Case Study on Credit Risk Modelling
This case study was developed by Asian Institute of Finance.

Asian Institute of Finance (AIF) focuses on developing human capital across the financial services industry in Asia. Established by the Bank Negara Malaysia and the Securities Commission, Malaysia to lead capacity building and standards setting for the financial services industry, AIF is committed to elevating Malaysia’s role as a premier provider of comprehensive solutions for the financial sector across the region.
THE BANK

The First Bank of Yogyakarta has been around for three decades. Its principal activities are the acceptance of deposits and the provision of loans. Its balance sheet comprised of personal, housing and a fair amount of corporate loans. Over time, the corporate loans portfolio grew rapidly in line with economic growth. In light of this development, the bank raised the sophistication of its risk management capacity, particularly in the oversight of credit.

Although The First Bank of Yogyakarta was not an internationally active bank, it imposed upon itself the Basel capital adequacy standards. The Chairman felt that it would curtail unfettered lending, promote judicious use of capital and provide a benchmark of overall financial health and capacity vis-à-vis other banks. In 1997-1998 during the Asian financial crisis, it faced its severest test when the rupiah was devalued and the resultant systemic repercussions were felt by the debtors of the bank. The bank registered two consecutive years of losses after an unblemished track record of yearly profits since its formation. Despite the collapse of many banks and corporations, it survived without the need for additional capital, the result of liquidity assistance from the central bank and diligent risk management.

KEEPING PACE WITH CAPITAL DEVELOPMENTS

In 2004, the Basel Committee on Banking Supervision issued a much upgraded version of the capital adequacy framework. With honourable intentions and great ambitions to raise the bar on risk management, the senior management decided that the bank should gravitate towards the Advanced version of the Internal Ratings Based approach in the derivation of capital to underpin credit risk. This was the most complex of the three options recommended in the framework. This decision, according to management, would provide the bank a quantum leap in credit risk management and also the means to keep up with the quantitative techniques of the big boys of banking. Pet-named the IRB Project, ground work commenced in 2006 and was targeted to be completed by January 2010.
THE IRB PROJECT

Judith joined the risk management team of the bank in 2005. Coming from a mathematical background, she always felt rather inadequate as a banker compared to her peers who majored in accounting, business and economics. Her initial years were spent doing mundane tasks such as generating the daily, weekly and monthly risk reports. Since the bank was not highly automated, a large part of her time was consumed extracting data and inputting them into spreadsheets so that the resultant report would appear meaningful and understandable for the perusal of her senior management. Her fortunes changed in 2008 when she was roped in to take charge of the IRB Project.

Judith meticulously pored over the Basel literature to obtain a holistic and an in-depth appreciation of capital in relation to banking. It was her way to catch up with her banking peers. Ultimately she wanted to establish how banks can develop a Basel II-compliant internal rating model to assess the credit risk of corporate borrowers. Judith gathered the following information which she considered as directly or indirectly pertinent to the IRB Project.

• **Brief Historical Evolution**

  The Basel Committee on Banking Supervision (“BCBS”) was established by the central bank governors of the Group of Ten countries in 1975 to formulate broad standards and guidelines for the supervision of banking institutions in member countries. In 1988, the BCBS introduced the Basel Capital Accord (also known as “Basel I”) which required banks to buttress capital based on perceived risk of various specified classes of assets\(^1\) regardless of the actual risk of individual exposures in each class. Consequently, Basel I did little to stop banks from assuming large disproportionate risks especially under good market conditions, exacerbating the proverbial ‘vicious cycle of risk’ (Figure 1).

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\(^1\) Banks’ assets were grouped into 5 categories according to credit risk, carrying risk weights of 0% (e.g. sovereigns), 10%, 20%, 50% and up to 100% (for most corporate exposures).
To address this shortcoming, a revised capital adequacy framework (known as “Basel II”) was issued by the BCBS in 2004, emphasizing a more risk-sensitive approach to risk assessment. Basel II required each exposure to be risk-weighted according to its underlying risk of default/non-repayment. Thus, a loan made to a high-risk corporate borrower (as assessed by the bank) will attract a higher risk weight (and hence, higher capital charge) compared to a low-risk corporate borrower. Consequently, if two banks have the same asset class composition but one bank has far more high-risk individual exposures within an asset class, then it will need to set aside more capital compared to its counterpart. The BCBS provides a range of options for banks to assess and quantify risks (in terms of credit and operational risk).

Although Basel II has now evolved into Basel III (in response to liquidity and capital concerns following the impact of the global financial crisis in 2008), the focus on credit risk in Basel II is an important step in enhancing the way banks manage risks vis-à-vis capital requirements.

**Basel II Framework Overview**

Basel II comprises 3 main pillars (Figure 2). The first pillar, relates to the minimum capital a bank needs to hold against its risk assets arising from credit, market and operational risks. While banks already ascribe to a minimum 8% capital charge against their risk assets under Basel I, Basel II focuses on refining the estimation of credit risk in banks’ loan portfolios and introducing the charge for operational risks (market risk estimation remains largely unchanged).
• A bank’s regulatory capital ratio is defined as:
Eligible capital / Risk Weighted Assets (RWA) where \( RWA = \sum \text{(market, credit and operational risks of a bank’s total assets)} \); of which several options are available to quantify credit and operational risks.

• Eligible capital = Bank’s equity + other forms of capital approved for recognition by the regulator/national supervisor.

• As in Basel I, Basel II requires banks to set aside a minimum capital ratio of 8% against their RWA. The main difference being that the computation of RWA under Basel II is more granular since it is commensurate with the level of risk present in each exposure/pool of exposures instead of a single risk weight that was prescribed to an entire asset class as practiced during Basel I. It is apparent from the capital ratio formula, that the higher the RWA (higher risk portfolio), the more capital a bank needs to hold, to preserve the capital ratio at a certain level.
OVERVIEW IN DERIVING THE RWA

Judith realized that the key challenge lies in deriving the RWA. To calculate the RWA for an aggregate portfolio, banks would first need to estimate and quantify the credit risk of each exposure/loan or pool of loans (in the case of retail customers) in its portfolio. To do so, the BCBS provides a range of options which banks can adopt (Figure 5), as well as the formulas by which these quantified risks are translated into capital charge for the bank.

The credit risk quantification of a bank’s exposure involves these main components (Figure 3):

- Probability of Default (“PD”)
- Loss Given Default (“LGD”)
- Exposure at Default (“EAD”) and,
- Effective Maturity (typically, a duration that reflects standard bank practice is used).

(The definitions of these components are provided in Exhibit A).

These risk components are fed as inputs into risk weight functions (provided by the BCBS for each main type of asset class) to derive the capital requirement and the equivalent RWA for the exposure. Effectively, higher risk exposures attract higher risk weights and hence, capital charge.

