Chapter 2:

Credit Risk; a survey of Literature
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2.1 Introduction

Financial institutions have faced difficulties over the years for a multitude of reasons. The major cause of serious banking problems continues to be directly related to lack of credit standards for borrowers and counterparties, poor portfolio risk management, or a lack of attention to changes in economic or other circumstances that can lead to deterioration in the credit standing of a bank's counterparties that bring credit risk.

Credit risk is simply defined as the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms. The goal of credit risk management is to maximize a bank's risk-adjusted rate of return by maintaining credit risk exposure within acceptable parameters. Banks need to manage the credit risk inherent in the entire portfolio as well as the risk in individual credits or transactions. Banks should also consider the relationships between credit risk and other banking risks. The effective management of credit risk is a critical component of a comprehensive approach to risk management and essential to the long-term success of any banking organization.
2.2 Overview of Credit Risk Concepts

In a bank's portfolio, losses stem from outright default due to inability or unwillingness of a customer or counterparty to meet commitments in relation to lending, trading, settlement and other financial transactions. Alternatively, losses result from reduction in portfolio value arising from actual or perceived deterioration in credit quality. Credit risk emanates from a bank's dealings with an individual, corporate, bank, financial institution or a sovereign. In addition, Credit risk may take the following forms:

- In the case of direct lending: principal/and or interest amount may not be repaid;
- In the case of guarantees or letters of credit: funds may not be forthcoming from the constituents upon crystallization of the liability;
- In the case of treasury operations: the payment or series of payments due from the counterparties under the respective contracts may not be forthcoming or ceases;
- In the case of securities trading businesses: funds/ securities settlement may not be effected;
- In the case of cross-border exposure: either the availability and free transfer of foreign currency funds may cease or the sovereign may impose restrictions.

In this backdrop, it is imperative that banks have a robust credit-risk management system, which is sensitive and responsive to these factors. The effective management of credit risk is a critical component of comprehensive risk management and is essential for the long-term success of any banking organization. Credit risk management encompasses identification, measurement, monitoring and control of the credit risk exposures.
2.2.1 Credit Risk models

I. Necessity of Credit Risk Model

Over the last decade, a number of the world’s largest banks have developed sophisticated systems in an attempt to model the credit risk arising from important aspects of their business lines. Such models are intended to aid banks in quantifying, aggregating and managing risk across geographical and product lines. The outputs of these models also play increasingly important roles in banks’ risk management and performance measurement processes, including performance-based compensation, customer profitability analysis, risk-based pricing and, to a lesser (but growing) degree, active portfolio management and capital structure decisions. The Task Force recognizes that credit risk modeling may indeed prove to result in better internal risk management, and may have the potential to be used in the supervisory oversight of banking organizations. However, before a portfolio modeling approach could be used in the formal process of setting regulatory capital requirements for credit risk, regulators would have to be confident not only that models are being used to actively manage risk, but also that they are conceptually sound, empirically validated, and produce capital requirements that are comparable across institutions. At this time, significant hurdles, principally concerning data availability and model validation, still need to be cleared before these objectives can be met, and the Committee sees difficulties in overcoming these hurdles in the timescale envisaged for amending the Capital Accord.

Models have already been incorporated into the determination of capital requirements for market risk. However, credit risk models are not a simple extension of their market risk counterparts for two key reasons:

- **Data limitations:**

  Banks and researchers alike report data limitations to be a key impediment to the design and implementation of credit risk models.
Most credit instruments are not marked to market, and the predictive nature of a credit risk model does not derive from a statistical projection of future prices based on a comprehensive record of historical prices. The scarcity of the data required to estimate credit risk models also stems from the infrequent nature of default events and the longer-term time horizons used in measuring credit risk. Hence, in specifying model parameters, credit risk models require the use of simplifying assumptions and proxy data. The relative size of the banking book – and the potential repercussions on bank solvency if modeled credit risk estimates are inaccurate – underscore the need for a better understanding of a model’s sensitivity to structural assumptions and parameter estimates.

- **Model validation:**

  The validation of credit risk models is fundamentally more difficult than the back testing of market risk models. Where market risk models typically employ a horizon of a few days, credit risk models generally rely on a period of one year or more. The longer holding period, coupled with the higher confidence intervals used in credit risk models, presents problems to model-builders in assessing the accuracy of their models. Similarly, a quantitative validation standard similar to that in the Market Risk Amendment would require an impractical number of years of data, spanning multiple credit cycles. (Basle, 1999)

II. **Potential benefits of credit risk models**

- Banks’ credit exposures typically cut across geographical locations and product lines. The use of credit risk models offers banks a framework for examining this risk in a timely manner, centralizing data on global exposures and analyzing marginal and absolute contributions to risk. These properties of
models may contribute to an improvement in a bank’s overall ability to identify measure and manage risk.

- Credit risk models may provide estimates of credit risk (such as unexpected loss) which reflect individual portfolio composition; hence, they may provide a better reflection of concentration risk compared to non-portfolio approaches.

- By design, models may be both influenced by, and be responsive to, shifts in business lines, credit quality, market variables and the economic environment. Consequently, modeling methodology holds out the possibility of providing a more responsive and informative tool for risk management.

- In addition, models may offer: (a) the incentive to improve systems and data collection efforts; (b) a more informed setting of limits and reserves; (c) more accurate risk- and performance-based pricing, which may contribute to a more transparent decision-making process; and (d) a more consistent basis for economic capital allocation.

- From a supervisory perspective, the development of modeling methodology and the consequent improvements in the rigor and consistency of the risk management processes relating to some parts of banks’ credit portfolios also hold significant appeal. In contrast to the current approach of the Capital Accord, a models-based approach may bring capital requirements into closer alignment with the perceived riskiness of underlying assets and portfolio concentrations. As such, it may allow a more comprehensive measure of capital requirements for credit risk and an improved distribution of capital within the financial system.
Furthermore, the flexibility of models in adapting to changes in the economic environment and innovations in financial products may reduce the incentive for banks to engage in regulatory capital arbitrage. (Basle, 1999)

2.2.2 Economic Capital Framework for Credit Risk Quantification

There are two metrics required to quantify Credit Risk. The first metric is calling Expected Loss (EL). EL in statistical terms is the average amount of credit losses per period that a credit manager should expect to lose. Strictly speaking, since this is an expectation, it is not risk and should be built into the cost of a transaction. The second metric gets to the heart of credit risk and is referred to as Economic Capital (EC). Where EL measures the anticipated average loss from a portfolio over the relevant time horizon, EC captures the variance or the uncertainty of the losses around the average. With its focus on uncertainty, EC quantifies the portfolio credit risk. These concepts are depicted in the loss distribution presented here (Figure 2.1).

Figure (2.1): The Metrics of Credit Risk

Source: Rich Jim and Curtis Tange
I. Expected Loss

Expected Loss is measured by multiplying together three factors: Probability of Default (PD), Expected Exposure (EE) and Loss Given Default (LGD). The logic behind multiplying these factors together is straightforward and depicted in the figure below (Figure 2.2).

Figure (2.2): Measuring Expected Loss

1. What is the probability of a counterparty defaulting?
2. If the counterparty defaults, what is our exposure?
3. How much of the exposure amount do we expect to lose?

Source: Rich Jim and Curtis Tange

The probability of default is determined by a counterparty or customer’s credit quality. In the case of large long-term deals with energy marketers, this can be based upon credit quality measures such as agency debt ratings. The way to measure expected exposure depends upon the nature of the exposure. For retail customers, this could be measured by current accounts receivable, whereas for merchant energy counterparties, the appropriate measure is accounts receivables plus current mark-to-market exposure of contracts plus the Expected Potential Future Exposure of contracts. Loss given default is determined by what remedies you may have to mitigate credit losses (e.g., LOC, parent guarantee). The resulting EL calculated for each individual counterparty in a portfolio is additive across all counterparties to identify the portfolio level EL.1

1 (Rich Jim and Curtis Tange)
II. Economic Capital

To be specific, EC is a measure of the amount of resources a firm must maintain to cover a “worst case” credit loss, and remain solvent. It should be clear that the amount of EC is driven by how an organization decides to define a “worst case” loss. The drivers of EC for a “worst case” loss are the same three drivers of EL:

- Counterparty/customer Credit Quality – the more likely a customer or counterparty is to default, the higher the “worst case” losses.
- Expected Exposure – the more exposure that you have to credit losses obviously leads to higher amounts of “worst case” loss.
- Loss Given Default – the loss you can recover from your defaulted exposures, the higher your loss given default and “worst case” loss will be.
- Portfolio Concentration and Correlation – having exposures to limited numbers of counterparties or concentrations in certain types of counterparties is like having all your eggs in one basket. This results in potentially large amounts of losses when things start going bad, resulting in larger “worst case” losses.
- Target Debt Rating – the more credit worthy you want your institution to be means that you have to be willing to cover an increasingly worsening “worst case” scenario. In other words, an “A” rated institution has to be able to weather a worse “worst case” loss than a “B” rated institution.

