optimal factor and weights selection following specified initial conditions (e.g. factor Y must be included)



Expert judgement

2 SAS models used as suggested baseline for judgmental modification
- Are the most important factors selected?
- Is the weight distribution consistent with intuition?

3 Factor/weight combinations are varied
- May specify in part and leave SAS to optimise remaining factors

Factor selection and weights

Multivariate analysis – Correlation Analysis (Multicolinearity)

- Correlation analysis examines how factors behave in relation to one another (i.e. how much "overlap" there is between the explanatory power provided by individual factors.
- Factors with high correlations (usually above 50%) in general share similar underlying drivers.
- The models should not include factors (or sets of factors), which are highly collinear or highly multicollinear.
- The correlation analysis between these factors helps us understand the relationships between the factors.
- Correlation measures the statistical relationship between two random variables. Correlation values always fall between -1 and 1.
- **A value of -1 implies perfect negative correlation, a value of 1 perfect positive correlation and zero no correlation at all**.

Multivariate analysis – Correlation Analysis (Multicolinearity)

- Two main approaches to the calculation of correlation are commonly used: Pearson Correlation Coefficient and Spearman Correlation Coefficient.

1

Pearson Correlation

- measures the linear relationship between two variable X and Y using the following formula
- does not capture non-linear relationships very well, for example if there is an exponential relationship between the variables.

$$CORR(X,Y) = \frac{COV(X,Y)}{\sqrt{V(X)\cdot V(Y)}} = \frac{E(X\cdot Y) - E(X)\cdot E(Y)}{\sqrt{\left(E(X^2) - E(X)^2\right)\cdot\left(E(Y^2) - E(Y)^2\right)}}$$

Where: COV (…) is the covariance, V(…) is the variance and E(…) stands for Expected Value.

2

Spearman Correlation

- Spearman Correlation Coefficient if non-linear relationships are assumed or cannot be ruled out.
- measures correlation using the rank order of the factor values of both variables. This correlation measure is thus also usable for ordinal variables.

$$CORR(X,Y) = 1 - \frac{\sum_{i=1}^{n} 6\cdot(R_{X,i} - R_{Y,i})^2}{n\cdot(n^2 - 1)}$$

Where: $R_{X,i}$ stands for the rank of value i of factor X and $R_{Y,i}$ for the rank of value i of factor Y.

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Logistic Regression

- A popular tool for credit assessment is the logistic regression.
- Logistic regression used as a dependent variable is a **binary variable that takes the value one if a borrower defaulted in the observation period and zero other**wise.
- The independent variables (x) are all potentially relevant parameters to credit risk.
- A logistic regression is often represented using the logit link function as :

$$PD = \frac{1}{1 + e^{-(\alpha + \sum \beta_i x_i)}}$$

where, where *βi* are the coefficients and *xi* are the factors

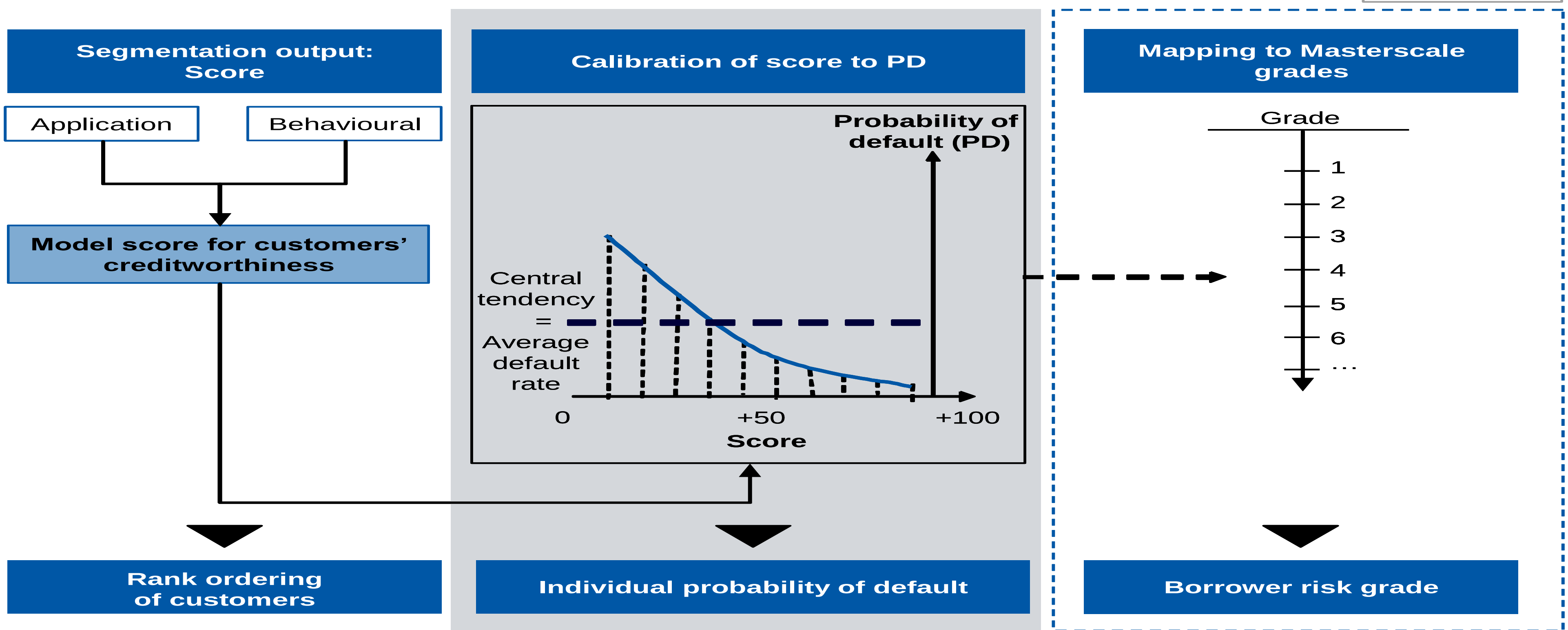
Statistical Methods for PD Model Development

Calibration of Score into PD

- Developing a PD model usually starts from developing a scoring model which aims to rank-order borrowers by risk.

