Response to Basle's Credit Risk Modelling: Current Practices and Applications

By the Committee on Regulation and Supervision

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Preface

The Global Association of Risk Professionals (GARP) is the world's largest organization of practitioners and researchers of financial risk management. GARP has a diverse international membership from a variety of backgrounds and institutions.

GARP was founded by a group of risk managers from financial institutions whose vision was to apply the techniques of risk management to a broad range of problems and challenges within financial institutions. GARP's mission is to serve its members by facilitating the exchange of information, developing educational programs, inspiring innovation, and promoting standards in the area of financial risk management.

GARP members discuss risk management techniques and standards, critique current practices and regulation, and help bring forth potential risks in the financial markets to the attention of other members and the public. The organization sponsors risk management related events through its network of active regional chapters in Europe, Asia and the Americas and is committed to the use of models in managing risk.

Risk management is taking on a more important role, as the global markets integrate across continents, and as the lines between the individual risk factors become increasingly blurred. Given industry developments, risk management practitioners can no longer rely solely on a transactional approach to manage firm-wide credit risk. More reliance is being placed on the use of quantitative methods to manage risk. These tools have received heightened attention because they provide management with an independent but more accurate, consistent and timely measure of risk.

GARP takes an active role in promoting productive relationships between bank regulators and risk management practitioners to ensure that industry views and concerns are accounted for during the regulatory policy development process. The Committee on Regulation and Supervision (the Committee) is a standing committee of GARP. Following the release of the Basle consultative paper "Credit Risk Modelling: Current Practices and Applications", the Committee took on the task of responding.

The organization and the Committee are uniquely qualified to comment on Basle's paper. Many of its members are experienced credit risk management practitioners that deal with credit risk models on a day-to-day basis. They represent a broad array of institutions in different geographic locations, but have a common interest in promoting risk management and the use of quantitative methods for managing said risk.

The Committee coordinated its efforts through periodic teleconferences, electronic mail, and solicitation for contribution from the organization as a whole. The following commentary and

recommendations are based on member observations of industry-wide credit risk management practices and their experience in dealing with proprietary and third party credit models. This document is unique in that it represents a broad consensus on a fairly technical issue, from risk practitioners representing a diverse set of organizations and geographic locations. The views expressed in this document are solely the view of the individual authors and are not necessarily the views of their respective institutions.

GARP appreciates the opportunity to comment on the Basle Committee's concerns and welcomes further dialogue. We acknowledge the concerns identified by the Basle Committee, but are confident that these issues can be addressed.

Finally, The Committee thanks the Global Association of Risk Professionals, its directors, and its members for sponsoring our effort.

- The Committee

Executive Summary

In April 1999 the Basle Committee on Banking Supervision (Basle Committee) issued its consultative paper titled "Credit Risk Modelling: Current Practices and Applications." The paper sought industry commentary concerning the use of credit risk models in calculating of regulatory capital. More specifically, the Basle Committee raised concerns about the many conceptual approaches being used to measure credit risk. Additionally, they are concerned about the lack of data available to accurately model credit events and the difficulties in validating model results. Lastly, the Basle Committee is concerned about the comparability of models across institutions and the models' limited application in today's banking activities. They argue that management must first demonstrate its confidence in these models by using them to actively manage its day-to-day credit risk before regulators supports using them as part of the regulatory capital assessment process.

GARP's Committee on Regulation and Supervision (the Committee) is a strong supporter of the use of models in the risk management process. Many of our members are experienced practitioners that deal with credit risk models on a day-to-day basis. We acknowledge the concerns raised by the Basle Committee but want to call attention to the progress the industry has made in developing rigorous credit risk models within a relatively short period of time. As risk practitioners overcome difficult problems and enhance existing models, they implement innovative models to solve new and more complicated problems.

While credit models may not be as pervasive as they should be in managing day-to-day risk, the banks that have had the foresight to invest in credit risk management are reaping great rewards. The Committee believes that credit risk models offer great advantages over the traditional transactional approach to credit risk management and are confident the banking community will continue to invest in their design and implementation. We recognize additional progress is needed if models are to become ubiquitous. Notwithstanding, the knowledge and expertise related to credit risk modeling exists and is greater than what is being recognized.

Two fundamental principles guide our response. Namely, we believe regulation should encourage competition and innovation. To this end, banks with superior risk management practices should be rewarded with lower capital requirements. Regulators can play an important role in facilitating further advancements in risk management and market competition by supporting the use of models in assessing regulatory capital.

The second principle is that the regulatory oversight process should be closely aligned with the bank's risk management activities. As institutions have developed their own proprietary credit models, a dual regime for measuring and managing risk has come to pass. Management relies on the output from its internal models to evaluate the adequacy of economic capital supporting the associated risk, and then evaluates the adequacy of its regulatory capital using the risk

weights listed in the 1988 Basle Accord. In this context, the current practice of maintaining separate and disparate processes for measuring and managing risk seems burdensome and counterproductive. Regulators should encourage institutions to develop risk management models that are comprehensive and well integrated into their risk management framework, not penalize institutions by insisting they maintain two independent risk measurement systems: one for internal risk management and a separate system for regulatory purposes.

With regards to the Basle's issues, the Committee believes that certain models have resolved many of the conceptual issues for particular products and businesses and that the industry should be afforded the flexibility of designing individual models that best capture the risk inherent in their activities. Granted, credit risk modeling is significantly more difficult than market risk modeling. The relative infrequency of credit events and the illiquid nature of assets in the banking book are a challenge for model developers. We, however, do not believe the quality of data should discourage the adaptation of models in assessing regulatory capital. Various statistical techniques combined with conservative assumptions will address most data scarcity issues.

Model validation, on the other hand, is a challenging issue with which bankers and regulators must contend. We concur with the Basle Committee's concern that backtesting has limited application in validating credit risk given the data scarcity issue. Nonetheless, stress testing, scenario analysis, and the use of sensitivity analyses can bolster the traditional model validation process and direct management's attention to portfolios that may be vulnerable to potential credit events.

The Committee encourages the industry to document thoroughly the parameters and assumptions used to model credit risk and set minimum stress testing requirements and the use of sensitivity analyses to validate model results. Likewise, we recommend that regulators develop minimum qualitative and quantitative guidelines to ensure a degree of transparency and level of consistency in risk reporting. These guidelines should also address issues of modularity and testability.

With regards to the comparability of models across institutions, the Committee acknowledges the difficulty of encouraging competition and innovation while at the same time ensuring a level playing field. Comparison should come through qualitative and quantitative guidelines as well as testing.

The Committee strongly objects to any attempt to standardize models. The adoption of standardized models would preclude a bank's use of those models in its business. This contradicts the Basle Committee's premise that banks must use their own internal models for both business decisions and regulatory capital. Moreover, the adoption of standardized models would discourage competition and innovation which has lead to the progress thus far in credit risk modeling.

Similarly, the Committee opposes any attempt to normalize models by requiring the use of addons, multiplication factors, or other penalty functions. The use of such penalty functions force models to produce identical results, and, therefore, penalty functions have the same disadvantages as the use of standardized models.

The Committee concurs with the Basle's assertion that bank management must first demonstrate its confidence in credit risk models by using them to manage the institution's day-to-day risk. Models and procedures used solely to satisfy regulators by generating statistics and reports can be superficial and misleading. The success of any such model plainly rests in an institution's ability and willingness to integrate these tools into the institution's daily risk management activities, which should include setting and calculating risk limits, reserving for credit losses and evaluating the adequacy of economic and regulatory capital. We, however, do not consider this an impediment for supporting the use of models in the regulatory capital assessment process, but rather a necessary requirement as it was in the Market Risk Amendment.

Correspondingly, we believe the onus is on risk managers to have a thorough understanding of their businesses, the inherent risks in these activities and the methods and models used to measure and manage these risks. The Board of Directors and senior management, on the other hand, should endorse the role of their risk management groups and ensure they have sufficient resources and authority to develop, implement, and use sound credit risk management models. This includes the ability of risk management to obtain the necessary data and information from all business units, and at the same time have the ability to effect change.

We therefore strongly encourage the Basle Committee to support the use of credit risk models in the assessment of regulatory capital.

The Committee believes the eventual goal would be for banks to use models across all assets and businesses to ensure risk is measured in a comprehensive and timely manner. This would be hard to accomplish in one step, so we recommend models be rolled out and integrated into the regulatory capital assessment process on a piecemeal basis as they are developed and proven to be an accurate measure of risk. Because credit risk is complicated and at present credit models can not be expected to capture every aspect of idiosyncratic risk, we suggest that banks be allowed to fall back on standardized capital allocations in situations where credit risk modeling is not reliable.

Regulators should accept models on a case-by-case basis. Models should be evaluated as to whether they are appropriate for the particular products, business, and institution. Regulators should consider the environment in which the model operates as well as the model. The acceptance of models, however, is not a static process. Bankers and regulators should expect credit models to evolve and improve over time, producing a corresponding improvement in credit risk management.

In the near future we encourage banks to set rigorous model acceptance standards and dedicate the appropriate resources to support the documentation process and ensure their proprietary models keep pace with industry developments. Likewise, we encourage the regulators to prepare its examining staff and equip them with the necessary tools to properly evaluate these models and their effectiveness in managing risk. We acknowledge the concerns identified by the Basle Committee, but are confident these issues have been and can be addressed. By supporting the use of models in the regulatory capital assessment process, regulators would facilitate a better link between credit risk models, an institution's risk management process and regulatory capital.

We are confident these challenges are manageable and that we will soon see the application of more models to accurately measure and manage credit risk from a regulatory and economic capital standpoint.

1 Introduction

The banking industry has undergone significant change over the past ten years. The development of capital markets and easy access to information has created a significant challenge for the banking industry. More and more financial transactions can be performed outside the banking sector, resulting in their increasing disintermediation. Additionally, the continuous evolution of traded instruments now allows the industry the flexibility to hedge or alter the risk in almost any position. These developments have changed the risk profile of banks, shifting bank management's focus away from simple asset liability and credit related risks, to today's environment, where bank management must deal with a broad array of risks as well as manage information.

There are three important regulatory documents that have shaped credit risk management activities in banks:

- The first document, "International Convergence of Capital Measurement and Capital Standards" (the Basle Accord), was published in July 1988 by the Basle Committee and later endorsed and adopted by central banks of several countries. One of the issues that this document addresses was the minimum capital requirement for the ratio of capital to risk-weighted on-balance sheet assets plus off-balance sheet equivalent exposures. The risk weights were set in alignment with the perceived credit risks associated with products / counterparties at that time.
- The second document is the 1996 Amendment or "BIS 98." This document extended the scope of risk measurement beyond credit risk to include market-related risk in the minimum regulatory capital assessment process.
- The third document is the current proposal to amend the regulatory capital rule for credit risk currently open for discussion. It consists of two parts: "Credit Risk Modelling: Current Practices and Applications" (April 1999) and "A New Capital Adequacy Framework" (June 1999). Together these documents will form the basis for a new framework, BIS 2000, which we expect will better integrate and quantify credit risk inherent in today's banking activities.

The original Basle Accord was an important first step in formulating a common international regulatory capital framework, but it has since outlived its usefulness. The shortcomings of the current standardized credit risk rules for regulatory capital are widely recognized. We believe they are well documented in the paper "Credit Risk and Regulatory Capital" published by the International Swaps and Derivatives Association (ISDA) in March 1998. The risk weights, for example, are not a good measure of credit risk. The risk weight assigned to corporate off-balance sheet instruments is half that assigned to the same risk for on-balance sheet exposures.

Risk weights assigned to certain countries and institutions are disproportionate to their inherent risk. A loan to triple-A rated corporation, for example, is weighted five times more than a similar loan to a bank in an emerging market county. The current methodology is inconsistent with the theory of investments. Principally, it fails to compensate lenders for the benefits achieved through portfolio diversification. A single loan is charged as much capital as a portfolio of smaller loans to unrelated counterparties. Furthermore, it does not create any incentive for credit mitigation. Banks using credit derivatives are subject to a more onerous capital charge for hedging credit risk relative to similar instruments used to hedge market risk.

The Market Rule Amendment enhanced the original regulatory risk based capital framework by recognizing the increased significance of market related risks in today's banking activities. It was especially innovative, in that that it linked the regulatory capital assessment process to a bank's internal risk management activities. The 1996 Amendment encouraged bank management to develop and use internal models to assess the regulatory capital needed to support its individual market related risks. Market risk measurement, however, can be relatively straightforward in a liquid market that provides an accurate indication of the fair value of securities. Illiquid instruments rarely account for a significant portion of a bank's trading book. Credit risk modeling, on the other hand, typically involves proprietary loans and other arrangements that are not freely traded and thus can not be priced with a high degree of precision.

While Basle is considering enhancing the existing credit risk measurement process to better capture risk, the proposed framework is intended to be a "one size fits all" approach to credit risk measurement. We believe credit risk modeling represents a better alternative and better risk management tool than that provided under the proposed standardized approach. Credit risk models are dynamic and can process a large number of transactions in a short period of time and can be tailored to capture the unique risks inherent in each product or sub-portfolio. Additionally, they can factor in the benefits of diversification and the other risks associated with credit related products, such as interest rate risk and liquidity risk. It makes no sense to go from one flawed system to an equally flawed system. We recognize additional progress is warranted if these models are to be used to effectively manage economic and regulatory capital. Notwithstanding, we believe the knowledge and expertise related to credit risk modeling exists and is greater than what is being recognized.