A properly developed EC framework incorporates these drivers in such a way to quantify the credit risk of an entire portfolio and (more usefully) attribute the credit risk back to the individual counterparties or business activities within the portfolio. A framework that is capable of doing this facilitates several useful credit risk management applications. These applications are highlighted in the next
Here we want to describe each of these components, which are necessary for credit risk assessment.

2.2.3 Default

1. Definition of Default

There are several possible definitions of ‘default’: missing a payment obligation for a few days, missing a payment obligation for more than 90 days, filing for bankruptcy, restructuring imposed by lenders, breaking a covenant triggering across-default for all lenders to the same entity. It depends on default definition.

A payment delay of a few days for individuals or small businesses is closer to ‘delinquency’ than default, to the extent that the likelihood of getting the payment remains high. ‘Payment default’ commonly refers to a minimum period, such as 3 months after due date. Bankruptcy and restructuring are default events, since they follow major failure of payment obligations.

Another view on default is ‘economic’. It occurs when the value of the assets of the Borrower dips below the value of the debt. This is economic default under the Merton (1974) model, implemented in instrumental default models such as KMV Credit Monitor. The definition of default is critical for estimating default probabilities and measuring historical default frequencies. Rating agencies usually consider that default occurs when missing a contractual payment. The New Basel Accord includes bankruptcy and restructuring as default events, and makes it necessary to build up histories of such events as well. Economic default differs from legal or conventional default rules, but serves for modeling default.

By definition, a debt instrument can experience a loss only if there has been a default. However, there is no standard definition of what constitutes a default. Different definitions may be used for different...
purposes. Typically, a default occurs when any of the following conditions are met:

1. A loan is placed on non-accrual
2. A charge-off has already occurred
3. The obligor is more than 90 days past due
4. The obligor has filed bankruptcy

The BIS reference definition of default for purposes of the New Basel Accord reflects many of these events: “A default is considered to have occurred with regard to a particular obligor when one or more of the following events have taken place.

1. It is determined that the obligor is unlikely to pay its debt obligations (principal, interest, or fees) in full
2. A credit loss event associated with any obligation of the obligor, such as charge-off, specific provision, or distressed restructuring involving the forgiveness or postponement of principal, interest, or fees;
3. The obligor is past due more than 90 days on any credit obligation; or
4. The obligor has filed for bankruptcy or similar protection from creditors.”

II. Probability of Default

The Probability of Default is the likelihood that a loan will not be repaid and fall into default. PD is calculating for each client who has a loan (for wholesale banking) or for a portfolio of clients with similar attributes (for retail banking).

III. Default measurement

The credit history of the counterparty / portfolio and nature of the investment are taking into account to calculate the Probability of

4 (Schuermann.Til, 2004)
Default. There are many alternatives for estimating this. Default probabilities may be estimated from a historical database of actual defaults using modern techniques like logistic regression. They may also be estimated from the observable prices of credit default swaps, bonds, and options on common stock. The simplest approach, taken by many banks, is to use external ratings agencies such as Egan Jones, Fitch, Moody’s Investors Service, or ‘Standard and Poor’s’ for estimating PDs from historical default experience. For estimation of default probability for small business, logistic regression is again the most common technique for estimating the drivers of default bases on a historical database of defaults. These models both are developed internally and supplied by third parties. A similar approach taken in retail default, uses the term "credit score" as a euphemism for the default probability, which is the true focus of the lender. There are many methods for estimating the default probabilities that will be described in the following parts:

A. credit rating

Rating ranks are the credit standing of debt issued by using coded letters for the ratings from agencies. Ranks are ‘ordinal numbers’, not absolute values of the level of risk, by contrast with default probabilities whose value quantifies the likelihood of default over a given horizon. Credit scoring is always confused with credit rating. However, we can say that the first stage is credit scoring, Through which we could obtain the probability of default or scores (these scores could be converted to probability of default as discriminated analysis method) and after that we could attain ranks or arrange credit ratings by using these scores.

B. External rating

Instead of calculating credit rating or on the other hand using the internal rating system, we could use External rating offered by rating
agencies. The main or global rating agencies are Moody's, Standard & Poor's (S & P) and Fitch. Ratings are assessments of the credit standing of a debt issue, materialized by coded letters (such as Aaa, Aa, etc.) that serve essentially the needs of investors to have a third Party view on the credit risk of debt. In addition, ratings rank risk rather than value risk. This is a major distinction between ratings and default probabilities, the latter is a Quantification of the default likelihood of a debt issuer. External ratings apply to various debt issues from corporate firms; banks and financial institutions; sovereign borrowers (country risk) and multilateral development banks. Ratings from agencies exist only for issues of large listed companies.

This creates a bias when assigning default frequencies is based on historical default statistics because the Sample of counterparties rated by agencies is usually not representative of the banks' portfolios. For bank corporate loans or market counterparties, external agency ratings are usually not available because borrowers are medium or small businesses. Banks need to rely on their own internal rating schemes to differentiate the risk of their exposures to these counterparties.5

C. Internal ratings

The New Basel Accord, expected to be implemented at year-end 2008, will require internationally active banks to use more risk sensitive methods for calculating credit risk capital requirements (Pillar 1 of the New Basel Capital Accord, or “Basel 2”).

The Accord allows a bank to calculate credit risk capital requirements according to either of two approaches: a standardized approach that uses agency ratings for risk-weighting assets and an internal rating based (IRB) approach, which allows a bank to use

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5 (Joel bessis, 2002)
internal estimates of components of credit risk to calculate credit risk capital. Institutions using IRB need to develop methods to estimate these key components.\textsuperscript{6} Internal rating systems are not public and are customized to each bank’s needs. There is a strong tendency towards harmonization due to the new regulations putting the rating system in a central position for evaluating capital requirements. Like external ratings, internal ratings are grades assigned to borrowers or facilities for ranking their risk related to each other.

As we know every bank has a specific method for building its model. Here this process is shown briefly in two figures. If the bank wants to build a new model it should follow figure (2.3) and if it wants to use the old model it could follow the figure (2.4).

Figure (2.3): Building a new model

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\textsuperscript{6} (Schuermann.Til, 2004).
Major steps for building a new model are:

1) Analysis of portfolio / Requirements
2) Building of model
3) Implementation / Institutionalization

For building a scoring or a rating model, the Major components and their common percentages are as below:

Figure (2.5): Building several rating models has shown a common profile

<table>
<thead>
<tr>
<th>Component</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>DATA-COLLECTION</td>
<td>40%</td>
</tr>
<tr>
<td>STATISTICAL ANALYSIS</td>
<td>30%</td>
</tr>
<tr>
<td>EXPERT DISCUSSIONS / BENCHMARKING</td>
<td>30%</td>
</tr>
</tbody>
</table>
As we could see, the most important component that has the most percentage in building a scoring model is data collection so we could understand that clear and sufficient data are very important for forming a new rating model.