<table>
<thead>
<tr>
<th>Figure 3</th>
<th>Aspects of Credit Risk Estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Risk Components</strong></td>
<td>• PD, LGD, EAD and M</td>
</tr>
<tr>
<td></td>
<td>• Estimation provided by banks, some of which are supervisory estimates</td>
</tr>
<tr>
<td><strong>Risk Weight Functions</strong></td>
<td>• Transforms the risk components into capital requirements which is then used to derive RWA</td>
</tr>
<tr>
<td></td>
<td>• Calculated via formulas provided by BCBS</td>
</tr>
</tbody>
</table>
To estimate the risk components, the BCBS permits 2 options (Figure 5).

- Standardised approach requires banks to derive the risk weights of loan exposures by using the ratings provided by external rating agencies (where available) and/or as provided by their national supervisor (for unrated borrowers).
- IRB approaches allow banks to estimate the risk components via their own internal models. Of the two IRB sub-options, the Advanced IRB approach is the most risk-sensitive as it requires all risk components to be estimated by banks themselves.

### Figure 5 Options for Estimation Risk Components

1. **Standardised**
   - Risk weights based on ratings by External Rating Agencies and/or supervisor criteria

2a. **Foundation IRB**
   - PD derived by banks’ own assessment, estimates of other components provided by regulator¹

2b. **Advanced IRB**
   - All risk components are derived by banks’ own assessments²

**Note:**

¹ There is no distinction between the foundation and advanced approach for retail exposures as banks must provide their own estimates of PD, LGD and EAD.
² Except for 5 sub-classes of assets identified as specialized lending where banks can map to supervisory risk weights.
The BCBS does not require banks to adopt any specific techniques for their internal models, so long as the inputs and processes meet minimum regulatory requirements and outputs are reliable, robust and representative of the risks of the underlying portfolio. The minimum requirements (Exhibit B) mainly pertain to rating system structure and input data integrity, since these anchor the estimation of the risk components used in the capital charge computation.

<table>
<thead>
<tr>
<th>Exhibit A: Definition of Risk Components</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PD</strong></td>
</tr>
<tr>
<td><strong>LGD</strong></td>
</tr>
<tr>
<td><strong>EL</strong></td>
</tr>
<tr>
<td><strong>EAD</strong></td>
</tr>
<tr>
<td><strong>M</strong></td>
</tr>
</tbody>
</table>
### Exhibit B: Key Basel II Minimum Requirements for IRB Approaches

**Rating system design – rating dimension**
- Qualifying system must have 2 separate distinct dimensions: (i) the risk of borrower default (based on borrower characteristics and irrespective of differences in the underlying specific transaction), and (ii) transaction-specific factors (such as collateral, seniority, product type, etc)
- Borrower rating reflects borrower’s ability and willingness to honour its loan obligations
- Banks’ rating systems may incorporate both dimensions separately (e.g. a PD rating and a LGD rating) or together (e.g a rating that reflects Expected Loss) so long as they can be distinguished

**Rating structure**
- Minimum 7 grades non-default, 1 for defaulted.
- Grades must cover reasonably narrow PD bands

**Use of models**
- Data used to build model representative of population of bank’s actual borrowers
- Model must be accurate on average, with reasonable predictors
- If using statistical models, bank must document methodologies
- Data may be sourced internally, pooled (with other banks) and/or externally

**Rating system operation - Stress tests**
- Estimation of rating migration
- Broadly matching internal grades to external rating categories (of rating agencies)

**Risk quantification**
- PD estimates must be long-run average of 1-year default rates, or longer if relevant
- Estimates must be representative of long-run historical experience
- Population in data used to develop rating model is comparable to bank’s exposures
- Comparable economic/market conditions with future outlook
- Reference default definition must be disclosed
- Length of underlying historical observation period used must be at least 5 years for at least 1 data source

**Periodic validation of internal estimates**

*Estimates must be grounded in historical experience and empirical evidence*

*The population of exposures represented in the data for estimation should closely match with bank’s exposures*

*LGD cannot be less than long run default-weighted average loss rate given default (economic loss)*

*Appropriate LGD estimates for high credit loss period*

*Estimates of LGD must have minimum data period of at least 1 economic cycle and no shorter than 7 years for at least 1 data source (for retail exposures, 5 years)*
Estimation of Probability of Default

The probability of default refers to the ability or capacity of a borrower to service/repay debt obligations. The higher this ability, the less likely the borrower will default. For a corporate borrower, its repayment ability is determined by various factors including business and financial performance, industry trends, management experience and strategies, funding lines, parental support etc.

To determine what factors are relevant, we turn to:

- Academic theory/research – which highlight various indicators from corporate financial statements that are predictive of creditworthiness
- Past experience – although not necessarily perfect, the past is a useful predictor of the future. Thus, a bank can use its past experience to identify key default drivers and develop a rating model.

**Figure 6 Illustration of the Determinants of PD**

- **Quantitative factors**
  - Profitability
  - Interest coverage
  - Leverage
  - Cash flows
  - Liquidity
  - Growth rates etc.
  - Operating cash flow/debt
  - Debt/equity
  - Profit margin
  - Current ratios etc.

- **Willingness to service debt**
  - Total asset
  - Market share
  - Corporate age
  - Group strength
  - Funding lines etc.

- **Ability to service debt**
  - Corporate age
  - Market position
  - Industry profile
  - Shareholder support
  - Reputation/track record
  - Credibility
  - Shareholding structure etc.
For many banks, the starting point to estimate a PD model is a sample of companies (both performing and defaulted) from its own portfolio spanning a historical time period where the borrowers’ debt servicing ability is known. From this sample, we identify key factors, relationships and trends that may explain why some firms default while others do not. We then use this past knowledge to develop a model to predict the behavior of future borrowers.

### Methodologies for Estimating PD

Two basic approaches can be used to estimate default risk.

1. **Judgmental or Expert-based Methods**  
   Expert models seek to embody the knowledge of experienced credit lenders into a set of rules (e.g. the 5Cs of credit), which can then be used as a reference criteria for evaluating new borrowers. The model’s factors are qualitatively selected based on these experts’ knowledge and are often given weights on the same basis. Judgemental methods have been in use by banks long before...
statistical methods became popular. This method is suitable when data is not readily available or for very specialised corporate classes of lending (e.g. specific-type project financing) for which historical or industry benchmarks may not be meaningful.

II. Statistical Methods  

Statistical theory and quantitative methods have advanced well to aid the modeling process and to reduce the subjectivity or guesswork common with judgmental methods. These methods can process voluminous data expeditiously and handle complex correlations that exist between variables. For those statistically inclined, some common techniques are discussed briefly in Appendix 1.

**Which Method(s) is/are the best?** The BCBS does not specify preference for a specific method (since the over-riding objective is for banks to develop risk management skills rather than simply to meet regulatory compliance). As such, any of the methods discussed earlier can be used to develop rating models.