Risk management and modeling activities have come a long way in short period of time. We believe there are credit models being used in today's marketplace that they are successfully used to price assets, measure risk, evaluate performance and make strategic decisions. It is clear, bank management regard robust credit risk models as useful risk management tools and stand to benefit from further advancements given the above noted benefits. Both institutions and regulators stand to benefit from further modeling advancements. Project plans are underway at many institutions to enhance existing models. We are confident risk practitioners will overcome the current obstacles and dedicate the necessary resources to produce models that can be used to effectively measure regulatory capital. Notwithstanding, we believe the regulatory community

can play a significant role in facilitating this effort by encouraging the use of credit risk models in calculating regulatory capital.

In the following paper, we respond to the concerns raised by the Basle Committee in their April 1999 document titled "Credit Risk Modelling: Current Practices and Applications". The organization of this paper follows that of Basle Committee's paper. We respond point-by-point to each Basle issue. In chapter 2 we discuss the benefits of modeling, current applications, our view on modeling prospects and the Basle Committee's concerns about banks actually using their models in their own business and about comparing model results across institutions. In chapter 3, we address the conceptual approaches to credit risk modeling and the qualitative factors identified by the Basle Committee to ensure a minimum level of transparency and consistency in reporting figures. We then discuss the issues concerning parameter specification and estimation in chapter 4, followed by a discussion of model validation in chapter 5. Our conclusion is chapter 6.

2 Credit Risk Models at Institutions

As financial institutions continue to expand across geographic boundaries and as the nature of loan and investment products become increasingly more complex, bank management have to look beyond the traditional transaction-by-transaction approach of managing credit risk if they are to manage risk in a consistent, timely and prudent fashion. Similarly, as hybrid products such as credit derivatives gain further acceptance, the line between the different risk elements are less clear, creating an increased need for credit risk models to better manage these risks.

2.1 Benefits of Credit Risk Models

Credit risk management models have gained widespread attention because they provide bank management with a more robust measure of the inherent risk in their institution and allows for a more timely and consistent means of measuring and managing risk. More specifically, the Committee believes models provide the following benefits:

- <u>A more comprehensive and consistent measure of risk</u>. Credit risk models can be a more effective risk measurement and management tool given their ability to quickly measure risk, taking into account an institution's internal risk management structure, portfolio composition and diversification, term structure, credit offsets, and collateral support
- <u>A more timely and objective measure of risk</u>: Credit risk models strengthen existing risk management practices by providing management with an independent but more accurate, timely and consistent measure of credit risk.
- <u>A more flexible approach to risk management</u>: Credit risk models provide management the flexibility to design a risk measurement and management tool that can be tailored to the specific risks inherent in its portfolio. These results can be easily aggregated across risk taking units and across financial institutions worldwide, providing a more accurate and comprehensive measure of the risk.
- <u>Improves the transparency between the various credit risk activities</u>: While management looks to limits, credit reserves and the allocation of economic capital as a means of controlling and managing risk, it is not readily apparent how the data elements of these activities are linked with one another. If credit models were fully integrated into the daily risk management activities, the link between these activities would be more readily apparent.

Industry developments stemming from the adoption of the Market Risk Amendment is a noteworthy example of benefits to be gained by linking models with the risk measurement and management process and the assessment of bank capital. While Value-at-Risk (VAR) models

pre-dated the adoption of the market risk amendment, significant advancements were spurred by the requirements and incentives set forth in the Amendment. Credit risk modeling developments are a natural extension of the advancements made on the market risk models due to the applicability of market risk techniques to credit risk measurement and due to the development of credit-related products (such as credit derivatives), which provides institutions with the ability to hedge their credit exposures in a manner analogous to market risk hedging techniques. The Committee recognizes credit risk modeling presents greater challenges than its market risk counterpart. Notwithstanding, the Group believes similar benefits are attainable on the credit risk management forefront if financial institutions are given the appropriate incentive to further develop existing systems and better integrate them into its day-to-day risk management system.

2.2 Model Applications

There are credit models that are being successfully used to price assets, measure risk, value performance and make strategic decisions. The degree to which institutions have developed and use credit risk models varies significantly. Notwithstanding, some key trends can be observed. Risk practitioners within GARP cite the following industry modeling approaches and examples:

• The most predominant model employed by financial institutions is the single credit exposure model. Their primary use is to ensure that credit risk incurred by the institution remains within its stated risk appetite and that the assessment of that risk occurs in a timely manner to allow for prompt corrective action if warranted.

Similarly, many financial institutions have developed models to price assets or calculate the likelihood of defaults on its commercial or retail loan portfolio. The principal benefit of said models is that they can process a great deal of information and provide an independent, timely and consistent measure of risk on a transactional or relationship basis.

One of the widely used applications of single exposure models has been to measure counterparty credit risk stemming from OTC derivative products. Many global banks use analytical models to measure potential credit exposure from a given transaction or a portfolio of transactions to a given counterparty. These models are used to evaluate whether a potential transaction would increase credit risk to a particular counterparty because of an added concentration of credit, or reduce risk through the benefits of product diversification. These models are often sophisticated enough to consider the effects of innovative marking-to-market and collateral agreements which work to reduce credit exposure. Additionally, they can factor in netting arrangements when appropriate, providing bank management with a more precise measure of the marginal assessment of credit risk resulting from a proposed transaction.

Single exposure models have been equally successful at Derivative Product Companies (DPCs) where they are used to set minimum capital levels to support the structured transactions booked in these companies. Since most DPCs have their own credit rating, these models have had to come under careful scrutiny of the credit rating agencies. In particular, these models must be able to perform various stress and sensitivity tests if they were to be accepted by the rating agencies as an effective risk management tool for assessing the adequacy of capital for these special purpose vehicles.

Many single exposure credit risk models, however, were developed to measure credit risk arising from a specific product / type of borrower. The results from these models, however, are not being aggregated with similar risks in other products / type of borrowers. A model, for example, which characterizes and measures counterparty trading related credit risk is typically not aggregated with on-balance sheet credit related products. In many instances, model results have not been fully integrated into the various credit risk management activities. Exposure data measuring conformance with approved transaction / relationship limits may not tie to the general ledger because they are processed by different measurement systems. Similarly, credit risk data from models used to price assets may not be used to risk rate assets or calculate economic capital.

• Portfolio-based models are the second most predominant forms of credit risk models employed by financial institutions. They are actively used to support business decisions through the application of "what-if" analysis on a relationship basis or bank portfolio levelly. Lending officers/traders have the ability to assess the impact of prospective transactions on their portfolios before consummating a deal.

Often, these models incorporate the ability to conduct stress tests and assess the impact of different events on the portfolio. A large European bank, for example, uses a portfoliobased model to manage its credit portfolio on a day-to-day basis. In particular, it is used to evaluate the impact from buying and selling bonds, loans and credit derivatives on the overall portfolio. The model provides management portfolio related information which includes concentrations of credit, product and counterparty distribution statistics, expected loss and their distribution figures as well as corresponding capital requirements.

It also informs management on how the portfolio may be adjusted to reduce said exposures, concentrations or increase the portfolio's return on capital. Portfolio-based models, however, are often computationally intensive, and therefore are often utilized to determine a post-transaction impact on the portfolio.

• The logical extension of portfolio models is the institution-wide application of credit risk assessment to produce an enterprise-wide assessment of the cost of credit and its impact on the allocation of economic capital. The most noteworthy models are the risk-adjusted return on capital (RAROC) models.

While, these models tend to be better integrated into a bank's risk management activities and are well positioned to best calculate regulatory capital, they are difficult and costly to implement because of the level of coordination required. Given their limited application, we do not have a good example of models that are being successfully used to measure and manage credit risk on an enterprise-wide basis.

2.3 Model Shortcomings

Credit models, systems and associated processes have a role to play in monitoring and managing credit risk exposures. We, however, recognize Basle's concern that few institutions use these models to actively manage their enterprise-wide allocation of credit and capital. Similarly, we recognize the problems associated with credit risk modeling and discuss these elements in detail in the following chapters. Risk practitioners within GARP cite the following reasons for the slow pace of model developments:

- The amount of computational time needed to process large portfolios, especially those resident in multiple geographies, involve a prohibitively long processing cycle. This has been a significant barrier for institutions with limited processing capacity, most of which are reluctant to consider other alternatives until after the year 2000.
- Multiple legacy systems, both custom developed and purchased packages, are often not compatible with each other, namely due to inconsistent data formats and / or level of exposure data. Again, many institutions have been preoccupied with solving other technological issues such as the Euro, Y2K or systems integration following a merger or acquisition. Accordingly, they have not seen the cost benefit to developing better-integrated systems given other priorities and a limited information technology budget.
- Many credit risk related activities are difficult to model. Credit-enhancement arrangements such as guarantees, collateral held, and netting agreements, for example, are difficult to model within a transaction processing systems due to their distinct nature. While certain portfolio models can take these into account, the specific nature of these agreements (e.g. jurisdiction, applicability in cross-border trading etc.) makes it difficult to accurately model their impact at both the transaction levels, and are even less precise at the portfolio and institution wide level.

Despite these difficulties, risk practitioners are continuing to create more robust, timely enterprise-level credit models. Institutions stand to benefit from more robust credit risk modeling in that these models often takes into account the benefits of portfolio or business line diversification, and thereby show a lower exposure to a specific product, borrower or geographic concentration than would otherwise be reported on a transaction-by-transaction basis. A number of institutions have development projects underway to enhance existing credit risk models. We discuss the prospects for credit risk modeling in greater detail in section 2.5

below. The primary benefit, however, is that modeling efforts to-date have furthered management's understanding of the nature of credit risk inherent in their organization.

2.4 The Parallel Risk Management Process

As institutions have developed their own internal credit models, a twofold approach for measuring and managing credit risk has come to pass. Institutions use their own models within specific business areas and or credit related activities to monitor and manage credit risk from an economic standpoint but also look to the risk based capital framework outlined by the Basle Accord to manage credit risk for regulatory capital calculation purposes. This approach, however, is inefficient for two reasons:

- It requires maintenance of two distinct models (with associated systems and infrastructure cost implications)
- It encourages management to develop distinct models to manage regulatory capital and economic capital, which can lead to a disconnect between an institution's business tactics in managing its internal risk management activities and the regulatory assessment of risk.

Currently, it is prohibitively difficult to bridge the gap between the two systems. If the appropriate incentives were created as was the case following the adoption of the Market Risk Amendment, the Committee believes there would be a convergence between the two risk management systems. We believe regulators should reward institutions for developing risk management models that are comprehensive and well integrated with its risk management framework, not penalize institutions by insisting they maintain two independent risk measurement systems: one for internal risk management, and a separate system for regulatory purposes.

2.5 Modeling Prospects

Despite the credit risk modeling shortcomings outlined in Section 2.3 above, it is clear that bank management regard robust and well-constructed credit risk models as a useful risk management tools. As mentioned above, they stand to benefit in that it provides them a better assessment of their risk. We can expect financial institutions to place even greater reliance on these models given the benefits outlined in Section 2.2 above, the increasing complexity of certain credit risk products and the increasing interest in developing risk adjusted return on capital systems to better manage firmwide economic and market capital

One of the recent developments within the industry has been the convergence of market and credit risk measurement techniques, some of which was fueled by the emergence of credit derivatives. This convergence is becoming more common at the product level where financial

institutions have been developing models which capture both credit and market risk given the hybrid nature of some of these products, and management's desire to evaluate the risk from both an accrual and mark-to-market standpoint. This is perhaps best illustrated by the development of CreditMetrics, an extension of the RiskMetrics product. We can expect management to place greater reliance on models that capture both market and credit risk given models provide an independent but more timely, accurate and consistent measure of this risk.

Lastly, there is increasing pressure on management to better manage shareholder value and economic capital given the highly competitive nature of the industry. Accordingly, more and more institutions are starting to drill down on performance figures to determine if a relationship, portfolio or product adds or detracts from the bottom line and / or firmwide risk. Return on capital models, such as risk-adjusted return on capital (RAROC) models, have received the most attention given they are applied across all bank activities and factor in the cost of regulatory and economic capital when assessing a particular relationship, product or a portfolio's profitability.

The Committee is confident added resources will be allocated to further develop existing risk management models, especially once institutions have resolved more immediate technological concerns such as the Y2K and systems integration issues for those institutions that have recently experienced a sizeable merger or acquisition. If the appropriate incentives were in place, we could expect to see even greater attention being paid to developing sophisticated, robust models and firmly believe the bank regulators can play such a role.

2.6 Comparing Models Across Institutions

Most institutions have approached credit risk modeling from a sub-portfolio basis or product basis because it has allowed management the flexibility to better capture the risks unique to that portfolio or product. Accordingly, the modeling methodologies may differ depending upon the product or portfolio. Certain products, for example, may have non-linear risks while others have simple linear risks, which require different modeling methodologies. Risks can then be aggregated at the highest possible level.

The Committee is not concerned that results, using different modeling methodologies, are being added together, namely because the risk is probably being over-stated since it does not take into account the benefits of diversification that may exist between sub portfolios or products. The frequency of capital calculation should depend upon the nature and volatility of risk inherent in the sub-portfolio or products. At a minimum however, the risk should be updated and reviewed as often as the most frequently updated sub-portfolio / product. As long as part of the portfolio is updated daily because it experiences greater change and other portfolios are updated on a less frequent basis because they are more stable– the overall portfolio should be updated daily because it is the most frequent.

Financial institutions each have a unique risk profile, risk appetite, and set of underwriting standards. The principal benefit to modeling is its flexibility to capture the distinct risks inherent in each institution / portfolio, and still provide management the ability to systematically capture and manage these risks. Since few models are designed to measure all forms of credit risks, a firm should be encouraged to use different models to best capture the risks unique to that sub-portfolio or product and then be allowed to aggregate the risks to express a summary measure of a specific type of credit risk.