**D. Rating criteria**

Rating criteria include both qualitative assessments of the counterparty’s credit standing, plus quantitative variables most of which are financial variables. Rating a corporate entity will always involve qualitative and judgmental components, simply because there are too many factors that influence the situation of a corporate and a financial entity. What follows cannot be comprehensive, but it provides an overview of the nature of rating criteria. The basis for assessing the credit risk of a company does relate to its fundamentals. These include all strengths, weaknesses, opportunities and threats (‘SWOT’) and any barriers to entry that provide a shield from competition. Among major factors, driving corporate firms’ health is industry, possibly oligopolistic, with few competitors; market share and size; diversification of products and services, and across countries; growth potential; technology; quality of products and services; plus all barriers to entry. Other factors include management quality and record of accomplishment. Some of these factors relate to the firm’s potential as well as to risk. Typical risk factors are business risk, possibly measured with the cyclical dynamics of sales or simply the economics of the industry, some of them are more stable across time than others (capital-intensive industries, consumer durable), or the level of vertical integration which drives the ratio of fixed to variable costs. 7

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7 (Joel Bessis, 2002)
<table>
<thead>
<tr>
<th>Nature of variable</th>
<th>Measures</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size</td>
<td>In terms of total assets, or</td>
<td></td>
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<tr>
<td></td>
<td>Sales or profit measures</td>
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<tr>
<td></td>
<td>Such as earnings before</td>
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<td></td>
<td>Interest, Taxes and Depreciation (EBITDA) or Net income</td>
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<td></td>
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<tr>
<td>Operating profitability</td>
<td>- <em>Operating return on assets is before interest,</em></td>
<td><em>Operating profitability amortization and taxes</em></td>
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<tr>
<td></td>
<td>- Operating margin or</td>
<td></td>
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<tr>
<td></td>
<td>Operating profit/sales</td>
<td></td>
</tr>
<tr>
<td>Financial profitability</td>
<td>Return on equity, or net</td>
<td>Depends on both</td>
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<tr>
<td></td>
<td>Income over equity</td>
<td>profitability and</td>
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<td></td>
<td>leverage or dept to</td>
<td></td>
</tr>
<tr>
<td>Financial structure</td>
<td>Debt to equity structure</td>
<td>Equity ratio</td>
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<tr>
<td></td>
<td>Debt/equity</td>
<td>usually based on financial</td>
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<td></td>
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<td>debt only.</td>
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<td></td>
<td>Debts structure or senior</td>
<td>seniory structure of debt</td>
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<td>Debts to subordinated debt</td>
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<td></td>
<td>Financial coverage ratio such</td>
<td>Measures the ability to</td>
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<td></td>
<td>As EBITDA a interest</td>
<td>face debt obligations from</td>
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<td></td>
<td>operating case flows.</td>
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<tr>
<td>Cash flow</td>
<td>Operating cash flow. Or free</td>
<td>'free case flow' is the cash</td>
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<td></td>
<td>Cash flow</td>
<td>flow generated from</td>
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<td>operations and operations</td>
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<td>only available to face debt</td>
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<td></td>
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<td>obligation Operating cash</td>
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<td></td>
<td></td>
<td>Flow is EBITA minus cash</td>
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<td></td>
<td></td>
<td>Locked into operations (in inventories)</td>
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<tr>
<td>Operating efficiency</td>
<td>Inventories turnover</td>
<td>Overall current operations</td>
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<tr>
<td></td>
<td></td>
<td>Efficiency</td>
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<td></td>
<td>Receivables in days of sales</td>
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<td></td>
<td>Payable in days of purchases</td>
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<td></td>
<td>Net cash cycle</td>
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<tr>
<td>Operating leverage</td>
<td>Ratio of direct and variable</td>
<td>Measures flexibility under</td>
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<td></td>
<td>cost to fixed cost</td>
<td>adverse conditions</td>
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<tr>
<td>Liquidity</td>
<td>Short-term cash and</td>
<td>Rations of liquid assets over</td>
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<tr>
<td></td>
<td>Investments over total assets</td>
<td>short-term liabilities</td>
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<tr>
<td></td>
<td>Current ratios and other variations</td>
<td></td>
</tr>
<tr>
<td>Market value assessment</td>
<td>Equity to book value</td>
<td>Measures the market</td>
</tr>
<tr>
<td>profitability</td>
<td>price to book value</td>
<td>current and future</td>
</tr>
<tr>
<td>Volatility of earnings and</td>
<td>From time series of sales and profit</td>
<td>Measures the business risk</td>
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<tr>
<td>and</td>
<td></td>
<td>its effect on profitability</td>
</tr>
</tbody>
</table>

Source: Joel bessis, 2002
IV. What is default rate distribution?

Why are default events correlated? There are several ways in which default events of two obligors, ABC and XYZ, can be, or appear to be, dependent. One is that the fortunes of XYZ are directly linked to those of ABC. This linkage would occur if ABC were one of XYZ's biggest customers. This relationship is very difficult to model and it ignores a much more important effective part of systematic risk. In this view, default events are not dependent at all: rather, default of ABC is indicative of the fact that we are in a bad state of the world, and so XYZ (and similar obligors) are more likely to default.

Viewed this way, correlation between default events of obligors can be thought of as a measure of how dependent they are on systematic factors. The figure below gives a good pictorial view:

Figure (2.7): Default rate volatility and default correlation are similar concepts

Each of the graphs shows the default rate in each state of the world for a particular type of obligor. Graphs A and B show the situation where
the average default rate is low, and C and D where it is high. More subtle is the distinction between the left two and right two graphs. For A and C we see that the default rates of the obligors are mildly sensitive to the state-of-the-world, but for B and D the sensitivity is considerably higher (remember that in going from left to right the average default rate remains the same). Consequently a portfolio of type D will be riskier than C because there is more uncertainty in the default rate: in bad years, it will suffer much worse. Of course, D is riskier than B also, but that is largely due to the difference in credit quality. If the default rate of an obligor does not depend at all on the state-of-the-world, then its default events will be uncorrelated with those of all other obligors\textsuperscript{8}.

\textbf{2.2.4 Exposure at default}

\textbf{I. How to define exposures}

In general, Exposure at Default (EAD) could be seen as an estimation of the extent to which a bank may be exposed to counterparty in the event of, and at the time of, that counterparty’s default. It is a measure of potential exposure (in currency) as calculated by a Basel Credit Risk Model for the period of 1 year or until maturity whichever is sooner. Based on Basel Guidelines Exposure at Default for loan commitments measures the amount of the facility is likely to be drawn if a default occurs.

Under Basel II, a bank needs to provide an estimate of the exposure amount for each transaction, commonly referred to as Exposure at Default (EAD), in banks’ internal systems. All these loss estimates should fully seek to capture the risks of an underlying exposure. Calculation of EAD is different under foundation and advanced approach. While under foundation Internal-rating based approach (F-IRB), calculation of EAD, is guided by the regulators, under the advanced

\textsuperscript{8} (Martin, Richard, 2004)
Internal-rating based approach (A-IRB) banks enjoy greater flexibility on how they would like to calculate EAD.

Under F-IRB Exposure at Default is calculated by taking account of the underlying asset, forward valuation, and facility type and commitment details. This value does not take account of guarantees, collateral or security (i.e. ignores Credit Risk Mitigation Techniques with the exception of on-balance sheet netting where the effect of netting is included in Exposure at Default). For on-balance sheet transactions, EAD is identical to the nominal amount of exposure. On-balance sheet netting of loans and deposits of a bank to a corporate counterparty is permitted to reduce the estimate of EAD under certain conditions. For off-balance sheet items, there are two broad types, which the IRB approach needs to address: transactions with uncertain future drawdown, such as commitments and revolving credits, and OTC foreign exchange, interest rate and equity derivative contracts.

Under A-IRB, the bank itself determines the appropriate EAD to apply to each exposure. A bank using internal EAD estimates for capital purposes might be able to differentiate EAD values based on a wider set of transaction characteristics (e.g. product type) as well as borrower characteristics. These values would expect to represent a conservative view of long-run averages, although banks would be free to use estimates that are more conservative. A bank wishing to use its own estimates of EAD will need to demonstrate to its supervisor that it can meet additional minimum requirements pertinent to the integrity and reliability of these estimates. All estimates of EAD should be calculated net of any specific provisions a bank may have raised against an exposure.

In terms of assigning estimates of EAD to broad EAD classifications, banks may use either internal or external data sources. Given the perceived current data limitations in respect of EAD (in particular
external sources), a minimum data requirement of 7 years has been set\(^9\).