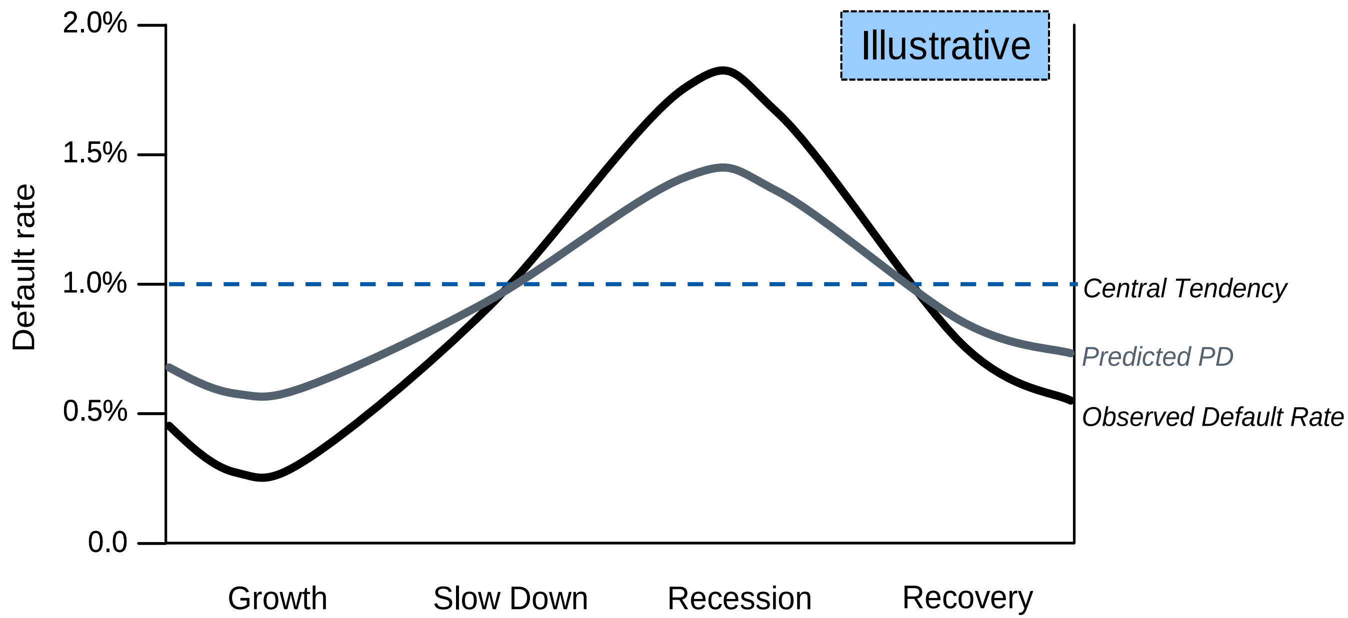
- In order to complete IRB PD requirements, the scores need to be calibrated to ratings that imply an absolute PD grade. **Calibration is the process by which different score ranges are mapped to different PDs** as illustrated in example below:

Illustrative



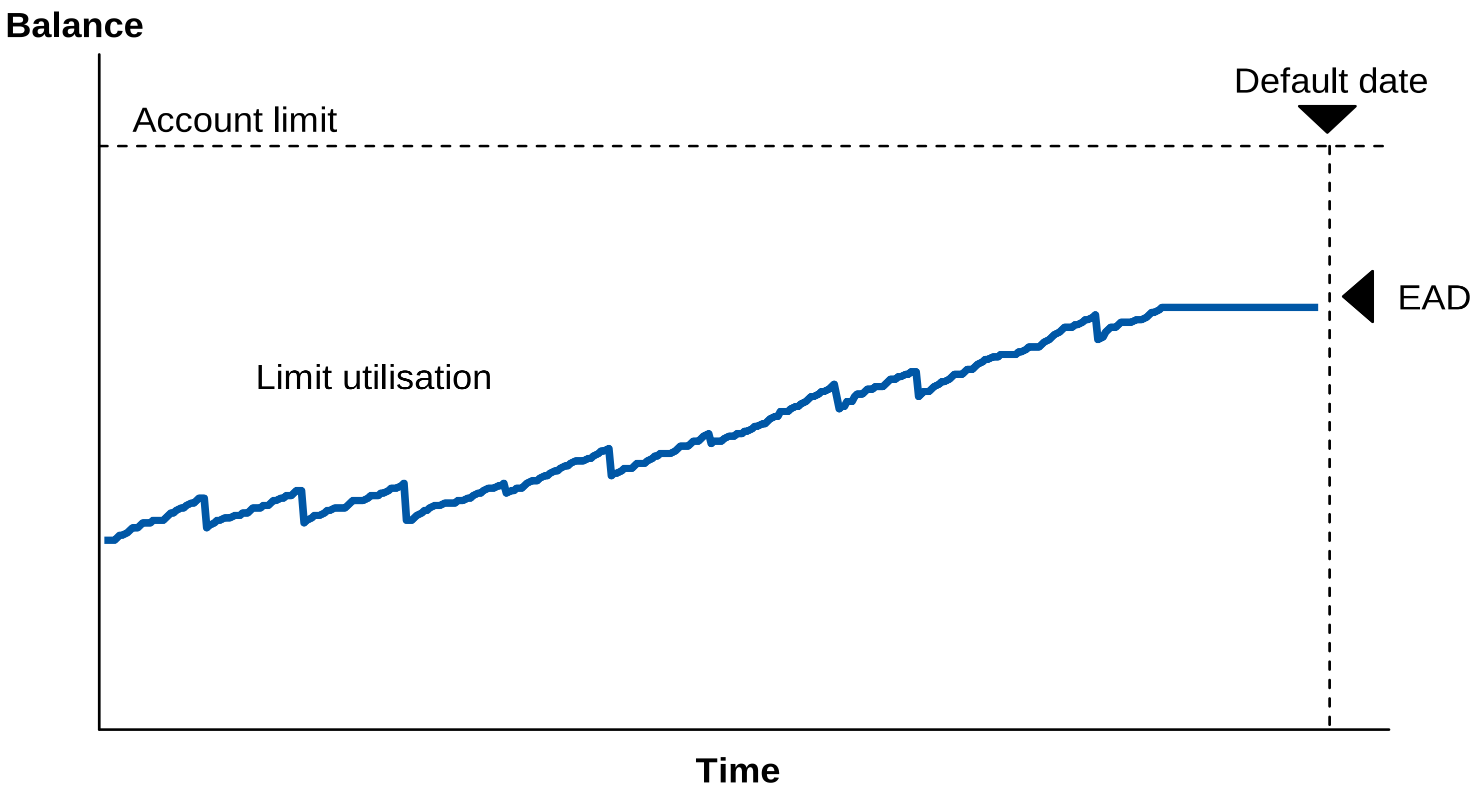
Estimating the Long-Run Average PD (Central Tendency)

- Basel II guidelines require estimation of long-run average PD for the purpose of capital computation.
- The estimation of long-run average PD involves estimating the default rates over a full economic cycle on a forward-looking basis.
- The economic cycle should contain a fair mix of economic downturn and economic growth periods which would reflect the potential occurrence of high default and low default periods.