The Committee is concerned about the Basle's focus on the disparate modeling approaches being employed by the market place. We recognize different approaches exist but are comforted by the fact they were intended to capture and mange the unique risks within that institution. Each institution's model should be expected to come up with different results given the difference in underwriting standards, risk appetite and credit culture at each institution. Model results are different because no two banks share the same portfolio constitution.

The Committee acknowledges the natural tension that exists in encouraging competition and innovation while at the same time ensuring a level playing field. The adoption of standardized models would preclude a bank's use of those models in its business. This contrasts the Basle Committee's premise that banks not maintain a mode for regulatory capital in concert with a model for their business applications. Moreover, the adoption of standardized models would discourage competition and innovation which thus far has lead to any progress at all in credit risk modeling.

The Committee strongly objects to any attempt to standardize models. Similarly, we oppose any attempt to normalize models by requiring the use of add-ons, multiplication factors, or other penalty functions. We consider this to be a significant regulatory burden and an inefficient use of bank resources. Penalty functions would naturally force a convergence of models to identical models or if not to identical models, then to models that give identical results. This would transfer the modeling responsibility from banks to regulators, thus again discouraging competition and innovation, if not leading to systemic risk as everyone is forced to measure risk in the same manner.

Instead of adopting standardized models or forcing standardized model results, the Committee encourages regulators to focus more on setting qualitative standards for the use of credit risk models similar to the approach taken under the Market Risk Amendment. These standards should address backtesting, stress testing, the use of model information in setting risk tolerance limits, internal risk ratings and the reserving process, and set minimum standards for establishing an independent risk-monitoring unit. Similarly, the Committee believes regulators should set specific minimum quantitative modeling parameters such as look back periods, confidence intervals, etc. to ensure there is a basic level of consistency across financial institutions.

As with the Market Risk Amendment, we encourages regulators to focus more on evaluating the specific models at each institution to ensure they accurately captures the risks inherent in that institution and ensure results are appropriately integrated into that bank's risk management activities. This would allow them to maintain control of the regulatory framework and supervision over the pace of development and adoption of credit models. Standardized reporting requirements of certain risk elements would facilitate the comparison of specific information across portfolios and institutions.

The logical next step would be for regulators to permit the use of models alongside and integrated into the capital adequacy rules (e.g. for specific products or business lines). Given the complexity of credit risk modeling, we do not expect management to develop a single model that captures all aspects of credit risk, but rather develop models that capture the unique risks in sub-portfolios or products. As model expertise and development improves, institutions should be permitted to role out models for parts of their businesses, e.g. business lines, products or even books as the respective models become available.

While institutions should conform to minimum quantitative and qualitative standards, institutions should be encouraged to use their own models which will best fit with their own businesses and discipline management to develop a detailed understanding of their own credit risk exposures and risk management infrastructure. Regulators could rely on filtering systems to identify potential outliers, i.e., banks showing the need of closer scrutiny. Nonetheless, the Committee is confident that the regulators could play a significant role in expediting the development of credit risk models by allowing them to be a part of the regulatory capital calculation process. This would clearly make credit risk modeling a priority, as it did following the adoption of the Market Risk Amendment.

3 Conceptual Approaches to Credit Risk Modeling

Basle rightly points out that there are many conceptual issues in designing a model. They are concerned whether the various approaches are sound and whether different approaches give very different answers. Basle's issues naturally break into two groups: those issues which address the objectives of a model and those which address measurement.

The objective should explicitly specify what should be captured by regulatory capital, and should be independent of the choice of model. Since each model must have precisely the same objective -- a consistently defined standard of regulatory capital, the differences resulting from various approaches become purely technical. In other words, the modeling questions focus on the quality of measurement, which should be assessed by materiality and practicality.

In this section we respond point-by-point to the issues raised by Basle, and raise a few issues of our own. For instance, we included a section on the issue of internal credit risk rating models, which is mentioned by Basle but not discussed in detail. Credit risk rating models, or credit analysis, is the oldest, best-established type of credit modeling, and so deserves some attention here.

Many of the issues Basle raised involve sophisticated mathematics or finance. The cost of greater accuracy is usually more effort and more sophistication. However one should not misinterpret the discussion of sophisticated mathematics or finance as an endorsement of complicated models. Sometimes very simple models can be as successful as sophisticated models. The selection of the model depends on the particular problem and the various constraints of the environment in which the model will operate.

Indeed, the Basle Accord is a model, or if is not exactly a model in form, then it serves as a model. While the assumptions and other variables that went into designing the Accord are not apparent, the resulting Accord is at present the only tool for computing regulatory capital.

The Committee views modeling with an open mind. Models should be compared based on their usefulness – not on their sophistication. The issues we discuss below apply to all models.

3.1 Capital Allocation for Credit Risk

Regulators require banks to hold capital to ensure the safety of the banking systems and to provide a fair and competitive environment. Capital acts as a cushion against losses to a bank's portfolio.

The industry speaks of both regulatory capital and economic capital. *Regulatory capital*, at present, is capital as calculated under the 1988 Basle Accord. *Economic capital* is the capital that a business naturally assigns to its risk. Ideally a bank's economic capital would be closely aligned with its risk. Basle is concerned that economic capital allocation is practiced only partially and unevenly among banks. We agree that that reflects the current state of affairs in managerial use of capital allocation in the industry.

As Basle states, economic capital for credit risk must be a function of potential credit losses. Also Basle holds implicitly throughout their discussion that regulatory capital should equal economic capital. This point needs explanation

Economic capital should have the property that more risk requires more economic capital. But even among banks that agree on that property, the precise definition may vary from bank to bank. Moreover, the definition may vary between various business units within the same bank. In some cases the reasons may be completely irrational and due to legacy policies or hurried decisions. In other cases the definition may vary because the cost of risk could include costs which are particular to that bank or business.

The Committee acknowledges that the various definitions of economic capital may need some attention. This does not pose a conceptual problem, but it is a practical issue which must be addressed if banks are allowed to use their internal credit models to compute both economic capital and regulatory capital.

To avoid confusion with the various definitions of economic capital, this paper uses the term regulatory capital and it interprets Basle's comments about capital to be about regulatory capital.

Given a time period, *credit losses* are the changes in the value due to credit risks of a portfolio between the beginning and the end of the time period adjusted for time value. This is a general definition; in practice one must clarify whether the change in value includes income, capital gains, taxes, and other financial flows.

The Basle Accord calculates capital for all risks: credit, market, liquidity, and any other risks. In the present discussion, both Basle and this response are concerned only with capital against credit losses. Obviously capital for non-credit losses can not be ignored and should be addressed separately from capital for credit risk.

At the beginning of a time period credit losses are unknown, and only potential credit losses are know. Therefore, potential credit losses must be approximated by a probability distribution. As Basle states, potential losses include both expected and unexpected losses. Because losses are uncertain, to move from credit losses to capital, one needs to select a confidence level. The confidence level, for example, would allow one to claim that credit losses will be less than \$100

MM with 99% confidence. Of course, the higher the confidence number, the higher the upper bound on losses.

Given a time horizon and confidence level, the *regulatory capital* for a portfolio equals the potential credit losses at the given confidence level. To be unambiguous, this is what regulatory capital should be - not what it is under the Basle Accord.

The definition of capital depends on a time horizon and confidence level acceptable to regulators, and a probability distribution. The time horizon and confidence level are chosen outside the models and are common to all models for computing capital. Whether or not the time horizon and confidence level are stated, they are implicit in all capital calculations. We discuss the time horizon and confidence level in more detail in the next section.

The above definition of regulatory capital assumes a static portfolio and static bank. In reality neither is actually static. Since the bank is not static, the actual probability of insolvency may differ from the theoretically computed probability of insolvency. If the bank has a long enough time horizon to react to new credit losses, the bank may reduce risk by selling assets, or increase capital by raising new funds. In this case, the true probability of insolvency should actually be less than the computed probability of insolvency.

Conversely, for a bank that does not react - by choice or by necessity - throughout the entire time period, the true probability of insolvency over multiple time horizons should actually be greater than the computed probability.

3.2 Measuring Credit Loss

The diversity of methods for measuring credit loss is a fact, and a welcome fact, of credit risk modeling. Their very diversity allows for reasonable methods to be available for a wide variety of credit exposures and different degrees of data availability. The issues respecting their appropriateness for computing regulatory capital are empirical and practical more than theoretical.

Basle's discussion of modeling credit loss treats time horizon first, then reviews prominent loss paradigms and mark-to-market paradigms.

Basle raised five key issues, the first of which is briefly, that the definition of default varies from institution to institution, affecting interpretation of default frequencies, and definition of loss given default likewise varies, making comparability more difficult.

The Committee agrees that default and loss given default definitions do vary among institutions, and believe this is a complication, but not a serious impediment. The remaining four issues will be handled in the discussions of time horizon, loss models and valuation models just below.

3.3 Time Horizon.

The time horizon of a credit capital requirement computation must be long enough to be meaningful, and short enough to be feasible given the data available. Basle expresses concern over what time horizon should be used for capital, given various types of assets and liquidity. It points out that little research has been done to date on selecting the correct time horizon. In particular, Basle cites a lack of information on sensitivity of the capital number to the choice of time horizon.

Any discussion about time horizon should respect the trade-off between time horizon and confidence level. If the targeted credit rating is held constant, the longer the time horizon, the higher the default rate, hence the lower confidence level for a given level of capital. Therefore, a longer time horizon may not result in a higher economic capital nor does a shorter time horizon dictate lower economic capital—both the horizon and the confidence level must be considered.

One may infer that in theory the time horizon does not matter very much. However, as we will argue below, practical considerations may dictate a best time horizon.

Basle identifies two approaches to specifying the time horizon. In the *liquidation period* approach the bank would calculate potential losses and capital using a different time horizon for each product, based on a reasonable liquidation period for the associated product. We agree that liquidation is one of several factors concerning the choice of time horizon.

In a second approach, the bank would calculate potential losses and capital using a common time horizon for all instruments. Obviously, the liquidation period approach could be more precise, while the second approach would be simpler to apply.

To discuss the two approaches to specifying the time horizon, one must discuss the factors affecting the choice. Basle listed some criteria given by banks for using one common time horizon. We paraphrase that list here.

- The time horizon should be long enough to allow the bank or the regulators to increase capital or reduce risk through loss-mitigating action. This action could include raising new capital, selling assets, or restructuring the bank.
- It should also be long enough to include the bank's normal business cycles of strategic planning, capital budgeting, and publishing of accounting statements.
- Finally, the time horizon should be long enough that subsequent calculations of the capital number contain meaningful, new information. In particular, it should be long enough that new information is obtained on counterparties and the economy.

We agree that the above criteria should be used in determining the correct time horizon.

If a bank chooses the liquidation period approach, the responsibility rests with the bank to demonstrate that a specific time horizon should apply to certain debt instruments or certain business units. On the other hand, a bank should not be allowed to cherry-pick the time horizon. Certain assets may require a much longer time horizon, but the choice should be made systematically.

There is a precedent for using one common time horizon. The market risk amendment provides solid precedent in that 'specific risk' is quantified for a 10-day time horizon. This applies to homogeneous assets, so the one common time horizon is appropriate. For a diverse portfolio of credit risk assets, one needs to be more deliberate in selecting a time horizon.

If a bank chooses one common time horizon for all instruments, then it must consider all the above criteria, as well as its particular asset mix, risk management expertise and experience. While we cannot argue for one, common time horizon for all banks, we would suggest that a one-year time horizon would generally be sufficient.

First, a one-year time horizon is not too short.

- The additional credit risk in longer-term deals will be partially captured in valuation at the time horizon. Longer-term deals exhibit higher volatility in terms of value changes because of the duration effect.
- Taking the confidence level discussed above and cash in-flows into consideration, it may not require more capital to underpin the risk. Probably most important and less discussed, the process of re-measuring capital frequently will capture the risk as time moves ahead. This rationale is also supported by the nature of defaults: not all defaults occur in the same measuring period.

Second, a one-year time horizon is not too long, that is to say, it does not overstate risk on short-term assets. Though the dollar loss to a portfolio in the short term is not large enough to cause insolvency, this un-quantified confidence may be false when transactions continue to trade and roll over. Using a shorter time horizon is similar to writing short-term out-of-the money options repeatedly and viewing it as a winning strategy. In addition, the shorter the time horizon, the higher the confidence level is required to achieve a targeted credit rating. Further, the annual default rates are difficult to be scaled down to short-term default rates, as the exact timing of credit events is unknown.

In addition, if the time horizon is too short and the bank cannot react within the short horizon, losses may actually accumulate over subsequent time horizons. In this case the probability of losses not exceeding the capital number in this or subsequent time horizons is actually lower than

the prescribed confidence level. If one chooses to use one common time horizon, a one-year time horizon is a sound upper bound to be used in computing regulatory capital.

The Committee believes that both approaches to the time horizon are valid. The bank should choose the approach that best fits its risk management practices.

3.4 Default Model vs. Mark-to-Market Model.

Basle identifies two different conceptual methods for modeling credit losses: default mode (DM) and mark-to-market (MTM). The basic issue with these methods is whether their differences bear on their suitability for specifying regulatory capital requirements.

Basle listed two key issues respecting these loss paradigms:

- The default model seems especially sensitive to the choice of time horizon, and its method of approximation poses difficulties in adjusting risk for longer-term vs. shorter-term exposures.
- Choosing between the methods seems basically an empirical issue of which best fits a given situation.