II. Types of exposures

There are many contractual exposures since term loans represent a large fraction of outstanding loans. Most other products raise exposure measurement issues because the amount at risk is unknown in advance. For banking credit exposures, relevant distinctions are ‘on-balance sheet’ versus ‘off-balance sheet’ transactions.

A. On-balance Sheet

In general, exposure differs from current usage because the amount at risk at future dates is uncertain. Exposure risk appears when we do not know the future usage of a banking line. The notable exception is term loans. Their amortization profile is a good proxy for the future exposures. Still, contractual repayments are subject to prepayments, and the effective maturity is a substitute. Effective maturity results from experience or models for mortgages. For many other credit lines, there is a commitment of the bank to let the borrower increase the usage by drawing on a credit line up to a certain amount left at the initiative of the borrower. Overdrafts, consumer loans and credit card balances are subject to renewal, and borrowers can make new drawings at their initiative. Rollover lines generate a long-term exposure, beyond the rollover dates. Committed lines of credit are on-balance sheet for the used fraction and off-balance sheet for the unused portion of the line. Borrowers draw a committed line whenever they need to, up to the maximum amount authorized. Project financing is subject to exposure uncertainty both for the construction phase and for the subsequent operation phase when the repayments occur. Uncertain exposures are the rule more than the exception. In all cases, the current usage of the line might differ from the future usage. It is necessary to define what

\(^9\) (Joel bessis, 2002)
are the expected exposures at future horizons and the exposure under default, which might increase when credit risk deteriorates. The New Basel Accord stipulates that EAD is a key input to the risk assessment process. A facility has only two characteristics bounding the exposure set from inception: maturity and authorization. For non-committed lines of credit, the current and expected usages are acceptable measures, although choosing which one is relevant is judgmental. The next date for reviewing the authorization is a good candidate for maturity, since the bank does not need to extend credit beyond this. The authorization remains a cap to all measures. The case of committed lines of credit differs from the above, even when the current usage differs from the authorization. The undrawn portion of the line is off-balance sheet, and the subsequent section addresses this special case.

B. Off-balance Sheet

The basic issue with off-balance sheet exposures is that it is never certain, and sometimes highly unlikely, that such contingencies given will move up to being on-balance sheet. Because of this uncertainty, the common rule is to assign weights lower than 1 to off-balance sheet contingencies to differentiate them from on-balance sheet exposures. This is similar to defining loan equivalents of smaller exposures. This is the regulatory treatment of off-balance sheet exposures, with the 50% factor. Because of the diversity of off-balance sheet commitments, it makes sense to differentiate their economic treatment. For committed lines of credit, the economic exposure is 100% of the commitment since the bank is contractually at risk for this total amount, even if there is no current usage. Regulations allow us to use a lower percentage because the likelihood of maximum usage remains remote in many cases. However, a borrower getting close to default is likely to fully draw the line. Third-party guarantees given have only a remote possibility of exercise, since only the default of the borrower triggers exercise. However, they are similar to direct exposures since the borrower’s
default triggers the guarantee as if there was a direct exposure. The regulatory view on guarantees given to a third party is that the risk is equivalent to a direct exposure. However, there is a wide spectrum of third-party guarantees, ranging from simple letters of comfort to first recourse 'full' guarantees. The former does not carry any real risk because there is no legal commitment. Legal commitments are equivalent to lending directly. Because of these wide variations of the 'legal strength' of bank commitments, there is a case for differentiating the risks. Other commitments, such as backup lines of liquidity for issuing commercial paper, look more like financial services than 'true' exposures. What triggers drawing is not the default of the client but a need to draw liquidity triggered by unlikely events. Hence, there is a case for differentiating them from other guarantees, but assessing the likelihood of materialization of the risk remains judgmental.¹⁰

In most cases, there are always hard data that bound exposures in time and amount. In addition, exposures are at book values or mark-to-model. The 'hard' data for banking exposures are:

- The amount and maturity of committed lines
- The amortization schedule for term loans
- The maturity of the authorizations
- The dates of reviewing the authorizations
- The current usage of committed lines

2.2.5 Loss given default

I. Definition of loss given default

The New Basel Accord will allow internationally active banking organizations to calculate their credit risk capital requirements using internal ratings based (IRB) approach, subject to supervisory review. One of the modeling components is loss given default (LGD), the credit

¹⁰ (Joel Bessis, 2002)
loss incurred if an obligor of the bank defaults. The flexibility to
determine LGD values tailored to a bank’s portfolio will likely be a
motivation for a bank to want to move from the foundation to the
advanced IRB approach. The appropriate degree of flexibility depends,
of course, on what a bank knows about LGD broadly and about
differentiated LGDs.

Since many U.S. banking organizations are likely to implement IRB,
banks and supervisors alike will soon need to understand LGD (as well
as other components), including various issues around it, to evaluate
actual or planned implementations of IRB by surveying the academic
and practitioner literature, with supportive examples and illustrations
from public data sources.\textsuperscript{11}

We begin with a simple model of a portfolio containing loans or other
products that might default. The definition of default might differ
between products, or it might allow discretion in determining whether a
default has occurred. At any given time, though, we assume that either
a particular loan has defaulted or it has not. For a defaulted loan, loss
given default (LGD) is the proportion of exposure that is lost. LGD is an
economic concept; it does not necessarily correspond to the amounts
reported under current financial reporting practices. Usually, LGDs are
imagined as taking values between zero and one. This seemingly
straightforward definition of LGD contains subtleties that complicate
measuring LGD in specific situations. Rather than focus on these, we
stay with the broad properties of LGD. We assume that in the absence of
default there is neither loss nor potential for gain. Thus, there is no loss
due to downgrade and no gain due to upgrade. We also assume that the
relevant economic loss can be measured. Until LGD is measured, it is a
random variable. Much of what follows involves an exploration of the
distribution of random LGD, but an important observation can be made
at the outset.

\textsuperscript{11} (Schuermann.Til, 2004)
The observation stems from the definition: LGD is independent of default. Two random variables are independent if knowledge of the value of one of them tells nothing about the value of the other. In this case, the first random variable is the default indicator. The default indicator equals one in the event of default and equals zero otherwise. The second random variable is LGD. LGD is imagined, before default, to have some expected value, distribution, or set of likely values. If the loan in fact defaults, there is no effect on the expected value, distribution, or set of likely values—consistent with its name, loss given default imagines the default event to have occurred. If the imagined event becomes real, there is no new information; the occurrence of the default has no effect on the distribution of LGD. By definition, LGD is independent of the default event that brings it into being.

The independence of LGD and default allows a simple bit of math that provides some insight. Credit loss requires a default; then, loss is equal to LGD. Stated symbolically,

\[ L = D \times \text{LGD} \]  

(1)

Where L is the loss on a loan, and D is the default indicator. Since the factors on the right hand side are independent, the expectation (E) operator passes through as follows:

\[ E[L] = E[D] \times E[\text{LGD}], \]  

(2)

Or

\[ EL = PD \times E\text{LGD} \]

This says that the expected loss on a loan equals its expected default rate (usually denoted "PD" for "probability of default") times the loan’s expected LGD rate. For example, if a loan has probability of default equal to 5% and expected LGD equal to 40%, its expected loss is 2%.
It is important to note the difference between the symbols: LGD is a random variable that has some distribution, and ELGD is the expectation of that random variable. Thus, ELGD is a moment or population parameter, and LGD itself is random. Similarly, PD is the population parameter of the random variable D. It is also important to note that (2) is specific to a given loan. Therefore, the expectation is of the distribution of the LGD of the loan. That distribution depends on the loan's distribution of default, as shown in a later section.

