Risk Quantification of Retail Credit: Current Practices and Future Challenges*

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*The views expressed in this paper are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of Philadelphia or of the Federal Reserve System.

I. Introduction

This paper examines current practices at U.S. banks for quantifying credit risk and estimating economic capital in retail portfolios.[1] In addition, the paper examines issues facing banks and their regulators in developing an internal ratings based (IRB) approach to setting capital requirements for retail exposures.

Within the last decade, many large banks have made substantial strides in incorporating quantitative credit risk models into business practices. Based largely on industry models (e.g. CreditMetrics, Credit Risk$^+$, KMV Portfolio Manager), an increasing number of institutions use credit risk models for risk management, allocating economic capital and measuring risk-adjusted returns at the business line level.

Developments in credit risk modeling are influencing, and being influenced by, the effort to reform the Basel Committee's standards for regulatory capital – Basel II.[2] A stated goal of this reform effort is to create a capital standard that is more sensitive to the risk of an institution. To achieve this goal, the Basel Committee proposes allowing banks with sufficiently sophisticated risk measurement and management systems to use their own internal systems determining key risk parameters entering into the regulatory capital calculation.

While the general principles of portfolio credit risk modeling are equally applicable for commercial and retail portfolios, industry and regulatory resources devoted to advanced credit risk models have largely concentrated on commercial loan portfolios. Thus, it is not altogether surprising that the initial Basel II consultative paper in 1999 on

[1] The term "economic capital" is defined here as the amount of capital allocated to a particular activity based on the activity's marginal contribution to economic risk.
[2] Basel Committee on Banking Supervision (2001a).

the reform of the capital standards contained very little explicit discussion of the retail portfolio. While the current Basel II proposal contains more explicit language discussing the special features associated with measuring retail credit risk, it is clear that work in this area is relatively underdeveloped.

This paper is an attempt to address this imbalance, as much of it is devoted to a discussion of the current state of bank practices for modeling retail credit risk and the associated calculation of economic capital. In addition, it will discuss some of the key challenges in using internal models for setting regulatory capital requirements for retail exposures. Information for this paper comes from a variety of sources including discussions with bank risk managers and modelers. Since much of the data and methodology gathered are proprietary, the paper discusses general principles behind various approaches and methodologies.

II. Characteristics of Retail Credits

For the purposes of this paper, the definition of retail lending is consistent with the one used in the current Basel proposal. Retail loans include loans to individuals or households, including credit card loans, mortgage loans, home equity lines of credit, auto loans, and other consumer loans. The Basel II proposal also includes in its definition of retail exposures low value loans to small businesses if those exposures are primarily managed on a pooled basis.

Retail loans are relatively small value loans, and, with economies of scale associated with information gathering and monitoring of larger loans, limited resources are devoted to analyzing the idiosyncratic risk of an individual borrower or facility. Retail lenders in the U.S. typically rely heavily on sophisticated statistical models of borrower performance for approving loans and generally track performance of those credits on a pool or segment basis.

The primary statistical tool for making retail credit decisions is credit scoring. The existence of extensive credit bureau data in the U.S. allows lenders to use a wealth of readily available data on individuals to estimate "bureau" scoring models. In addition to standardized bureau scoring models, banks often buy or develop customized scoring models tailored to the bank's own client population. Many companies with a sufficiently large retail portfolio employ "application" scoring models that allow an institution to incorporate additional information collected during the loan application process.

In addition to "scoring" customers at the time of application, scoring models are used in a dynamic way for managing accounts and for internal bank analytics. Many lenders obtain updated or "refreshed" bureau scores on a monthly basis and some use "behavioral scores" that factor in the borrower's performance on accounts with the bank. Scoring on a dynamic basis is used for a wide variety of purposes including credit line changes, collections and analyzing account profitability.

In summary, a central feature of the modern retail credit business is the wide scale use of statistical models for decision making. Yet, despite this extensive use of sophisticated statistical tools for managing retail credit portfolios, industry efforts to model credit risk "loss distributions" are relatively new and relatively less developed than in the commercial lending area.

There are a number of likely reasons for this. First, the economies of scale in loan evaluation and loan monitoring create economic incentives to devote a greater share of lender resources to the evaluation of idiosyncratic risk factors for large loans. While this does not automatically translate into more resources devoted to modeling commercial portfolio losses, the greater effort and technical expertise devoted to analyzing volatility of individual commercial loans helped spur the development of more sophisticated commercial portfolio risk measurement systems.

A second factor accounting for the more rapid development of commercial credit risk models is the long history of rating agency evaluations for commercial firms with publicly traded securities. These agency ratings, along with the extensive data available for publicly traded firms, provide extremely useful benchmarks for the development of quantification methods for commercial portfolios. As a result, most banks with internal credit risk models benchmark their internal loan grading systems to equivalent agency ratings.[3] The extensive pricing data on publicly traded securities also allowed modelers to more directly incorporate innovations in financial economics, e.g., option pricing models, into their credit risk models.