In the default mode method a credit loss is recorded when and only when the credit instrument defaults, so changes in the credit risk rating other than default do not count as a credit loss (or gain). The mark-to-market method computes a credit loss (or gain) when the credit instrument changes in credit risk ratings, including default. The change from one credit risk rating to another is called a *transition* or *migration*. So the default mode method is a special case of the mark-to-market method: the default mode method uses only two credit risk ratings: not defaulted and defaulted.

Marking-to-market is an important risk management issue for both banks and regulators. In the context of accounting, marking-to-market includes both the method of establishing a fair market value and the act of recording that value, but here we are concerned with the issue of modeling the potential change in value due to default and/or credit rating transition. (The related issue of valuing an asset is discussed below, as is the issue of potential change in value due to changes in credit risk spreads.) Models for credit risk spreads may be used with either of the above two methods, though a model that does not recognize changes in credit risk ratings is not likely to recognize changes in credit risk spreads.

One can analyze default mode and mark-to-market by going back to the purpose of capital. One of the tools for rescuing a distressed portfolio is to liquidate portions of that portfolio. Each instrument will be liquidated at its fair market value. That fair market value will most definitely reflect the most current credit risk rating, so realizing any credit loss due to the credit risk rating transition. Thus the default mode method would not accurately measure credit losses, while the mark-tomarket method with a sufficient number of credit risk ratings would more accurately model credit losses.

In order to use the mark-to-market method, the bank would have to accurately measure the value of the portfolio at both the start and the end of the period. The mark-to-market method of approximating credit losses makes no sense if the bank does not have an accurate measure of the starting value. Moreover, as time passes, an inability to mark-to-market will only introduce greater uncertainty into the measurement of current and future credit losses.

Thus the default mode method is simply less accurate and precise. Firstly, it fails to account for the full change in value of the portfolio due to credit events. Secondly, over time the starting value of the portfolio is unknown because it has not been revalued. We do not rule out the use of default mode models, but we acknowledge that such models would have to be coupled with conservative assumptions or other adjustments to adequately compensate for their obvious shortcomings. Data issues surrounding the use of credit risk transitions and loss given default are discussed below.

To measure credit losses precisely, one must start with the current, correct marking-to-market value of the portfolio and apply the mark-to-market method for measuring potential losses. **The Committee believes that the mark-to-market method is the more accurate and sound method for measuring potential losses.**

3.5 Credit Risk Ratings.

Basle writes, "Within most credit risk modeling systems, a customer's internal credit risk rating is a key – if not the sole – criterion for determining the expected default frequencies applicable to the various credit facilities associated with that customer."

Though Basel only mentions credit risk ratings in passing, the Committee believes that credit risk ratings deserve attention alongside the other credit risk modeling issues. Credit risk ratings are crucial to a credit risk model. Indeed, the credit risk rating of an asset or entity is the most fundamental factor in determining potential credit losses.

Banks use a variety of methods for determining credit risk ratings. Some banks use internal methodologies, while other depend on external sources such as rating agencies or consultants. Few institutions place complete reliance on external ratings when taking on credit risk. In many instances, the credit risk accepted by the bank is only approximately addressed by available external ratings. Most often, external ratings are used as a check to confirm that the institution's credit assessment is not significantly adrift from the view of other market participants.

Whether the internal credit risk rating is arrived at by the bank's credit staff through classical credit analysis or by a credit risk model based on complex mathematical analysis, it is an important component of a credit risk management model. However arrived at, credit risk ratings can be mapped to default rates and rating transition rates, though with a degree of consistency that may be better or worse than a given benchmark of external ratings.

Attempts to automate or out-source credit risk ratings would undermine both the credit risk management model as well as a bank's entire credit risk management culture. Complacency in the determination of credit risk ratings could lead to gross miscalculations of risk as well as systemic risk. The Committee believes that banks are and should be ultimately responsible for determining and maintaining their credit risk ratings.

3.6 Discounted Contractual Cash Flow vs. Risk Neutral Valuation.

Before computing the risk in a portfolio the bank needs to value the portfolio. Basle discusses two methods for valuing credit risk instruments: the *discounted contractual cash flow* approach (DCCF) and *risk neutral* approach (RNV). As with the credit loss methods, the issue is whether either of the two poses a material problem for computing regulatory capital.

Basle expressed one key issue in this area: The choice of discounted cash flow vs. risk-neutral valuation pricing models seems to be a trade-off between sensitivity to data input quality on the one hand, and model assumptions on the other. In other words, the choice is another empirical issue.

We agree; the choice is fundamentally a matter of what data is available, and the degree of comfort the bank finds with the necessary assumptions,

In the *discounted contractual cash flow* approach a loan or bond would be priced by discounting the cashflows using the appropriate discount curve. This curve would be constructed to take account of the uncertainty of the cashflows, including the uncertainty of the loss given default. Usually the discount curve is constructed from one interest rate, the debt instrument's internal rate of return.

The *risk neutral* approach arises from derivative pricing methods. The risk neutral valuation approach treats the coupon payments and principal payment as options which are paid in full only if the asset is not in default. Risk neutral valuation explicitly associates a probability of default, and loss given default, with each debt instrument, so each cash flow is contingent on there being no default. Next each cash flow is discounted by one discount curve, namely, a riskless discount curve.

Basle analyses and compares the two approaches. They state, for example, that the discounted contractual cash flow approach does not account for the differences in the seniority of the debt

instrument, so a senior loan and subordinated loan would be discounted using the same discount curve.

We agree with Basle that it is inaccurate to discount a senior loan and subordinated loan using the same discount curve, but we disagree that this is a shortcoming of the discounted contractual cash flow approach. The approach does not require discounting the two loans using the same discount curve, though that is one possible way to apply the discounted contractual cash flow approach. The discounted contractual cash flow approach may be modified to be as sophisticated or as simple as the user likes. The discounted contractual cash flow approach is a sound approach to accurately valuing debt instruments.

However, the discounted contractual cash flow approach treats every debt instrument as an exception. Every debt instrument has its own, unique discount curve and internal rate of return. If a bank chooses the discounted contractual cash flow approach, it should take care the discount curves and internal rates of return are consistent and comparable across debt instruments.

The risk neutral approach is also a sound approach, as well as a more modern and robust approach, to accurately valuing debt instruments. But as with the discounted contractual cash flow approach, a bank that chooses to use risk neutral valuation should take care the discount curves and internal rates of return are consistent and comparable across debt instruments.

We should point out there are at least as many valuation approaches as there are products and markets. Indeed, many valuations are simply legacies of the past, inefficient, and due eventually to give way to new, more accurate pricing methods. Until they do, these inefficient legacy valuation methods are an issue for risk managers to the extent that they conduce to consistent, systemic mis-pricing.

However, capital computation is mainly concerned with changes in prices, and to that extent model accuracy is less an issue.

No matter the approach used, the final benchmark should be the market value (current or forward, implied or observed); since after all one is concerned about its liquidation value. Because both approaches employ certain techniques of calibration to the market, the results should be not materially different. The Committee believes that the discounted contractual cash flow approach, risk neutral valuation approach, and any other method that produces accurate market valuations are appropriate for computing the values of a bank's portfolio.

There will inevitably be cases where new or unusual approaches will have to be used. Whatever approach is used, it should suit its application, be well documented, and able to withstand scrutiny. 3.7 Offsets, Collateral and Other Credit Risk Mitigation.

While not specifically addressed by the Basle paper under Credit Loss Measurement, one of the most significant innovations in banking is credit risk mitigation: the ability to reduce risk without diminishing business. These innovations include collateral, credit derivatives, and securitization. Risk can also be naturally reduced through offsets when a bank holds both long and short position in a particular credit risk.

Although credit risk mitigation is not of the same analytical nature as most of Basle's other issues, it may be quantified, and affects the most important model input, namely exposure. Here we refer to actual net exposure to an entity as opposed to exposure due to a single product.

While the precise effect of the mitigation method may depend on legal issues as well as technical issues, **the Committee strongly believes that modeling credit risk mitigation is inseparable from other issues of credit risk models**. Indeed, the same techniques that apply to Basle's other issues apply to credit risk mitigation.

While modeling credit risk mitigation is too large a topic to discuss in detail here, credit risk mitigation is an important to credit risk management and should be encouraged. The Committee believes that regulators should encourage credit risk mitigation by allowing credit risk management models to accurately measure the effect such methods have on the aggregate risk.

3.8 Probability Density Functions

For a given time horizon the Probability Density Function (PDF) of credit losses completely describes a bank's potential losses and their corresponding likelihood. Since the calculation of capital would be based on the PDF, Basle raises several issues with regard to it.

Basle states that at present there is no agreement on the shape of this distribution, and many models do not calculate the exact shape of the distribution. Basle states that the PDF is skewed towards large losses so that large losses are more likely than they would be in the case for a comparable normal distribution. Also Basle is concerned that small changes in the confidence level would result in large changes in the capital.

Indeed, there is no agreement on the shape of the PDF for credit losses; the shape is not a wellknown standard PDF. If a bank's credit portfolio were thoroughly diversified, then the PDF would be a normal probability density function, completely determined by its mean and standard deviation. But typically a bank's portfolio is not truly diversified. Due to the binary nature of individual credit losses, portfolio concentrations, and the non-independence of individual credit losses the PDF is definitely not a normal distribution. The shape of the distribution depends partially on the individual losses, particularly when there are concentrations such that individual losses are large relative to the overall size of the portfolio. Choosing whether to treat individual losses as binary or continuous will definitely affect the shape. But the shape of the distribution's shape or, more importantly, the shape of the distribution's tail, will depend mostly on correlation inputs.

The Committee believes that the lack of agreement on the shape of the PDF poses no problem to using internal credit risk models to calculate regulatory capital. Indeed, the uniqueness of the PDF to each institution promises a more accurate capital number.

Moreover, the lack of agreement on the shape of the PDF does not preclude its calculation. Many analytical and computational methods exist for computing a PDF. Two such methods are convolution and Monte Carlo.

The Committee believes that the best credit risk models will explicitly calculate the PDF. By computing the PDF one has much more information than simply the capital number. With the exact PDF in hand, one could answer any conceivable question about the PDF and resulting capital number.

Banks that use models that do not explicitly calculate the PDF would have to compensate by providing additional information. For example, if the model approximates the distribution by a well-known distribution, then the bank should demonstrate that the model upholds certain basic principles, such as:

- The approximation is indeed a close approximation, and
- The approximation is conservative in the sense that any errors in the approximation result in a higher capital number.

Finally, we address Basle's concern that small changes in the confidence level would result in large changes in the capital number. For the reasons given above, a credit loss PDF usually has fat tails, which means that events of large value are more likely than they would be under a comparable normal distribution. Small changes in the confidence level therefore result in larger changes in the capital number than would result for a comparable normal distribution.

The Committee does not believe this points to a problem with credit risk models. If regulators are satisfied with the confidence levels they have chosen, then banks and regulators should accept the resulting capital numbers whether or not they are sensitive to the choice of confidence level.

The uneasiness with confidence levels and capital numbers seems due not to the shape of the PDF, but to other issues such as the accuracy of the PDF. Indeed, if the PDF is incorrectly calculated or is highly unstable due to assumptions and parameter choices, that would be a

different issue. A careful sensitivity analysis, as discussed below under Validation, should help diagnose a clearly incorrect or unstable PDF.

3.9 Conditional vs. Unconditional

According to the Basle definition, an unconditional model reflects "relatively limited borroweror facility-specific information", while the conditional model incorporates explicit macro economic factors besides the borrower-specific information. The Basle paper points out that unconditional models do not adjust expectations for seasons of adverse economic conditions, while conditional models adjust explicitly; on the other hand, it concedes that conditional models' explicit adjustments may lag the economy by some months due to the time needed to process econometric data. Overall Basle seems to favor the conditional models for their explicit handling of the economic climate, on the theory that the credit model should account for changes in the economic environment, not just assume constant model parameters.

The Committee agrees that in difficult times, the risk manager must explicitly change the parameters, whether that be default probabilities or macroeconomic parameters which determine the default probabilities. Every good model's output must reflect the macro economic environment. Some models do it by building macroeconomic changes into the model itself, others by adjusting the model's parameters, e.g. change in credit spreads, default rates, etc. As recent studies have shown, the different approaches' unique frameworks seem irreconcilable on the outside, yet produce quite similar results. While a built-in econometric model seems an advancement on the one side, it poses many problems on the other. Most saliently, any explicit econometric model introduces more assumptions and, therefore, further opportunities for error.

Any model's acceptability depends less on its framework, and more on producing an output consistent with the current economic environment. The Committee believes that it does not and should not matter if this is achieved by adapting either the model or the parameters.

3.10 Approaches to Credit Risk Aggregation

Basle identifies two opposite approaches to pooling data, the *top-down* and the *bottom-up* approaches. Both approaches (and hybrids of the two) are used in practice. The central issue is whether either of the two opposite approaches presents a material problem to the use of credit models for regulatory capital.

Basle expressed three key concerns: (1) "the degree to which a bank can distinguish meaningfully between borrower classes," (2) the accuracy of the aggregate data for a top-down

approach, and (3) the comparability of the aggregate to the bank's actual portfolio. They point to a possible disguising of loan-specific effects if the latter two concerns are not met.

The top-down approach is typified in models of consumer, credit card, or other retail portfolios, and justified in these because a large number of entities allow certain statistical theories to apply.

The bottom-up approach is typified in models of custom corporate and capital market assets. Due to the large variability among assets and entities, exceptions and concentrations, and the severity of individual losses, a single statistic can scarcely model each individual risk. Here the model must account for each asset's unique features.