In practice, there is independence between an LGD and the default that brings it into being. Correlation does enter the picture, but only at the portfolio level. A given LGD might be correlated with other LGDs or with other defaults. As a practical matter, if in a given year there have been a number of defaults involving a certain kind of collateral, and if the LGD on these defaults has been greater than usual, then it is likely that subsequent defaults involving similar collateral will also produce LGDs that are greater than usual. Separately, an unusually large number of defaults, by itself, might also bring about LGDs that are greater than usual. Thus, "correlated LGD" stems from analysis at the portfolio level. This analysis uses portfolio risk models that provide an estimate of economic credit capital.¹²

This seemingly straightforward definition of LGD contains subtleties that complicate measuring LGD in specific situations. Rather than focus on these, we stay with the broad properties of LGD. We assume that in the absence of default there is neither loss nor potential for gain. Thus, there is no loss due to downgrade and no gain due to upgrade.

We also assume that the relevant economic loss can be measured. Until LGD is measured, it is a random variable. Much of what follows involves an exploration of the distribution of random LGD, but an important observation can be made at the outset.

¹² (Frye Jon, 2004)
The traditional credit culture stipulates that lending is primarily dependent on the credit standing of borrowers, not on covenants or guarantees. The rationale behind this prudent Rule is that there is always a residual, small or significant, risk whatever the guarantees. In addition, the credit standing of the borrower ultimately makes the loan perform or not. However, ignoring the value of guarantees would be misleading given their importance in lending decisions, and their mitigating effect on loss under default. The loss in the event of default is the amount at risk at default time less recoveries. The New Basel Accord recognizes that some guarantees deserve recognition in assessing losses.\(^\text{13}\)

The recovery rate is 100% minus the loss given default. The loss in the event of default, or loss under default, is:

\[
\text{Loss given default} = \text{exposure} \times (1 - \text{recovery rate \%}) = \text{exposure} \times \text{LGD\%}
\]

II. Recovery rates and guarantors
Recovery data from historical experience serves for valuing such forfeit. Historical recovery rates are available from rating agencies for bonds. They are the ratio of the post-default price of a bond to its pre-default price. Such rates vary inversely with the level of seniority of debt and are evidently higher for a secured debt than for an unsecured debt. The evidence shows that recovery rates vary widely from one transaction to another and from one type of guarantee to another. Therefore, there is a need to differentiate the recovery rate by transaction type, seniority level compared to other debts and guarantee type. Potential recoveries in the event of default are uncertain. Recoveries require legal procedures, expenses and a significant lapse of time. They occur in the future, are context dependent (the situation of an obligor at the time of default) and depend on the nature of credit risk mitigates. Collateral

\(^{13}\) (Joel bessis, 2002)
might not be accessible. Real assets are subject to deterioration simply because there are many incentives to take them away when debtors know that they will loose them. Legal guarantees are subject to enforceability risk, or recourse risk. Covenant values depend on the borrower’s ability to recover from credit deterioration at the time of a breach. Figure (2.8) summarizes the basic mechanisms of the credit-enhancing effect of guarantees. Collaterals transform credit risk into legal plus asset value risk. Third-party guarantees and support reduce the default probability of the joint entity ‘borrower guarantor’. Covenant values depend on how banks use them to prevent further risk deterioration.\textsuperscript{14}

Figure (2.8): the risk-enhancing impact of guarantees

\begin{center}
\begin{tikzpicture}
  \node[rectangle, draw] (collateral) {Collateral};
  \node[rectangle, draw, right of=collateral, xshift=2cm] (transform) {Transforms credit risk Into asset risk};
  \node[rectangle, draw, below of=collateral] (third-party) {Third party Guarantees};
  \node[rectangle, draw, right of=third-party, xshift=2cm] (risk-transfer) {Risk transfer to ‘Guarantor + borrower’};
  \node[rectangle, draw, below of=third-party] (covenants) {Covenants};
  \node[rectangle, draw, right of=covenants, xshift=2cm] (corrective-actions) {Pre-emptive proactive Corrective actions};

  \draw[->] (collateral) -- (transform);
  \draw[->] (third-party) -- (risk-transfer);
  \draw[->] (covenants) -- (corrective-actions);
\end{tikzpicture}
\end{center}

In addition, the main guarantees that increase the recovery rates are:

- Collaterals; which are asset seized by the lender if the borrower defaults.
- Third party protections; for guarantees, the guarantor fulfils the obligation of the Borrower if he defaults. For insurance or credit derivative protections, a third party provides a payment to the lender under default.
- Covenants; which are contractual clauses such as maximum debt cover ratio or a legal Obligation not to diversify away from the

\textsuperscript{14} (Joel bessis, 2002)
Core business. Breaches of covenants trigger an obligation of prompt repayment, which prevents the borrower from continuing operations unless he gets a waiver. They are strong incentives to renegotiate with lenders in such instances.

Collaterals serve to limit both the lender’s loss under default and the borrower’s risk taking propensity. A borrower is reluctant to give up the collateral whenever it has more value than the debt. Whenever the borrower’s upside is higher than the value of debt, he has a powerful incentive to comply with the covenants. On the other hand, a third-party guarantee does not provide any incentive for the lender to limit his risk propensity. However, it does reduce the probability of default, since default occurs only when both the primary borrower and the guarantor default. This is the ‘double default’ or ‘joint default’. It provides a rationale for valuing the third-party guarantee as a reduction of the default probability, moving down from the borrower’s default probability to the joint default probability of both obligors. The New Accord simply stipulates that the benefit of the third-party guarantee is a risk transfer to the guarantor. Expands the framework for valuing joint default probabilities in all cases where there is a borrower and a guarantor, which also includes insurance and usage of credit derivatives.

Another credit risk mitigate is the ‘support from a third party’, often a holding company of a borrower that is a subsidiary. Although support is informal and not contractual, it ‘looks like’ a third-party guarantee. Its value depends on the supporting entity incentives and willingness to face the obligations of the direct borrower. The common practical way to value guarantees is to summarize their effects into a recovery rate.

### III. LGD Modeling

The reforms under Basel 2 will allow banks to develop their own internal risk estimates of key parameters, including (under the advanced IRB approach) LGD. Under Basel 2, PD needs to be model at the obligor level, LGD at the facility level. Any modeling effort will depend on the
availability of historical data reflecting the bank lending experience. The factors (or drivers or explanatory variables) included in any LGD model will likely come from the set of factors which are founded to be important determinants for explaining the variation in LGD. They include factors such as place in the capital structure, presence and quality of collateral, industry and timing of the business cycle.

Any model would likely work with data having the structure where an observation is LGD for instrument i at time t. Broadly, there are three approaches to obtain average LGD for a portfolio: dollar weighting, default weighting and time weighting.

1. Dollar-weighting: for a given period (say one year)

\[
\frac{\text{total } \$ \text{ lost}}{\text{total } \$ \text{ exposure of defaulted loans}}
\]  

(3)

2. Default-weighting: For a given period (say one year), assuming the LGDs of the instruments in the portfolio are known:

\[
\frac{\sum LGDs}{\# \text{ of LGDs}}
\]

(4)

3. Time weighting: the average over time of either dollar weighted or default weighted LGDs of the instruments in the portfolio.

Of the three, the last (time weighting) is the least desirable as it smoothes out high LGD years with low ones and may therefore understate expected LGD. There is substantial evidence that the aggregate default rate and LGD are correlated positively, and time weighting will mask this correlation. A drawback of default weighting is that loan size information is averaged out (and hence lost). Approaches that are more sophisticated involve formal modeling using regressions or more complicate techniques, such as neural networks. By using a model to impose structure on the data, the data quantity problem from the contingency table approach is mitigated, but building, implementing and
maintaining the more sophisticated models can be a challenge. Highly complex models are often prone to overfitting, meaning that “field” or out-of-sample performance can be quite poor relative to model fit (or in-sample performance). Basic regression models tend to be more robust than complex approaches but at the cost of lower accuracy. Defaults resulting in 100% recovery (0% LGD) are probably somewhat special and should be model separately. Put differently, it is likely that there may be different factors driving this process, or that the factors should be weighted differently.\(^\text{15}\)

IV. LGD measurement and estimation

Loss Given Default is the magnitude of likely loss on the exposure: this is termed the Loss Given Default (LGD), and is expressing as a percentage of the exposure. Loss Given Default is facility-specific because such losses are generally understood to be influenced by key transaction characteristics such as the presence of collateral and the degree of subordination.

