CREDIT RISK MODELLING:

CURRENT PRACTICES

AND

APPLICATIONS

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Credit Risk Modelling: Current Practices and Applications
Executive Summary

1. Summary and objectives

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 recognises that credit risk modelling may indeed prove to result in better internal risk management, and may have the potential to be used in the supervisory oversight of banking organisations. However, before a portfolio modelling 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 modelled 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 backtesting of market risk models. Where market risk models typically employ a horizon of a few days, credit risk models generally rely on a time frame 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. By the same token, 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.

The Committee welcomes additional efforts in addressing these and other key issues, and looks forward to a constructive dialogue with the industry. The Committee is seeking comments on this report from all interested parties by 1 October 1999.

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This report on credit risk modelling will serve two primary purposes:

- Provide a description of current practices and issues in credit risk modelling. The foundation for this review includes material culled from public conferences and private presentations by market practitioners, including banking institutions, model vendors and researchers. The report is also based on the results of an extensive survey conducted by the Task Force of modelling practices at 20 large international banks located in 10 countries.
- Assess the potential applications and limitations of credit risk models for supervisory and/or regulatory purposes. In this regard, the future analysis and conclusions of the Task Force will be considered in the context of the Basle Committee's overall review of the Capital Accord.

2. 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, centralising data on global exposures and analysing 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, modelling 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 modelling methodology and the consequent improvements in the rigour 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.

While the above points highlight various benefits of the modelling process, there are still a number of significant hurdles, discussed below, that need to be overcome before a modelling approach may be evaluated for use in the setting of regulatory capital requirements.

3. Summary of issues

In its evaluation of models, the Task Force separated the issues it identified into three main categories: conceptual methodology, parameter specification and estimation, and validation. Some major points regarding these categories are discussed in the subsequent section. (The Appendix to the report provides a matrix summary of other key issues.)

Conceptual methodology

The Task Force observed a range of practices in the conceptual approaches to modelling. We would welcome a dialogue with the industry in order to assess the materiality of these choices on a model's accuracy and their impact on the size of required capital if models were to be used for regulatory purposes. The different choices observed include the following:

- Different approaches to the measurement of credit loss. Most banks employ either of two conceptual definitions of credit loss: the default-mode paradigm, in which a credit loss arises only if a borrower defaults within the planning horizon, and the mark-to-market (or more accurately, mark to model) paradigm, in which credit deterioration short of default is also incorporated. Banks may also choose to adopt different time horizons for monitoring credit risk.

- Different methodologies for the measurement of exposure and loss given default. For example, in measuring exposure to a line of credit, some banks employ a largely judgemental approach for estimating recovery values of loans in the event of default, while others rely on more empirically based techniques.

- Unconditional and conditional models. Unconditional models typically reflect (relatively limited) borrower or facility-specific information, while conditional models also incorporate information on the state of the economy.
- Different approaches to the aggregation of credit risk. Credit risk may be measured at the individual asset level, as is typically the case with large corporate and capital market instruments; conversely, aggregate (pooled) data may be used to quantify the risk of smaller loans with similar risk profiles.
- Different techniques for measuring the interdependence of factors that contribute to credit losses. For example, banks may utilise various methods for measuring the correlation between defaults and rating migrations.

Parameter specification and estimation

- The specification of the process of default and rating migration is severely constrained by a lack of data on the historical performance of loans and other modelled variables. The difficulties in the estimation of key parameters are exacerbated by the long time horizons used in credit risk models, which suggest that many years of data, spanning multiple credit cycles, may be needed to estimate the process of default. Even if individual default probabilities could be modelled accurately, the process of combining these for a portfolio might still be hampered by the scarcity of data with which to estimate reliably the correlations between numerous variables.
- The data limitations also encourage the use of various simplifying assumptions, for example: (a) the determinants of credit loss are assumed to be independent from one another; (b) certain variables, such as the level of loss given default in some models, are treated as non-random variables, while estimated parameters and structural model assumptions are treated as if they were "true" (i.e. known with certainty); (c) borrowers within pre defined risk segments are taken to be statistically identical; and (d) model parameters are assumed to be stable. These assumptions are often based on subjective judgements, and there is generally little empirical analysis supporting the choices made by model-builders. It is also not yet standard practice to conduct sensitivity testing of a model's vulnerability to such assumptions. In practice, the

estimation of some model parameters, such as the assignment of an internal loan grading or assignment of an obligor to one or more industry sectors, may also require some judgement. The impact of such judgements or assumptions on model accuracy is not well understood.

- Due to the current limitations on internal default data, model parameters often reflect, to some degree, the pooling of information from several sources. The reliability of such data, and its comparability with a bank's own portfolio characteristics or default experience, is a key consideration in evaluating model accuracy.

Validation

- If internal models were to be used in setting regulatory capital requirements, regulators would need some means of ensuring that a bank's internal model represents accurately the level of risk inherent in the portfolio and the required regulatory capital. For market risk models, backtesting provides a way of continually checking model performance.
- Banks have indicated the use of higher confidence intervals in the measurement of credit risk than those used for market risk. It is unclear whether such high confidence intervals can be estimated reasonably accurately, and it is not yet well understood what the effect of modelling assumptions is on the extreme tails of the distributions, and hence on the amount of capital needed to support risk-taking. Furthermore, there is still an issue as to whether the use of high confidence intervals would produce capital requirements that are highly model-dependent, or are not comparable across institutions. It is this and other constraints that highlight the challenges and importance of both the internal and external validation processes.
- At present, there is no commonly accepted framework for periodically verifying the accuracy of credit risk models; going forward, methods such as sensitivity testing are likely to play an important role in this process. Finally, it is important to note that the internal environment in which a model operates – including the amount of management oversight, the quality of internal controls, the rigour of stress testing, the reporting process and other traditional features of the credit culture – will also continue to play a key part in the evaluation of a bank's risk management framework.

PART I: INTRODUCTION

1. Overview

Over the last decade, a number of the world's major banks have developed sophisticated systems to quantify and aggregate credit risk across geographical and product lines. The initial interest in credit risk models stemmed from the desire to develop more rigorous quantitative estimates of the amount of economic capital needed to support a bank's risk-taking activities. As the outputs of credit risk models have assumed an increasingly large role in the risk management processes of large banking institutions, the issue of their potential applicability for supervisory and regulatory purposes has also gained prominence.

This report provides a description of the state of practice in credit risk modelling, and assesses the potential uses of credit risk models for supervisory and/or regulatory purposes, including the setting of regulatory capital requirements. In preparing this report, the Basle Committee's Models Task Force (the "Task Force") reviewed material culled from numerous public conferences and private presentations by market practitioners, and conducted an extensive survey of modelling practices at 20 banking institutions located in 10 countries. This review highlighted the wide range of practices both in the methodology used to develop the models and in the internal applications of the models' output. This exercise also underscored a number of challenges and limitations to current modelling practices.

From a supervisory perspective, the development of modelling methodology and the consequent improvements in the rigour and consistency of credit risk measurement hold significant appeal. These improvements in risk management may, according to national discretion, be acknowledged in supervisors' assessment of banks' internal controls and risk management practices.

From a regulatory perspective, the flexibility of models in responding to changes in the economic environment and innovations in financial products may reduce the incentive for banks to engage in regulatory capital arbitrage. Furthermore, a models-based approach may also bring capital requirements into closer alignment with the perceived riskiness of underlying assets, and may produce estimates of credit risk that better reflect the composition of each bank's portfolio. However, before a portfolio modelling approach could be used in the formal process of setting regulatory capital requirements, regulators would have to be confident that models are not only well integrated with banks' day-to-day credit risk management, but are also conceptually sound, empirically validated, and produce capital requirements that are comparable across institutions. At this time, significant hurdles – principally concerning data limitations and weaknesses in model validation – still need to be cleared before these objectives can be met. Indeed, it is these two key issues that differentiate credit risk models from their market risk counterparts. The Task Force sees difficulties in overcoming these hurdles in the timescale envisaged for amending the Accord.

2. Internal Applications of Credit Risk Models

Credit risk modelling methodologies allow a tailored and flexible approach to price measurement and risk management. Models are, by design, both influenced by and responsive to shifts in business lines, credit quality, market variables and the economic environment. Furthermore, models allow banks to analyse marginal and absolute contributions to risk, and reflect concentration risk within a portfolio. These properties of models may contribute to an improvement in a bank's overall credit culture.

The degree to which models have been incorporated into the credit management and economic capital allocation process varies greatly between banks. While some banks have implemented systems that capture most exposures throughout the organisation, others only capture exposures within a given business line or legal entity. Additionally, banks have frequently developed separate models for corporate and retail exposures, and not all banks capture both kinds of exposures.

The internal applications of model output also span a wide range, from the simple to the complex. For example, only a small proportion of the banks surveyed by the Task Force is currently using outputs from credit risk models in *active* portfolio management; however, a sizable number noted they plan to do so in the future. Current applications included: (a) setting of concentration and exposure limits; (b) setting of hold targets on syndicated loans; (c) risk-based pricing; (d) improving the risk/return profiles of the portfolio; (e) evaluation of risk-adjusted performance of business lines or managers using risk-adjusted return on capital ("RAROC"); and (f) economic capital allocation. Institutions also rely on model estimates for setting or validating loan loss reserves, either for direct calculations or for validation purposes.

3. Key Challenges to Regulatory Application

The Task Force recognises that credit risk modelling may indeed prove to result in better internal risk management at banking institutions. However, key hurdles, principally concerning data limitations and model validation, must be cleared before models may be used in the process of setting regulatory capital requirements.

The specification of the process of default and other factors leading to changes in credit quality is severely constrained by a lack of data on the historical performance of loans and other modelled variables. The difficulties in specification are exacerbated by the longer-term time horizons used in measuring credit risk, which suggest that many years of data, spanning multiple credit cycles, may be needed to estimate key parameters accurately. Therefore, due to the current limitations, model parameters often reflect, to some degree, the use of simplifying assumptions and the pooling of information from several sources. The materiality of these choices on the model's estimate of risk is unclear as it is not yet standard practice to conduct sensitivity testing of a model's vulnerability to such assumptions.

Before internal models could be used to set regulatory capital requirements, regulators would need some means of ensuring that a bank's internal models accurately represent the level of risk inherent in the portfolio. The effect of modelling assumptions on estimates of the extreme tails of the distributions is not well understood. It is unclear whether the high target credit loss quantiles used in the measurement of credit risk, and the resulting estimates of economic capital, can be estimated with an acceptable degree of precision. For market risk models, backtesting provides a way of continually checking model performance. At present, there is no commonly accepted framework for periodically verifying the accuracy of credit risk models. Were models to be used for regulatory purposes, supervisors would need to rely on internal and external validation procedures, and might be required to develop both qualitative and quantitative standards to ensure that modelling processes are reasonable and the quality of output is comparable across banking institutions.

The Task Force welcomes additional efforts in addressing these and other key issues, and hopes to engage the industry in a constructive dialogue going forward. .The Committee is seeking comments on this report from all interested parties by 1 October 1999.

4. Organisation of The Report

The remainder of this report is organised as follows: Part II presents an analysis of the conceptual approaches to credit risk modelling. Part III focuses on the various methodologies used for parameter estimation. Finally, Part IV addresses model validation practices at major banking institutions. In each section of the report, the discussion of the concepts and practices is followed by a subsection that highlights the key issues raised. The Appendix contains a matrix summary of the key issues.