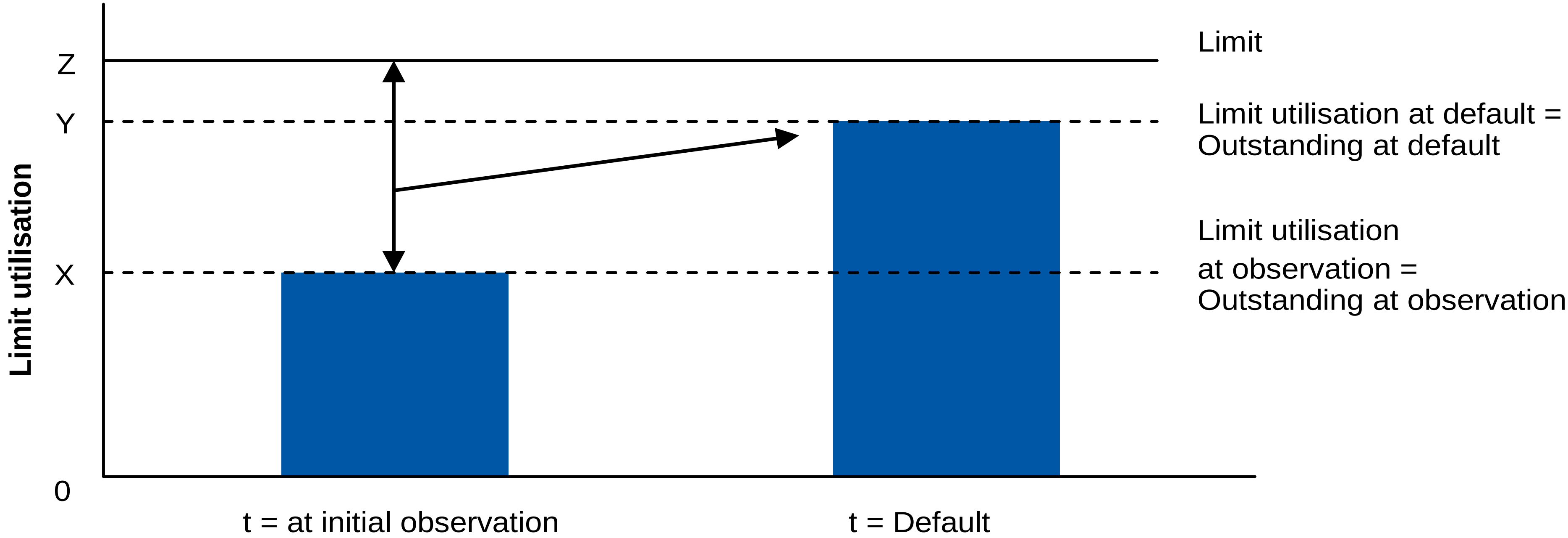
Statistical Methods for EAD Estimation

- Term based facilities
- Revolving based facilities
- Estimation of Credit Conversion Factor (CCF) for revolving facilities



Statistical Methods for EAD Estimation

Estimation of Credit Conversion Factor (CCF) for revolving facilities



EAD = Current Exposure + CCF x (Limit – Current Exposure)

$$\textbf{CCF} = \frac{\text{Expected additional utilisation at default (drawdown)}}{\text{Initial limit headroom (headroom)}} = \frac{Y - X}{Z - X} = \frac{OS_{t=0} - OS_{t=-12}}{L_{t=-12} - OS_{t=-12}}$$

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Statistical Methods for LGD Model

- As defined by Basel II, LGD is the estimate of the full economic loss in the event of default, expressed as a percentage of EAD.

- The main contributors to the economic loss are:

  - Write-offs of principal and interest

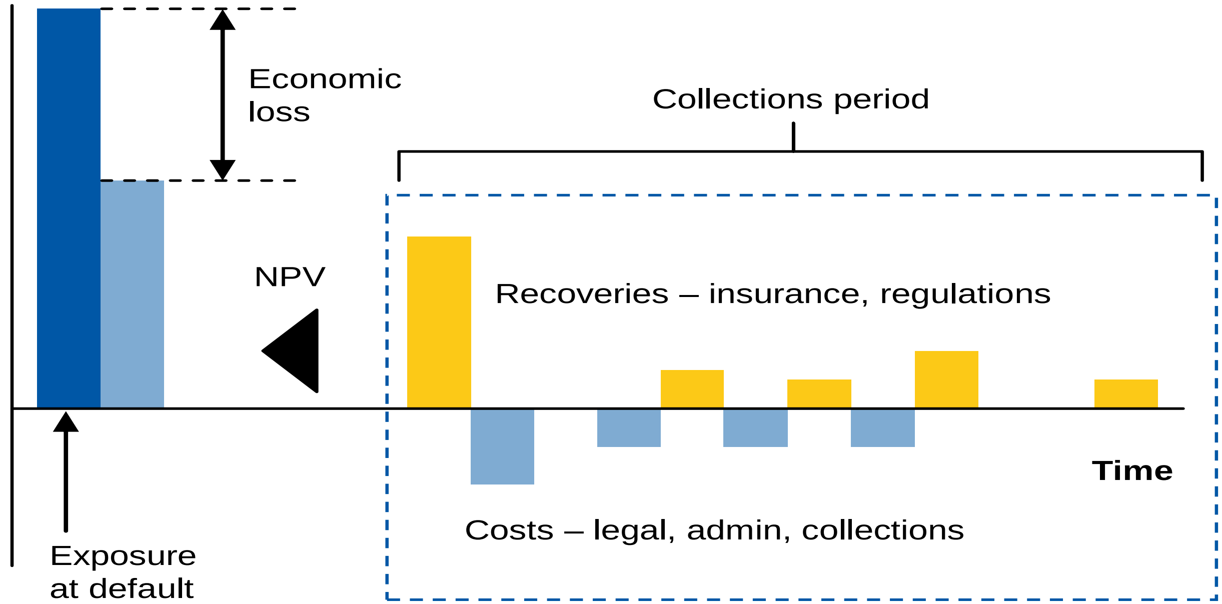
  - Time value of money, caused by the time lag between default and recovery

  - Cost of administrating default

Statistical Methods for LGD Model

The Loss Given Default (LGD) Framework

The mathematical formula for calculating Loss Given Loss is defined as:

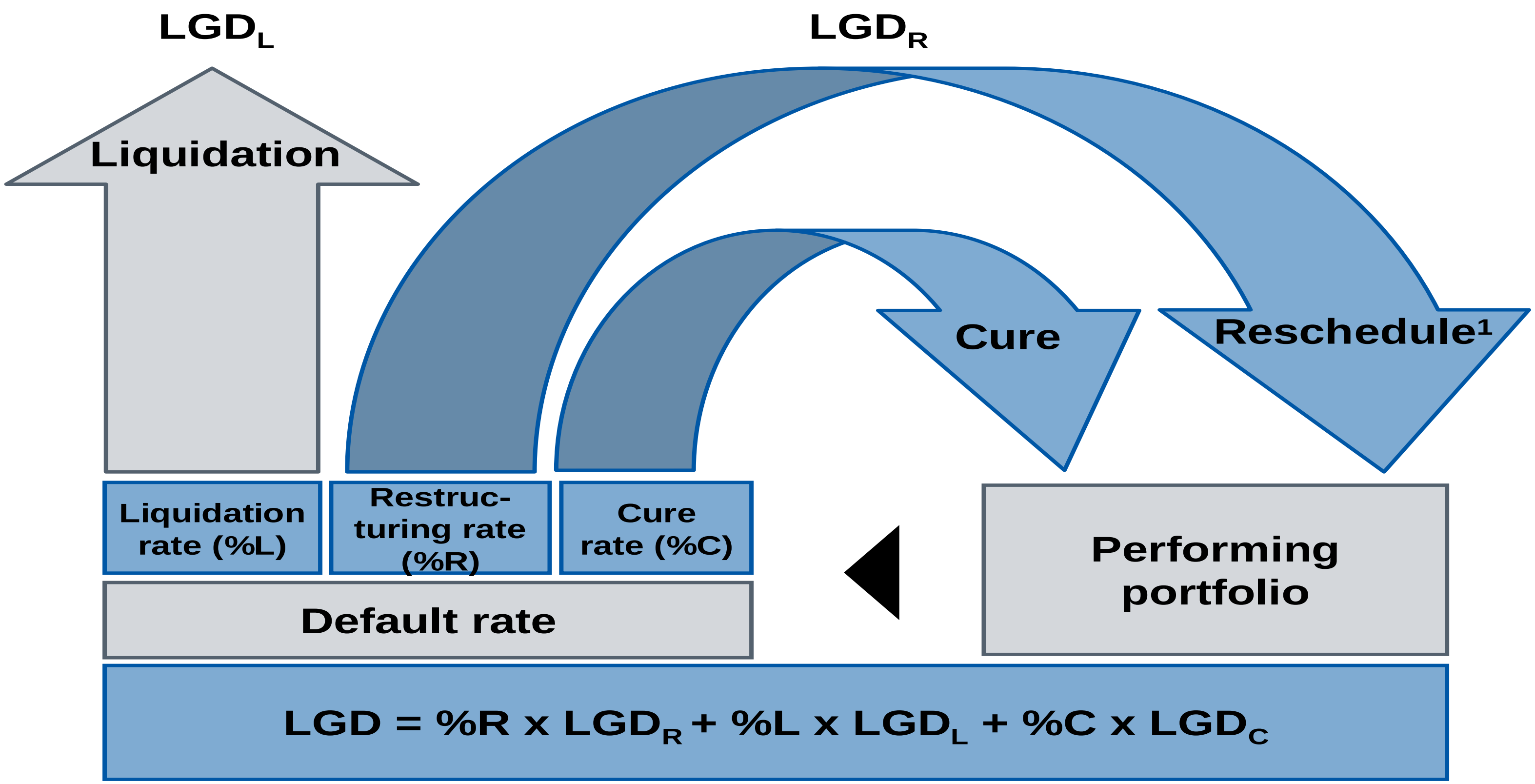


$$
\begin{aligned}
LGL\,(\%) &= \frac{economic\ loss}{EAD} + indirect\ workout\ cost\ (\%) \\
&= \frac{EAD - NPV\ of\ \sum(recoveries - direct\ costs)}{EAD} + indirect\ workout\ cost(\%) \\
&= 1 - \frac{NPV\ of\ \sum(recoveries - direct\ costs)}{EAD} + indirect\ workout\ cost(\%)
\end{aligned}
$$

Statistical Methods for LGD Model

A defaulted borrower may go down one of three post-default paths:

- Cure
- Reschedule or restructure
- Liquidation



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Statistical Methods for LGD Model

- Under IRB, its required to consider the impact of an economic downturn on LGD.

- As shown below.

  “468. A bank must estimate an LGD for each facility that aims to reflect economic downturn conditions where necessary to capture the relevant risks. This LGD cannot be less than the long-run default-weighted average loss rate given default calculated based on the average economic loss of all observed defaults within the data source for that type of facility.

  International Convergence of Capital Measurement and Capital Stand, June 2006

Why Validation is Crucial?

…….........The existence of "Model Risk" element in every risk model used led to the requirement to have in place a rigorous validation process ………....

What is "Model Risk" ?

- "the risk of a model does not perform the tasks or capture the risks it was designed to".
- In the context of Basel II "Model Risk" it can be referred to the risk that models used in calculation of regulatory capital do not meet the required standards set out.

What are the sources of Model Risk?

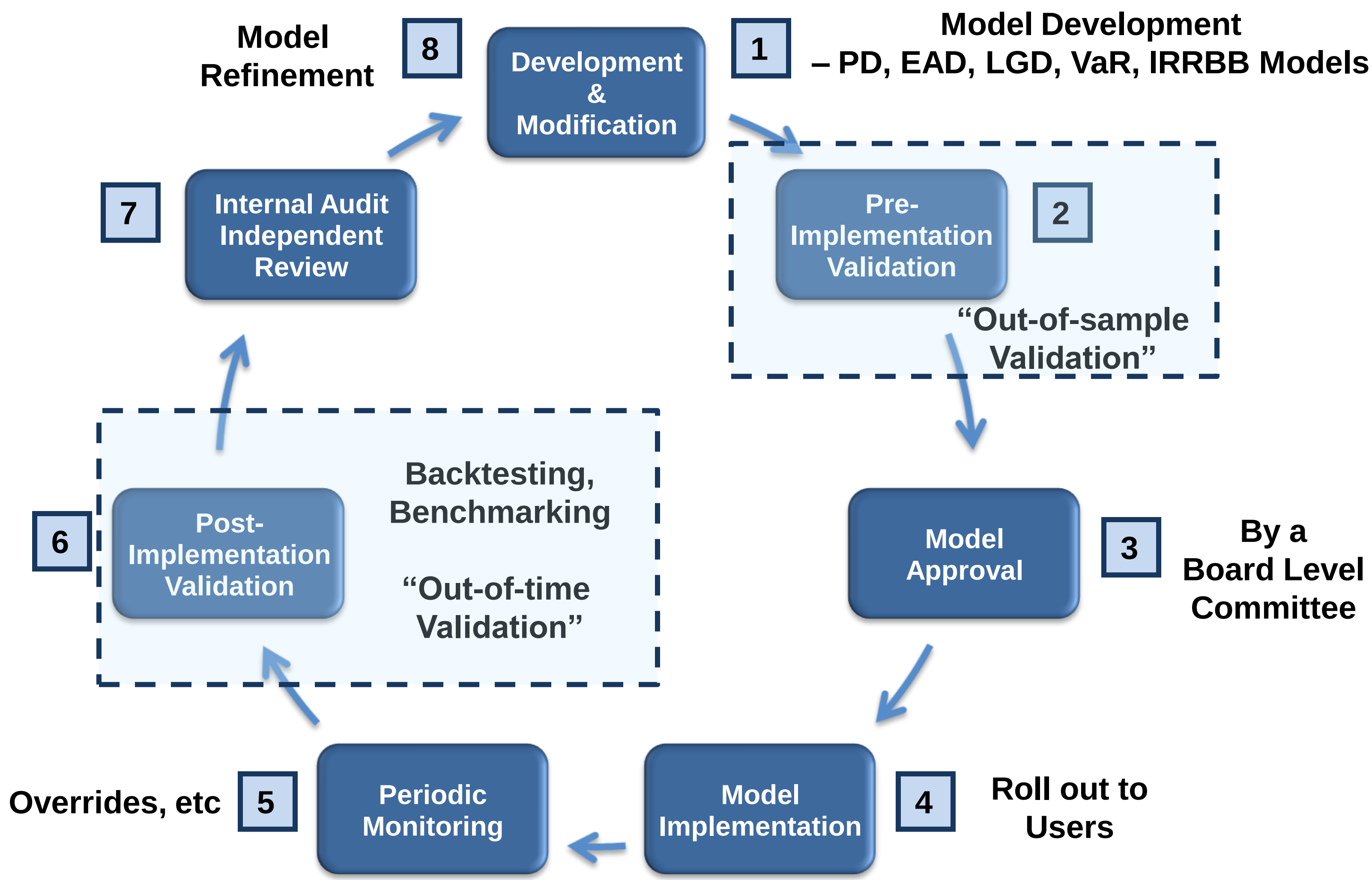
- Incorrect development data
- Incompleteness of data coverage during development
- Assumptions used are not consistent with the modeling problem
- Inappropriateness of the theoretical model
- Complex codes exposed to errors
- Misinterpretation of the information by the user
- Misapplication of the models