Loss Given Default is determined in one of two ways. Under the foundation methodology, LGD is estimated through the application of standard supervisory rules, which differentiate the level of Loss Given Default based upon the characteristics of the underlying transaction, including the presence and type of collateral. The supervisory rules and treatments are chosen to be conservative. The starting point proposed by the Committee is use of a 50% LGD value for most unsecured transactions, with a higher LGD (75%) applied to subordinated exposures. For transactions with qualifying financial collateral, the LGD is scaled to the degree to which the transaction is secured, using a haircut methodology adapted from that described for the standardized approach. For transactions with qualifying commercial or residential real estate collateral, a separate set of supervisory LGD values and

\(^{15}\) (Schuermann.Till, 2004)
recognition rules are applied. All other transactions are viewed as unsecured for this regulatory purpose.

In the advanced methodology, the bank itself determines the appropriate Loss Given Default to be applied to each exposure, based on robust data and analysis that is capable of being validated both internally and by supervisors. Thus, a bank using internal Loss Given Default estimates capital purposes might be able to differentiate Loss Given Default values on the basis of a wider set of transaction characteristics (e.g. product type, wider range of collateral types) as well as borrower characteristics. As with PD estimates, these values would be expected to represent a conservative view of long-run averages, although banks would be free to use more conservative estimates. A bank wishing to use its own estimates of LGD will need to demonstrate to its supervisor that it can meet additional minimum requirements pertinent to the integrity and reliability of these estimates.

Once a default event has occurred, loss given default includes three types of losses:

- The loss of principal
- The carrying costs of non-performing loans, e.g. interest income foregone
- Workout expenses (collections, legal, etc.)

In the other view there are broadly three ways of measuring LGD for an instrument:

A. Market LGD: observed from market prices of defaulted bonds or marketable loans soon after the actual default event

B. Workout LGD: The set of estimated cash flows resulting from the workout and/or collections process, properly discounted, and the estimated exposure.

C. Implied Market LGD: LGDs derived from risky (but not defaulted) bond prices using a theoretical asset-pricing model.

Here these ways of estimating LGDs will be described:
A. Market LGD
For defaulted bonds and loans that trade in the market, one may observe prices directly so long as a trade has actually occurred. The rating agency recovery studies are based on this approach. The actual prices are based on par = 100 ("cents on the dollar") and can thus be easily translated into a recovery percentage (or LGD as 100% minus the percentage recovery). These prices have some desirable properties since they are observed early and are a reflection of market sentiment at that time. After all, they are the result of a market transaction and hence less subject to debate about proper valuation. These prices reflect the investor has expected recovery, suitably discounted, and thus include recoveries on both discounted principal and missed interest payments. In the Moody’s dataset, as well as restructuring costs and uncertainty of that restructuring process. for example, they are observed in the market one month after the first occurrence of the default event. This price is therefore the market’s expected present value of eventual recovery.

B. Workout LGD
LGD observed over the course of a workout is a bit more complicated than the directly observed market LGD. Attention needs to be paid to the timing of the cash flows from the distressed asset. Measuring this timing will affect downstream estimates of realized LGD. The cash flows should be discounted, but it is by no means obvious which discount rate to apply. For example, the debt restructuring could result in the issuance of risky assets such as equity or warrants, or less risky ones such as notes, bonds or even cash. In principle, the correct rate would be for an asset of similar risk. Importantly, once the obligor has defaulted, the bank is an investor in a defaulted asset and should value it accordingly, possibly at the bank’s hurdle rate. Inappropriate candidates include the coupon rate (set ex ante of default, so too low) and the risk-free (or Treasury) rate.
C. Implied Market LGD

An entirely different approach one could take to obtain an estimate of LGD is to look at credit spreads on the (much larger universe of) non-defaulted risky (e.g. corporate) bonds currently traded. Although these new methods have not yet fully migrated into the bank’s credit risk arena, they are used in the trading room for fixed income products and credit derivatives and as such are often used as a check against more conventional credit rating models. Moreover, some credit portfolio models require credit spreads as an input parameter. The spread above risk-free (i.e. Treasury) bonds is an indicator of the risk premium demanded by investors. However, this spread reflects EL, and thus both PD and LGD, as well as liquidity premiums. Only recently have models been developed which allow one separately to identify these two parameters from bond spreads (see, for instance, Bakshi, Madan and Zhang (2001) and Unal, Madan and Guntay (2003). Unal, Madan and Guntay (2003) find that on average, recovery rates obtained in this way lie systematically below the “physical” recovery rates (their terminology) as implied by studies such as Altman and Kishore (1996).\textsuperscript{16}

2.2.6 Correlation

Default correlation is a measure of the dependence among risks. Along with default rates and recovery rates, it is a necessary input in the estimation of the value of the portfolio at risk due to credit. In general, the concept of default correlation incorporates the fact that systemic events cause the default event to cluster. Coincident movements in default among borrowers may be triggered by common, underlying factors. Within the context of retail portfolios, systemic events might include macroeconomic events such as changes in the rate of unemployment or geographically specific events. Nagpal and Bahar (2001) as the relationship between default probabilities and joint default

\textsuperscript{16} (Schuermann.Til, 2004)
probabilities define default correlation. They note that historical rates of default support the idea that credit events are correlated. This correlation is a critical factor in the estimation of the tails of the overall credit loss distributions. Thus, failure to recognize the impact of shocks to the portfolio through default correlation will ultimately underestimate the measures of risk and economic capital required to manage that risk. In contrast with other residential loan portfolios in which one would anticipate that default correlation could be very low, understanding default correlation is critical in the lower credit quality portfolios of sub-prime lenders. Several authors have documented the relationship between the initial credit quality of the portfolio and default correlation in commercial portfolios. Generally, as credit quality declines, the importance of default correlation increases. For example, Zhou (1997) shows implied default correlations based on Z-values that are almost zero for highly rated firms but substantial for lowly rated firms even over short time horizons. Using corporate bond and loan portfolios, Lucas et al. (2001) provides numerical results showing that for a given correlation, a higher portfolio quality lowers extreme credit loss quintiles. Similarly, Loffler (2003) finds that correlation uncertainty is a more significant factor for B-rated portfolios as compared with BBB-rated portfolios for uncertainty in the 1% VaR. Although these studies deal with commercial loan and bond portfolios, the management of a sub-prime loan portfolio is analogous to the management of a non-investment grade bond portfolio. The significance of default correlation increases as the internal ratings of the lender decline. Thus, it is likely that ignoring default correlation in the development of credit risk models for sub-prime portfolios would lead to considerable model risk. There are several methodologies currently employed in the development of default correlations within portfolios as discussed in Zhou (1997). For example, Loffler (2003) estimates default correlations based on the joint distribution of asset values. As discussed in Crouhy et al. (2000), equity prices are often used as a proxy to estimate asset correlations given
that asset values are not directly observable. One commonly employed method is the identification of a benchmark for the purpose of developing asset return correlations and then mapping these into default correlations. The approach requires making assumptions about the relationship between asset prices and default. However, this approach is not applicable within a retail context as there is no asset price for the individual borrower. Alternatively, default correlations can infer from historical default volatilities. A default correlation coefficient is estimated based on the assumption that all loans within the risk class have identical default rates. Thus, applying such an approach to subprime portfolios assumes that internal credit rating assignments are consistent. Specifically, Cowan and others have followed the exchangeable models framework of Frey and McNeil (2002). Their paper extends the existing literature as it provides the first insight into the credit risk inherent in a sub-prime portfolio. As noted by Carey (1998), extreme events in the portfolio loss tail can lead to the insolvency of a financial institution. Given the greater credit risk associated with sub-prime portfolios would indicate that ignoring default correlations would cause a substantial understatement of the riskiness of sub-prime loan portfolios.