PART II: OVERVIEW OF CONCEPTUAL APPROACHES TO CREDIT RISK MODELLING

In surveying a significant number of credit risk models, the Task Force encountered a range of conceptual modelling approaches. In this report, we do not propose to make a taxonomy of these approaches, but aim to discuss key elements of the different methodologies we reviewed. We begin this section by introducing the concepts of economic capital allocation and the probability density function of credit loses, then move on to a discussion of various constituent elements of credit risk models. These are: (1) choice of time horizon and review of default-mode and mark-to-market approaches to measuring credit loss; (2) probability density functions; (3) conditional/unconditional models; (4) approaches to credit aggregation; and (5) approaches to dependence between default events (default correlations, etc.).

The choices of conceptual methodology that a bank makes when building a credit risk model are largely subjective ones, based on considerations such as the characteristics of the bank's loan portfolio and its credit culture. While this section raises many conceptual issues regarding the various approaches, the question of the materiality of each is an empirical one. As such, the Committee welcomes further dialogue with the industry in order to assess the impact of these choices on a model's accuracy and performance.

1. Economic Capital Allocation for Credit Risk

A. Probability density function of credit losses

When estimating the amount of economic capital needed to support their credit risk activities, many large sophisticated banks employ an analytical framework that relates the overall required economic capital for credit risk to their portfolio's ***probability density function of credit losses (PDF),*** which is the primary output of a credit risk model. Exhibit 1 illustrates this relationship. A bank would use its credit risk modelling system (described in detail below) to estimate such a PDF. An important property of a PDF is that the probability of credit losses exceeding a given amount X (along the x-axis) is equal to the (shaded) area under the PDF to the right of X. A risky portfolio, loosely speaking, is one whose PDF has a relatively long and fat tail. The ***expected credit loss*** (shown as the left-most vertical line) shows the amount of credit loss the bank would expect to experience on its credit portfolio over the chosen time horizon. Banks typically express the risk of the portfolio with a measure of ***unexpected credit loss*** (i.e. the amount by which actual losses exceed the expected loss) such as the standard deviation of losses or the difference between the expected loss and some selected target credit loss quantile.

The estimated economic capital needed to support a bank's credit risk exposure is generally referred to as its required economic capital for credit risk. The process for determining this amount is analogous to ***value at risk (VaR)*** methods used in allocating economic capital against market risks. Specifically, the economic capital for credit risk is determined so that the estimated probability of unexpected credit loss exhausting economic capital is less than some target insolvency rate.[1]

Capital allocation systems generally assume that it is the role of reserving policies to cover expected credit losses, while it is that of economic capital to cover unexpected credit losses. Thus, required economic capital is the additional amount of capital necessary to achieve the target insolvency rate, over and above that needed for coverage of expected losses. In Exhibit 1, for a target insolvency rate equal to the shaded area, the required economic capital equals the distance between the two dotted lines.[2] Broadly defined, a ***credit risk model*** encompasses all of the policies, procedures and practices used by a bank in estimating a credit portfolio's PDF.

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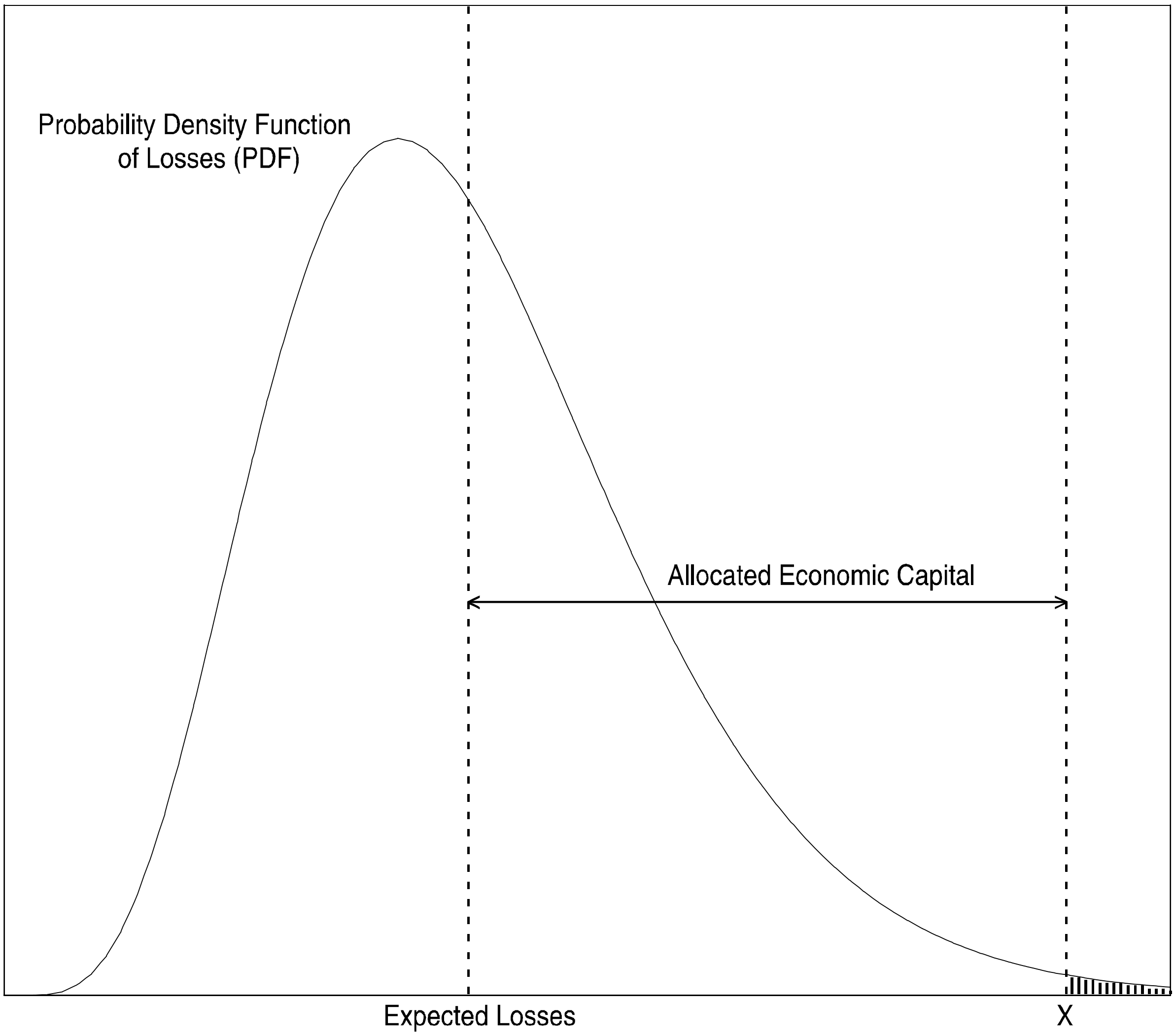
[1] In practice, the target insolvency rate is often chosen to be consistent with the bank's desired credit rating, although this insolvency rate would have to take into account risks other than credit risk in order to be meaningful. For example, if the desired credit rating is AA, the target insolvency rate might equal the historical one-year default rate for AA-rated corporate bonds (about 3 basis points).

[2] The majority of banks considers economic and regulatory capital to be independent from one another and thus does not incorporate regulatory capital requirements in the calculation of economic capital. However, a few institutions appear to incorporate the costs of regulatory capital into their pricing methodology. This may be reflected in the inclusion of a regulatory capital "surcharge" when allocating capital across product lines. This add-on aims to reflect a regulatory burden if regulatory capital requirements exceed economic capital requirements. (In theory, banks could also include a regulatory capital credit in instances where economic capital calculations are higher.) Furthermore, while approximately half the surveyed banks allocated economic capital against credit risks, a few of these banks continue to use regulatory – rather than economic – capital requirements for risk-adjusted performance measurement, though they plan on moving towards the latter.

Exhibit 1


Probability Density Function
of Losses (PDF)
Allocated Economic Capital
Expected Losses
X

B. Key Issues

- Given that most of the credit risk models reviewed are still in an introductory phase, most of the institutions surveyed by the Task Force have not fully allocated capital along various product types or business lines. The frequency with which banks revisit economic capital allocation decisions also varies, from monthly to yearly. Most allocate capital and profit/loss on a somewhat micro basis, such as at a sub-portfolio, business or product line level, rather than at the bank level.

2. Measuring Credit Loss

In general, a portfolio's ***credit loss*** is defined as the difference between (a) the portfolio's ***current value*** and (b) its ***future value*** at the end of some ***time horizon.*** The estimation of the current portfolio's PDF involves estimating (a) the portfolio's *current* value and (b) the probability distribution of its *future* value at the end of the planning horizon. The precise definitions of current and future values – and, hence, virtually all of the operational details of the credit risk model – follow from the specific concept of credit loss that is of interest to the model-builder. Within the current generation of credit risk models, banks employ either of two conceptual definitions of credit loss, termed the ***default mode (DM)*** paradigm or the ***mark-to-market (MTM)*** paradigm. The remainder of this section discusses the choice of time horizon, followed (in sections B and C) by a discussion of the alternative loss paradigms.

A. Time horizon

A bank's decision on the time horizon over which it monitors credit risk can follow one of two approaches. First is the "liquidation period" approach, in which each facility is associated with a unique interval, coinciding with the instrument's maturity or with the time needed for its orderly liquidation. Alternatively, an institution may choose to apply a common time horizon across all asset classes.

Most of the banks surveyed adopt a one-year time horizon across all asset classes. A minority utilise a five-year approach or modelled losses over the maturity of the exposure. A small number use other horizons, while some noted they might run their models for more than one horizon. A number of vendor models allow users to select an asset-specific (or portfolio-specific) holding period horizon based on the unique structure of each underlying exposure.

The considerations mentioned for the choice of a modelling horizon of one year were that this reflected the typical interval over which: (a) new capital could be raised; (b) loss mitigating action could be taken to eliminate future risk from the portfolio; (c) new obligor information could be revealed; (d) default rate data may be published; (e) internal budgeting, capital planning and accounting statements are prepared; and (f) credits are normally reviewed for renewal. For the banks that chose a “hold-to-maturity” approach, the considerations included the following: (a) exposures were intended to be held to maturity; and (b) there were limited markets in which the credits could be traded.

B. Default mode paradigm

Within the DM paradigm, a credit loss arises only if a borrower defaults within the planning horizon. To illustrate, consider a standard term loan. In the absence of a default event, no credit loss would be incurred. In the event that a borrower defaults, the credit loss would reflect the difference between the bank’s ***credit exposure*** (the amount it is owed at the time of default) and the ***present value of future net recoveries*** (cash payments from the borrower *less* workout expenses).

The current and future values of credit instruments in the DM paradigm are defined in a manner consistent with the underlying two-state (default vs. non-default) notion of credit losses. For a term loan, the ***current value*** would typically be measured as the bank’s credit exposure (e.g., book value). The (uncertain) future value of the loan, however, would depend on whether or not the borrower defaults during the planning horizon. If the borrower does *not* default, the loan’s ***future value*** would normally be measured as the bank’s credit exposure at the end of the planning horizon, adjusted so as to add back any principal payments made over the period. On the other hand, if the borrower were to default, the loan’s future value (per dollar of current value at the beginning of the horizon) would be measured as one *minus* its ***loss rate given default (LGD)***. The lower the LGD, the higher the recovery rate following default.