How Model Risk Can Be Managed?

- Appropriate Governance and Standards on model development
- Control over model implementation
- Effective model validation process and framework
-

Model Risk Management Lifecycle

Model risk management is an iterative and on-going process.



6 Principles in Model Validation

The validation subgroup of the Accord Implementation Group (AIG) of the Basel Committee outlines the following 6 principles in model validation:

6 Principles in Model Validation

Principle 1	▪ Validation is fundamentally about assessing the predictive ability of an FI's risk estimates and the use of ratings in credit processes.
Principle 2	▪ FI's have primary responsibility for validation.
Principle 3	▪ Validation is an iterative process.
Principle 4	▪ There is no single validation method.
Principle 5	▪ Validation should encompass both qualitative and quantitative elements.
Principle 6	▪ Validation processes and outcomes should be subject to independent review.

Source : Basel Committee Newsletter No. 4 (January 2005) - Update on work of the Accord Implementation Group related to validation under the Basel II Framework

Frequency of Model Validation

1

Back-testing & Benchmarking

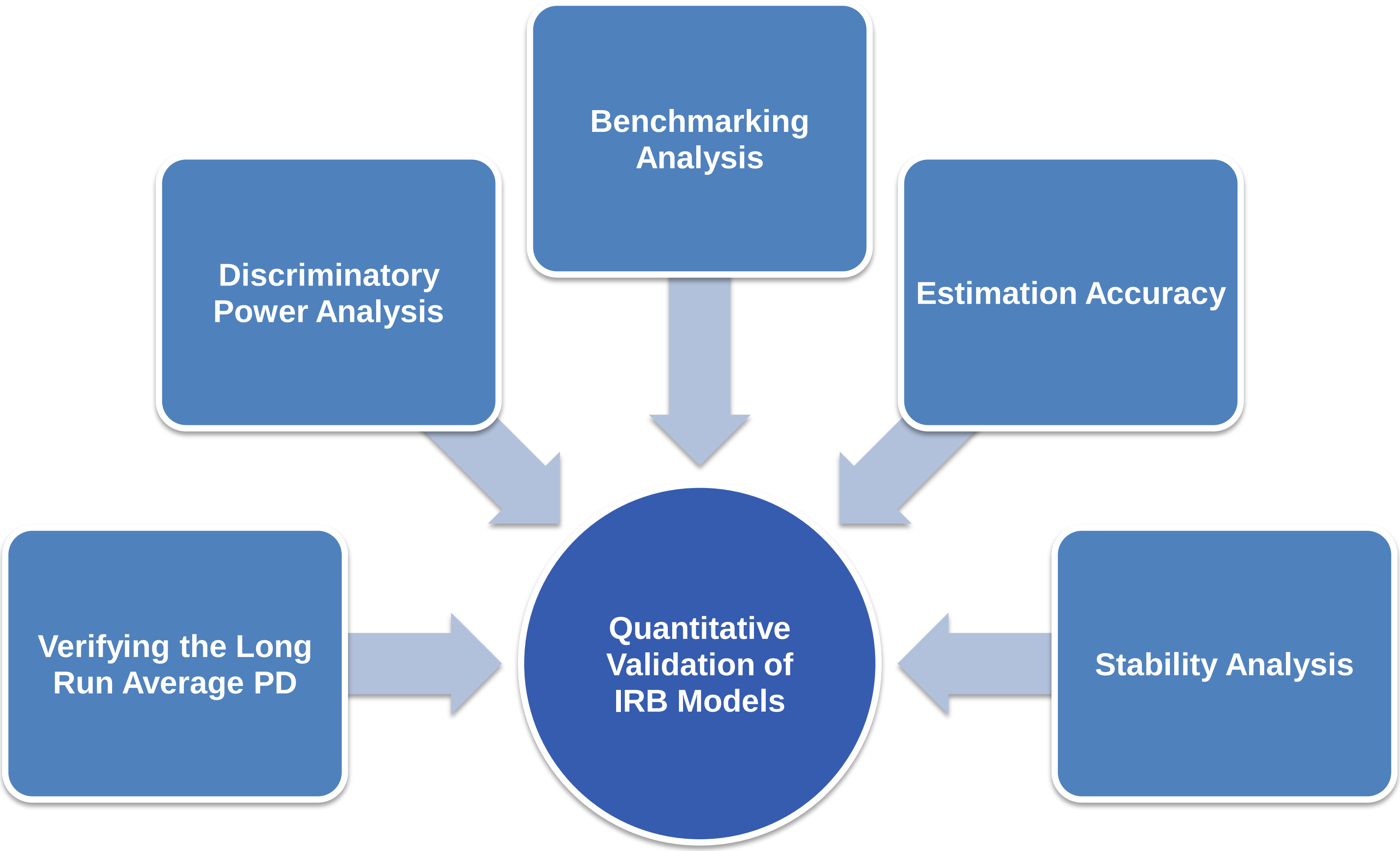
- Initial Validation (New/ revised models) – Pre-Implementation of the model
- Post Implementation Validation (Existing models) – At least annually

2

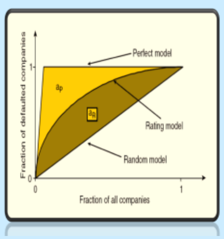
Periodic Monitoring

- Example of Quarterly monitoring
  i. Population stability assessment
  ii. Rating migration analysis
- Example of Semi-annually monitoring
  i. Review of rating model usage, tests on judgmental components
  ii. Override analysis – frequency and reasons