Combining risks does not follow the usual arithmetic rules, unlike income. The summation of two risks, each equal to 1, is not two. It is usually lower because of diversification. Quantification based on correlations shows that the sum is in the range of 0 to 2. This is the essence of diversification and correlations. Diversification reduces the volatility of aggregated portfolio income, or Profit and Loss (P&L) of market values, because these go up for certain transactions and down for others, there by compensating each other to some extent. Moreover, credit risk losses do not occur simultaneously.\footnote{Joel bessis, 2002}

Individual risks and their correlations drive the portfolio risk and the extent of the diversification effect, which is the difference between the

\footnote{Joel bessis, 2002}
(arithmetic) sum of these individual transaction risks and the risk of the
sum. Because portfolio risk depends so much on interdependencies
between individual transaction risks, they play a key role in portfolio risk
models. Various techniques serve for capturing the correlation, or
diversification, effect:

- Correlations quantify interdependencies in statistical terms, and
  are critical parameters for valuing the random changes in portfolio
  values. Basic statistical rules allow us to understand how to deal
  with sums of correlated random individual values of facilities.
- When dealing with discrete default events, the credit standing of
  individual obligors depend on each other. Conditional probabilities
  are an alternative view of correlations between individual risks
  that facilitates the modeling of some random events.
- When looking forward, the ‘portfolio risk building block’ of models
  relies on simulations of random future changes of value, or
  ‘returns’, of transactions, triggered by risk events. Forward-
  looking simulations require generating random values of ‘risk
  factors’ in order to explore all future scenarios and determine the
  forward distribution of the portfolio values. Such random scenarios
  should comply with variance and correlation constraints between
  risk factors. Special techniques serve to construct such
  simulations. Several examples use them later on for constructing
  portfolio loss distributions.
- Correlation and Volatility of a Sum of Random Variables

The volatility of a sum depends on the correlations between variables. It
is the square root of the variance. The variance of a sum is not, in
general, the sum of the variances. It is the sum of the variances of each
random variable plus all covariance terms for each pair of variables.
Therefore, Joel Bassis start with the simple case of a pair of random
variables and proceed towards the extension to any number of random
variables. The general formula applies for determining the portfolio loss
volatility and the risk contributions to the portfolio volatility of each individual exposure. Hence, it is most important.

For two variables, the formulas are as follows:

\[ V(X + Y) = \sigma^2 (X + Y) = V(X) + V(Y) + 2\text{Cov}(X,Y) \] (5)

\[ V(X + Y) = \sigma^2(X) + \sigma^2(Y) + 2\rho_{xy} \sigma(X)\sigma(Y) \]

The covariance between X and Y is Cov(X, Y), V(X) is the variance of X, s(X) is the standard deviation and \( \rho_{xy} \) is the correlation coefficient. Since the covariance is a function of the correlation coefficient, the two above formulas are identical. If the covariances are not zero, the variance of the sum differs from the sum of variances. The correlation term drops out of the formulas when the two variables are independent:

\[ V(X + Y) = \sigma^2(X) + \sigma^2(Y) \] (6)

\[ \sigma(X + Y) = \sqrt{\sigma^2(X) + \sigma^2(Y)} \]

The variance of the sum becomes the sum of variances only when all covariances are equal to zero. This result is valid only when all variables move independently of each other. The volatility is the square root of the variance. Since the variance of the sum is the sum of variances and the volatility is less than the sum of volatilities. It is the square root of the sum of the squared values of volatilities.

**Visual Representation of the Diversification Effect**

The diversification effect is the gap between the sum of volatilities and the volatility of a sum. In practice, the random variables are the individual values of returns of assets in the portfolio. The diversification effect is the gap between the volatility of the portfolio and the sum of the volatilities of each individual loss. A simple image visualizes the formula of the standard deviation of a sum of two variables. The visualization shows the impact of correlation on the volatility of a sum. A vector
whose length is the volatility represents each variable. The angle between the vectors varies inversely with correlation. The vectors are parallel whenever the correlation is zero and opposed when the correlation is -1. With such conventions, the vector equal to the geometric summation of the two vectors representing each variable represents the overall risk. The length of this vector is identical to the volatility of the sum of the two variables. Visually, its length is less than the sum of the lengths of the two vectors representing volatilities, except when the correlation is equal to + one. The geometric visualization shows how the volatility of a sum changes when the correlation changes (Figure 2.9)

Figure (2.9): Geometric representation of the volatility of the sum

Of two random variables

![Geometric representation of the volatility of the sum](image)

Figure (2.10) groups different cases. The volatilities of the two variables are set to one. The only change is that of their correlation changes. The volatility of the sum is the length of the geometric summation of vectors 1 and 2. It varies between 0 when the correlation is -1, up to 2 when the correlation is +1. The intermediate case, when correlation is zero, shows that the volatility is $\sqrt{2}$.\textsuperscript{18}

\textsuperscript{18}Joel Bessis, 2002
2.2.7 Concentration

I. Portfolio Concentration and Correlation Risk

Both correlation risk and concentration risk are related measures of portfolio risk. Correlation risk relates to the loss association. Concentration risk designates here the effect of size discrepancies. Pure correlation risk is measured by the 30% asset correlation, independent of the sizes of exposures. Pure size concentration is measured by a concentration index, such as the diversity score, or concentration curves.

II. Diversification and Correlation Effects

In general, when the risks of two obligors correlate, the risk is higher if they have large exposures. There is an interaction between size and correlation.

III. Concentration Risk: Diversity Score

Concentration characterizes size discrepancies. The individual loss given default weights, ratios of the individual loss given default to the total loss given default, measure exposure sizes. Synthetic views of portfolio size concentration, other than reporting the largest individual weights, include such measures as the diversity score and concentration curves.
The diversity score is an index synthesizing the discrepancies of exposure of individual facilities. There are as many concentration indices as there are metrics for risk. Alternative metrics include exposure weights, loss given default weights or capital allocation weights, each of them being the ratio of the individual measure to the total portfolio measure. There is a concentration index, or diversity score, for each metric. The diversity score is a number that is always lower than the actual number of facilities. The lower the ratio, the higher the risk concentration along the selected dimensions. The diversity score is the number of equal size exposures equivalent to the weight profile of individual exposures. The diversity score DS is the following ratio:

$$DS = 1 / \sum_{i=1}^{n} w_i^2$$

(7)

The $w_i$ are the weights of facilities, using one risk metric, for instance exposure or loss given default of individual facilities. If all weights were equal to $1/n$, with $n$ the number of obligors, the ratio would be

$$1 / (\sum_{i=1}^{n} 1/n^2), \text{ or } 1/(n/n^2) = n$$

The diversity score is commonly interpreted as the number of uniform exposures ‘equivalent’ to the number of actual unequal exposures. It is a convenient measure to capture pure size concentration effects, as opposed to correlation effects. The ratio of the diversity score to the actual number of exposures is always lower than one whenever there are size discrepancies, and the gap measures pure concentration risk figure (2.11) provides the diversity scores for exposure and capital allocation. Both numbers are lower than the actual number of exposures, 50. The ratios of these diversity scores to this actual number of exposures, 50, measure the level of concentration in terms of weight
discrepancies. Note that the capital diversity score combines effects, concentration and diversification, since capital allocations capture the retained risk post-diversification effect.\(^\text{19}\)

**Figure (2.11): Concentration risk**

<table>
<thead>
<tr>
<th>Diversity score exposure</th>
<th>35.02</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concentration index exposure</td>
<td>70.04%</td>
</tr>
<tr>
<td>Diversity score capital (in excess of EL)</td>
<td>33.22</td>
</tr>
<tr>
<td>Concentration index capital</td>
<td>66.45%</td>
</tr>
</tbody>
</table>

**IV. Concentration Curves**

A second measure of concentration risk is the 'concentration' curve, or 'Gini' curve. The Curve shows the cumulated exposure, or any alternative risk metric, such as capital, as a function of the number of exposures. The curve cumulates the risk metric (exposure) sorted by descending values. A uniform exposure portfolio would have a straight-line concentration curve. The higher the curve above the straight line is, the higher the concentration risk. In the exposure concentration curve of Figure (2.12), the first five biggest obligors represent 21% of the total portfolio exposure; the first 10 biggest obligors represent 40% of the total portfolio exposure, and so on. The curve hits 100 % when all 50 exposures cumulate. The slope is steeper at the beginning of the curve because the largest exposures are the first along the X-axis. Steepest slopes also characterize concentration because they imply that a lower number of the largest risks concentrate a larger fraction of the total risk.