Can a credit model accommodate different attributes for individual loans and pools of other products (e.g. credit cards and mortgages) and still capture the real risk in these products? Current practice enters individual characteristics of commercial credits and uses the pooled data for sub-portfolios such as mortgages, personal loans, and credit cards. Basle's paper is concerned that the pooled data may not be reliable and may hide "specific risk" in the pools.

When considering the attributes of individual loans or pooled data, the difference may be semantic. Any good credit risk model should key on each asset or entity's perceived riskiness. Internal ratings supplemented by external ratings should be used in the analysis. For certain asset categories, where the risk is deemed homogenous between different customers and a track record of losses exists over a certain period, a pooled approach should be used. First, the pooled data naturally captures correlation among individual counterparties. Second, the pooling method is possibly the only practical answer because those pools sum a large volume of small accounts. In fact this method is at the core of the asset-backed securities market.

For capital markets and major clients where counterparties are fewer and each one's exposures significant, the bottom-up approach should be preferred. The choice of method is driven by simple pragmatism and business orientation.

The Committee believes that both bottom-up and top-down approaches are valid, but the top-down approach should be used only when the specific risks of the underlying assets can be captured. As the most prominent models do not focus on this issue, refinement to these models may be indicated.

3.11 Correlations between Credit Events

It is well known that the percentage of defaults over time is highly variable, both within individual credit risk rating groups and among all entities collectively. The variability arises, not from sudden inaccuracies in credit risk ratings, but from a shift in the average credit worthiness of all entities. Thus defaults are non-independent, as are credit risk rating transitions. (Non-

independence is the more precise term for these phenomena, but some simply refer to it as nonzero correlation.)

The non-independence of defaults and rating transitions is the biggest reason the probability distribution function of losses is not a normal distribution. Thus correctly modeling the non-independence is key to accurately calculating capital.

Basle recognizes that the non-independence of defaults and rating transitions is one of the main contributors to losses. Basle is also concerned with the non-independence of other credit events including credit exposures and losses given default. Banks, too, tend to be well aware of possible significant correlation among their customers. However, Basle concludes, "Credit risk models do not attempt to explicitly model correlations between different types of risk factors," ¹ but expresses concern with the various approaches to modeling the non-independence of defaults and credit risk rating transitions.

We agree that data limitations are partially responsible for not modeling the non-independence of different types of risk factors. Technical difficulties are another reason. While we do not know of production models that model the non-independence of different types of risk factors, we would not conclude that modelers ignore this issue. For some products and businesses the non-independence is either irrelevant or insignificant. For others, model users compensate for the non-independence by making conservative assumptions about one or more of the risk factors.

Most effort on the non-independence of risk factors has focused on default and credit risk rating transitions. Basle identifies two classes of models called *structural models* and *reduced-form models*. Basle is concerned with which methodology is more appropriate and how big the impact in capital calculations.

Structural models attempt to explain default or credit rating transitions by hypothesizing some explicit microeconomic feature of the product or entity.² For example, a credit or its corresponding business entity may be modeled as having stochastic assets. The assets' growth and volatility are inferred from entity-specific information and market data to compute a preliminary default probability. Unfortunately, this preliminary probability is not accurate enough, so it is adjusted to an average of actual historical probabilities of default of similar entities. Here "similar entity" is determined by the characterization of the credit.³

Reduced-form models do not attempt to explain default or credit rating transitions, they simply select a statistical process to describe default or credit rating transition.⁴ Non-independence of default between different credits is modeled by allowing non-independence between the

¹ P. 31.

² PortfolioManager and CreditMetrics are examples of structural models.

³ KMV is the model we have in mind here.

⁴ CreditRisk+ and CreditPortfolioView are examples of reduced-form models.

corresponding probabilities of defaults. One particular implementation, for example, describes the non-independence of defaults by a factor model.⁵ The country, region, and industry are factors in a factor model of the probability of default. It is easy to see how the characterization of credit is explicitly used in the model.

Given the fundamental difference between the two approaches, they naturally also differ in how they model non-independence. Non-independence is a general property and may be modeled in various ways, but will depend in any case on the characterizations of credits.

These different conceptual approaches seem to agree in how they measure losses and potential losses for a single product or entity. It is less clear how different approaches to non-independence affect their measurement of a portfolio of exposures.

The difficulty in measuring non-independence stems from instability. One problem, for example: the correlation matrix is usually reflects historical (typical) correlation between different risk factors. The conditional correlation, however, might be very different from the typical one. Typically correlation between defaults between two different emerging-markets countries' bonds is almost zero. However during extreme market moves (crises), correlation might rise significantly, leading to larger losses. Diversification for a portfolio investing in both countries can therefore be reasonable in "normal" market conditions and highly correlated during financial turmoil. In our view a proper solution is to introduce an explicit correction to reflect the tendency to be over-correlated during extreme events.

The Committee believes that both structural models and reduced-form models are theoretically sound and the differences are immaterial. This is supported by recent research which compared two models.⁶

⁵ CreditRisk+ is an example of such a model.

⁶ Michael Gordy, "A comparative anatomy of credit risk models," Board of Governors of the Federal Reserve System (Dec. 1998) shows that CreditMetrics and CreditRisk+ produce similar results as long as they are calibrated correctly.

4 Parameter Specification and Estimation

Basle describes several issues associated with parameter specification and estimation. The overriding theme in their critique of current credit risk modeling practices is that data is scarce or difficult to capture, practitioners often make questionable assumptions about parameters if data is unavailable, and models are sensitive in (an unknown way) to these parameters. In Basle's view, the implication of these issues is that internally based credit risk measurement could be highly inaccurate.

We believe that in most cases, practitioners can make parameter specification choices that are conservative when certain data is lacking. In addition, through a globally mobilized effort to increase the sharing of various types of data required for credit risk modeling, combined with the development of standardized interfaces for credit data, we believe data quality will improve dramatically. With respect to model parameter sensitivity, regulators could develop appropriate credit risk systems requirements that would include sensitivity analysis and backtesting processes. The appropriate national supervisors could enforce these requirements.

The issue of potential model inaccuracy should be addressed in the context of current standard methods described by the Basle Accord. In particular, it is highly unlikely that a collection of weights, developed with minimal statistical justification, could lead to results that are more accurate than an internally developed credit risk model that uses all available credit data. We posit that a well-developed internal system, audited by national supervisors, would in fact produce much more accurate credit risk measurement than the current standard approach.

4.1 Characterization of Credit

The characterization of a credit is fundamental to measuring credit risk, whether it is the credit risk of an individual entity or the credit risk of a portfolio. A characterization of a credit includes a determination of its country, region within the country, industry, and other factors which may influence the credit. In general, a characterization may include any information about the entity which is exogenous to the credit. So the characterization could also include a determination of countries, regions, and industries that do business with the credit.

The characterization of a credit either explicitly or implicitly enters into the ultimate credit risk rating, probability of default, and credit risk rating transitions. The characterization also plays a role in the quantification of correlation of default between different credits.

Thus the characterization of a credit is fundamental to credit analysis and to credit risk management models. Understanding how a bank characterizes a credit would help explain how it models credit risk. In addition, it provides a direct view into the diversity of an institution's

portfolio. It is synonymous with understanding your counterparty's business and reacting to potentially adverse economic or business events.

The Committee recognizes that difficulties could arise in characterizing credits. For example, if an entity does business in more than one country how does one assign a country to that entity? On would reasonably suppose that the country should be some kind of weighted average of all the countries the entities does business in. Then are the weighting by assets, revenues, profits, or yet another financial parameter? There is no single answer is not clear and rather each bank should be allowed to develop its own characterization of credit with clear supervisory overview.

Also by maintaining a record of it characterizations, it will help build a database which will help develop better models and help to calibrate those models. The database should also include relevant credit data such as changes in the characterization or changes in the credit risk rating. Also the database should include transaction data such the draw-down on a credit facility. Banks should maintain databases of the characterizations of credits. Such a database would be quite valuable to both the industry and regulators. Therefore standards should be established so that characterizations of various banks are easily comparable.

The Committee recommends that banks explicitly characterize all their credits and reports this data along with credit exposures so that concentrations and other information are easily transparent.

4.2 Default Probability and Credit Risk Rating Transition Probability

The Basle Report enumerates several issues associated with default probability and transition probability estimation. These issues are related either to the lack of high quality data, subjective assessments of credit quality, and the unsuitability of bucketing certain obligors. *Expected default frequency* is another name for the default probability of a given obligor within a specific time period.

Transition probabilities are probabilities of migrating from a current credit rating to another credit rating within a specific time period. While the Report distinguishes between default and ratings migration, it is noted that ratings migrations information contains default information. This is true on two levels - explicitly by including the default state as one of the migration states⁷, and implicitly through the relationship between migration, rating level, and default probability. We therefore feel that the issues associated with default probability can be subsumed under migration estimation issues.

⁷ Moody's and Standard and Poor's migration matrices include default

Basle identifies two approaches for estimating risk rating transitions - the *actuarial-based approach* and the *equity-based approach*. In both cases, the report cites lack of data, subjective judgment, or improper credit mapping as being the main issues.

Within the actuarial approach, Basle describes two version - *credit scoring* and *risk segmentation* methods. In credit scoring, credits are given a score that corresponds to a default probability. While the report does not explain how the scores are arrived at, it is mentioned that default probabilities are essentially mapped to scores by using historical default data of loans and/or bonds. The Report cites the lack of data being the main limiting factor in this approach.

Certainly for many markets, data is scarce. However, this is not true for every market. Where data is available and is of high quality (such as the US corporate market), then it should be used. In cases where data is not available or is of poor quality, a "standard approach" (or some highly conservative assumption about default probability) given by Basle could be applied.

In many cases data is lacking simply because currently there is not robust data distribution channels and incentives. While one European bank may not have significant default data on corporates outside its country, a bank would most likely have a much better data set on corporates within its country. With the approval of internal credit risk modeling, a bank would clearly have more incentive to improve the infrastructure for capturing and maintaining default data. The other effect of this approval would be increased role of the data vendors. As data gets better and more plentiful, vendors would facilitate bank-to-bank data distribution.

In the risk segmentation, credits are bucketed into groups that have certain common characteristics. The group statistics are again based on historical data of loan or bond performance. Basle posits that it is inaccurate to pool credits into risk segmentations which have certain common credit characteristics, especially since they are assumed to be statistically identical within a group. We submit that for large groups of credits, this is most likely not an egregious assumption. Relaxing the "statistically identical" assumption could test our hypothesis. This could be achieved through randomly changing (or stressing) the migration and default probabilities within a group and then rerunning the analytics.

The equity-based approach uses equity/debt structure and volatility of equity to estimate default. Unlike the first approach, this model requires current and historical equity prices in order to estimate default probabilities.

Basle indicates that model builders make subjective judgments when data is lacking. While this is true, we feel that subjective judgments occur in all modeling. In fact, a "subjective judgment" is a form of a model assumption. Appropriately, a model builder should make simple yet conservative judgments, understand the sensitivity of the results to these judgments, and provide thorough documentation. For example, if a firm has default data but no other transition data, then a simple method would be to construct a consistent transition matrix that has the default

probability inferred from the data. In general, certain assumptions need to be made to find a unique transition matrix. To test the soundness of these assumptions, the model builder could compare the transition matrix to historical data or test the sensitivity of the results to different migration probabilities.

We agree with Basle that it is difficult to extrapolate data for US to other countries. In fact, we do not condone this extrapolation in many cases. Rather, in some cases it is appropriate to take a more "conservative" approach when data is lacking. By conservative, we mean methodologically conservative. As mentioned above, where data is seriously lacking for a broad market, then credit risk could be measured by a standard approach.

Alternatively, very conservative default assumptions could be applied. Obviously, in the near term this poses a non-symmetric problem. Banks tend to have a disproportionate number of customers within their own county. Though this is reasonable and generally leads to a sounder relationship between the bank and customer, it may also be problematic. If banks that tend to have less information and history on their customers, does this lead to greater uncertainty? And if so, do such banks need to hold more capital? This will depend on the quality of the data available. The same data availability disparity exists between large corporations and middle-market corporations. Again, where data is lacking, standard methods or conservative migration and default probabilities could be applied and enforced by national supervisors.

Basle points out that public debt ratings transitions may not be appropriate for bank credits. While it may not be appropriate to solely rely on public debt ratings transitions, these matrices contain much information on migrations and defaults that could be effectively used for a large number of credits. Certainly many bank credits are private companies, loan and bond recoveries differ, and covenants contain many option-like features. Nevertheless, pure default and transition probabilities could be inferred from public debt ratings transitions for a large number of credits. While blindly extrapolating may be crude, such an approach could be applied in a conservative manner. One could extrapolate using the worst transition matrix for a given class of public credits for the worst year. For example, one could use 1991 and 1992 transition and default data to extrapolate for sub-investment grade credits. In addition, in order to extrapolate more accurately, one could further analyze available transition data. For example, sufficient data exist to break down by country, industry, or other criteria. Of course, a bank should determine whether simple extrapolation is appropriate our whether significant differences exist between entities in data set and those not.

Certainly the responsibility rests with the bank to prove that the relevant default data is robust. If regulation were devised to allow an institution to convert to an internal model, it would encourage banks to improve upon data capture.

Basle maintains that there is not enough default and migration history in internal databases. This is true in many cases. However, banks can be conservative in estimating transition probabilities. As mentioned above, one could take the worst migration year for a given credit class. Another

approach would be to shock the migration matrix, skewing the probabilities towards default. In addition, a hybrid approach of using public information coupled with internal default data could be applied.