Statistical Methods for Validation- Ensuring Reliability of IRB Risk Models



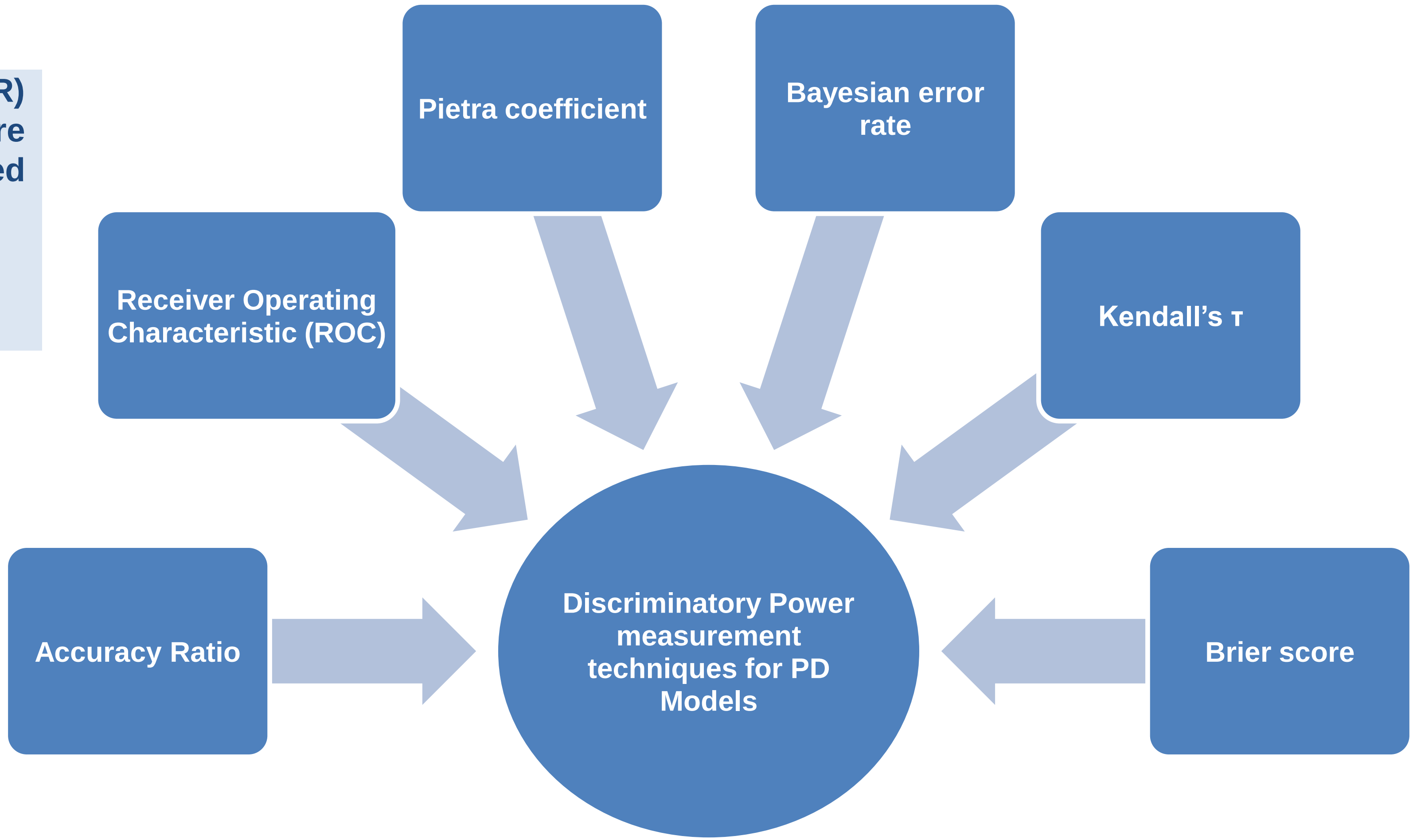
Statistical Methods for Validation - Ensuring Reliability of IRB Risk Models

Key Quantitative Validation Aspects			
	Discriminatory Power	**Estimation Accuracy**	**Stability of the model**
What is measured ?	▪ Ability of a model to differentiate between default and non-default cases **or** differentiate between high risk and low risk.	▪ Ability to assign accurate long term estimates (i.e. PD, EAD, LGD) to each obligors.	▪ Stable relationship between model factors and credit quality over time
Typical Tests 	▪ Accuracy Ratio ▪ KS Statistics ▪ Benchmarking against external agency rating ▪ Benchmarking against internal expert ratings	▪ Comparison of the model estimates versus the actual observed rates at a given error bounds	• Monitor model performance over time , such as monitoring accuracy ratio over time with confidence level • Migration matrix

Statistical Methods for Discriminatory Power Measurement

The validation subgroup of the Accord Implementation Group (AIG) of the Basel Committee in its Working Paper No. 14 (May 2005) Studies on the Validation of Internal Rating Systems suggested various techniques for quantitative validation of IRB risk parameters namely PD, EAD and LGD covering **discriminatory power** and calibration.

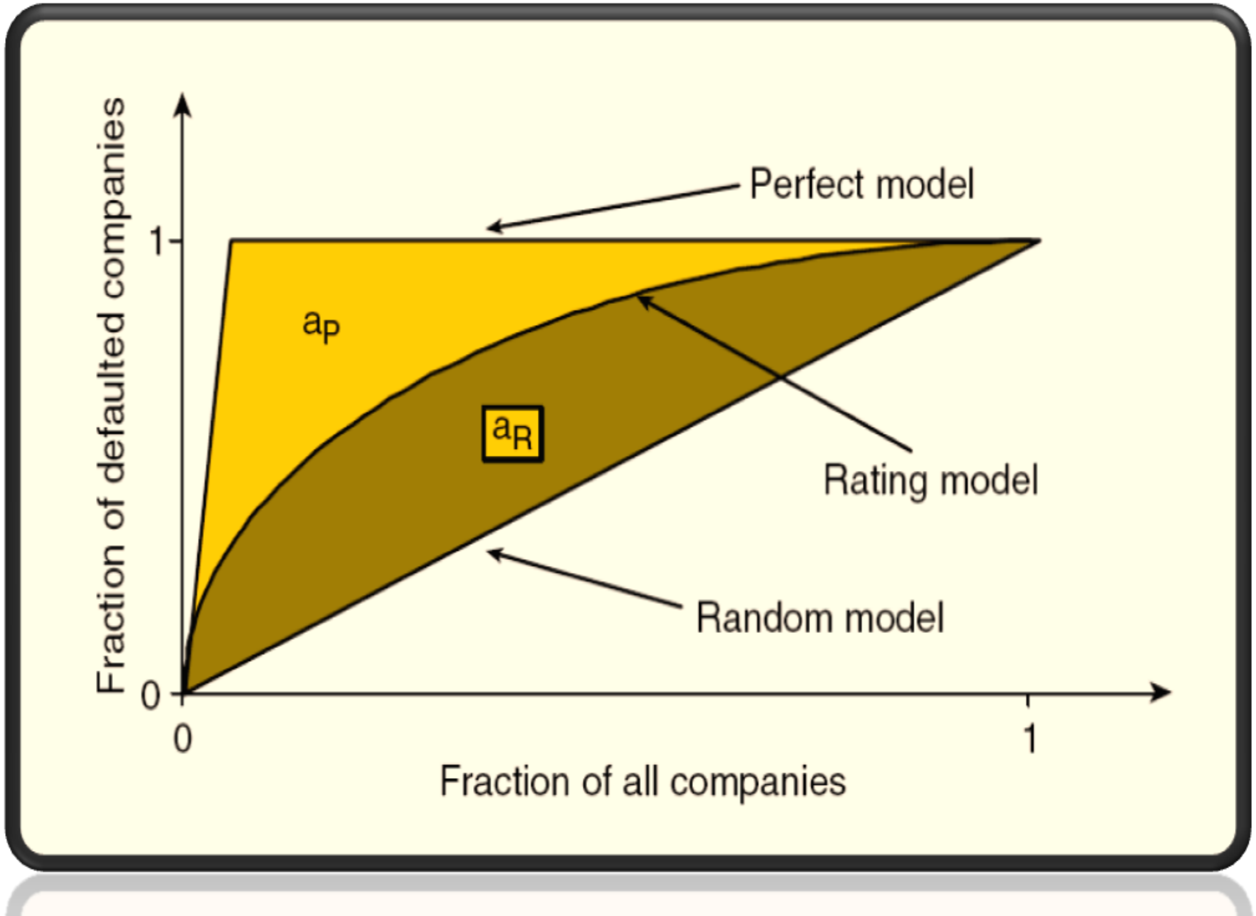
Accuracy Ratio (AR) and ROC are commonly used discriminatory power measurement techniques.