Note that at the time the credit risk model is being used to estimate the portfolio’s PDF – the beginning of the planning horizon – the current values of credit instruments are assumed to be known, but their future values are uncertain. Within DM-type credit risk models, therefore, for each *separate* credit facility (e.g. loan vs. commitment vs. counterparty risk) a bank must impose or estimate the joint probability distribution with respect to three types of random variables: (1) the bank's associated credit exposure,[3] (2) a zero/one indicator denoting whether the facility defaults during the planning horizon, and (3) in the event of default, the associated LGD. In addition, to derive the PDF for the bank *as a whole*, the model-builder must determine the joint distribution of these variables *across* the *different* facilities comprising the portfolio.

An illustration: the mean/standard deviation approach

To illustrate the above concepts, it is useful to relate the above variables to the mean and standard deviation of a portfolio's credit losses.[4] Some systems for allocating economic capital against credit risk typically assume that the shape of the PDF is well-approximated by some family of distributions (e.g. the beta distribution) that could be parameterised by the mean and standard deviation of the portfolio's losses.[5] Market practitioners generally term this methodology the ***unexpected losses (UL) approach.*** Under the UL approach, the economic capital allocation process generally simplifies to setting capital at some multiple of the estimated standard deviation of the portfolio's credit losses.

Within the DM paradigm, the UL approach requires estimates of a portfolio's expected and unexpected credit loss. A portfolio's expected credit loss (μ) over the assumed time horizon equals the summation of the expected losses for the individual credit facilities:

$$(1) \quad \mu = \sum_{i=1}^{N} EDF_i \; LEE_i \; \overline{LGD_i}$$

where for the i[th] facility, $\overline{LGD_i}$ is the expected loss rate given default, EDF_i is the facility's expected probability of default (often termed the ***expected default frequency*** or ***EDF***), and LEE_i is the bank's expected credit exposure (often termed the ***loan equivalent exposure*** or ***LEE***).

[3] As described below, for certain types of credit instruments, such as commitments and OTC derivatives, a bank's credit exposure over the planning horizon is generally *not* known with certainty.

[4] At some risk of inconsistent terminology, practitioners often refer to the standard deviation of credit losses as the portfolio's ***unexpected loss.***

[5] Recent advances in computing capabilities have made it more feasible to estimate PDFs using Monte Carlo simulation methods.

The portfolio's standard deviation of credit losses (σ) can be decomposed into the contribution from each of the individual credit facilities:

$$(2) \quad \sigma = \sum_{i=1}^{N} \sigma_i \; \rho_i \,,$$

where σ_i denotes the stand-alone standard deviation of credit losses for the i[th] facility, and ρ_i denotes the correlation between credit losses on the i[th] facility and those on the overall portfolio.[6] The parameter ρ_i captures the i[th] facility's correlation/diversification effects with the other instruments in a bank's credit portfolio. Other things being equal, higher correlations among credit instruments – represented by higher ρ_i – lead to a higher standard deviation of credit losses for the portfolio as a whole.

Under the further assumptions that (a) each facility's exposure is known with certainty, (b) customer defaults and LGDs are independent of one another, and (c) LGDs are independent across borrowers, the stand-alone standard deviation of credit losses for the i[th] facility can be expressed as

$$(3) \quad \sigma_i = LEE_i \sqrt{EDF_i\,(1 - EDF_i\,)\,\overline{LGD}_i^{\,2} + EDF_i\, VOL_i^2}\ ,$$

where *VOL* is the standard deviation of the facility's *LGD*.

These equations provide a convenient way of summarising the overall portfolio's credit risk (within the DM framework) in terms of each instrument's $EDF, \rho, \overline{LGD}, VOL,$ and *LEE*. They also serve to highlight those aspects of the credit risk modelling process that determine its overall reliability, namely (a) the accuracy of parameter estimates as representations of the future, and (b) the validity of the model's underlying assumptions, such as assumptions of independence among random variables, assumptions that certain variables are known with certainty, and the distributional assumption that maps UL to a target credit loss quantile.

Internal risk rating systems, EDFs and rating transition matrices

As illustrated by the UL approach, the EDF – the probability of a particular credit facility defaulting during the time horizon – is a critical model input. This is true not only for DM-type credit risk models, but also for MTM-type models (discussed below). Within most

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[6] Typically, the economic capital allocation (for credit risk) against the i[th] facility would be set at some multiple of that facility's marginal contribution to the portfolio's overall standard deviation of credit losses.

credit risk modelling systems, a customer's ***internal credit risk rating*** (as determined by a bank's credit staff) is a key – if not the sole – criterion for determining the EDFs applicable to the various credit facilities associated with that customer; generally all the customer's facilities are presumed to default concurrently, or not at all.

Most of the large, internationally active banks reviewed by the Task Force assign risk ratings to each large corporate customer. Each large corporate customer, for example, might be placed into one of, say, 10 possible risk rating categories or buckets. In general, the process of arriving at a credit rating for a customer or facility can be described as containing one or more of the following three elements: (a) the traditional "spreading of numbers" in which financial and other characteristics of the customer (e.g. country and business sector code) are incorporated into a relatively subjective approach to determining grades; (b) the use of vendor-supplied commercial credit scoring models; or (c) the use of internally developed credit scoring models. Increasingly, banks are also assigning internal risk ratings, or their equivalent, to small- and middle-market business customers, and even to individual retail customers based on credit scoring models and other information (see below).

Often, a bank will establish a concordance schedule that relates its internal risk rating categories to some external rating standard, such as S&P's or Moody's ratings for corporate bonds. For example, a grade-1 loan may be deemed roughly equivalent to an S&P bond rating from AA to AAA, a grade-2 loan equivalent to a bond rating of single-A, and so on. Under such a scheme, the worst internal grade, say grade-10, would typically correspond to the "***worst state***", termed the "***default***" state. Given this concordance, an EDF can be interpreted as representing a loan's probability of ***migrating*** from its current internal rating grade to default within the credit model's time horizon.

The likelihood of a customer migrating from its current risk rating category to any other category within the time horizon is frequently expressed in terms of a rating ***transition matrix*** similar to that depicted in Exhibit 2. Given the customer's current credit rating (delineated by each row), the probability of migrating to another grade (delineated by the columns) is shown within the intersecting cell. Thus, in the exhibit, the likelihood of a BBB-rated loan migrating to single-B within one year would be 0.32%. Since under the DM paradigm only rating migrations into the default state lead to changes in the values of loans, only the last column of this matrix would be relevant. Within the MTM paradigm (discussed below), however, the other columns of the transition matrix also play a critical role.

Exhibit 2

Sample credit rating transition matrix

(Probability of migrating to another rating within one year as a percentage)

Credit rating one year in the future

		AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**Default**
Current credit rating	AAA	87.74	10.93	0.45	0.63	0.12	0.10	0.02	0.02
	AA	0.84	88.23	7.47	2.16	1.11	0.13	0.05	0.02
	A	0.27	1.59	89.05	7.40	1.48	0.13	0.06	0.03
	BBB	1.84	1.89	5.00	84.21	6.51	0.32	0.16	0.07
	BB	0.08	2.91	3.29	5.53	74.68	8.05	4.14	1.32
	B	0.21	0.36	9.25	8.29	2.31	63.89	10.13	5.58
	CCC	0.06	0.25	1.85	2.06	12.34	24.86	39.97	18.60

Source: Greg M Gupton, Christopher C Finger and Mickey Bhatia, *CreditMetrics – Technical Document*, Morgan Guaranty Trust Co., New York, April 1997, p.76.

Note: The credit rating transition matrix is based on the historical migration frequencies of publicly rated corporate bonds.

C. Mark-to-market paradigm

In contrast to the DM paradigm, within the MTM paradigm a credit loss can arise in response to deterioration in an asset's credit quality short of default. In effect, the MTM paradigm treats the credit portfolio as being marked to market (or, more accurately, marked to model) at the beginning and end of the planning horizon, with the concept of credit loss reflecting the difference between these valuations.

MTM-type models recognise that changes in an asset's creditworthiness, and its potential impact on a bank's financial position, may occur due to events short of default. Hence, in addition to EDFs, these models must also incorporate (through the rating transition matrix described above) the probabilities of credit rating migrations to non-default states. Given the rating transition matrix associated with each customer, Monte Carlo methods are generally used to simulate migration paths for each credit position in the portfolio. For each position, the simulated migration (and the risk premium associated with the instrument's end-of-period rating grade) is used, in effect, to mark the position to market as of the end of the time horizon.

Most MTM-type credit models employ either a ***discounted contractual cash flow (DCCF) approach*** or a ***risk-neutral valuation (RNV) approach*** for purposes of modelling the current and future (mark-to-market) values of credit instruments.

Discounted contractual cash flow approach

The DCCF methodology is commonly associated with J.P. Morgan's CreditMetrics™ framework. The current value of a loan that has not defaulted is represented as the present discounted value of its future contractual cash flows. For a loan having a particular internal risk rating (comparable to, say, BBB), the credit spreads used in discounting the contractual cash flows would equal the market-determined term structure of credit spreads associated with corporate bonds having that same grade. The current value of a loan would be treated as known, while its future value would depend on its uncertain end-of-period risk rating and the term structure of credit spreads associated with that rating. Thus, the value of a loan can change over the time horizon, reflecting either a migration of the borrower to a different risk rating grade or a change in the market-determined term structure of credit spreads. One of the rating grades to which a loan can migrate over the planning horizon is "default". Obviously, the present value of a defaulted loan would not be based on the discounting of contractual cash flows. Rather, as with DM-type models, in the event of default, the future value of a loan (in dollar terms) would be given by its recovery value, equal to one minus the LGD.

Risk-neutral valuation approach

Although it is easily understood and implemented, the DCCF approach is not fully consistent with modern finance theory. Typically, identical discount rates are assigned to all loans to firms having the same internal risk rating or EDF. Consequently, if a firm has not defaulted as of the planning horizon, the future values of its loans do not depend on the expected LGDs of the loans. Senior and subordinated loans to a single firm would have the same future discount price, regardless of differences in expected recovery in the event of future default. Furthermore, finance theory holds that the value of an asset depends on the correlation of its return with that of the market. Under DCCF, however, loans to two identically rated firms receive the same discount rates, even if the two firms are not equally sensitive to the business cycle or to other systematic factors.

To avoid these problems, the RNV approach imposes a structural model of firm value and bankruptcy based on the work of Robert Merton.[7] In this framework, a firm goes into default when the value of its underlying assets falls beneath the level needed to support its debt. Instead of discounting *contractual* payments, the RNV method discounts *contingent* payments: if a payment is contractually due at date *t*, the payment actually received by the lender will be the contractual amount only if the firm has not defaulted by date *t*; the lender receives a portion of the loan's face value equal to 1-LGD if the borrower defaults at date *t*, and the lender receives nothing at date *t* if the borrower has defaulted prior to date *t*. A loan can thus be viewed as a set of derivative contracts on the underlying value of the borrower's assets. The value of the loan equals the sum of the present values of these derivative contracts. The discount rate applied to the contracts' contingent cash flows is determined using the risk-free term structure of interest rates and the risk-neutral pricing measure.