In the three approaches described, there is a significant dependence on historical loan, bond, or equity performance data. An institution should understand and document this dependence. Of course, a model should be designed with data in mind, but we should be careful to distinguish between data used to justify a model and data used to calibrate a model. In particular, if data is used to calibrate a model, then data should be accurate. For example, if an entity is reported as transitioning ratings or defaulting, then both old and new ratings must be accurate. Such data should therefore be accurately updated.

Generally speaking, no matter which method is selected for measuring default and migration probabilities, it should be documented. An institution should carefully document all data sources and missing data. Furthermore, an institution should explain how missing data is estimated and give justification for its methodology. Certainly different estimates of missing data will lead to different results. Therefore, an institution should examine the sensitivity of the results to the parameter estimation assumptions.

Of course, defaults are rare. However, data availability/organization could be improved by incentives - the approval of internal credit risk models, coupled with strict oversight and auditing procedures, would give more incentive for institutions to gather, capture, distribute, and share this data. In the current paradigm, there is not much incentive to increase the quality of default databases at least from the regulatory point of view.

The Committee believes that common sense, simplicity, conservative judgment, strict documentation policy, and sensitivity analysis are the key ingredients in measuring default and migration probabilities. We also recommend that Basle develop policies that encourage banks to estimate these probabilities in this manner. In such a framework, banks would spend more time and resources understanding, measuring, and storing default and migration events and less time on regulatory arbitrage. As a result, a clearer and more accurate picture of global credit risk will evolve.

4.3 Loss Rate Given Default

Loss given default (LGD) is the loss on a credit risky asset given that the asset is in default. It is one minus the recovery rate for a given asset. LGD can vary from zero to 100 percent. It is not known before default, but is known only after the workout. More precisely, the LDG usually varies as time progresses from default through workout. One could mark the loss given default exactly at the time of default if the relevant asset has a market price. Or one could wait to workout to mark the LGD. The loss on the asset tends to be higher if one liquidate the assets

immediately after default as opposed to waiting for the workout. In any case, when for the purposes of modeling credit losses, the LGD must be approximated.

The loss given default depends crucially on the asset; the type, amount, and liquidity of collateral; and the country and the legal system of the defaulting party. The type of asset includes derivative contracts, credit facilities, loans, bonds, and credit guarantees. Among all these assets the LGD can vary greatly.

While LGD is certainly influenced by the asset type, it will also vary greatly across countries and legal systems. Banks have vast experience with bankruptcy and workouts in the US and Europe and the LGD can be estimated reasonably accurately. In other legal systems the loss resulting from a counterparty default and the handling of collateral is much less clear.

Basle discusses several methods for approximating loss given default. The simplest method approximates it by a single number, which may be an expected value or a conservative upperbound on the expected value. Another method approximates the LGD by a probability distribution, such as a beta distribution.

Basle raises several issues regarding how LGDs are modeled. The first issue concerns the estimation of LGD which depends on the reliability of pooled historical data. In the US and Europe, financial institutions have enough combined experience to make the quality of the data very high. As pointed out by Basle, the LGDs in less developed countries, especially countries with less developed legal systems, are highly uncertain. Accordingly, proactive risk managers insist that the banks' internal models assign an overly pessimistic estimate of the recovery given default.

This will both improve the model inputs and, over the next several years, allow the models to be validated. As the industry becomes further motivated to extend their credit risk models, various institutions will collect and make available pooled databases of LGDs. This data will most likely be continually updated and organized by factors to shield the identities of the parties.

Basle also has stated that for portfolios containing both large and small deals, assuming that the LGDs are certain instead of stochastic may underestimate the probability of taking large credit losses. Simple estimation shows that this effect, while real, is small and is overwhelmed by the uncertainties in default probabilities. This may be quantified either though stress testing of the model or through numerical analysis outside the model. The Committee believes that it is sufficient to model LGDs as a constant.

Basle is concerned that internal models assume independence of LGD for different facilities for one and the same borrower, since this is clearly false. We agree that this is a serious flaw in any model that should not be taken lightly. Credit models should accurately measure the loss given default to a counterparty, and if data is insufficient, then conservative estimates should be used. Basle is further worried that most internal models assume that the LGDs between borrowers are mutually independent, and that this would cause an underestimation of the probability of large losses for banks with substantial concentration of credits within a single industry. While this is a demonstrated mathematical effect, it is overwhelmed by potential correlation between defaults in the same industry. Moreover, incorporating such correlations would make the credit model needlessly complicated. At this time, there is little benefit to modeling and collecting data on correlations in LGDs.

In conclusion, **the Committee believes that the resolution is to use robust estimates of loss given default.** The imprecision caused by the variability of LGD and correlations are small in comparison to default and the expected loss given default.

4.4 Credit Spreads

The credit spread is the rate above the risk free rate that the market charges for the credit risk component of asset value. Theoretically one could identify the portion of the spread due solely to credit, and solely to components such as liquidity, and supply & demand factors. In practice, the entire spread is referred to as the credit spread.

Credit spreads enter credit models in two ways:

- Computing present value, and
- Measuring risk due to changing credit spreads

The issue of computing present value was already discussed above in the section on portfolio valuation. The issue here is to quantify the risk due to the stochastic nature of credit spreads. Basle is concerned whether there is sufficient data to model the stochastic properties of credit spreads. They are also concerned that some models simply assume constant spreads. Spread risk and the volatility of credit spreads can translate to price volatility, particularly when the widening of spreads is due to a downward migration in credit quality. Models, which do not capture credit spread changes, will not reflect the true risk on a mark-to-market basis.

Credit spread changes can be due to "non-credit" factors such as supply & demand and liquidity. For instance, in the US market, spreads of high yield bonds may widen dramatically during a rally in the US treasury market. Although the spreads have widened, interest rates have also declined dramatically and price volatility may be low relative to the spread volatility. Therefore, credit spread risk could just as easily be classified as market risk. Banks and regulators find it more convenient to place it under credit risk. This is certainly the most convenient place to put it, and it is fine to classify it this way as long as the risk is not double counted under both market risk and credit risk.

Changes in credit risk ratings due to rating agency actions or other negative changes in market perception of credit quality will more likely result in increased price volatility of the asset. For example, if there is a sudden widening in spreads in emerging markets due to an actual change in market perception of the credit risk, prices will show marked declines relative to US treasuries and the market as a whole. This volatility of credit ratings is significant because it can increase the credit losses in a portfolio. In particular, the risk of stochastic credit spreads is most significant when the portfolio is already stressed.

Marking the credit risk to market requires leading edge technology. Few banks actually mark their credit risk to market and report their credit exposure separately. This effectively allows them to run a financing desk without marking the credit risk component of the risk to market. For instance, many banks own an asset and sell it forward without showing the potential effects of credit down grades of the forward buyer on their profit & loss. This is because they do an upfront evaluation of the credit risk of the buyer and express this as an exposure. This practice is also standard on many swap desks. There is growing concern that these trading books are not truly marked-to-market.

As mentioned above credit spreads reflect supply & demand and liquidity. The credit spread is most definitely not constant over time and even within the relatively short time period of one year, credit spreads can change drastically. Models need to capture this risk. This does not necessary demand a sophisticated model. For example, a model may account for spread risk outside the default model. As long as the model accounts for spread risk, the model is sound.

The Committee believes that credit risk models should account for credit spread risk. Moreover, the model should capture the tendency for spread risk to be greatest during crises.

4.5 Exposure Levels

Credit exposure is the maximum amount that a bank risks losing due to a default, and depends heavily on the nature of the transaction. Here we discuss individual product exposures as opposed to net-exposures which are discussed in the previous chapter under Offsets. For loans the exposure is easily calculated. However, even for traditional instruments, like credit lines and letters of credit, the exposure may be larger than estimated since, under worsening credit, a party may find it cheaper to draw down a line of credit than to raise money through alternative channels. Another example of a product with an uncertain exposure is a derivative contract.

The current exposure of derivative instruments requires sophisticated models since

- it depends on the "in-the-money-ness" of the contract, which is determined by current market conditions; and
- due to standard netting arrangements, it depends on the other derivative contracts with the same counter party;

• it changes with time as market conditions change.

Although the maximum future exposure with a counterparty is random, depending on future market conditions, the probability distribution of the maximum exposure can be modeled using standard trading models.

Basle has stated that the *loan equivalent exposure* (LEE) for lines of credit may depend on the customers credit quality since the customer may find the committed credit line to be the cheapest source of funds. While this issue merits study and data collection, it is perhaps less important than better analysis of the customer's credit worthiness.

The ability of financial institutions to simultaneously model both market events and credit events, is rapidly improving. The total credit exposure to a counterparty can now be calculated by using sophisticated Monte Carlo techniques⁸ to simulate the mark-to-market of all the counterparty's derivative contracts.

Basle is concerned with negative correlations between credit exposure and the credit worthiness of a counterparty. For example, the mark-to-market value of a derivative contract (e.g., an oil contract) may be correlated with the credit worthiness of a counterparty (e.g. an oil producer). This re-emphasizes the need for internal models to be used by proactive risk managers.

In conclusion, variable exposures and, in particular, variable exposures that are not independent of with credit events can significantly influence credit risk. The variable exposure is most significant for products such as letters of credit or certain derivative contracts. In cases where it is significant, **the Committee recommends that models absolutely consider the variability and non-independence.** In case where data or models are inconclusive, models should error on the conservative side.

4.6 Correlations among Defaults and/or Rating Transitions

Models for non-independence are built on top of models for default and rating transitions, so naturally models for non-independence vary depending on the underlying model for default and rating transitions.

Basle identifies two approaches to calibrating models to default and rating transitions data. One is the *actuarial-based approach* and the other is the *equity-based approach*. The actuarial-based approach may be applied in models which identify entities by various risk factors. Both structural and reduced-form models discussed above may use this approach. The correlations are then determined by historical data corresponding to the risk factors. (The name actuarial-based is misleading.)

⁸ For example, NumeriX's Monte Carlo engine.

The equity-based approach is applied only to structural models. It infers correlation from the historical equity prices of the entities.

Given the importance of non-independent (or correlation), Basle raises several issues:

- There is not enough data to support the model's default and transition processes,
- Simplifying model assumptions may not be justified,
- To date there is little sensitivity analysis on correlation assumptions and parameters,
- One or both of the above two models may not be sound, and
- There is a lack of data especially outside the United States to calibrate the processes.

We agree with Basle that non-independence is one of the most challenging intellectual issues of developing a sound credit risk model. But with that said, one should be aware that there are simple solutions which are superior to the Basle Accord. It is possible to conservatively model credit losses without ever considering non-independence of default and transitions – it is sufficient to assume they are independent. For example, suppose historical default rates over a one-year time period are 2% on average but in any one-year time horizon were never greater than 5%. Then a model calibrated to a 5% default rate and independent defaults will calculate a sound regulatory capital number. In fact, in the cases of an investment grade portfolio, such a model would compute a capital number that is less then that imposed by the Basle Accord.

The Committee asserts that there are techniques and sufficient data to support those techniques for modeling the non-independence of default and transition. The main problem to date is that virtually no resources have been put into saving and analyzing data. With incentives to develop and use credit models, banks will overcome any obstacles.

4.7 System Capacity & Management Information Systems

Basle enumerates three main issues associated with systems capabilities required for proper credit risk processing and reporting. These issues are as follows:

- Insufficient data is being gathered
- Performance
- Systems Upgrades

We would like to comment on and clarify some of these issues. To this end, we refer to the very simple generic architecture for a credit risk model depicted in the Appendix of this document.

There are four types of data which are necessary to populate a credit risk model:

- Current Market Data. This corresponds to current corporate bond and equity prices.
- Historical Default Data. This corresponds to historical default and migration rates and loss severity.
- Derivative and loan data. This corresponds to the contractual data related to the actual transactions being processed.
- Counterparty Data. This corresponds to the data specific to a given counterparty.

Not all institutions use bond prices, equity prices, *and* historical default data, but these are all depicted for the sake of thoroughness. To be sure, reality is clearly much more complicated since data in each of these cases lives on disparate systems, locations, and platforms. Indeed, the heterogeneity of data sources is one of the problems facing credit risk systems implementation.

Data quality issues actually arise in each of the classes of data above. However, we will focus on the market and historical data availability issues. In terms of market data inputs, data insufficiency can occur because a particular name does not have traded bonds or the associated equity is thinly traded. This is not a new problem - an implementation of an internal market risk model would face exactly the same dilemma. This is often addressed through mapping the particular credit name to another name of similar characteristics that has sufficient data. While this is mapping is often subjective, we posit that it is a reasonable approach if care is taken when choosing a mapping. In particular, if done properly, mapping could lead to conservative estimates of risk.

Suppose A is a credit that requires a mapping and B is a potential target mapping credit. There are two obvious choices one can make for mapping. Firstly, one could aggregate the positions in A with the positions in B. In this approach, one is effectively imposing a perfect default correlation between A and B. In the second approach, one retains A as a separate entity and simply uses the default term structure that is applicable to B. In this approach, one could retain an industry/country default correlation value implied by the credit risk model, or impose a zero correlation between A and B. Under the constraint that mapping should lead to conservative estimates of risk, then the type of mapping chosen should depend on the institution's chosen risk confidence interval and how A and B exposures aggregate. If an institution has a very high confidence interval and B exposures do not hedge their exposures, then it is conservative if the institution has a low confidence interval (or is computing average risk) and/or A exposure significantly hedges B exposure.