Because companies are usually less homogenous in nature (compared to retail customers), the reality is that most banks use a combination of some statistical methods (especially in relation to the quantitative information) and expert-based judgment (to account for important qualitative factors) for their corporate PD models. Figure 7 provides an example of such a hybrid model.

**Process of Model Development**

So how exactly does a bank develop a PD model? This section describes the major steps involved, using historical data as a starting point.
### Step 1 – Determine what the model is supposed to measure
- **Asset class** for which model will apply – corporate, small enterprises, retail etc
- **Model outcome?** It is not enough to just distinguish between defaulters and non-defaulters, banks require a number of rating outcomes to differentiate the risk of their borrowers. A range of 10 to 20 grades is typical.
- **Forecast horizon?** How far ahead do we want the model to predict? A 1-year horizon is the norm.

### Steps 2 & 3 – Extract the historical data needed
Once model objectives are clear, we assemble a sample of companies from a historical database within the bank (or from other external or pooled sources).
- **How many companies?** The appropriate sample size depends on the number of rating grades. Example, a 7-grade rating scale would require a sample of about 1,000 companies. Both non-defaulted and defaulted companies should be included (a rule of thumb is, for every 10 non-defaults, we need 1 default in the sample).
- **Data over what length of time?** Basel requires that data collected span a minimum period of 5 years (e.g. to develop a model in 2013, we collect data for borrowers that exist between 2008-2012, or earlier if available).
• **Type of data?** Typically financial measures such as profitability, leverage, liquidity, cash flow adequacy etc obtained from company financial statements. Usually, data of a few financial years are collected for each company.

**Step 4 – Transform raw data into suitable format for modeling**

The raw sample data undergo a series of preparatory steps including cleaning and transformation into ratios and other useful forms that support modeling.

- Key validation tasks include checking data for mistakes, missing values, expected relationships, value range etc.

- The cleaned data is then transformed into formats (e.g. ratios, log values) that facilitates standardization and provides better comparison of a company’s financial profile (e.g. gearing ratio is better than absolute debt levels).

- It is common to arrive at a long-list of 40 to 60 ratios before these are short-listed during the modeling process.

**Step 5 – Building the model**

Prior to modeling, randomly divide total sample into 2 parts:

- The training sample - contains the bulk of data points and is used to develop candidate models

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**Figure 9 Example of Sample Dataset**

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<th>Status</th>
<th>Corporate Age</th>
<th>FYE</th>
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<th>GrossProfitRaw</th>
<th>PBITRaw</th>
<th>Sales, TL</th>
<th>RetainedProfitRaw</th>
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<th>Sales, CA</th>
<th>NetTL,TotDebt</th>
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<td>135%</td>
<td>68%</td>
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<tr>
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<td>166%</td>
<td>84%</td>
<td>4%</td>
<td>-59%</td>
<td>4%</td>
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</tr>
</tbody>
</table>
The test sample – usually smaller in size, it is only used to test each candidate model’s predictions. This sample is crucial because the true test of a model’s predictions is on data that the model has not seen before.

Both train and test samples should have exclusive members and the ratio of defaulting to performing companies should be similar in both.

Various techniques are available for building a default rating model. The factors that predict corporate default probability can generally be framed as a basic regression equation:

\[ Y = \text{function} \left( X_1, X_2, \ldots, X_n \right) \] - where \( Y \) is the dependent variable i.e. Probability of default and \( X_n \) are the independent factors that are predictive of default.

A LOGIT model simply expresses this function as a logarithmic scale,

\[ \text{LOG} \left( Y \right) = \text{EXP} \left( w_0 + w_1 X_1 + w_2 X_2 + \ldots + w_n X_n \right) \] - where \( Y = PD \), \( w_n \) = coefficients/weights, \( X_n \) = default factors. [LOG and EXP are the natural logarithm function and exponential function (i.e. the reverse of LOG) respectively. The outcome of a LOGIT model has a value between 0 and 1 and can be interpreted directly as PD]

We illustrate building a PD model using a LOGIT technique (note: as explained in Appendix 1, the results of a LOGIT model can be directly interpreted as PD). The modeling process is shown by Figure 10.

**Figure 10** Building a PD model with a LOGIT modeling technique

- Group input ratios by risk category (e.g. profitability ratios, gearing ratios etc)
- Regress each ratio against borrower outcome in train sample, check accuracy statistic (e.g. \( R^2 \))
- Discard ratios with poor predictive ability (low \( R^2 \))
- Find pairwise correlation of remaining input ratios in each risk category
- Pool ratios with correlation > 50% into sub group
- From each sub group, choose input ratio with best \( R^2 \)
- Combine ‘best ratios’ to derive candidate models
- Test candidate models with test sample, check accuracy statistic
- Choose candidate model with highest predictive accuracy
**Steps 6 & 7 – Selecting the final model**

The optimal model has a high level of predictive accuracy, manageable number of explanatory variables that are not highly correlated with one another and is consistent with prevailing theories. In the earlier example of the LOGIT model (where its output directly translates into PD), a very popular test of model accuracy involves measuring the forecasted default (as predicted by the model) with the actual default probabilities.

- The model predictions for every company in the test sample are grouped into say 10 percentile groups. Subsequently, the average PD is calculated for each group. Based on the total obligors in each group, derive the expected number of defaults per group. This is then compared to the actual number of realized defaults per group. This information is summarized for all 10 groups to derive the statistic that indicates how well the model predicts.

<table>
<thead>
<tr>
<th>Company</th>
<th>Group</th>
<th>Predicted PD (by Model)</th>
<th>Average PD of Group</th>
<th>Expected no. of defaults (Group)</th>
<th>Realised no. of defaults (Group)</th>
<th>Accuracy Stat (Group)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1</td>
<td>1.00%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>1</td>
<td>2.00%</td>
<td>2.67%</td>
<td>0.08</td>
<td>0.01</td>
<td>85%</td>
</tr>
<tr>
<td>C</td>
<td>1</td>
<td>5.00%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>2</td>
<td>7.00%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>2</td>
<td>8.00%</td>
<td>9.00%</td>
<td>0.27</td>
<td>0.50</td>
<td>42%</td>
</tr>
<tr>
<td>F</td>
<td>2</td>
<td>12.00%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>:</td>
<td>3</td>
<td>:</td>
<td>:</td>
<td>:</td>
<td>:</td>
<td>:</td>
</tr>
<tr>
<td>:</td>
<td>4</td>
<td>:</td>
<td>:</td>
<td>:</td>
<td>:</td>
<td>:</td>
</tr>
</tbody>
</table>

**Qualitative Adjustments**

For corporate models, it is typical for banks to incorporate *qualitative factors* – such as parental support, size etc – which are not readily captured by a quantitative model and/or make certain overrides that may be necessary (e.g special purpose entities of large corporate groups).