Intuitively, the risk-neutral pricing measure can be thought of as an adjustment to the probabilities of borrower default at each horizon, which incorporates the market risk premium associated with the borrower's default risk. The size of the adjustment depends on the

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[7] The RNV approach is commonly associated with KMV's PortfolioManager™ framework and KPMG's Loan Analysis System™, but has also long been used by market participants to price derivatives.

expected return and volatility of the borrower's asset value. If asset return is modelled consistent with the Capital Asset Pricing Model (CAPM) framework, then the expected return can be expressed in terms of the *market* expected return and the firm's correlation with the market. Thus, consistent with standard finance theory, the pricing of loans under RNV adjusts not only for the EDF and LGD of the borrower, but also for the correlation between borrower risk and systematic risk.

D. Key Issues

Interpretation of default

- In credit risk models, a loan is deemed to be in default once it migrates to a pre defined "worst state". However, the definition of the "worst state" is not precise, and varies between institutions, thus affecting relative measures of default, credit loss and, ultimately, the PDF.8 The comparability of credit loss estimates between different institutions is also affected by the choice of adjustments that banks may incorporate in the measurement of credit loss, such as workout expenses or carrying costs.

Choice of time horizon

- As noted earlier, most banks in the survey measure credit loss over a one-year time horizon. The reasons put forward for this choice generally favour computational convenience rather than model optimisation; furthermore, banks do not appear to test the sensitivity of their model output to the chosen horizon. The reasonableness of this decision rests on whether one year is indeed a period over which either (a) fresh capital can be raised to fully offset portfolio credit losses beyond that horizon, or (b) risk-mitigating actions, such as loan sales or the purchase of credit protection, can be taken to eliminate the possibility of further credit losses. In assessing the capacity of models to meet various risk management and capital allocation needs, the choice of horizon would appear to be an important decision variable.

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[8] Note that the definition of default used in credit risk models is not equivalent to that used for legal purposes. Depending on the particular banking institution, a loan may be deemed to be in "default" if the loan is classified "substandard", if payments are past due, if the loan is placed on non-accrual status, or if recovery proceedings are initiated.

- The ability of a default mode model to capture the effects of potentially adverse credit events, due to the model's "two-state" nature (i.e. default and non-default), may be particularly sensitive to the assumed length of the planning horizon. For example, it is not clear whether a DM-type model with a one-year horizon is capable of accurately representing the riskiness of a portfolio of multi-year term loans. In order to increase the sensitivity of the DM approach to maturity differences among exposures, banks sometimes apply various *ad hoc* adjustments, such as measuring an instrument's EDF over its entire maturity (e.g. measuring a one-year EDF for a one-year loan, a two-year EDF for a two-year loan, and so forth.) A possible concern is that adjustments of this sort may lead to internal inconsistencies within the modelling framework, as multi-year EDFs may be used in combination with loss correlations calculated on the basis, say, of one-year time horizons.

DM versus MTM models

- Both the DM and MTM paradigms attempt to measure losses from adverse changes in credit quality. While various justifications are put forward in support of one paradigm vs. another (e.g. the multi-state nature of a MTM model, the simplicity of a DM type model), the determination of model "superiority" is largely influenced by the fit between model output and model application. For example, an institution that utilises credit risk models for performance measurement purposes associated with a buy-and-hold portfolio might reasonably opt for a (simpler) DM model. In contrast, certain pricing decisions for a portfolio of more liquid credits may require a loss measurement definition that incorporates potential shifts in credit spreads.

Discounted cash flow vs. risk-neutral valuation approaches

- The dichotomy between the DCCF and RNV approaches to pricing may be sharper in theory than in practice. In each methodology, a loan's value is constructed as a discounted present value of its future cash flows. The approaches differ mainly in how the discount factors are calculated. The DCCF method takes a nonparametric approach to estimating these discount factors. Public issuers of debt are grouped into rating categories. Credit spreads on the issuers are then averaged within each "bucket". Alternatively, the RNV method is highly structural – it imposes a model that prices each loan simultaneously in a single unified framework. In practice, the calibration of the market risk premium in the model typically makes use of credit spreads from the debt market.

- Econometric theory shows that highly structural estimators make efficient use of available data but are vulnerable to model misspecification, whereas nonparametric estimators make minimal use of modelling assumptions but perform poorly where data are scant or noisy. The two approaches will, in general, assign different values to any given loan. Nonetheless, if debt markets are reasonably efficient and the assumptions of the RNV model are approximately valid, then the two methods ought to produce similar aggregate values for well-diversified portfolios.

3. Probability Density Functions

A. Measurement

Each model examined aims to quantify a portfolio's credit risk via the concept of a PDF of credit losses over a chosen time horizon. Many models reviewed seek to estimate explicitly the full PDF; statistics such as the mean and standard deviation or a chosen target credit loss quantile can then be calculated readily. Examples of this approach include the vendor models CreditRisk^{+TM}, PortfolioManager^{TM}, CreditPortfolioView^{TM}, and CreditMetrics^{TM} in its Monte Carlo formulation.

Other proprietary and vendor models (including the unexpected losses approach and CreditMetrics^{TM} in its analytical formulation) aim only to generate the first two moments of the distribution, i.e. its mean and standard deviation; the full PDF remains implicit in the model. There seem to be two main reasons for this technique: (a) for purposes of analytical simplicity or computational speed, the model seeks to establish only the mean and standard deviation from the outset; no particular functional form for the PDF is assumed; (b) due to data or computational constraints, the full PDF is available for some but not all sub-portfolios; for the other sub-portfolios, only the means and standard deviations are calculated; consequently, only the mean and standard deviations are calculated for the total portfolio.

A consensus within the industry about a "standard" shape of the PDF has yet to emerge. This stands in contrast with market risk models, where the normal distribution is frequently used as a standard or benchmark. Observed portfolio credit loss distributions are markedly non-normal. They are typically skewed towards large losses, and leptokurtic (i.e. for a given mean and standard deviation, the probability of large losses occurring is greater than would be the case if the distribution were normal). One reason why no industry "standard" portfolio credit loss PDF has emerged is that the modelling of losses from individual credit exposures is more difficult than is the case for market risk, and a wide range of simplifying assumptions is made. Individual losses might be assumed to be binary, or else to follow one of a range of continuous distributions. The portfolio PDF that results from aggregating these individual credit exposure losses will depend strongly upon these assumptions (and upon assumptions made in estimating credit correlations).

B. Key Issues

- The precision with which it is possible to estimate the very high quantiles of distributions used in credit risk models is a key consideration. In discussions with the Task Force, banks indicated a choice of target credit loss quantiles in the range of 99-99.98%, with the majority converging in the middle. This contrasts with the range of target loss quantiles chosen for internal (as opposed to regulatory) purposes in market VaR models, which fell in the range of 95-99%.[9] There are two conceptual reasons which stress the importance of this issue given the higher quantiles used in credit risk: the size of the estimation error, and the impact of the shape of distributional tails.[10] (Another issue is the ability of a particular model to estimate a PDF; this is essentially an empirical question, which is discussed in the validation section.)
- The second consideration is that, owing to the sensitivity of the tail of the PDF to modelling assumptions, alternative assumptions that appear reasonable may nevertheless imply large differences in estimates of very high quantiles.

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[9] Note that due to the long-tailed nature of the distributions of credit risk models, the range of required capital corresponding to choice of a target loss quantile within the 99.0–99.8 interval can be wider than the range corresponding to the 95.0–99.0 interval used in market risk models.

[10] These difficulties are exacerbated by the sensitivity of a PDF's tail to parameter estimates. See Michel Crouhy and Robert Mark, "A Comparative Analysis of Current Credit Risk Models", September 1998.

4. Conditional versus Unconditional Models

A. Definition of approaches

In a sense, all models are conditional:they seek to incorporate some current information about the credit quality of each borrower and credit facility. That being said, it is nevertheless possible to distinguish between ***unconditional*** models that reflect relatively limited borrower- or facility-specific information, and ***conditional*** models that also attempt to incorporate information on the state of the economy, such as levels and trends in domestic and international employment, inflation, stock prices and interest rates, and even indicators of the financial health of particular sectors.

Examples of unconditional credit risk models are the UL approach, CreditMetrics™ and CreditRisk+™. All three modelling frameworks base EDFs and derived correlation effects on relationships between historical defaults and borrower-specific information such as internal risk ratings. The data is estimated over (ideally) many credit cycles. Whatever the point in the credit cycle, these approaches will predict similar values for the standard deviation of losses arising from a portfolio of obligors having similar internal risk ratings. Such models are currently not designed to capture business cycle effects, such as the tendency for internal ratings to improve (deteriorate) more during cyclical upturns (downturns). Note, however, that this does not assert that the models will predict the same standard deviation of portfolio losses for an unchanging set of obligors throughout a cycle. As obligors are upgraded and downgraded, their expected default rates will be revised downwards or upwards.

One example of a conditional credit risk model is McKinsey and Company's CreditPortfolioView™. Within its modelling framework, rating transition matrices are functionally related to the state of the economy, as the matrices are modified to give an increased likelihood of an upgrade (and decreased likelihood of a downgrade) during an upswing (downswing) in a credit cycle. This qualitative phenomenon accords with intuition and is borne out by some research. Other vendors follow different conditional approaches. In KMV's PortfolioManager™, for example, the estimates of asset values, rates of return and volatility are based, in part, on current equity prices, which are inherently forward-looking.

B. Key Issues

- Most credit risk models implemented to date reflect actuarial-based unconditional estimates of EDFs/rating transitions and correlations that are designed to capture long-run average values of these parameters. At a given point in time, however, such long-run averages may seriously misrepresent the short-term outlook, which may well be highly dependent on the state of the economy.[11] Both EDFs and correlations are likely to vary systematically with the course of the business cycle. In contrast to actuarial-based unconditional models, a conditional model of the type set out above incorporates in its formulation the possibility that the holding period interval may be a period of high expected default. Additionally, unconditional approaches to estimating EDFs will not reflect important variables known to affect loan performance. On the other hand, conditional techniques may also have drawbacks; for example, a conditional model may underestimate losses just as the credit cycle enters a downturn and overestimate losses just as the cycle bottoms out. Further, a full reflection of business cycle effects is a complex and difficult process, raising the possibility that parameter estimates may be subject to considerable uncertainty.

- Ultimately, the question of whether unconditional or conditional approaches to credit risk modelling offer a bank the best prospects for model stability and reliability is an empirical one.

5. Approaches to Credit Risk Aggregation

A. Top-down and bottom-up approaches

Within most credit risk models, broadly the same conceptual framework is used in modelling individual-level credit risk for different product lines; differences in implementation arise primarily in the ways the underlying parameters are estimated using available data (see Part III for a discussion of parameter estimation). For most of the banks surveyed, credit risk is measured at the individual asset level for corporate and capital market instruments (a so-called *"**bottom-up" approach***), while aggregate data is used for quantifying risk in consumer, credit card or other retail portfolios (a so-called ***"top-down" approach***). However, while the literature on credit risk models tends to make a distinction between these

[11] See Pamela Nickell, William Perraudin and Simone Varotto, "Stability of Ratings Transitions", September 1998. This study identifies and quantifies (using Moody's ratings histories) various factors, such as domicile and industry of obligor, which influence rating transitions probabilities. The study also demonstrates, using ordered probit models, that estimates of transition matrices can be improved by conditioning on the stage of the business cycle.

two approaches, the differences are less clear-cut in practice. For example, different models may be classified as "bottom-up" given their use of borrower-specific information to "slot" loans into buckets, even though underlying parameters may be calibrated using aggregate data.