\(^{19}\) (Joel bessis, 2002)
2.2.8 Diversification

A lot of work has been carried out over the last years regarding the diversification effect within a portfolio of credit instruments. Most of this research has considered correlation as a good proxy for dependence. (Servigny de Arnaud & Olivier Renault, October 2002) The lower the correlation among loans in a portfolio, the greater the potential for a manager to reduce a bank's risk exposure through diversification.\(^{20}\)

2.2.9 Granularity

"Granularity" means large disparities in loan sizes within the portfolio. Carey (2000) demonstrates the importance of portfolio "granularity" (large on unexpected loss distributions).

A second issue is the effect of outliers on simulated loss distributions. A few extreme outliers can seriously affect the mean, variance, skewness, and kurtosis of an estimated distribution, as well as the correlations among the loans implied in the portfolio. In a market risk model context, Stahl (1998) shows how only 5 outliers out of 1,000, in

\(^{20}\) (Saunders. Anthony, 2002)
terms of foreign currency exchange rates, can have a major impact on estimated correlations among key currencies. With respect to credit risk, the danger is that a few big defaults in any given year could seriously bias the predictive power of any cross-sectional test of a given model.

Figure (2.13) shows that expected losses are relatively unaffected, but that unexpected losses, particularly in the extreme 99.9 percent extreme tails of the distribution, are sensitive to both the size disparity across loans (rows 1 and 2 of figure 2.13) and large loans to single borrowers (rows 3 and 4 of figure 2.13).

Figure (2.13): the Impact of Loan Size Distribution on Portfolio Losses

<table>
<thead>
<tr>
<th>Simulation Parameters</th>
<th>Mean</th>
<th>95%</th>
<th>99%</th>
<th>99.5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base case, 500 loans, random sizes</td>
<td>0.67</td>
<td>2.01</td>
<td>2.98</td>
<td>3.39</td>
</tr>
<tr>
<td>Base case, 500 loans, equal sizes</td>
<td>0.65</td>
<td>1.73</td>
<td>2.37</td>
<td>2.58</td>
</tr>
<tr>
<td>Base case, no one-borrower limit</td>
<td>0.66</td>
<td>2.09</td>
<td>3.38</td>
<td>4.16</td>
</tr>
<tr>
<td>Base case, 5% limit on lending to a Single borrower</td>
<td>0.66</td>
<td>2.11</td>
<td>3.14</td>
<td>3.55</td>
</tr>
<tr>
<td>Base case, 5% limit on lending to a Single borrower</td>
<td>0.66</td>
<td>2.11</td>
<td>3.14</td>
<td>3.55</td>
</tr>
</tbody>
</table>

Source: Saunders. Anthony

2.3 Credit Risk Mitigation techniques

Collaterals, loan contracts and covenants serve to control the borrower’s risk-taking propensity and increase recoveries under default. Structures are Special Purpose Vehicles (SPVs) that have no credit standing by themselves: they offer credit risk protection from collateral and from covenants ruling the life of the SPV, which customizes both default probabilities and recoveries according to the seniority level of lenders. The regulators recognized the risk mitigating effects of various forms of guarantees received in the ‘foundation’ approach of the New Basel Accord of 2001. Recoveries reduce loss under default and if their value is reasonably certain,
they reduce the capital charge. Losses for credit risk depend directly on recovery rates, making these key inputs for measuring credit risk. The New Accord provides strong incentives for building up data on recoveries. Recoveries depend on the nature of protection, making it necessary to differentiate them according to the nature of guarantees. Collaterals are assets seized by lenders in the event of default. Third party guarantees are contractual obligations of a guarantor to act as a substitute for the primary borrower if he defaults on his payment obligations. A third-party guarantee is a legal obligation. Support, from the head of a group to a subsidiary, is informal. It designates the supportive behavior of holding companies towards subsidiaries whose credit standing deteriorates up to default. Support is like third-party guarantees except that there is no binding legal agreement. Credit derivatives are similar to guarantees and insurances, but they are distinct contracts from loans and relate to underlying assets that are not necessarily those of lenders. Sellers of credit derivatives are sellers of a protection, or insurers, buyers of credit derivatives are buyers of protection. Whenever there is an exposure to the risk of a pair of obligors, through guarantees or credit derivatives, default occurs when both obligors default. This is a ‘double’, or ‘joint’, default event of the primary borrower and the guarantor. Its probability depends on how interdependent their risks are. Covenants are contractual clauses, imposed on borrowers, the breach of which triggers a prompt repayment of outstanding debt. Covenant breaches require waivers from lenders, implying renegotiation, to continue operations. Structures are the ultimate stage of protection shield for lenders. The SPV protects lenders with covenants ruling the structure’s behavior, allowing for early default events before potential losses of lenders get too high and corrective actions triggered by breaches of covenants.\(^{21}\)

\(^{21}\) (Joel bessis, 2002).
2.3.1 Collateral

Collaterals are assets that the lender seizes and sells if the borrower fails to perform his debt obligations. The original credit risk turns into a recovery risk plus an asset value risk. Collateral is also an incentive for the borrower to fulfill debt obligations effectively, mitigating moral hazard in lending. Should he fail in his obligation, the borrower loses if the value of the collateral is higher than debt. Several types of collaterals are as below:

- Cash & Marketable Securities
- Non-marketable Securities
- Accounts Receivable Inventory
- Accounts Receivable & Inventory
- Fixed Assets and/or Equipment
- Fixed Assets and/or Equipment – Boats
- Fixed Assets and/or Equipment – Airplanes
- Commercial Real Estate
- Residential Real Estate
- Pledge of Subsidiary Share
- All Assets/Debenture
- Commodities
- Secured – Other
- Unsecured
- Unknown

2.3.2 Credit risk transfers

I. Third-Party Protections

Third-party protections include guarantees, support of a parent company, insurance and protection against credit risk from the seller of credit derivatives. The latter is a much newer concept than the others are, and has different characteristics detailed in subsequent chapters (58 and 59). Third-party guarantees are commitments, ranging from very
formal obligations to simple statements, to face the obligations of a primary borrower if he fails to do so. Support is informal. It designates the ‘willingness’ of a parent company to support a subsidiary one which is unable to face its debt obligations. Legally enforceable guarantee simply a contract, even though the enforcement of this contract is subject to various legal uncertainties. Hence, all formal third-party protections are subject to legal risk. When effective, third-party protections transform the credit risk on the borrower into a credit risk on both borrower and guarantor. Default occurs only if both borrower and provider of protection default together (double default). The corresponding default probability becomes a joint probability of default of both of them. This joint default risk of the borrower and guarantor is different from a pure transfer of risk to the guarantor, because such a transfer would simply consider that the exposure is on the guarantor rather than on the borrower, which is not the economic reality. However, the New Basel Accord adopts this second view and does not grant ‘joint default probability’ benefits.

II. Guarantees

Guarantees allow entering into transactions that would not be feasible without them. A simple guarantee is an obligation of a third party to fulfill the obligation of a borrower if he does not comply with his debt obligation. Guarantees are widely used in common transactions or in more structured deals such as back-to-back deals. In trade financing, they play a key role since they make trade financing feasible. In back-to-back deals, X does not want to lend directly to Y, but might be willing to lend to a higher credit-standing third party. The third party T lends to Y and repays X and, in exchange for this service, gets a spread. Instead of issuing a formal, guarantee that Y will repay X, the third-party makes the market between counterparties that would not enter into a transaction directly. Few contractual guarantees can be forced easily. Some are binding, when the guarantor has to fulfill the obligations of a
defaulting borrower. However, the range of guarantees covers a wide spectrum of obligation levels. Letters of intention, as their name implies, are not binding. Some guarantees are dependent on recourses of third parties other than the guarantor. The ‘strength’ of a guarantee is context-dependent: it depends on its nature, the legal environment(s) that is (are) relevant, current practices and the context when the lender exercises his right.

III. Support

Support designates an informal relationship. Usually, ‘support’ applies between a parent company and subsidiaries within a group. A holding company might not let a subsidiary default, although there is no binding rule applied to this. The effectiveness of support depends on intra-group economic links and the behavior of the supporting entity.