- These qualitative factors are calibrated against the data with typically a ‘weights of evidence’ approach to derive their final weights.
• Subsequently, the statistical model and qualitative factors are combined, typically with regression, to generate the final rating model. An example:

\[ Y \text{(PD)} = [w_0 + w_1X_1 + w_2X_2 + \ldots + w_nX_n] + [z_1Q_1 + z_2Q_2 + \ldots + z_nQ_n] \]

where \( z_n \) = weights and \( Q_n \) = Qualitative factors

**Steps 8 & 9 – Implementing the model**

• Instead of having distinct PDs for each borrower, banks usually devise percentile groups that map to a rating scale with a number of grades as illustrated in Figure 11.
• Each new borrower is evaluated with the model and given a rating (with corresponding PD) that commensurate with its credit profile.

**Figure 11** Mapping PDs into a Rating Scale

<table>
<thead>
<tr>
<th>Rating</th>
<th>PD Masterscale Risk Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>1</td>
<td>0.0000%</td>
</tr>
<tr>
<td>2</td>
<td>0.0119%</td>
</tr>
<tr>
<td>3</td>
<td>0.0168%</td>
</tr>
<tr>
<td>4</td>
<td>0.0240%</td>
</tr>
<tr>
<td>5</td>
<td>0.0346%</td>
</tr>
<tr>
<td>6</td>
<td>0.0500%</td>
</tr>
<tr>
<td>7</td>
<td>0.0733%</td>
</tr>
<tr>
<td>8</td>
<td>0.1095%</td>
</tr>
<tr>
<td>9</td>
<td>0.1636%</td>
</tr>
<tr>
<td>10</td>
<td>0.3033%</td>
</tr>
<tr>
<td>11</td>
<td>0.5108%</td>
</tr>
<tr>
<td>12</td>
<td>0.8573%</td>
</tr>
<tr>
<td>13</td>
<td>1.5114%</td>
</tr>
<tr>
<td>14</td>
<td>3.4872%</td>
</tr>
<tr>
<td>15</td>
<td>5.9459%</td>
</tr>
<tr>
<td>16</td>
<td>7.7740%</td>
</tr>
<tr>
<td>17</td>
<td>10.0928%</td>
</tr>
<tr>
<td>18</td>
<td>12.5000%</td>
</tr>
<tr>
<td>19</td>
<td>15.0000%</td>
</tr>
<tr>
<td>20</td>
<td>25.0000%</td>
</tr>
</tbody>
</table>

Each rating grade maps to a PD band. These PD can be re-calibrated when underlying risk profiles or lending conditions change.
MODELING LOSS GIVEN DEFAULT

LGD Derivation
Accurate LGD estimation requires extensive data on collateral recovery, a task made more difficult by the sometimes protracted recovery process and that LGD models must measure *economic loss* in order to comply with the IRB requirements. Economic loss includes the opportunity cost to the bank when a borrower defaults. LGD is expressed as a percentage of the loan outstanding at the time of default. Mathematically,

\[ \text{LGD} = 1 - \text{Recovery rate} \]

where Recovery rate = Amount collected – cost of collection

As shown by Figure 12, the estimation of LGD involves two components i.e. (1) recoveries and (2) costs. The choice of discount rate is another component, as these amounts need to be discounted to present value.
Explanatory Variables for LGD Estimation

<table>
<thead>
<tr>
<th>Facility</th>
<th>Collateral</th>
<th>Macro economic &amp; other variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Type and seniority (loan, bond, subordinated loan etc)</td>
<td>• Type (cash, stock, specialised assets, financial guarantee etc)</td>
<td>• GDP growth rate, interest rate, prices etc</td>
</tr>
<tr>
<td>• Exposure amount</td>
<td>• Book and/or market value</td>
<td>• Bank workout details and costs</td>
</tr>
<tr>
<td>• Level of collateralisation (Loan to Value)</td>
<td></td>
<td>• Borrower characteristics (type of firm, industry, etc)</td>
</tr>
</tbody>
</table>

Source: Adapted from the Basel II Risk Parameters, Engelmann B. & Rauhmeier R.

**Estimating Recovery** The recovery rate depends on how the defaulted facility is structured and its collateral (if any).

- In terms of collateral disposal, the recovered amount depends on market value and can be a fraction of the original collateral value if disposed in a fire sale.
- Depending on the types of facility and collateral, a bank can estimate these recovery values from its own historical or market experience, with the methods described in Section 3.3. Some banks may also prefer to run simulations of future what-ifs scenarios (e.g. events that could change asset values) to arrive at these expected recovery rates.

**Estimating Costs** Similar to estimating recovery values, workout costs can be estimated for collections from facility and collateral. Usually, these workout costs arise from (a) asset disposal, and (b) general costs (i.e. administrative), which can take a long time to finalise when the recovery process is protracted.

- In practice, costs estimation is typically based on expert judgment of the time and costs involved for the main stages of workouts and may be guided by a sampling of previous cases if available.
LGD Estimation Approaches

The process for estimating workout LGDs is complex even when banks use simple models. Few banks have built highly accurate statistical models of LGD. It is not surprisingly therefore, that a bank may simultaneously use a few approaches based on the pool of transactions that define the banking book, including more simple approaches that are easier to implement when data is scarce.

Available approaches include subjective and objective methods:

- **Subjective** method estimates recovery based on expert opinion and is normally adopted when banks have insufficient data to model LGD.

- **Objective** methods, on the other hand, are based on historical or market data to estimate loss rates.
  - **Market LGD approach** - the market prices of traded bonds or loans shortly after their default are compared to their par values to derive the loss rates. All recoveries and costs need to be discounted as well in order to derive the workout LGD.
❖ **Implied market LGD** – given that the credit spreads of traded non-defaulted bonds and loans are indicative of expected loss, their market price may be used to derive implied LGD.

❖ **Implied historical LGD** – involves indirectly deriving LGD from *historical/actual* loss rates. However, if using actual historical values, the method would require an onerous amount of recovery data spanning several years. Further, collateral values are correlated often to economic cycles. Hence, using actual values may understate the LGD estimates (when applied to different time periods).

    The easier adaptation of this method is the *formulaic approach* in which LGD is calculated using *expected* (instead of actual) values for collateral haircuts, recovery rates, administrative costs and other costs of carry. These expected values can be derived from historical data or expert opinion. This approach also allows for adjustments to take into account economic cycles, forecasts etc.

- **Statistical methods** More sophisticated methods may be needed by highly specialized lending transactions or specific portfolios whose recovery is asset dependent (e.g. airplane or power plant financing). Models take into account individual characteristics of loan facilities, collaterals and other risk factors including macroeconomic variables. Examples of statistical methods include regression for LGD based on historical recovery rates and simulation of project cash flows for specialized lending.