Models adopting a bottom-up approach attempt to measure credit risk at the level of each loan based on an explicit evaluation of the creditworthiness of the portfolio's constituent debtors. Each specific position in the portfolio is associated with a particular risk rating,[12] which is typically treated as a proxy for its EDF and/or probability of rating migration. These models could also utilise a micro approach in estimating each instrument's LGD. The data is then aggregated to the portfolio level taking into account diversification effects.

For retail customers, the modelling process is conceptually similar; however, due to the sheer number of exposures, models tend to adopt a more top-down empirical approach. In this instance, loans with similar risk profiles, such as credit scores, age and geographical location, are aggregated into buckets, and credit risk is quantified at the level of these buckets. Loans within each bucket are treated as statistically identical. In estimating the distribution of credit losses, the model-builder would attempt to model both the (annual) aggregate default rate and the LGD rate using historical time-series data for that risk segment taken as a whole, rather than by arriving at this average through the joint consideration of default and migration risk factors for each individual loan in the pool.

B. Key Issues

- As noted above, the distinction between top-down and bottom-up models is typically not precise; the key consideration is the degree to which a bank can distinguish meaningfully between borrower classes. Even in so-called bottom-up models, banks frequently rely on aggregate data to estimate individual borrower parameters; an example is the practice of mapping individual borrower ratings (a bottom-up methodology) to a transition matrix calculated from pooled data, whether published by rating agencies or calculated from internal statistics (an average of aggregate top-down data). Also of key importance is the accuracy of aggregate data, and its comparability to a bank's actual portfolio; if these two

[12] For simplification, the assumption made throughout the report is that ratings are associated with borrowers. In practice, however, the rating process is more complex, and a rating may be associated with each specific facility belonging to a borrower. See Part III for additional detail.

standards are not met, the use of aggregate data can potentially disguise idiosyncratic loan-specific effects to which a bank is exposed.

6. Correlations between Credit Events

A. Overview

While no bank with a diversified portfolio would expect all – or even nearly all – of its obligors to default at once, experience shows that the factors affecting the creditworthiness of obligors sometimes behave in a related manner. Consequently, in measuring credit risk, the calculation of a measure of the dispersion of credit risk (i.e. its standard deviation, or indeed the full PDF) requires consideration of the dependencies between the factors determining credit-related losses, such as correlations among defaults or rating migrations, LGDs and exposures, both for the same borrower and among different borrowers.[13] Various models achieve this in very different ways, and authors have sought to draw comparisons and contrasts between the methodologies.[14]

B. Cross-Correlations between Different types of Credit Events

At least in theory, across different bank customers, one might expect to observe significant correlations among (a) default events/rating migrations, (b) LGDs and (c) exposures. For example, the financial condition of firms in the same industry or within the same country may reflect similar factors, and so may improve or deteriorate in a correlated fashion. Similarly, for firms within the same industry, LGDs, as well as exposures due to drawdowns of credit lines, may tend to increase (decrease) relative to their long-run averages in periods when the average condition of firms in that sector is deteriorating (improving).[15]

While banks tend to be well aware of these potential relationships, their ability to model such correlations is often limited in practice. In general, owing to data limitations, credit risk models do not attempt to explicitly model correlations between different types of risk factors.

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[13] This treatment stands in contrast to calculation of the *expected loss* for a portfolio, which is simply equal to the sum of the expected losses for the separate obligors**.**

[14] See for example Crouhy and Mark .

[15] In principle, within MTM-type models, correlations among credit spread term structures, and between credit spreads and defaults/rating migrations, LGDs, and exposure levels would also be relevant. As discussed below, however, virtually all applications of MTM models treat the term structure of credit spreads as fixed and known over the time horizon, thus abstracting from such correlation effects.

Specifically, correlations between defaults/rating migrations and LGDs, between defaults/rating migrations and exposures and between LGDs and exposures are typically assumed to equal zero. According to the Task Force's findings in virtually all credit risk models the only correlation effects considered at present are the correlations between defaults/rating migrations of different customers. Broadly, banks have adopted either a ***structural approach*** or a ***reduced-form approach*** for handling default/rating migration correlations.

C. Correlations among defaults or rating migrations

Structural models

As exemplified by the CreditMetrics™ and PortfolioManager™ modelling frameworks, under the structural approach the model-builder would typically posit some explicit microeconomic model of the process determining defaults or rating migrations of individual customers. A customer might be assumed to default if the underlying value of its assets falls below some threshold, such as the level of the customer's liabilities. Within the MTM framework, the change in the value of a customer's assets in relation to various thresholds is often assumed to determine the change in its risk rating over the planning horizon. For example, given a customer's current risk rating (say, equivalent to BBB), an extremely large positive change to its net worth (appropriately scaled) might correspond to an upgrade to AAA, while an extremely large negative realisation might generate a downgrade to default, etc.

In general, the random variable assumed to determine the change in a customer's risk rating, including default (e.g. customer asset value or net worth) is called the ***migration risk factor***. Thus, within structural models, it is the correlations between migration risk factors (across borrowers) that must be specified (estimated or assumed) by the model-builder. In turn, these correlations between migration risk factors determine, implicitly, the correlations among borrowers' defaults or rating migrations.

Reduced-Form Models

Examples of the reduced-form approach are the CreditRisk^{+}™ and CreditPortfolioView™ credit risk modelling frameworks. In contrast to structural models, which assume a specific microeconomic process generating customers' defaults and rating migrations, reduced-form models typically assume a particular functional relationship between customers' expected default rate/migration matrix (or a sub-portfolio's expected default rate) and so-called ***background factors***.[16] These background factors may represent either (a) observable variables, such as indicators of macroeconomic activity, or (b) unobservable random risk factors. Within reduced-form models, it is the dependence of the financial condition of individual customers on common or correlated background factors that gives rise to correlations among customers' default rates and rating migrations.

D. Key Issues

- Although the above discussion may suggest that the structural and reduced-form approaches are based on irreconcilable views of the world, recent literature on the subject suggests they are not.[17] It is ultimately an empirical issue whether one approach performs better or worse in specific circumstances.
- The assumptions and approximations used in estimating default correlations highlight various conceptual and empirical questions, including: (a) whether the choice of risk factor distribution functions, e.g. normality or gamma, makes a material difference to model output; (b) whether the technical approximations introduced have a material impact; and (c) whether the default correlations generated by the different models are within the same range, result in a correct correlation structure, and are stable over the planning period.

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[16] Conditional on the values of these background factors, reduced-form models typically assume independence among the defaults and rating migrations of different customers.

[17] Recent studies argue that there is good agreement between the CreditMetrics™ and CreditRisk+™ PDFs, at least in the region above two standard deviations from the mean. See for example Koyluoglu, H. Ugur and Andrew Hickman, "A Generalised Framework for Credit Risk Portfolio Models", draft, September 1998, and Michael Gordy, "A Comparative Anatomy of Credit Risk Models", Board of Governors of the Federal Reserve System, December 1998.

PART III: PARAMETER SPECIFICATION AND ESTIMATION

There are four main types of credit events which may contribute to the level of credit losses in credit risk models: (1) a change in LGD; (2) a change in creditworthiness (reflected in a credit rating migration or a change in EDF) over the planning horizon; (3) a change in the applicable credit spread for MTM models; and (4) a change in a bank's exposure with respect to a particular credit facility.

Credit risk models tend to be modular – involving completely separate sub-models for each of these four credit events. This treatment follows market practice: while correlations *between obligors* due to credit events are introduced in various ways (see the previous section), most models assume zero correlation *between credit events* of different types, although such correlations may in fact be significant; for example, defaults are assumed to be uncorrelated with LGDs, changes in spreads and exposures. Given this assumption, the sub-models for each credit event generally do not interact with one another. Below, we discuss various modelling issues pertaining to each sub-model type. The Task Force encourages additional study by the industry to assess the materiality of these issues and the effects of the various estimation methods on model output.[18]

1. LGDs (loss rate given defaults)

The availability of historical loss data typically dictates the degree of complexity and the choice of methodology in modelling LGDs. Parameters may be estimated from data on the historical performance of individual loans or corporate bonds (common for wholesale credits), or from aggregate time-series data for pools of loans (common for consumer credits).

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[18] Practitioners have observed that measurement of credit risk in a portfolio typically depends more on the quality of model inputs than on details of the modelling approach. As a rule, model outputs are most sensitive to assigned EDFs, expected LGDs and default correlations. Most important is that these model inputs be unbiased estimates of their true values. Consider first a static portfolio of non-traded instruments. Say, for example, that a particular rating grade is associated with EDFs ranging from 8 to 16 basis points, and that the user inputs a single average EDF of 12 basis points for all borrowers of this grade. Even though the assigned EDF may significantly overstate or understate a given borrower's true default likelihood, the individual errors will tend to wash out at the aggregate portfolio level. Much more damaging is a systematic error. Under some rating schemes, an average EDF over the business cycle may systematically overstate or understate a grade's true conditional EDF at a particular point in time. Similarly, poorly constructed factor models may miss significant components of systematic risk, and thereby systematically bias downwards the input default correlations. These types of errors can cause required capital to be substantially underestimated.

A. Modelling assumptions

Within the current generation of credit risk models, LGDs are usually assumed to depend on a limited set of variables characterising the structure of a particular credit facility. These variables may include the type of product (e.g. business loan or credit card loan), its seniority, collateral and country of origination. For a given credit exposure, the values of these facility variables would determine the credit facility's *expected* LGD.[19]

In some models, LGDs may be treated as deterministic and known in advance, while in others they may be treated as random. In the latter case, for a given set of facility characteristics, the random components of LGDs are usually assumed to be identically distributed over time and across all borrowers. The probability distribution for each LGD is sometimes assumed to take a specific parametric form, such as that of a beta distribution.

Models generally assume zero correlation among the LGDs of different borrowers, and hence no systematic risk due to LGD volatility. Furthermore, it is common to assume independence among LGDs associated with the *same* borrower. As noted above, model-builders also generally assume that LGDs are independent of the other three types of credit events (e.g. the LGD associated with the default of a firm in a particular sector would be independent of the degree to which other firms in that sector were defaulting or being downgraded).

B. Estimation

For a given set of facility characteristics, the underlying parameters of the probability distribution for LGDs are generally inferred by pooling information from several sources, including: (a) internal data on the bank's own historical LGDs, by risk segment, when available; (b) loss data from trade association reports and publicly available regulatory reports; (c) consultants' proprietary data on client LGDs; (d) published rating agency data on the historical LGDs of corporate bonds; and (f) the intuitive judgements of experienced lending officers.

[19] Within the group of banks surveyed, obligors' internal risk ratings are typically combined with facility-specific LGDs that reflect seniority, collateral and other obligor characteristics. Most banks use broad facility ratings as an approximation of expected loss. However, a few institutions appear to incorrectly adjust for seniority in both ratings and LGDs.

The sophistication of estimation methods varies considerably across banks.[20] The weights associated with each source also differ greatly. While some banks appear to rely almost exclusively on LGD parameters set intuitively, other institutions with access to large amounts of historical data may rely heavily on objective empirical analysis. Even in the latter case, however, data limitations and other issues generally imply that the LGD parameters, to some degree, reflect the pooling of quantitative information from several sources and subjective judgement.