Source : Basel Committee Working Paper No. 14 (May 2005) Studies on the Validation of Internal Rating Systems

Statistical Methods for Discriminatory Power Measurement – Accuracy Ratio

Accuracy Ratio (AR) is a method to measure the ability of a rating model to separate higher from lower probability of defaults among obligors, i.e., to relative risk rank. AR indicates how well the model concentrates the defaulters in the riskiest rating grades..

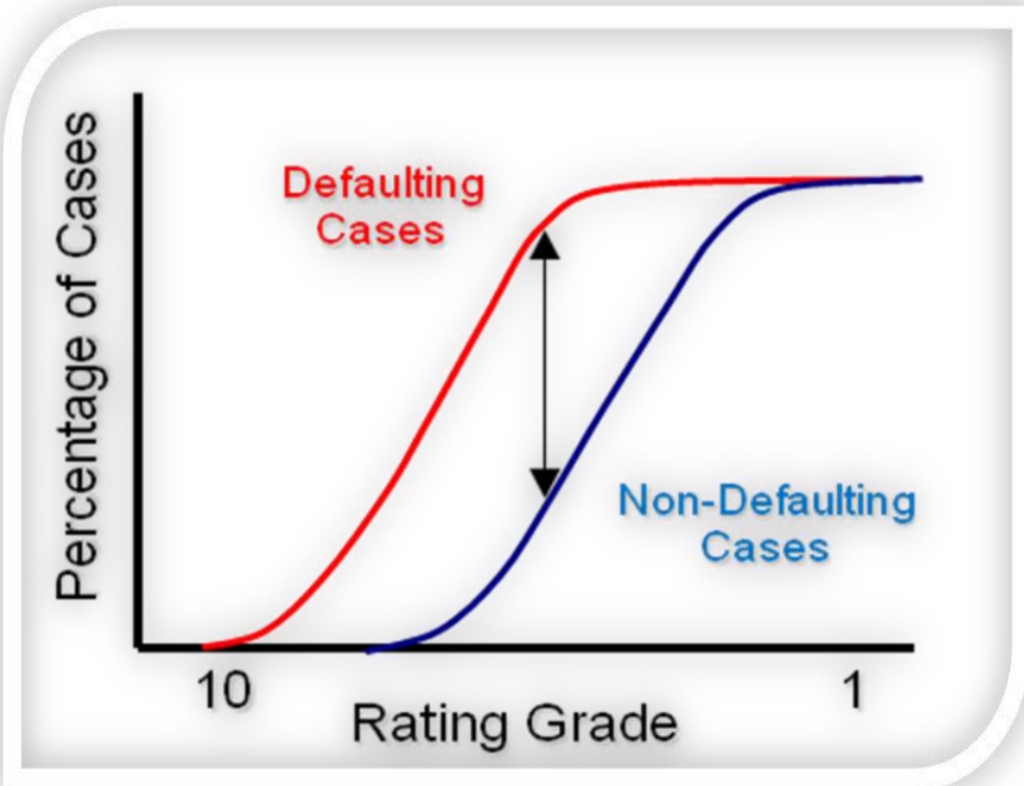


- AR is the ratio of the area $\mathbf{a_R}$ and the area $\mathbf{a_P}$.
- The formula is shown below:

$$AR = a_R / a_P$$

- The value of AR ranges from 0% to 100%, where the higher the ratio, the better the model is.
- **What would be the AR value to conclude a model / factor is predictive / still relevant?**

The **KS Statistic** is another method to measure the ability of a scorecard to discriminate the good from the bad obligors. It is defined as the maximum vertical distance between the empirical cumulative distribution of goods and the empirical cumulative distribution of bads when evaluated as a function of the score or factor to be evaluated.



The formula is shown below:

KS = max (abs(cumpercent_default(r) - cumpercent_non_default (r)))

where r is the rating grade / pool

What would be the KS value to conclude a model / factor is predictive / still relevant?