**Estimating an LGD model – Example from Banking Practice**

A common approach used by banks is to adapt the implied historical LGD to a *formulaic* approach where expected values rather than actual, are used for LGD estimates.

The estimation of an LGD model with the formulaic approach involves estimating these key elements:

- **Collateral values** - The main classes of collateral are distinguished by *liquidity* and *seniority* with respect to the bank’s claim on the collateral. For transactions where the collaterals are fairly standardized, they can be grouped into a few homogeneous groups and loss rates can be assigned to these groups based on the various methods described earlier.

- **The administrative costs** – are usually estimated with expert opinions, unless adequate data exists within the bank.

- **The cost of carry** (i.e. the discount rate) – to reflect the time taken to realize the recovery, the underlying risk and the opportunity cost to the bank. Typically, the discount rate used may be based on the contractual loan rate, effective original loan rate and/or expected interest rate curves as well as the underlying funding cost of the bank.
• Exposure At Default (“EAD”) – For those facilities that are contingent in nature (e.g. overdrafts, trade financing lines), the EAD may be significantly different at the time of default compared to from the initial draw down date. Hence, an estimation of the likely draw down is needed.

**Formulating a Look-up Table**  Figure 14 illustrates a look-up table which groups the main classes of collaterals by their liquidity and seniority of claims. Based on historical or market experience, average LGDs are assigned to each main class of collaterals which are then mapped into a facility grading scale.

• In the example below, facility grade A is associated with an LGD of 15% or less (for transactions fully backed by cash or marketable securities) while facility grade B has an LGD of 25% (for transactions that are less well-secured by the same type of collaterals), and so forth.

• This approach is intuitive and easier to implement especially during the early stages of developing LGD models by a bank. Later, when more loss data is available, these simpler models can be replaced with successively more sophisticated statistical models.

**Figure 14**  Look-up Table Approach for LGD

<table>
<thead>
<tr>
<th>Grade</th>
<th>Estimated LGD</th>
<th>Cash and Marketable Securities</th>
<th>Receivables and Inventory</th>
<th>Fixed Assets</th>
<th>Real Estate</th>
<th>Intangible Assets</th>
<th>Unsecured</th>
</tr>
</thead>
<tbody>
<tr>
<td>-</td>
<td>0%</td>
<td>150% Secured</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>15%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>25%</td>
<td>Minimally Secured</td>
<td>150% Secured</td>
<td>150% Secured</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>32%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>37%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>45%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>55%</td>
<td>Minimally Secured</td>
<td>Minimally Secured</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>G</td>
<td>80%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>100%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
**Basel II Requirements for LGD Estimates**
Basel II requires banks to use conservative LGD estimates. Some key requirements to this effect include:

- LGD estimates should reflect economic downturn conditions.
- A margin of conservatism must be added to LGD estimates.
- Dependencies between borrower, collateral and collateral provider risks must be considered.

**EXPOSURE AT DEFAULT ESTIMATION**

**Defining EAD**
Exposure at default (“EAD”) is defined as the outstanding amount or gross exposure of the facility at the time of a borrower’s default.

- For on-balance sheet facilities with explicit limits, the EAD is relatively straightforward. It is the book value of the loan outstanding on the bank’s balance sheet. In other words, the current outstanding drawn amount.
- However, for credit facilities that are revolving in nature (e.g. overdrafts), a credit conversion factor (“CCF”) has to be estimated and applied to the undrawn limit (as borrowers can potentially further draw down on the facility until default occurs) to derive the estimated total EAD, as illustrated in Figure 15.

![Figure 15 Defining EAD](source: Eric Kuo - “Sound Credit Risk Experience Sharing” – Vietnam FSA Presentation 2007)
Banks frequently employ a few methods to estimate the CCF and in turn the EAD (especially for non-defaulted facilities). The easiest and perhaps most practical way to find the CCF is to use realized estimates which may be derived from a set of past observations measured at specific reference dates (usually 1 year) prior to default.

**Basel II Requirements for EAD Estimation**

- EAD is to be estimated at facility level for AIRB banks.
- These estimates must be based on long run experience with a margin of conservatism.
- All exposures are measured gross of specific provisions or partial write offs.
- EAD estimates must be calculated using a default-weighted and not a time-weighted average.

**Process of EAD Estimation**

The process of estimating EAD is similar to PD or LGD estimation. It requires a reference or sample data where the realized defaults are used as a basis to make future predictions for non-defaulted obligors.

Due to their complexity, the discussion in this section will not go in-depth into the mathematical or technical aspects of model estimation but instead focus on the principal aspects of how EAD is estimated by banks in practice.

(a) **Establish a Reference Data Set**

Define:
- Event of default (consistent with definition used for PD and LGD estimation and within IRB guidelines).
- Observation period covered (ideally over 1 economic cycle) and reference date/horizon for the sample of defaulted facilities/obligors (normally 1 year prior to default).
- For IRB purposes, the observation period should cover at least 7 years for corporate exposures and should include a period of downturn conditions if possible.

(b) **Collect Data for Sample Borrowers**

- Exposure size and limits.
- Drawn and undrawn amounts.
- Utilisation percentage as at reference date.
- Time to default.
- Rating at reference date, if any.
• Status of facility at reference date (e.g. normal, warning, monitoring etc)
  – if a bank has a warning system for actively monitoring its loan portfolios, this
    factor should be prioritized as a key driver (over more static indicators such as
    rating).

(c) Data Cleaning and Processing
• Clean data for outliers, missing values etc.
• Segment borrowers into homogenous groups by facility types (since it is necessary
  to estimate EAD by facility type/class).

(d) Estimating EAD
• For each facility type/class with a fixed/on-balance sheet commitment, find the:
  ❖ Average loan amount outstanding (as a percentage of original loan amount)
    at the reference date. This is then used as a proxy for future EAD of similar
    facilities.
• For off-balance sheet facilities (e.g. overdrafts)
  ❖ Compute the increase in the usage of the facility from origination date to the
    reference date (typically, 1 year prior to default) for each observation and facility
    type.
  ❖ Obtain the average or mean of all observations – this is the proxy for CCF of the
    relevant facility type. Example: from past observations of defaulted overdraft
    facilities in the bank’s portfolio, it was found that overdrafts were 90% drawn
    1 year prior to default. Thus, we can apply a CCF of 90% to calculate the
    appropriate EAD of a future overdraft facility. In the case of a $100 million
    overdraft, the equivalent EAD is hence $90 million.

DETERMINING RISK-BASED CAPITAL CHARGE

In the preceding sections, it was explained how to estimate the various risk components
(PD, LGD, EAD and M) for the corporate borrower class. This section illustrates how these
components are combined to derive the capital charge and risk-weighted assets for the
loans made to this borrower class. In other words, how much capital a bank has to set
aside against the credit risks posed by these loans.