C. Key Issues

- The reliability of pooled LGD data is a key consideration, as it will affect the accuracy of estimation results. This issue is particularly important for international exposures and institutions: in setting parameters for corporate customers, even those located outside the United States, some banks appear to rely almost entirely on historical loss studies for publicly rated US corporate bonds. Extrapolating these results to other countries may be problematic, owing to differences in bankruptcy laws and workout practices.
- For portfolios characterised by distributions of exposure sizes that are highly skewed, the assumption that LGDs are known with certainty may tend to bias downwards the estimated tail of the PDF of credit losses.
- More problematically, the assumption that LGDs between borrowers are mutually independent may represent a serious shortcoming when the bank has significant industry concentrations of credits (e.g. commercial real estate loans within the same geographical region). Furthermore, the independence assumption is clearly false with respect to LGDs associated with similar (or equally ranked) facilities to the same borrower.

[20] This is particularly the case for complex financial instruments supporting securitisation activities. For example, it is not uncommon for banks to assume that the LGD for a subordinated loan functioning as a credit enhancement for a pool of securitised assets would be comparable to the LGD of a corporate loan secured by similar assets. In the event of default, however, the subordinated loan will tend to exhibit a much greater expected loss rate and loss rate volatility than would the senior corporate loan. This is because the former is typically thinly traded, and will, by design, generally absorb a disproportionately larger share of the credit losses on the underlying asset pool.

- The assumption of independence of default intensities may contribute to an understatement of losses to the extent that LGDs associated with borrowers in a particular industry may increase when the industry as a whole is under stress.
- The sample periods for estimating LGDs are often relatively short.

2. Defaults/Rating Migrations

Credit risk models generally relate the process determining customer defaults or rating migrations to two types of parameters: (1) for each customer, the EDF or rating transition matrix, and (2) across customers, the correlations among defaults and rating migrations. Procedures for estimating these parameters are described below.

A. Estimation of EDFs/rating transition matrices

Two methods are generally used for mapping observable data historically into customer-specific EDFs/transition matrices: ***actuarial-based methods*** and ***equity-based methods***.

Actuarial-based approaches

Actuarial-based methods are used to calibrate EDFs or rating transition matrices in both structural and reduced-form models. The basic approach involves using historical data on the default rates of borrowers to predict the expected default rates/rating migrations for customers having similar characteristics.[21] One such approach utilises formal credit scoring models to predict corporate and/or retail customer EDFs. While some banks have developed their own in-house credit scoring models for corporate and/or retail customers, others purchase credit scores from external vendors. For corporate customers, historical data for developing internal credit scoring models are generally based either on the bank's own historical data on loan performance (relatively rare), or on the historical default experience within the corporate bond market. Techniques for estimating borrower default models are well researched within the economics literature; data availability tends to be the critical limiting factor.

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[21] In the case of structural credit risk models, EDFs and/or rating transition matrices and default correlations are *not* the actual parameters used in specifying the model. Rather, the actual parameters represent the means, variances and correlations associated with the underlying *migration risk factors*. However, in general, there is a one-to-one mapping between the two sets of parameters and, in practice, actuarial-based methods calibrate the latter by "reverse-engineering" them from the former. (See Gupton et al., op.cit., p.92.) Likewise, in reduced-form models, the underlying model parameters are typically calibrated to be consistent with assumed or estimated EDF/transition matrices and default correlations for individual assets or pools of assets.

A second actuarial approach (referred to herein as "***risk segmentation***") involves grouping borrowers into discrete "buckets" or "risk segments" based on observable characteristics. Within any risk segment, all borrowers, and the stochastic properties of their underlying migration risk factors, are assumed to be statistically identical. Thus, all customers in the same risk segment would be assumed to have the same EDF/transition matrix. For large corporate borrowers, risk segments are typically defined on the basis of factors such as the borrower's internal credit rating, size, country and industrial sector. For retail customers, risk segmentation would normally be based on the product category (e.g. credit cards or residential mortgages) and borrower-specific information, such as credit score (if available), country and state/province. Given the assumption that all borrowers within a segment have the same EDF and/or rating transition matrix, the model-builder would attempt to estimate these parameters from average historical default and/or rating migration data of borrowers in that segment. In practice, however, data availability may severely limit the length of time over which such an average can be calculated, especially if the risk segments are defined very narrowly.

Equity-based approach

This approach, most often associated with the Merton model, is used exclusively for estimating the EDFs of large and middle-market business customers (within structural models), and is often used to cross-check estimates generated by actuarial-based methods. This technique uses publicly available information on a firm's liabilities, the historical and current market value of its equity and the historical volatility of its equity to estimate the level, rate of change and volatility (at an annual rate) of the economic value of the firm's assets. Under the assumption that default occurs when the value of a firm's assets falls below its liabilities, expected default probabilities can be inferred from the option models. Alternatively, using an approach pioneered by KMV Corporation, it is possible to calculate the number of standard deviations the current asset value is away from the default threshold, termed the "***distance to default***." Given a firm's estimated distance to default, its EDF is calculated as the historical default frequency for firms having the same distance to default, derived from a proprietary KMV database on the historical default experience of publicly rated businesses.

B. Key Issues

- In estimating EDFs for retail customers, banks typically rely on internal historical data, supplemented with publicly available loss or default rate information from other lenders or consultants. When using such supplemental information, the model-builder must usually determine judgementally whether the underlying population to which these data apply is similar to the risk segment under study; if not, the model-builder will often attempt to make the data more comparable through subjective adjustments. It is sometimes the case that, for a particular risk segment, historical data are available for loss rates but not for default rates. In this event, model-builders may attempt to infer the historical default rates from the loss rate data by making assumptions regarding the historical LGDs.[22] Furthermore, the degree to which banks rely on empirical data (such as financial statement analysis) in assigning particular credits to risk segments – corresponding to the credit's main industry, or location of revenue – varies greatly. Typically, the process involves a high degree of subjectivity.

- Data availability generally dictates the methods used to estimate EDFs/transition matrices. With regard to large corporate customers, at most banks internal credit ratings are a key variable – or in some cases the sole criterion – for assigning borrowers to risk segments. However, most banks have retained historical aggregate performance data by broad loan types or lines of business, but not by risk grade. Furthermore, while banks with internal economic capital allocation systems have generally been warehousing performance data by risk grade, such databases generally go back only a few years, at best. In addition, some banks do not re-evaluate the assignment of exposures to particular risk segments in a timely or consistent manner.
- Since banks typically have comparatively little useful default/migration data internally, they often attempt to estimate EDFs/transition matrices using historical performance studies published by the rating agencies and, sometimes, other researchers. Such studies often report historical default, loss and rating migration experience, by rating category, over time spans covering 20 or more years. However, in some cases, the geographical and industry composition of these published data may not be appropriate to the characteristics of the loan portfolio being modelled. (For example, published rating agency data are often dominated

[22] For example, a bank may rely on aggregate data on loss rates, and make an assumption on the typical LGD associated with a given portfolio. If the LGD is assumed to be fixed, the default rate is given by the loss rate divided by the LGD.

by US experience.) Using inappropriate transition matrices will result in incorrect assessments of credit risk.[23] Where possible, the migration data for corporate bonds are sometimes adjusted judgementally to incorporate either information from a bank's own internal loan performance databases, or analysis of historical migrations at peer institutions.

- To use bond experience data, a bank must first develop or assume some correspondence between its internal rating categories and the grading systems used by the rating agencies. Such correspondences are commonly developed using four basic methods, either singly or in combination. The first method involves matching historical default frequencies within each internal rating grade to the default frequencies, by rating category, reported by the agencies. The second method compares a bank's own internal grades with those of the rating agencies for borrowers that are rated by both. However, such comparisons may not be possible for major segments of the portfolio, such as middle-market customers, or non-US business firms. The third approach attempts to expand the population of firms for which such comparisons are possible by constructing pseudo-credit agency ratings for firms not formally rated by the agencies. This is accomplished by estimating the relationship between agency ratings and financial and other characteristics of firms using publicly available data for agency-rated firms. Lastly, the fourth approach involves subjective comparison of the bank's criteria for assigning internal grades with the rating agencies' published rating criteria.

3. Correlations among Defaults and/or Rating Transitions

A. Estimation

Within both structural and reduced-form models, the interdependence between defaults and/or rating transitions is a key determinant of a portfolio's PDF. Structural models parametrise this interdependence in terms of the correlations among customers' migration risk factors, which are often interpreted as being represented by customers' asset values or net

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[23] See Pamela Nickell, William Perraudin and Simone Varotto, "Stability of Ratings Transitions", September 1998. This study examines Moody's ratings histories over a 27-year period, indicating the influence of shifts in geographical and industrial composition of the data set upon published "average" transition matrices, and develops an ordered probit technique for deriving transition matrices which are appropriate to the characteristics of the credit exposures in the portfolio (e.g. industry and domicile of obligor, and stage of business cycle).

worth positions. In the context of reduced-form models, the interdependence between customers' defaults/rating migrations reflects the assumed or estimated processes relating observable and unobservable background factors to EDFs or rating transition matrices. The effects of interdependence may be modelled at the level of either individual credit exposures (common for middle-market and large corporate customers) or pools of relatively homogeneous exposures (common for retail portfolios).

While some banks appear to set correlations among migration risk factors largely through a judgmental process, most banks appear to use approaches that, while retaining some subjectivity, rely heavily on empirical analysis. Among the banks interviewed by the Task Force, empirical approaches to calibrating models' correlation parameters tend to be actuarial-based or equity-based; sometimes both types of approach are used to cross-check one another.

Actuarial-based method

The first approach is an extension of the risk segmentation approach to estimating EDFs/transition matrices (discussed above), and is used in calibrating correlation parameters in both structural and reduced-form models. Within each risk segment, borrowers are assumed to be statistically identical. Given the EDF for a particular risk segment, mathematically there is a one-to-one relationship between the variance of the risk segment's default rate and the correlation of the migration risk factors associated with the loans in that risk segment.[24] Thus, an estimate of the default correlation among the loans is often reverse-engineered from an estimate of the historical variability of the risk segment's aggregate default rate.[25] A broadly similar reverse engineering method can be used to infer migration risk factor correlations between borrowers in different risk segments from the historical covariance between the aggregate (annual) default rates for those risk segments.

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[24] This result requires that the overall default rate for the loans within the risk segment be serially uncorrelated from one year to the next (assuming the modelling horizon for migrations is one year).

[25] This procedure involves a two-stage process. In the first stage, the means, variances and covariances of aggregate default rates are used to estimate *default* correlations between loans of various types. (For loans within the same bucket, this technique is illustrated in Gupton et al., op.cit., Appendix F: Inferring Default Correlations from Default Volatilities.) In the second stage, correlations between migration risk factors are inferred from the *default* correlations generated in the first step. The relationship between default correlations and migration risk factor correlations is developed in Chunsheng Zhou, "Default Correlation: An Analytical Result," Board of Governors of the Federal Reserve System, May 1997. See also Gordy .