In terms of historical default data, lack of sufficient data is an issue. Technically, we are faced with the conundrum that there is no specific data on a particular obligor until after a migration or default has occurred. This is the same issue faced with modeling any rare event by actuarial methods. Insurance companies write policies covering a wide range of hazards such as tornadoes, floods, and hurricanes. Some of these events are rarer than the default of a triple-A obligor. However, insurers have for the most part successfully managed their risk by invoking

quantitative methods. In fact, much of the content of *Extreme Value Theory* was motivated by risk theoretical problems in insurance. Thus, effective risk modeling can occur without a complete data set.

Market data *gathering* problems due to disparate locations, systems, platforms, and vendors could be addressed in the same manner that they are in the market risk model implementation. In fact, the market data gathering component could leverage off of existing data warehousing or distributed technologies in place an institution's market risk system. We feel that this is a generic data integration problem.

Concerning default data gathering, certainly the most complete data set is the sum of all available data sets from vendors, institutions, and regulators. Risk measurement accuracy and efficiency could be enhanced by data sharing coupled with the development of a standard default data interface. While we would be reluctant to force banks and other institutions to share data, **the Committee believes there will be a natural tendency for institutions to share or sell data, thus making available more complete and accurate data sets.**

The performance issues should be addressed in the context of the processing components of the credit risk system. There are data gathering processes, the statistical processing of the actual market and/or default data, and the risk processing itself. Processing performance issues lead to synchronicity problems. If market or default data is stale due to slow data gathering or statistical processing, then the risk processing will be inaccurate. On the other hand, if risk processing is too slow, then results are stale.

Stale model parameters are the effect of slow processing of the actual market data. One possibility for addressing the stale data issue is through an add-on factor. Specifically, an institution could compute sensitivities of the risk numbers to the underlying market risk and historical default rate parameters. This sensitivity calculation could be broadly based. If an institution is using an equity-based model, then sensitivity to market indices could be computed. One could then add on an amount that reflects the sensitivity multiplied by particular market move. A similar add-on could be computed for corporate spread based models or even actuarial historical default based models. Note that here we are talking about add-on factors to the data inputs - not the model outputs.

Concerning the risk processing performance, this could be improved in a number of ways. If an institution uses simulation based techniques, then this simulation could be distributed to many different computers. This could be achieved with sophisticated distributed computing techniques and architectures. But there are simple methods of distributing the processing as well. For example, a "risk server" could "broadcast" the simulation paths on a weekly basis to computers ("computation clients") throughout the institution. File transfer protocol (FTP), email, or posting simulation paths to a web page could achieve this. The computation clients could then use the simulation paths to re-value particular portions of the portfolio several times. The result of a multi-revaluation by a given computational client would be a list of losses at the

given default times of each counterpart. The risk server would then request the results from these computational clients and then perform an aggregation. Aggregation performance would then depend on the required report granularity.

While performance is clearly an issue, it should not be considered a roadblock for internal credit risk models. The Committee asserts that these performance issues have been overcome in particular cases and those solutions will be extended in the future.

Compared to firm wide market risk systems, credit risk systems require much more granularity of certain data. This is because market risk data can be aggregated by risk factors such as S&P 500 and 10 Year USD Swap Rate, while credit risk systems need to aggregate by counterparty, master agreement, and transaction on the capital markets side and by obligor on the lending side. This data should currently already reside in various systems, platforms and databases. The "systems upgrade" related to the contractual data would include the development of a counterparty data warehouse/mart and integration from the various disparate sources into this database. Again, we feel these are generic albeit large-scale systems integration and development problems that could be solved by committing applicable time and resources.

While there is most likely a large upgrade required for the contractual and counterparty data, we are not convinced that extensive systems upgrades are required for the statistical data processing. For equity or corporate spread based models, the systems upgrades should be similar to those required for market Value-at-Risk. In the case of historical default data, the systems upgrade is primarily related to the development of a default database. Furthermore, various well-known vendors provide off-the-shelf solutions for all of the major default models. If an institution chooses a vendor solution, then the systems upgrade amounts to a software installation coupled with substantial but feasible data integration.

Concerning upgrades in general, the question is whether an institution is willing and/or able to commit time and resources to such a large-scale endeavor. Institutions are well aware of the required systems development and that profitability will be the overriding factor in the credit risk method decision-making. The Committee believes an institution's decision to undertake such a project would then most likely result from a cost benefit analysis of developing an internal credit risk system vis a vis using the standard approach.

5 Validation

The key validation issue for banks and their regulators is whether both may rely on a particular credit model or implementation of a model in the matter of computing appropriate regulatory capital requirements. This chapter explores the scope of that issue and presents our perspective and recommendations. To foreshadow them briefly, we believe validation faces the manageable obstacles of further investment in time and planning for regulators and regulated, but can already clear the intellectual obstacles that have been advanced against such use of credit models.

The Basle remarks highlight the following concerns:

- credit data limitations are a key impediment,
- the banking book (not marked to market) is large, and significant losses may accumulate in it, unnoticed, and
- attempts to validate credit models by closely replicating the validation procedure for market risk models are simply not feasible—data is insufficient and the planning horizon is too long.

The idiosyncrasies of credit risk and the scarcity of credit risk data, which raised conceptual issues and parameterization issues, have also complicated the validation process. The Basle paper puts it (Section 3, page 10),

...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. ... 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.

In one perspective, these reservations as to validation are entirely appropriate and wellfounded. In another, it is axiomatic that comparison is basic to all analysis. At base, credit models as a group has to be compared, not to perfect foreknowledge, but to the existing riskbased capital guidelines, with or without incremental adjustments.

In the Basle Committee's April 1999 discussion, validation is approached in particular as an extension of validation for market risk models. In some sense that is natural, because of the obvious analogy between the two classes of risk. In another sense it obscures the real substance of regulatory validation.

Validation of credit risk modeling for regulatory capital purposes should have one overriding criterion: Does the proposed approach to estimating appropriate regulatory capital represent significant incremental improvement over the presently approved procedures?

The tight linkage to market risk modeling also obscures an issue arising from the relative scarcity of detailed credit experience across the spectrum of actual credit exposures. A valid credit risk model is not a machine (actual or virtual) to be turned loose on an input dataset and trusted to produce a finished estimate of a bank's proper capital requirement without further human involvement. It is rather a carefully constructed tool or group of tools designed to assist the modeler in making valid estimates.

When the credit risks across the banking and trading books of an institution are to be summed up in a capital requirement, what is called for is model-assisted, numerically sophisticated analysis. The analysis uses the model or models, and may be modified for particular characteristics of the risk portfolio, data or pricing availability, or limitations of the current edition of the model. What must be validated includes the model or models *and the way they are used* to compute the regulatory capital requirement.

The standard for validation of credit-risk-modeled estimations of regulatory capital has to be the material incremental improvement over the simple, clear-cut, but very approximate rules first laid out in 1988. There is no necessary linkage, for example, between the values produced by a given institution's credit models and the current regulatory capital levels, per se. The current regulatory capital levels were derived from an historical process of judgment and adjustment in the various supervisory jurisdictions to cover all the risks of a bank, credit and otherwise.

Despite the complexity of credit risk models, there are sufficient tests, namely stress tests, scenario analysis and sensitivity analysis, to demonstrate the soundness of a credit risk model. Only backtesting, which works so easily for market risk models, is of limited use for credit risk models. To compensate, we propose adjustments to traditional backtesting as well as putting more emphasis on the other tests.

Assuming a parallel investment of time and expertise from regulators, the Committee believes our recommendations for addressing validation are sufficient to guarantee confidence in credit risk models. The following sections illustrate our position that credit risk models are ready to meet the material incremental improvement validation standard, with much improved consistency and accuracy.

5.1 Backtesting

Backtesting, in the sense contemplated for market risk models by the Market Risk Amendment, does not work very well for credit models. Basle states that a similar standard for credit risk management models would require an impractical number of years of data. The main problems lie in the quality and abundance of data and in the relevant time frame. We agree.

As the Basle document puts it, "The methodology applied to backtesting market risk VAR models is not easily transferable to credit risk models..." They cite primarily the limited availability of data for testing, then remark that banks' alternatives to backtesting generally

compare the credit market with current market data, while assuming the "normality" or appropriateness of current market conditions. They also point out that measuring expected losses is not the same as measuring the unexpected losses. Undoubtedly, today's credit risk backtesting lacks precision in estimating the outlier credit loss levels against which capital should be kept.

The issue with backtesting, then, is to identify those cases for which backtesting is feasible, and where it is not, to describe a more limited role for backtesting and to propose what other routes to validation may fill the shoes of backtesting as relied on in the Market Risk Amendment, so as to afford regulators the confidence they need to rely on a credit model.

Backtesting is the process of testing the accuracy of a model under the fundamental assumption that markets will behave tomorrow as they did yesterday. Backtesting consists in verifying that 'ex-ante' model results match 'ex-post' data within the model's confidence interval. This process requires the use of historical scenarios.

Backtesting is usually assumed to be testing with a long time series. But it may also include testing with one historical event (which is a special use of scenario analysis). While one event ca not tell us as much as a time series of events, the one event test gives us some information.

In the case of a market risk management model, the backtest may be applied to an abundant series of observed actual market price movements and corresponding modeled movements, providing both regulators and risk managers a common reference over which to discuss the model's validity. Indeed, the expression "'x' out of 250 daily trading outcomes were not covered by the risk measures" is indisputable to both regulators and risk managers.

The existence of such a common reference performs the role of a 'third opinion' on which regulators and risk managers can rest. This third opinion, however, differs in kind from the opinions of regulators and risk managers, because the market provides it by an objectively defined procedure, not by the judgment of individuals. Backtesting may be considered a robust tool for validation when there is sufficient history to be able to approximate the probability density function of losses with a high degree of confidence.

For credit risk, the longer gestation period of most credit losses, the relative infrequency of expected losses, and the lack of homogeneity from one set of credit exposures to another, also combine to hinder backtesting's approximation. Perhaps with the accumulation of more and more detailed historical data, backtesting with a long time series will in time become feasible for some longer-term wholesale exposures. That does not appear to be an immediate prospect.

In certain cases backtesting is feasible. Backtesting may have a role in testing loss experience on consumer loans and receivables, where the population of borrowers is so large and the credit loss cycle short enough to obtain reasonable approximations. As mentioned above, a certain variety of scenario analysis recapitulates a particular historical episode of market conditions to test its effect on credit portfolios. There is valuable information in that.

For the most part, however, backtesting has been prominent in credit risk modeling by analogy with market risk models, not because it was obviously feasible. It is doubtful, for example, that anyone has attempted to backtest the present risk-based capital guidelines, which are the regulatory credit risk "model" presently in force.

Therefore, to validate credit models generally, one needs an appropriate substitute for backtesting. The solution is to squeeze more information out of existing data. Here the Committee recommends working with both virtual portfolios and fictional time-series of credit events, as well as broader measures of historical credit loss experience aggregated at a higher (and available) level.

If it should turn out that the more approximate loss and pricing data require a confidence interval about a credit model's estimate that is broader than we are used to with market risk models, that is an adjustment of accustomed perspective, not an argument against validation.

We agree with Basle that up to now there has been only isolated progress in attempting to find appropriate substitutes for full backtesting. We recommend that both the industry and regulators work to develop and reach consensus on methods that will serve.

5.2 Stress testing

Stress testing is used to value portfolios under extreme unfavorable changes in input variables and under chaos scenarios where more than one unexpected unfavorable change in variables occurs. Several stress tests may be appropriate for any given portfolio.

A credit risk management model calculates losses based on the implicit probabilities it assigns to various events. Stress testing answers the question, "Under extreme but possible variables scenarios, how much can this portfolio lose?"

Unlike back testing, stress testing does not necessarily use historical scenarios. Its purpose is actually quite the opposite. Stress testing seeks to analyze potential future scenarios. More than anything, stress testing serves to explore the logical implication of a model's internal structure combined with extreme assumed values, such as default rates, default correlations, or sudden credit spread widening. Stress testing has a unique place in operating credit risk management - exploring the possible impact of a large change in the environment or the customer.

As an element of the validation process, stress testing can contribute insight and evidence of the credit model's internal consistency and realism in responding to extreme values of assumptions, and unusual combinations of assumptions. Since the most basic validation process has to take as a reference specific loss experiences suffered by specific institutions on specific credit exposures, stress testing explores the plausibility of extrapolating the actual, "base-line" experiences out to extreme values. One validation tool is a comparison of the credit-modeled capital projections with available actual experience. A financial institution's historical experience combined with data shared or published by other financial institutions is useful.

Since the quantity and quality of data are insufficient to support backtesting, the process of comparison will inevitably require exploring the differences between the credit exposures that produced the actual experience and the exposures measured by the credit model. Though detailed credit history is relatively scarce, there is a wealth of high-level aggregate credit experience in banks' historical results that can feed such comparisons legitimately. A credit modeling approach that can approximate the loss distributions demonstrated (at a high level) over many institutions and many years certainly has predictive value, and stress testing using these scenarios can illustrate the reasonableness of the model's "interpolation" across the differences in credit portfolios and economic climates.

Thus stress testing serves at least two purposes. One is to overcome uncertainties in the model by testing scenarios, which are not explicitly addressed by the model. The other purpose is part of the regular business review, namely, to test scenarios which one may intuitively know the bank may be vulnerable to but which the model may not pick up.

The Committee agrees with Basle that few banks use stress testing. **The Committee recommends that banks formally incorporate stress testing into their regular risk management process.** Banks should develop and document policies and procedure for running stress tests. They should determine a specific schedule for running these tests and tests should be relevant to the current market environment. For example material current news or rumors of significant market events that could impact the bank's portfolio should be occasions for specific stress tests.