In calculating the Basel II capital charge, note that:
• Minimum regulatory capital i.e. the total capital ratio (incorporating credit, market and
  operational risks) is 8% (i.e. at the same level set in Basel I)
• The RWA are calculated via the risk weight functions provided by the BCBS.
IRB Capital Charge

The IRB approach is based on measures of unexpected loss ("UL") and expected loss ("EL"). Note that the risk-weight functions produce capital requirements for the UL portion. Meanwhile, the EL portion (i.e. the general or loan loss provisions made by a bank) is treated separately. We will briefly explain in a later part of this section, how the UL and EL are combined to calculate the overall capital ratio of a bank.

Figure 17 Concept of Expected and Unexpected Loss

Source: Eric Kuo - “Sound Credit Risk Experience Sharing” – Vietnam FSA Presentation 2007
Risk Weight Function for Credit Risk (Corporate Class)

The formula as provided by the BCBS applies to a *non-defaulted* exposure and is set out below.

**Definitions**
- In the AIRB approach, the PD, LGD, EAD and sometimes, effective maturity $M$, are estimated by the bank.
- Tenor ($b$) and correlation ($R$) are derived from PD estimates via the functions provided by the BCBS.
- $K$ denotes capital requirement, expressed as a number.
- RWA denotes risk weighted assets, expressed in currency amount.
- BIS ratio means the minimum capital ratio that is specified by the national supervisor, e.g. 8% for most countries.
- Capital denotes the total capital (in currency amount) that a bank must set aside for its loan book exposure.
- $\ln$ denotes the natural logarithm.
- $e$ denotes the exponential function.

---

**Figure 18** Risk Weight Function for Corporate Class

Basel estimate a general form of unexpected loss formula for banks to calculate the capital.

<table>
<thead>
<tr>
<th>Factors in Basel 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>• PD</td>
</tr>
<tr>
<td>• LGD</td>
</tr>
<tr>
<td>• EAD</td>
</tr>
<tr>
<td>• Tenor</td>
</tr>
<tr>
<td>• Correlation</td>
</tr>
</tbody>
</table>

1 Year PD is considered, instead of cumulative PD

Based on historical data

Current status of EAD

$$B = [0.11852 - 0.05478 \times \ln(PD)]^2$$

$$0.12 \times \left[ 1 - \frac{e^{0.05478 \times \ln(PD)}}{1 - e^{0.05478 \times \ln(PD)}} \right] + 0.24 \times \left[ 1 - \frac{e^{0.05478 \times \ln(PD)}}{1 - e^{0.05478 \times \ln(PD)}} \right]$$

$$K = \left[ \frac{LGD}{\ln[0.11852 - 0.05478 \times \ln(PD)]} \times 0.05478 \times \ln(PD) \right] - M \times EAD$$

$$RWA = K \times 12.50 \times EAD$$

$$Capital = RWA \times BIS \text{ Ratio}$$
Case Study On Credit Risk Modelling

- $N$ denotes the cumulative distribution function for a standard normal random variable and $G$ denotes the inverse of that function. These functions are found in MS Excel as “NORMSDIST” and “NORMSINV” respectively.
- If the calculation results in a negative capital charge for an exposure, a zero capital charge is applied instead.
- The capital requirement, $K$ for a defaulted exposure is equal to the greater of zero and the difference between its LGD and the bank’s best estimate of expected loss.

Further Explanatory Notes (for some figures adopted in the above BCBS formula):

- The standard effective maturity, $M$ is determined by BCBS at 2.5 years for FIRB, while for AIRB, $M$ is the greater of 1 year or the effective remaining maturity of the facility (maximum remaining time to full discharge the contractual obligation). For most cases, $M$ will be no greater than 5 years. For short-term facilities of less than 1 year, $M$ is the greater of 1 day and the remaining maturity.
- The confidence level is fixed at 99.9% (0.999) (i.e. a bank is expected to suffer losses that exceeds its capital on average, once in a thousand years). This high level was chosen partly to protect against potential estimation errors of risk parameters by banks and also to reflect that not all banks’ capital are comprised of equity (most banks have Tier 2 capital such as subordinated bonds in their capital structure, which have less loss absorption capacity than Tier 1).
- The asset correlation $R$, reflects the degree of dependence of borrowers with the economy. Higher PD borrowers are less correlated with the economy as their risk is driven more by idiosyncratic reasons. The boundary is set at 12% (0.12) for the worst credit (i.e. 100% PD) and 24% (0.24) for the best credit (i.e with 0% PD). The pace of increase is dependent on the borrower’s PD, with a scaling factor of 50 set for corporates. For SMEs, a size factor can be applied to the above formula, which has the effect of reducing the correlation.
- The RWA is determined by the capital requirement $K$, expressed as a percentage of the EAD and the reciprocal of the minimum Basel capital ratio of 8% (i.e 12.5).
Computation of a Bank’s Capital Charge – Examples

Example I

Assume a bank lends $100 million to Company A for a period of 5 years. The loan is secured by the corporate’s building which is currently valued at $60 million. The bank’s credit department has assigned a borrower rating of 5 (with corresponding PD of 1.35% on the bank’s rating scale) and a facility rating of E (which maps to a LGD of 45% on the bank’s scale). How much capital would the bank need to set aside for the loan to Company A?

(Note: The bank has an internal credit rating system to rate its borrowers, with grade 1 being the best and grade 10 being the worst/highest risk. Each grade corresponds to a PD that the bank has calculated from its past experience. It also has a facility rating scale from A to H, with each grade corresponding to a specific LGD derived from the bank’s own historical data. The bank calculates its capital requirements based on AIRB).

Answer

At the time of loan origination, the capital requirement for Company A’s loan is computed as follows.

- Look up the corresponding PD and LGD for the corporate’s assigned borrower and facility ratings. PD = 1.35% and LGD = 45%.
- The effective maturity, M is 5 years.
- Applying the above risk components into the BCBS formulas in Figure 19:
  - Correlation, R = 0.1811
  - Maturity adjustment or tenor, b = 0.1256
  - Capital requirement, K = 0.1074
- Using the risk-weight function, RWA = K x 12.5 x EAD, Company A’s loan is risk-weighted at $134.251 million.

If a minimum capital ratio of 10% is required by the regulator, the capital charge for this loan would be 10% of $134.251 million or $13.425 million. This is the bank’s unexpected loss if Company A were to default. In other words, if this $100 million were the only loan made by the entire bank, it will need to hold $13.425 million as capital (to absorb any potential unexpected loss should the borrower default). From this example, it becomes clear that banks would need to hold more capital for higher-risk and unsecured loans (since PD and/or LGD would increase) and/or if the minimum regulatory capital is raised.
The expected loss to the bank, should Company A default is calculated as $EL = PD \times LGD \times EAD$ or in this case, $0.61$ million. This is often equated as the cost of doing business for which banks habitually provide for a certain percentage in its reserves. Assume that the bank, as a matter of policy, makes a general provision of 1% for all its loans. In our simple example of the $100$ million loan, this works out to $1$ million, which exceeds the EL of the loan by $0.39$ million.