Equity-based method

This methodology, used solely within structural models, is based on Merton's model of firm equity values, and assumes that the underlying migration risk factor for each borrower equals the underlying value of the firm's assets. In principle, therefore, an estimate of this correlation can be calculated from estimates of firms' historical asset values, as inferred from historical equity prices using the Merton model. In practice, however, some vendors have observed that such estimates tend to be quite unstable. To mitigate this problem, KMV econometrically averages the asset value correlations across the customers within various risk segments, defined in terms of the borrower's industry and country, and possibly other characteristics.[26]

B. Key Issues

- Specification of the process of defaults/rating migrations is severely constrained by a lack of data on the historical performance of loans. Reflecting the longer-term nature of credit cycles, even in the best of circumstances – assuming no model mis specifications or parameter instability – many years of data, spanning multiple credit cycles, would be needed to precisely estimate EDFs/rating transitions and correlation parameters. At most banks, however, data on historical loan experience tends to cover only a few years, at best.
- To make the estimation process manageable, model-builders tend to invoke many critical simplifying assumptions. These often include the following: (a) joint normality or other parametric assumptions on the probability distributions of the migration risk factors; (b) cross-independence between migration risk factors and LGDs, credit spreads and exposures; (c) the assumption that borrowers within pre defined risk segments are statistically identical; (d) the assumption that within risk segments, default and rating migration frequencies are independent from one year to the next; and (e) stability of model parameters.
- To an unknown degree, estimation of the extreme tail of a credit portfolio's PDF (the focus of credit risk models) may be quite sensitive to these assumptions. In practice there is generally little analysis supporting the assumptions. Nor is it

[26] More rigorously, it is assumed that firms' asset values conform to a linear variance-components or factor model.

standard practice to conduct sensitivity testing of a model's vulnerability to key parameters or assumptions. Moreover, when estimating credit risk, practitioners generally presume that all parameters and assumptions are known with certainty, thus ignoring credit risk issues arising from parameter and model uncertainty and/or instability.[27]

- Actuarial-based parameter estimates are inherently backward-looking, while in theory, the equity-based approaches are forward-looking. However, many of the assumptions underlying the equity model appear stylistic. These include the belief that: (a) all equity price movements reflect changes in the underlying economic values of firms, rather than any changes in the market price of equity risk; and (b) equity prices fully reflect all available information – this efficient market assumption may be particularly questionable in countries without strong public disclosure policies. Ultimately, the relative accuracy of actuarial-based versus equity-based methods is an empirical issue.

- Outside the United States, there is less historical data on corporate bond performance for use in calibrating EDFs and correlations. Historical data on loan performance is even less readily available. Use of US data for obligors in other countries is likely to be highly problematic, owing to differences in bankruptcy laws and banking practices. Furthermore, even within the United States, there are reasons to suspect that publicly rated corporate bonds may exhibit lower EDFs and different correlation patterns than, for example, loans to middle-market borrowers, which tend to be smaller and less diversified.

[27] Accounting for uncertainty in parameter estimates can significantly increase measured credit risk. See Gregory R Duffee, "On Measuring Credit Risks of Derivative Instruments," *Journal of Banking and Finance*, 20, pp. 805-833 (1996).

4. Credit Spreads

A. Overview

This area appears to be at an early stage of development. Most users of MTM models appear to treat the term structures of the credit spreads as fixed and known for purposes of credit risk modelling.[28]

B. Key Issues

- It is difficult to obtain reliable credit spread data, even for more developed markets. Spreads between the yield of an obligation and that of a risk-free bond do not typically correct for differences in liquidity. At the time of writing, the Task Force is unaware of any study that evaluates the potential sensitivity of PDF estimates to the assumption that spreads are fixed and known under the MTM approach.

5. Exposure Levels

A. Overview

For many types of credit instruments, a bank's exposure is not known with certainty, but rather may depend on the occurrence of future random events. One example of such "***credit-related optionality***" is a committed line of credit where, for a fixed period of time, a bank agrees to advance funds, up to a predefined limit, at the customer's discretion. An observed characteristic of such lines is that a customer's drawdown rate tends to increase as the customer's credit quality deteriorates, reflecting the reduced availability or higher costs of alternative sources of funding.[29]

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[28] Some studies have begun to question the efficiency of bond markets, and hence the utility of estimates of default probabilities based on the term structure of credit spreads. See also the preceding discussion on issues related to modelling correlations of defaults/rating migrations.

[29] A second example is a derivative transaction, where a bank's counterparty credit risk will typically vary randomly over the life of the contract, reflecting changes in the amount by which the contract is "in the money." A further example of credit-related optionality, relevant in an MTM setting, is a change in a facility's terms due to changes in a customer's financial condition. Under "grid pricing", for example, credit spreads are reset periodically based on changes in the underlying customer's credit rating or other indicators of financial condition. Similarly, prepayment options embedded in loans may generate credit-related optionality, since customers experiencing rating upgrades may tend to exercise the prepayment option in order to refinance at lower credit risk spreads, whereas customers experiencing downgrades will not.

The credit-related optionality associated with a line of credit is usually represented by treating the drawdown rate as a known function of the customer's *end-of-period* credit rating. To illustrate, consider a one-year line of credit that is, initially, completely undrawn. Conditional on the customer's credit grade at the *end* of the planning horizon, the assumed end-of-period drawdown rate would be based on the average historical drawdown experience of customers having that future grade.

In the DM framework, since only two future credit "ratings" are relevant – default and non-default – a somewhat simpler approach is often employed. In effect, the undrawn credit facility is converted into a loan equivalent exposure (LEE) to make it comparable to a term loan. Ideally, the LEE would be calculated as the expected drawdown under the line in the event that the customer were to become insolvent by the end of the period.[30] (Note that if the customer remains solvent, the size of the drawdown is irrelevant in DM models, since credit losses would equal zero.)

B. Key Issues

- Methods for dealing with credit-related optionality are still evolving. The Task Force observed great diversity in practice. For example, with respect to committed lines of credit, some banks implicitly assume that future drawdown rates are *independent* of future changes in the customer's credit quality. Such assumptions may lead to systematic underestimates of the LEEs for lines of credit that, in turn, lead to underestimates of the credit risks associated with such instruments.
- Issues also arise in the treatment of credit-related optionality in derivative contracts. Given current technologies, it is very difficult to conduct simultaneous Monte Carlo simulations of both the credit risk model and the bank's VaR model(s), which could be used to simulate random changes in the contract's mark-to-market value over its lifetime. Thus, optionality is generally incorporated into credit risk models by associating with each derivative instrument a non-random LEE, which equals the instrument's current mark-to-market value plus an add-on for future exposure. Methods for calculating this add-on vary greatly in terms of sophistication. Some banks set these add-ons to zero, effectively ignoring

[30] For a plain vanilla term loan, the LEE would equal the amount of the loan.

potential future exposures, while at other institutions they reflect in some way the historical price volatility of the underlying reference asset. [31]

- Within most credit risk models, model-builders assume that any unexpected future change in the bank's exposure with respect to a given OTC derivative contract is independent of both (a) changes in all other OTC contracts and (b) changes in the credit quality of the bank's counterparty. Both assumptions may bias the output of credit risk models. For example, counterparty credit risk exposures may be positively correlated across contracts (e.g. a bank having a large positive exposure with respect to oil futures contracts could expect a significant change in oil prices to move these contracts into or out of the money together). Similarly, in certain contracts, the extent to which a bank is "in the money" may be negatively correlated with changes in the credit quality of its counterparty.[32]

6. Implementation: Data Gathering and System Capabilities

A. Data availability and system capabilities

An extensive historical picture is required to build an accurate credit risk model given the infrequency of default events. As such, it is important that model parameters are updated in a timely manner in order to capture all current available information. Due to data limitations, however, in practice parameter re-estimation occurs on a somewhat infrequent basis, ranging from monthly to yearly; some banks have only just begun to systematically collect the necessary data. The modelling of portfolio credit risk also requires considerable systems capabilities; in some cases, collecting the data needed takes several weeks.

The degree of difficulty faced by institutions in culling required data was in part contingent on the methodology of the chosen model. For example, models which use actuarial-based methods and rely on the correlation structure between industries to introduce

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[31] For example, at some banks the add-on is such that the implied LEE generates a standard deviation of credit losses for that facility (on a stand-alone basis) that is identical to that obtained by a VaR-type model in which both the borrower's default and the contract's mark-to-market value are jointly simulated (through Monte Carlo simulation).

[32] Such transactions are termed "wrong-way" derivative contracts. To illustrate, consider an interest rate swap (with a cyclically sensitive counterparty) where the bank pays a floating rate and receives a fixed rate. A large negative macro economic shock might tend to generate a mark-to-market gain on the derivative position (as short-term interest rates fall in the economy), while at the same time tending to lower the counterparty's credit quality.

dependence between obligors may be limited in the frequency with which new data becomes available, while those using equity-based estimation methods may be updated in a more timely manner.

B. Key Issues

- As noted above, the time commitment needed to run the models varies according to the chosen methodology. Models that attempt to approximate the PDF analytically may be executed in minutes. However, many of the models reviewed use Monte Carlo simulation to characterise the full distribution of portfolio losses. Given the number of sources of variability and the number of positions to be estimated, this process can be computationally burdensome and can take several days or longer. Therefore many banks are unable to explicitly estimate the portfolio PDF, and instead adopt various simplifying assumptions which permit an analytical approximation of the distribution, perhaps at the cost of including certain sources of variability. Banks in the future may be able to solve computational problems to some extent by fine-tuning the simulation algorithms actually used, and introducing more efficient programming techniques.
- Other institutions estimate the PDF of credit losses at a point in time, and presuppose that the composition of the portfolio will remain static over a given interval. In such instances, PDFs are subsequently re-estimated relatively infrequently, from weekly to yearly. In extreme cases, the initial PDF has never been updated. In determining the optimal frequency of PDF re-estimation, the speed and magnitude of change in the composition of a given bank's credit portfolio appears to be key factor which should be considered.

PART IV: VALIDATION

1. Summary of Validation Policies and Issues

The components of model validation can be grouped into four broad categories: (a) backtesting, or verifying that the *ex-ante* estimation of expected and unexpected losses is consistent with *ex-pos*t experience; (b) stress testing, or analysing the results of model output given various economic scenarios; (c) assessing the sensitivity of credit risk estimates to underlying parameters and assumptions; and (d) ensuring the existence of independent review and oversight of a model. At present, few banks possess processes that both span the range of validation efforts listed and address all elements of model uncertainty. This suggests that the area of validation will prove to be a key challenge for banking institutions in the foreseeable future.

A. Differences in credit versus market risk models

The Market Risk Amendment outlined both qualitative and quantitative standards for the use of models in assessing regulatory capital requirements. In reviewing the applicability of such requirements to the credit risk arena, it appears that qualitative standards – such as management oversight – will play a similarly important role in assessing the accuracy of credit risk models. However, the application of quantitative standards to credit risk models is likely to pose a key challenge.

B. Key Issues

- 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; hence, the predictive nature of a credit risk model does not derive from a statistical projection of future prices based on comprehensive historical experience. 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. Thus, 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 modelled credit risk estimates are inaccurate – underscores the need for a better understanding of a model's sensitivity to structural assumptions and parameter estimates.

- The validation of credit risk models is also fundamentally more difficult than the backtesting of market risk models. Where market risk models typically employ a horizon of a few days, credit risk models generally rely on a time frame of one year or more. The longer holding period, coupled with the higher target loss quantiles used in credit risk models, presents problems to model-builders in assessing the accuracy of their models. 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.
- At most institutions, the relative size of the banking book and the length of the relevant planning horizon are much greater than those of the trading account. Hence, errors in measuring credit risk are more likely to affect the assessment of the bank's overall soundness. Moreover, it is more likely that significant losses can accumulate unnoticed in the banking book, as it is not marked to market.

2. Backtesting

A. Overview

The methodology applied to backtesting market risk VaR models is not easily transferable to credit risk models due to the data constraints noted above.[33] The Market Risk Amendment requires a minimum of 250 trading days of forecasts and realised losses. A similar standard for credit risk models would require an impractical number of years of data given the models' longer time horizons.