5.3 Sensitivity Analysis

The primary validation issue with sensitivity analysis is the character and extent of its contribution to an overall validation of a particular credit model, as installed and used. We believe sensitivity analysis to be a key component in validation, since it pierces the apparent opacity of a model to show how it reacts to changes in portfolio, assumptions or market environment. The Basle document pointed out chiefly that apparently only a few institutions tested the sensitivity of their models' output to parameter values or critical assumptions. Some proprietary models, they noted, do not give the user insight as to what the key structural and parameter assumptions underlie the model. Lastly, none of their respondents attempted to estimate the error in their estimated distribution of credit losses.

We agree with the Basle authors that the main validation difficulty respecting sensitivity analysis is simply that more of it needs to be done, since it is a useful tool.

Sensitivity analysis is the process of exploring how a model's predictions change in response to an incremental change in one or more risk factors, assumptions, parameters, or input on economic and market conditions. The analysis may show the change at the margin with a single input, or may explore the effect of jointly changing a group of inputs, so as to explore, for example, the working of the portfolio effect with changing composition or time horizon. *Risk factors, assumptions* and *parameters*, as used here, are treated as defined terms, as follows.

Risk factors are the fundamental drivers of the risk in a given portfolio, regardless of the model being used to quantify it. Unlike model assumptions and parameters that require extensive time series data, exposures to risk factors can be listed in factual and descriptive reports such as consolidated views of debtors' exposures by country, industries, external or internal ratings, instrument type, time to liquidation, liquidation values.

A *model's assumption* is a general hypothesis on the behavior of one or more variables defined in the model. Assumptions are typically simplifying devices based on business experience. It is current practice for risk model builders to start the engineering process with a set of assumptions and then attempt to 'relax' these assumptions in an effort to increase its scope.⁹ This 'relaxation' generally introduces additional new assumptions and parameters. As a result, model output sensitivity to certain assumptions, as Basle sought to find among its respondents, may be difficult if not impossible to compute since relaxing or modifying a central assumption really means using a different model. To be sure, sensitivity analysis can be carried out on other assumptions such as the liquidation period.

A *model parameter* is a number estimated on past data series and being used as a constant in the future for the calculation of the output. One of the major assumptions underlying risk models is the stability through time of these generally historical sample-dependent parameters. It is widely recognized that this stability breaks down in major crises not only within a risk class (such as market risks or credit risk) but also across risk classes often through rapid deterioration in asset liquidity.¹⁰ As a result recent history has shown more occurrences of events than models would have anticipated.¹¹

⁹ See for example 'CreditRisk+ Model', CSFB, 1997, Appendix A

¹⁰ See G30, 'Improving counterparty risk management practices', June 1999, Appendix A: 'Risk Measurement, Liquidity Risk and Leverage Estimation'.

¹¹ 'Risk Professional', Issue 1/5 July/August 99, Richard Hoppe article, pages 15-16

Credit models attempt to forecast credit losses based on assumptions and choices of variables, just as other models do. Sensitivity analysis assists understanding of the models by demonstrating how changes in model assumptions or the variables' values affect the credit losses.

We have asserted that sensitivity analysis is a key to credit model validation. While not covering the all the validation concerns, sensitivity analysis is the best tool for illustrating the transparency (or lack of it) of the model's assumptions and structure, by demonstrating incremental sensitivity of its output to its various inputs. At a minimum, sensitivity analysis can show that the model's response to a change in input value is directionally rational and proportionate across the spectrum of different types of inputs. This should alleviate the "black box" concerns that more complex models may inspire.

As a diagnostic for validation, sensitivity analysis can demonstrate input/output relationships not only at the margin of currently experienced values, but at parameter, risk factor, correlation and time horizon values far above and below current experience, mapping the behavior of the model. Such analysis serves not only to help validate a model for a particular range of applications, but may also point out limitations in the model's reach that would help define the range over which the model should be considered valid.

Another way to validate the model's quality is to 'backtest' it within the institution by showing how the availability of its sensitivity analysis reports in a time preceding major historic credit losses would have allowed the institution to eliminate or reduce these losses. This procedure should be specific to an institution and 'back-tested' against its own credit loss experience.

In addition to testing model's rationality and accuracy, sensitivity analysis serves other important objectives. First, it is one way to quantify and relate the risk factors found in a given portfolio, highlighting areas where data time series and stress testing will be most required in the current portfolio credit structure context. ¹² Second, it spells out which variables (or variables' value change) have the largest impact on the capital number allowing 'portfolio dependent' stress testing practices as described in the Market Risk Amendment. ¹³ Third, it allows disclosing additional risk profile information to the public.

Tailoring an institution's regular procedures for sensitivity analysis to reflect its own history and business environment would make the disclosures just mentioned particularly helpful. Such a discipline might result in an ongoing, easy to read status report on the current credibility of the portfolio risk calculation, most likely including data described in several Basle documents that

¹² See also G30, 'Improving counterparty risk management practices', June 1999, recommendation 12: 'Contextual Information'.

¹³ Section B5 ' Stress testing', c) 7. "In addition to the scenarios prescribed by supervisory authorities...a Bank should also develop its own stress tests which it identifies as most adverse based on the characteristics of its portfolio..."

have addressed the need for more risk disclosure and transparency.^{14 15} Accordingly, the Committee recommends that sensitivity analysis procedures be specifically designed for the use of a particular institution having its specific business experience and relevant history.

Once exposures and sensitivities to key risk factors, assumptions and parameters are being routinely provided, attention can turn to discussing with business management the likelihood of crisis in the areas were the portfolio is most exposed.¹⁶

The Committee recommends that sensitivity analysis be an integral part of credit model validation and is a central element in a credit model's analytic tool-kit. Credit Risk quantification models should be fully described in a comprehensive document spelling out:

- the risk factors handled by the model,
- the model's assumptions and parameters, and
- the sensitivities of the model output to changes in exposures to risk factors and
- sensitivities to changes to model assumptions and parameters (Delta VAR's).

In the Market Risk document, the Basle uses a full section¹⁷ to specify a minimum set of risk factors that a market risk model should incorporate in order to be validated. With Credit Risk, too, a minimum set seems prudent, albeit recognizing that valid models may vary widely in structure, level of detail and integration across risk portfolios. **The Committee encourages the regulators to issue a minimum list of risk factors that credit risk models should address.**

As an adjunct to assumptions sensitivity analysis for validation, one could estimate the risk of a set of relevant typical portfolios using different models based on different assumptions, to measure the magnitude of the risk measure change. This comparison of standard risk portfolios across models would likewise serve the understanding of the risk measure, and its validation.

5.4 Management Oversight and Reporting

We have pointed out elsewhere that to be valid, an individual credit model must fit some range of credit exposures and uses at the banking organization where it is to be used. The key validation issue in this section is whether the institution itself is ready to support, supervise, and rely on the model.

¹⁴ 'Public disclosure of trading and derivative activities', February 1999.

¹⁵ 'Best practices for Credit Risk Disclosures', a consultative paper issued in July 1999.

¹⁶ 'Report of the Task Force on Risk Assessment', IIF, March 1999, Recommendation 3.

¹⁷ Section B3, 'Specification of market risk factors'.

Under the heading of "Management Oversight and Reporting" the Basle document expresses concerns, in brief compass, over (1) the way the model is to fit into the internal credit environment of the institution, (2) the quality of senior management oversight and understanding, (3) the internal organizational rigor in requiring fully developed validation analyses as a reflection of management oversight, and (4) the adequacy of internal controls on the quality of key data input to the model.

As to the first concern, the success of a model depends as much on the way the model itself is used as it does on the environment in which the model operates, especially given many credit models' considerable complexity. Recent history in the derivative markets has repeatedly demonstrated that errors are more likely to occur when a model is abused, even when the fundamental model is sound.

The use of proprietary credit risk models empowers risk management with a renewed scope and responsibility. It is no surprise then that we recommend increasing investment in risk management to ensure that both the credit risk model and the environment in which it operates are reliable.

But the rest of the organization must also get ready to support the credit model—to supply portfolio characteristics and other data in a consistent form and with sufficient detail. That may imply considerable investment and management time spent on improving and regularizing the flow of data.

At the other end of the modeling process, the institution should get ready to receive and interpret the model's results, and then take the results as a basis to recommend management decisions affecting the bank's credit exposures. That represents a substantive adjustment in the internal management of the business. Without this organizational adaptation, it will be more difficult to keep operating units motivated enough to commit to maintain data quality. Such changes will not necessarily be rapid, but should be slated by every institution intending to rely on credit risk models.

As to the second concern, effective management oversight is necessary, and consists of investing senior management time in understanding the salient issues. Then they should establish a clear and specific set of policies that prescribe the environment in which model-based credit risk management takes place. Beyond the general principles of risk management policies, credit risk policies should in particular describe in detail the internal credit risk ratings criteria and the way the institution interacts with higher-risk counterparties.

Senior managers should also be responsible for ensuring that the infrastructure is set up. Given the importance of credit risk management, senior management should allocate sufficient resources to cover the following areas properly: (i) regulatory relations unit (an up-and-coming area in the field of a credit model-based risk management), (ii) model development, and (iii) unit model validation and stress testing unit. Other bank policies may need to be adjusted as well, particularly those involving performance measures that relate to commitments of economic capital or regulatory capital. Ideally, a thoughtful implementation of credit risk models should cause the two numbers to converge.

Besides policies and infrastructure, the nature of overseeing and validating the use of credit risk models suggests that we adjust perspective on the roles of three interested parties to the credit risk modeling process: risk managers, external auditors (and reviewers,) and bank regulators. Regulators and risk managers are unlikely to have an objective reference as is generated in the field of trading risks as a basis to discuss the validity of the proprietary measurement system. As a consequence, all three groups will need to work consultatively toward a consensus about the quality of the proprietary measurement system, and work out ways to reconcile diverging opinions over their validity.

Thus far progress in credit risk management has come through the innovation on the part of credit risk management. It is a basic tenet that users of a system are best qualified to design, develop, and apply that model. Therefore **the Committee endorses that credit risk managers continue to have the responsibility and authority to build their own models.**

At the same time we recognize the basic conflict of interest that the risk management group is both the designer and user of the credit risk model. Independent review is essential and prudent from both the supervisors' and senior management's viewpoint.

Therefore, **the Committee recommends that independent reviews should be made available to and discussed with regulators.** Rigorous standards regarding the construction and the operation of the credit risk model need to be defined and progressively improved.

This ongoing interplay among risk managers, (external) auditors and regulators would be in based on the following principles:

- oversight should be quasi-continuous, i.e., the pace of meetings and on-site inspection should be significantly increased.
- the new set-up should apply only to a limited group of banks that have already completed an introductory phase. Within that earlier phase, regulators should gain confidence over time that the model's environment, its structure, and its performance over a certain period of live testing, are satisfactory.
- the different parties should relate to each other on the principle of full consensus. Independence should be attributed to regulators, (external) auditors and risk managers, and validation would be conferred by full consensus between these parties. Validation would be temporary, i.e., it would need to be continuously assessed and renewed going forward.

As to the third concern expressed in the Basle document, the actual scarcity of fully developed validation analyses at present owes to the newness of the genre and to the absence of any powerful short-term incentive to incur the incremental investment of resources. The Committee believes that such analyses would accelerate sharply once a credible possibility of near-term regulatory acceptance for capital purposes appears. Just as credit modeling is more complex, credit model validation is more laborious, hence the importance of an incentive.

As to the fourth concern, we agree with Basle that internal controls on the quality of data are essential and a substantial challenge.

Nevertheless, it is also a basic tenet of risk management that institutions be organized to avoid potential conflict of interest. This applies to the credit models, and to the data gathered and supplied to it as well. Model builders should be independently audited, and credit rating assignors or reviewers should act independently from loan officers, for example. Independent reviews should thoroughly examine the effectiveness of both the model and the environment in which it operates. Great care should be given to data integrity and to the coherence and soundness of all input parameters. The quality of the data it can rely upon is basic for a credit model. Poor or inconsistent data quality quickly degrades the quality of the model's output.

In summary, the Committee believes these principles of management oversight and review, conscientiously applied, are essential and provide an underpinning for growing reliance on credit risk modeling.

6 Conclusion

The Committee asserts that internal credit risk models are an immense improvement over the current Basle Accord and offer the most effective means of encouraging sound risk management. We therefore strongly encourage the Basle Committee to support the use of credit risk models in the assessment of regulatory capital.

The eventual goal would be for banks to use models across all assets and businesses to ensure risk is measured in a comprehensive and timely manner. As a practical matter, models should be rolled out and integrated into the regulatory capital assessment process on a piecemeal basis as they are developed and proven to be an accurate measure of risk.

Regulators should accept models on a case-by-case basis. Models should be evaluated as to whether they are appropriate for the particular products, business, and institution. Regulators should consider the environment in which the model operates as well as the model.

Each individual bank must take responsibility for developing a model which is appropriate for its use. In addition, the bank must demonstrate that its choices and assumptions are sound. Banks should set rigorous model acceptance standards and dedicate the appropriate resources to support the documentation process and ensure their proprietary models keep pace with industry developments.

Likewise, regulators should develop minimum qualitative and quantitative guidelines to ensure a degree of transparency and level of consistency in risk reporting. In addition, regulators need to prepare their examining staff and equip them with the necessary tools to properly evaluate these models and their effectiveness in managing risk.

We are confident these challenges are manageable and that we will soon see the application of more models to accurately measure and manage credit risk from a regulatory and economic capital standpoint.

Appendix: Components of a Credit Risk Model