- This difference or surplus is allowed to be treated as Tier 2 capital, which together with Tier 1, makes up the total capital of the bank. Therefore, in making the $100$ million loan, the bank needs to have $13.035$ million as Tier 1 capital and $0.39$ million as Tier 2 capital to make up the $13.425$ million in total capital that is required.

- (Note: under Basel II IRB approach, banks may recognize the surplus as Tier 2 capital up to a maximum of 0.6% of credit risk-weighted assets only. Where the difference is negative however, banks must deduct the difference from Tier 1 capital).

### Table: Basel II Capital Requirement

<table>
<thead>
<tr>
<th>Factors</th>
<th>Inputs</th>
<th>1.35%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PD</td>
<td>LGD</td>
<td>45%</td>
</tr>
<tr>
<td>EAD</td>
<td>M</td>
<td>$100m</td>
</tr>
<tr>
<td>Tenor b</td>
<td>Correlation R</td>
<td>0.1256</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Basel II Capital Requirement</th>
</tr>
</thead>
<tbody>
<tr>
<td>$EL = PD \times LGD \times EAD$</td>
</tr>
<tr>
<td>$0.1074 \times 12.5 \times $100m$</td>
</tr>
<tr>
<td>$134.251$</td>
</tr>
<tr>
<td>$13.425$</td>
</tr>
</tbody>
</table>

The expected loss to the bank, should Company A default is calculated as $EL = PD \times LGD \times EAD$ or in this case, $0.61$ million. This is often equated as the cost of doing business for which banks habitually provide for a certain percentage in its reserves. Assume that the bank, as a matter of policy, makes a general provision of 1% for all its loans. In our simple example of the $100$ million loan, this works out to $1$ million, which exceeds the EL of the loan by $0.39$ million.
Case Study On Credit Risk Modelling

Example 2

Company B is a large trading company and has applied for an overdraft facility with a total limit of $500 million for its working capital from Bank Y. The bank has agreed to provide this facility on a clean basis after assessing Company's B credit rating to be strong i.e. AA on the bank's rating scale. The overdraft facility is available for drawdown at any time by Company B, reviewed on annual basis and is not subject to any conditions that allow the bank to cancel the facility without notice to the borrower.

Assume Bank Y uses the following PD scale and from its past experience, knows that overdraft limits tend to be 95% drawn-down 1 year prior to a company's default.

<table>
<thead>
<tr>
<th>Rating</th>
<th>PD(%)</th>
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<tbody>
<tr>
<td>AAA</td>
<td>0.03</td>
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<tr>
<td>AA</td>
<td>0.25</td>
</tr>
<tr>
<td>A</td>
<td>1.09</td>
</tr>
<tr>
<td>BBB</td>
<td>2.2</td>
</tr>
<tr>
<td>BB</td>
<td>8.6</td>
</tr>
<tr>
<td>B</td>
<td>13.9</td>
</tr>
<tr>
<td>CCC</td>
<td>20.5</td>
</tr>
<tr>
<td>CC</td>
<td>27</td>
</tr>
<tr>
<td>C</td>
<td>32.1</td>
</tr>
<tr>
<td>Default</td>
<td>100</td>
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To calculate the capital charge for this loan at origination:

- 1-year PD for AA rating = 0.25%
- LGD for clean/unsecured facility= 100%
- EAD = CCF x Facility limit = 95% x $500 million = $475 million
- Effective maturity M = 1 year

Using the formula in Figure 19:

- Tenor b = 0.1996, Correlation R = 0.2259 , Capital requirement, K = 0.0616
- RWA = K x 12.5 x EAD = 0.0616 x 12.5 x $475 million = $365.877 million.

If the minimum capital ratio for banks is 8%, the capital charge for this overdraft would be 8% x $365.877 million, or $29.270 million.
If, in the third year after granting the overdraft, it was suddenly discovered that there had been financial irregularities with Company B’s cash flow, calling into question its ability to fully repay the overdraft (which has since been fully drawn down), is the capital charge still sufficient?

Assume, the bank downgrades Company B’s rating to ‘C’ upon hearing this news.

- Update the following factors: PD for C rating = 32.1%, EAD = $500 million and using the formula in Figure 19, $K = 0.4197$

  $\text{RWA} = 0.4197 \times 12.5 \times 500 \text{ million} = 2,623.125 \text{ million or a capital charge of } 209.85 \text{ million (8% x 2,623.125 million)}$

  The bank will now have to top up $180.58 \text{ million more in capital ($209.86 \text{ million} - $29.27 \text{ million, an increase of 7 times!})}$ when Company B’s credit profile deteriorates (assume no other provisions have been made earlier, in our simplistic example).

As this example illustrates, significant negative changes in credit risk of the loan book are punitive to banks. Thus the more risk-sensitive regime of Basel II compels banks to improve their risk management capabilities and develop robust risk systems in order to manage their capital requirements.
## Key Features of Some Statistical Modeling Techniques

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<tr>
<th>Discriminant Analysis</th>
<th>LOGIT / PROBIT</th>
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<tr>
<td>• Discriminant analysis is a classification technique that can be applied to corporate bankruptcy prediction as per Altman as far back as 1968.</td>
<td>• The methods are well founded econometric techniques specifically designed for analyzing binary dependent variables.</td>
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<td>• In discriminant analysis, a linear combination of the independent variables is formed and this then serves as the basis for assigning cases to groups. Thus, information contained in multiple independent variables is summarised into a single index or score.</td>
<td>• LOGIT refers to a logistic transformation of the dependent variable whilst PROBIT is a normal distribution transformation instead. Their respective methods are thus theoretically sound.</td>
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<td>• In discriminant analysis, the weights are estimated so that they result in the ‘best’ separation between the underlying groups—in our case the ‘good’ companies from the ‘bad’ companies.</td>
<td>• The results generated can be interpreted directly as default probabilities. The significance of the model and the individual coefficients can be directly tested.</td>
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<td>• The stability of these models can also be assessed more effectively than for other techniques.</td>
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<td>• The LOGIT model is expressed as below</td>
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| | \[
| \text{LOG}(p/(1-p)) = w_0 + w_1 x_1 + w_2 x_2 + ... + w_m x_m |
| | In the equation above the symbol \( p \) represents the ‘probability’ that the \( i^{th} \) applicant is a good; the \( w \)'s are estimated coefficients (or weights) derived from the underlying data; the \( x \)'s are the values of the independent variables which range from 1 to \( m \) in number over a set of cases numbered as \( i \). The symbol \text{LOG} \ represents the natural logarithm function whilst the \text{EXP} \ symbol is the reverse of the \text{LOG} \ or exponential function. |