B. Key Issues

- Given the limited availability of data for out-of-sample testing, backtesting estimates of unexpected credit loss is certain to be problematic in practice. This was reflected in the responses to the Task Force survey: none of the participating banks indicated that a formal backtesting programme for validating estimates of credit risk – or *unexpected* loss – was operational. Where analyses of exante estimates and expost experience are made, banks typically compare estimated credit risk losses to a historical series of actual credit losses captured over some

[33] The term "backtesting" is used in a broader sense in the context of credit risk models, compared to its definition in the context of market risk modelling and its respective regulatory framework.

years. However, the comparison of *expected* and *actual* credit losses does not address the accuracy of the model's prediction of *unexpected* losses, against which economic capital is allocated. While such independent work on backtesting is limited, some literature indicates the difficulty of ensuring that capital requirements generated using credit risk models will provide an adequately large capital buffer.[34]

- Banks employ various alternative means of validating credit risk models, including so-called "market-based reality checks" such as peer group analysis, rate of return analysis and comparisons of market credit spreads with those implied by the bank's own pricing models.[35] However, the assumption underlying these approaches is that prevailing market perceptions of appropriate capital levels (for peer analysis) or credit spreads (for rate of return analysis) are substantially accurate and economically well founded. If this is not so, reliance on such techniques raises questions as to the comparability and consistency of credit risk models, an issue which may be of particular importance to supervisors. [36]

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[34] See Pamela Nickell, William Perraudin and Simone Varotto, "Ratings Versus Equity-Based Credit Risk Modelling: An Empirical Analysis," September 1998. This empirical study implemented and evaluated representative examples of two of the main types of credit risk models (ratings-based and equity price-based) and assessed their performance on an out-of-sample basis using large portfolios of eurobonds. Both models failed to provide an adequately large capital buffer across the 10-year sample period; the portfolios experienced "exceptions" at several times the rate predicted by VaR calculations based on the models' output.

[35] Peer group analysis attempts to estimate the capital needed to achieve a hypothetical target credit rating for a given activity (complete business lines or broad product groupings) from the capitalisation rates of competitors engaged in that activity**.** Banks may also compare the internal hurdle rate with the expected risk-adjusted rate of return that could be achieved by investing in corporate bonds having a particular credit rating. This exercise may point out the need to re-estimate the model's parameters, depending on the implied level of capital allocation. See Federal Reserve System Task Force on Internal Credit Risk Models, "Credit Risk Models at Major U.S. Banking Institutions: Current State of the Art and Implications for Assessments of Capital Adequacy," May 1998.

[36] A few survey participants relied on such alternative methods for backtesting. These included: (a) comparing loan pricing implied by the model with market pricing; (b) attempting to check the consistency of the main drivers of modelling output (internal ratings and recovery rates) through comparison with external benchmarks such as Moody's and S&P; and (c) backtesting on virtual portfolios given the scarcity of data on credit events. See for example Jose Lopez and Marc Saidenberg, "Evaluating Credit Risk Models", September 1998.

3. Stress Testing

A. Overview

Stress tests aim to overcome some of the major uncertainties in credit risk models – such as the estimation of default rates or the joint probability distribution of risk factors – by specifying particular economic scenarios and judging the adequacy of bank capital against those scenarios, regardless of the probability that such events may occur. Stress tests could cover a range of scenarios, including the performance of certain sectors during crises, or the magnitude of losses at extreme points of the credit cycle.

B. Key Issues

- In theory, a robust process of stress testing could act as a complement to backtesting given the limitations inherent in current backtesting methods. However, it does not appear that banks have dedicated a significant amount of resources to devising appropriate stress testing procedures. Of the banks participating in the survey, approximately half claimed to conduct stress testing on the portfolio, and a number of other institutions indicated they are in the process of developing such methods. However, in most cases, the procedure is not formally developed, or is carried out only sporadically. Scenarios covered include deterioration in credit ratings or market spreads, changes in LGDs, shifts in default probabilities and changes in correlation structures.

4. Sensitivity Analysis

A. Overview

The practice of testing the sensitivity of model output to parameter values or to critical assumptions is also not common. In the case of certain proprietary models, some parameter (and even structural) assumptions are unknown to the user, and thus sensitivity testing and parameter modification are difficult.

B. Key Issues

- A minority of banks indicated they conduct sensitivity analysis on a number of factors, including: (a) EDF and volatility of EDF; (b) LGD, and (c) assignment of internal rating categories. However, the depth of the analysis differed between banks. Furthermore, none of the respondents attempted to quantify the degree of potential error in the estimation of the probability distribution of credit losses, though a few compared the results generated by the internal model with those from a vendor model.

5. Management Oversight and Reporting

A. Overview

Much of the above discussion has focused on the mathematical and technical aspects of validation. Equally as important, however, is the internal environment in which a model operates. The amount of senior manager oversight, the proficiency of loan officers, the quality of internal controls and other traditional features of the credit culture will continue to play a key part in the risk management framework.

B. Key Issues

- Given that the current generation of credit risk models is in its infancy, many of the individuals involved in model development currently also function as the ultimate users – the banks' risk managers. However, few banks have subjected their models to an independent review and audit. As credit risk models become an integral part of an active business performance measurement and compensation scheme, banks will need to ensure proper oversight over the models in order to avoid potential conflicts of interest. This potential is apparent in the area of internal loan rating systems. While a number of institutions are currently attempting to validate their internal ratings through the use of credit scoring models, the majority continue to assign ratings to counterparties solely according to the judgement of a loan officer.
- Banks typically maintain documentation on the credit risk modelling process and the underlying methodology, as well as the results of any stress testing procedures. However, in estimating model parameters, banks at times rely on proprietary consultant data derived via undisclosed methodologies. Furthermore, the fact that validation analyses are generally undeveloped also raises concerns regarding the effective quality and completeness of the oversight process.

APPENDIX

Credit Risk Modelling - Conceptual Issues				
Item:	Description:	Range of Practice:	Issues/concerns:	Page # Reference
Credit Loss Definition	How is loss defined?	• Both M-T-M and Default Mode (DM) processes are used/ promoted. • Some banks include workout expenses and carrying costs while others don't.	• Materiality of loss definition (i.e. should we use M-T-M or DM) not clear.	16
Time Horizon	Over what time period should losses be measured?	• Most use a one-year horizon.	• Very little sensitivity analysis done to date. • What horizon should be used for capital (e.g. one year, life of loan, etc.)?	16
Credit Risk Aggregation	The distinction between entering individual loan attributes vs. attributes of a pool.	• Most banks enter individual characteristics of commercial credits and pool real portfolios.	• Reliability of pooled data. • Pooled data hide "credit-specific" risks.	29
Probability Density Function (PDF)	The method used to generate, and the use of, the PDF.	• Models do not specify the specific distribution	• No agreement on the "family" of distributions to use.	26
Credit Quality Correlations	How co-movement among credit ratings and defaults is considered.	• Implicit vs. explicit • Explicit (ratings vs. sector)	• Is one method better than the other? • Is there significant difference in reported results?	31

Conditional vs. Unconditional	Are the results of the model dependent on the current state of the economy?	• Currently most models are unconditional and a few are conditional.	• Depending on the method chosen, risk can be understated or overstated depending on the location within the business cycle.	28
Internal Applications	Does the process provide company-wide application/use of the model, or is it only applied to exposures within certain businesses? How are banks using their credit models internally?	• Very few (if any) banks have developed a fully integrated company-wide model to measure credit risk. • Usage varies significantly. Some of uses noted include: credit concentration limits, ALL guideline, and RAROC input.	• If banks do not use these systems for internal allocations of credit, how much confidence can be placed in the processes?	

Credit Risk Modelling - Parameter Specification Issues				
Item:	Description:	Range of Perspective:	Issues/concerns:	Page # Reference:
Loss Given Default Rates (LGDs)	Determination of how much loss will occur once a credit has defaulted	• Most banks use a combination of historical data and intuition to determine LGD rates. • LGD modelling methodology varies; however, most models use beta distribution.	• Lack of sensitivity analysis. • Lack of historical information.	35
Risk Ratings and Expected Default Frequency	Determination of what the expected default risk is within individual credits and/or pools of assets.	• Internal risk and public debt ratings are used in most cases for individual credits. • For pools of credits, the bank's internal historical charge-off rates are typically used.	• Questionable accuracy of internal systems being able to determine EDF. Most systems combine EDF and LGD.	38
Risk Rating Transitions	Projection of future movements in risk ratings and to default.	• A number of banks rely on public debt rating information (i.e. historical information). • Other banks have produced transition matrices based on internal historical information.	• Public debt rating transition matrices may not be appropriate for bank credits. • Internal systems may not be accurate or have enough history.	38
Credit Correlations	Determine the co-movement between assets. For M-T-M process, need to measure correlation between risk rating movements, as well as default.	• Most models use correlation data generated from equity price movements. • Other banks rely on their judgement to establish correlations.	• Is it reasonable to use equity information to estimate correlations for bank credits? • Lack of historical data is a very significant problem for this parameter. • Outside the United States, there is even less information.	41

Credit Spreads	Determine the appropriate credit spreads to use to discount future cash flows for M-T-M purposes.	• Banks tend to use credit spreads commonly quoted in the market for loans that fall into public debt rating buckets.	• How is "liquidity" element of credit spreads taken into consideration?	45
Exposure Levels (e.g. amount drawn at default)	Determine the appropriate exposure amount to use within the model.	• Banks attempt to determine a credit equivalency when the exposure is not known with certainty (e.g. undrawn commitments). • Banks attempt to determine future and average exposure amounts or estimate a credit equivalent amount on market-driven instruments.	• Accuracy of estimates.	45
Characterisation of Credit	Determine the appropriate industry and country in which to slot the credit.	• Banks using a combination of judgement and financial statement information based on sales and assets.	• Accuracy of judgement-based characterisations. • Lack of information to fully support industry/country assignments.	43
System Capacity	Are bank systems able to capture needed data and can data from multiple systems be combined?	• Significant differences in how information is collected and what is collected.	• Insufficient information being collected. • Significant system upgrades/changes needed if information is to be collected.	47
Management Information Systems	Is accurate, timely and understandable information being prepared for management?	• Reporting processes tend to be in the very early stages of development.	• Some applications take a great length of time to run analysis.	47

Credit Risk Modelling - Validation Issues				
Item:	Description:	Range of Practice:	Issues/concerns:	Page # Reference:
Management Oversight	What is the current state of bank management's ability to provide reasonable oversight to this area?	• Most knowledge/expertise of modelling process currently lies in backroom analytics.	• Line management and senior management need to gain understanding of strengths and weaknesses.	54
Backtesting	Verification that actual losses correspond to projected losses.	• No banks have completed any significant backtesting. • Limited availability of historical data is a big hurdle.	• To date there is no way to verify accuracy. • Questions remain as to how to adequately backtest.	51
Stress testing	Determine the model results under various economic scenarios.	• Some institutions are doing work in this area; however, to date, we have not seen comprehensive work.	• Few institutions are doing stress testing.	53
Sensitivity Analysis	Assess the sensitivity of results to changes in the inputs (parameters)	• Very limited work completed in this area to date.	• Sensitivity information is very limited. Significant enhancements needed to understand effects of parameter changes.	53
Internal Review and Audit of Models	Does bank have an independent review process to determine the reasonableness of the models?	• Most banks do not have an internal review process in place.	• Lack of independence in reviewing these processes.	54