Statistical Methods for Discriminatory Power Measurement – Kendall's Tau

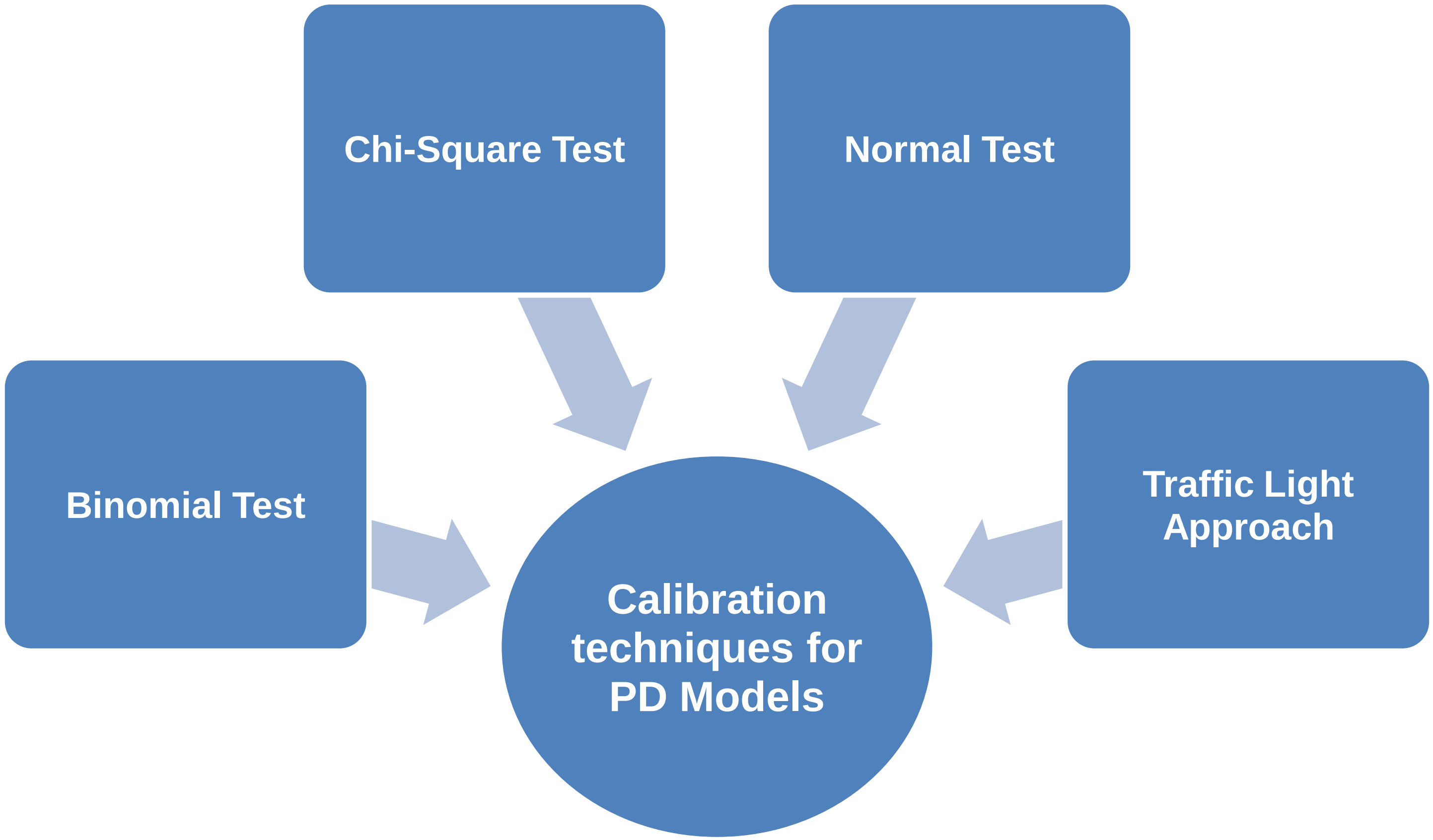
- Kendall tau rank correlation coefficient (or simply the Kendall tau coefficient, Kendall's tau or tau test(s)) is a non-parametric statistic used to measure the degree of correspondence between two rankings and assessing the significance of this correspondence.
- Usually used for rank-ordering capability of Low Default models or in benchmarking exercise.
- In other words, it measures the strength of association of the cross tabulations.
- Kendall tau is a statistical test performed on non-parametric models, hence no assumed distribution is necessary.
- The larger the distance between the two sets of rankings, the more dissimilar the two lists are.
- Kendall tau (τ) is calculated as follows:

$$\frac{n_c - n_d}{\frac{1}{2}\, n\,(n-1)}$$

where, nc is the number of concordant pairs, and nd is the number of discordant pairs in the data set.

Statistical Methods for Calibration of Rating Model

The validation subgroup of the Accord Implementation Group (AIG) of the Basel Committee in its Working Paper No. 14 (May 2005) Studies on the Validation of Internal Rating Systems suggested various techniques for quantitative validation of IRB risk parameters namely PD, EAD and LGD covering discriminatory power and **calibration**.



Source : Basel Committee Working Paper No. 14 (May 2005) Studies on the Validation of Internal Rating Systems

Statistical Methods for Low Default Probability

How to measure discriminatory power of a model / portfolio with Low Default Probability (LDP)?

BENCHMARKING

1

Benchmarking

- Benchmarking against **Expert panel ranking/judgment** – comparing the internal models ranking versus the expert panel's ranking

2

Benchmarking

- Benchmarking against **External Rating or benchmark model** – comparing the internal model's rating versus the external rating agencies (such as S&P, Moody's, Fitch) rating.

Statistical Methods for Low Default Probability

Example : Benchmarking the Internal PD Model against S & P Rating Grade

Borrower	Internal Grade	S & P Rating	Differences (notches)	Match
A	AA	A-	1	Yes
B	A-	BBB	2	No
C	BBB+	BBB	1	Yes
D	BBB-	BBB	1	Yes
E	BB+	BBB-	1	Yes
F	A	A+	1	Yes
G	BBB+	A+	3	No
H	CCC+	CCC+	0	Yes
I	BBB-	B	4	No
J	BB	BB-	1	Yes

- From the example above, 7 out of 10 sample borrowers (70%) have a match [For illustration purpose, matching statistics of 70% and above would be considered Excellent].

- Based on the acceptance threshold, it can be concluded that the internal rating has comparable ranking ability with the external rating. However, further investigation would be required on borrowers B, G & I on the substantial differences.

Statistical Methods for Validation of EAD and LGD

- The mean squared error or MSE of an estimator is one of many ways to quantify the amount by which an estimator differs from the true value of the quantity being estimated.

- As a loss function, MSE is called squared error loss. MSE measures the average of the square of the "error." The error is the amount by which the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate.

- **EAD / LGD Models with lower MSE have smaller differences between the actual and predicted values** and thus they predict actual recoveries more closely.

$$MSE = \frac{\sum (r_i - \acute{r}_i)^2}{n - 1}$$

- where *ri* and *ŕi* are the actual and estimated LGD/EAD. The variable, n, is the number of observations in the sample.

- Drawback of this measure : What is the threshold?

Key Challenges

1. Availability of data to perform model development and independent validation especially to set a side out-of sample and out-of-time sample.

2. Availability of long term data to estimate long run average PD and down turn LGD.

3. Sufficient default data to perform meaningful statistical validation. Low default portfolio.

4. Incorporating Economic and Market Variables – availability of such data.

5. Availability of data electronically – manual data collection may be required which would be time consuming.

6. Expertise and skill set of the model developer and validator – technical and statistical knowledge is crucial.

7. Availability of tools and system to perform model validation – automation of model validation.

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Maybank

Maybank has always been the leader in financial services in Malaysia, and is rapidly becoming a more visible presence across Asia. Our Vision, Mission and Core Values are at the Heart of what we do:

Our Vision: To be a Regional Financial Services Leader

Our Mission: Humanising Financial Services Across Asia

Our Core Values: T.I.G.E.R.

Teamwork	Integrity	Growth	Excellence & Efficiency	Relationship Building
We work together as a team based on mutual respect and dignity	We are honest, professional and ethical in all our dealings	We are passionate about constant improvement and innovation	We are committed to delivering outstanding performance and superior service	We continuously build long-term and mutually beneficial partnerships

The Maybank Group is Malaysia's financial services leader with a network of over 2,100 offices in 17 countries worldwide.

We have 2,100 Offices Worldwide	**Maybank Group is Established in 17 Countries**	**With 42,000 employees globally servicing our clients**
We serve 21 million customers in the markets which we operate in	**We have a market capitalization of US$22 billion**	**Total assets of US$135 billion**

Questions & Answers