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<th>Neural Networks</th>
<th>Multiple Linear Regression (MLR)</th>
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<td>• A neural network looks for patterns in training sets of data, learns these patterns, and then develops the ability to correctly classify new patterns or to make forecasts and classifications.</td>
<td>The multiple linear regression equation can be expressed as follows:</td>
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| • Neural networks excel at problem diagnosis, decision making, prediction, classification, and other problems where pattern recognition is important and precise computational answers are not required. | \[
<p>| P_i = w_0 + w_1 x_{i1} + w_2 x_{i2} + ... + w_m x_{im} |
| | • In the equation above the symbol ( P_i ) represents the ‘probability’ that the ( i^{th} ) applicant is ‘good’; the ( w )'s are estimated coefficients (or weights) derived from the underlying data and the ‘( x )' are the key factors that are predictive of default. |
| | • The regression model seeks to establish a linear relationship between all the borrower’s characteristics and the default variable ( P_i ). |</p>
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<th><strong>Structural Models</strong></th>
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<td>• Unlike models of association, structural models are a cause-and-effect type of model – they help explain why any default will occur.</td>
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<td>• For any limited liability company, a technical default will occur whenever the asset value of the firm (or its intrinsic value) falls below the value of its liabilities, as per the following identity: Asset Value = Value of Equity + Value of Liabilities</td>
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<td>Therefore, Value of Equity has to be negative if Asset Values (in the future) drop below Value of Liabilities, for this relationship to hold.</td>
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<th><strong>Decision Trees</strong></th>
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<td>• This method build models by using sets of ‘if-then’ split criteria for classifying borrowers into two or more groups. The sample is subdivided and assigned to sub-groups or nodes according to decision rules and the process is iterative until the end-node is reached ie. when the sub-groups cannot be spit further.</td>
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<td>• Non linear relationships and interactions present in the data can be easily identified with this method.</td>
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<td>• Particularly suited for sample data that has a limited number of predictive variables which are known to be interactive.</td>
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Appendix 2

Economic foundations of the risk weight formulas (BCBS)

In the credit business, losses of interest and principal occur all the time - there are always some borrowers that default on their obligations. The losses that are actually experienced in a particular year vary from year to year, depending on the number and severity of default events, even if we assume that the quality of the portfolio is consistent over time. Figure 1 illustrates how variation in realised losses over time leads to a distribution of losses for a bank:

While it is never possible to know in advance the losses a bank will suffer in a particular year, a bank can forecast the average level of credit losses it can reasonably expect to experience. These losses are referred to as Expected Losses (EL) and are shown in Figure 1 by the dashed line. Financial institutions view Expected Losses as a cost component of doing business, and manage them by a number of means, including through the pricing of credit exposures and through provisioning.

One of the functions of bank capital is to provide a buffer to protect a bank’s debt holders against peak losses that exceed expected levels. Such peaks are illustrated by the spikes above the dashed line in Figure 1. Peak losses do not occur every year, but when they occur, they can potentially be very large. Losses above expected levels are usually referred to as Unexpected Losses (UL) - institutions know they will occur now and then, but they cannot know in advance their timing or severity. Interest rates, including risk premia, charged on credit exposures may absorb some components of unexpected losses, but the market will not support...
prices sufficient to cover all unexpected losses. Capital is needed to cover the risks of such peak losses, and therefore it has a loss-absorbing function.

The worst case one could imagine would be that banks lose their entire credit portfolio in a given year. This event, though, is highly unlikely, and holding capital against it would be economically inefficient. Banks have an incentive to minimise the capital they hold, because reducing capital frees up economic resources that can be directed to profitable investments. On the other hand, the less capital a bank holds, the greater is the likelihood that it will not be able to meet its own debt obligations, i.e. that losses in a given year will not be covered by profit plus available capital, and that the bank will become insolvent. Thus, banks and their supervisors must carefully balance the risks and rewards of holding capital.

There are a number of approaches to determining how much capital a bank should hold. The IRB approach adopted for Basel II focuses on the frequency of bank insolvencies arising from credit losses that supervisors are willing to accept. By means of a stochastic credit portfolio model, it is possible to estimate the amount of loss which will be exceeded with a small, pre-defined probability. This probability can be considered the probability of bank insolvency. Capital is set to ensure that unexpected losses will exceed this level of capital with only this very low, fixed probability. This approach to setting capital is illustrated in Figure 2.

![Figure 2](image-url)
The curve in Figure 2 describes the likelihood of losses of a certain magnitude. The area under the entire curve is equal to 100% (i.e. it is the graph of a probability density). The curve shows that small losses around or slightly below the Expected Loss occur more frequently than large losses. The likelihood that losses will exceed the sum of Expected Loss (EL) and Unexpected Loss (UL) - i.e. the likelihood that a bank will not be able to meet its own credit obligations by its profits and capital - equals the hatched area under the right hand side of the curve. 100% minus this likelihood is called the **confidence level** and the corresponding threshold is called **Value-at-Risk (VaR)** at this confidence level. If capital is set according to the gap between EL and VaR, and if EL is covered by provisions or revenues, then the likelihood that the bank will remain solvent over a one-year horizon is equal to the confidence level. Under Basel II, capital is set to maintain a supervisory fixed confidence level.

So far the EL has been regarded from a top-down perspective, i.e. from a portfolio view. It can also be viewed bottom-up, namely from its components. The EL of a portfolio is assumed to equal the proportion of obligors that might default within a given time frame (1 year in the Basel context), multiplied by the outstanding exposure at default, and once more multiplied by the loss given default rate (i.e. the percentage of exposure that will not be recovered by sale of collateral etc.). Of course, banks will not know in advance the exact number of defaults in a given year, nor the exact amount outstanding nor the actual loss rate; these factors are random variables. But banks can estimate average or expected figures. As such, the three factors mentioned above correspond to the risk parameters upon which the Basel II IRB approach is built:

- **Probability of default (PD)** per rating grade, which gives the average percentage of obligors that default in this rating grade in the course of one year
- **Exposure at default (EAD)**, which gives an estimate of the amount outstanding (drawn amounts plus likely future drawdowns of yet undrawn lines) in case the borrower defaults
- **Loss given default (LGD)**, which gives the percentage of exposure the bank might lose in case the borrower defaults. These losses are usually shown as a percentage of EAD, and depend, amongst others, on the type and amount of collateral as well as the type of borrower and the expected proceeds from the work-out of the assets.

The Expected Loss (in currency amounts) can then be written as \( \text{EL} = \text{PD} \times \text{EAD} \times \text{LGD} \) or, if expressed as a percentage figure of the EAD, as \( \text{EL} = \text{PD} \times \text{LGD} \).
References


Eric Kuo (2007), Sound Credit Risk Experience Sharing, Vietnam FSA Presentation.

Oyama and Yoneyama (2005), Advancing Credit Risk Management through Internal Rating Systems, Bank of Japan.