While these reasons help explain why credit risk modeling developed more quickly in the commercial loan setting, there are also some significant advantages for credit modelers measuring risk in retail portfolios. In particular, the heavy reliance in retail lending on statistical scoring models means that judgmental factors play a relatively smaller role in the retail portfolio. In principle, with fewer judgmental factors entering the evaluation of individual credits, retail portfolios should be more amenable to quantitative risk modeling. A key problem in commercial credit risk modeling is estimating the quantitative risk parameters associated with a particular grading system

[3] See Carey and Treacy (1998) for a detailed discussion of bank internal rating systems.

and ensuring that loans are appropriately graded. If loans are scored, then the quantitative meaning of a particular grading system is more transparent.

Nonetheless, current bank practice in modeling retail lending risk typically concentrates on estimating first moments of performance, i.e., expected losses and delinquency rates, rather than on modeling higher moments of the loss distribution. In part this can be attributable to the tendency of business managers to focus on expected profitability rather than on measures of volatility. In addition, many practitioners in the retail lending area mistakenly believe that the law of large numbers implies that the distribution of retail outcomes will show little variability around the first moments of the distribution. From this proposition they conclude that significant departures from expectations are solely the result of model error or poorly designed business practices.

Theoretically, the law of large numbers implies that the idiosyncratic components of individual loan risk will be relatively unimportant, but it does not imply that movements away from the mean generated by systematic risk factors will be small. The importance of systematic factors in loss volatility can only be determined by empirical analysis.

The view that significant departures from expectations are solely the result of model error or poorly designed business practices, a view still common among commercial lenders as well, can be described as the "banker" view of risk. The banker view emphasizes the endogenous components of credit risk, in particular the role of risk management processes and controls in reducing that risk. This contrasts with the "finance view" that emphasizes the exogenous components of risk resulting from underlying stochastic processes affecting a chosen portfolio. The finance view stresses the role of risk management in accurately measuring risks and ensuring that the company maximizes its objectives by choosing from the efficient risk/reward set of opportunities.

Of course, there are endogenous and exogenous components to the loss volatility of a given portfolio of loans. Using the performance statistics from an institution's internal data provides a method for implicitly incorporating the effect of endogenous business processes on loss volatility.

III. Measuring Credit Risk: Some Theoretical Fundamentals

In general, the credit risk models for retail exposures currently in use at U.S. banks are based on a default-mode modeling approach, rather than a mark-to-market model. Therefore, for ease of exposition, we will confine our discussion to default-mode models in this paper.

Consider an individual loan with a given probability of default (PD), percentage loss given default (LGD), and dollars of exposure at default (EAD), where all of the relevant parameters are measured over a one year time horizon. The dollars of expected loss on the loan is then:

$$EL = PD \times LGD \times EAD \tag{1}$$

Assuming independence among these parameters and a known EAD, then it is relatively easy to show that the standard deviation (SD) of loss per dollar of exposure for this loan is:[4]

$$SD = \sqrt{(\sigma_{PD}^2 \times LGD^2 + PD \times \sigma_{LGD}^2)} = \sqrt{(PD \times (1 - PD) \times LGD^2 + PD \times \sigma_{LGD}^2)} \tag{2}$$

SD is a stand-alone measure of risk.

If we measure the standard deviation of losses for the portfolio, we get:

$$SDP = \left[\sum_{i} \sum_{j} \rho_{ij} SD_i SD_j \right]^{.5} \tag{3}$$

where ρ_{ij} is the correlation between asset i and j. As is apparent, estimating this model requires estimates of the cross asset correlation parameters.

To determine the appropriate level of economic capital for any loan portfolio requires establishing a relevant probability threshold (e.g., 99.95% probability that losses will be less than capital within one year). To translate an estimate of SDP to economic capital requires some assumption about the underlying distribution of losses (e.g. Normal, Beta, etc.) or, alternatively, the use of stochastic simulation methods to determine the tail of the distribution.

An important decision made early on in the Basel II process was the determination that the state of portfolio credit risk modeling was insufficiently developed for direct use in setting regulatory capital. In particular, concern was expressed over the reliability of current methods of estimating correlation parameters and questions were raised about the ability of external supervisors to validate such estimates. While the Basel Committee suggested that internal portfolio models would eventually become the basis for setting regulatory capital, it proposed to move immediately to a simplified approach to the use of internal ratings in the determination of regulatory capital. The internal ratings based approach, or IRB, allows bank's to use their internal loan ratings categories as a basis for setting regulatory capital. However, capital requirements are set based on risk parameters estimated separately for each ratings category.

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[4] For a more complete discussion of measuring loan loss volatility see Ong (1998).

In a model of portfolio loss distributions, the economic capital associated with a particular asset (or a sub-portfolio of assets) depends on its contribution to portfolio risk, and *in general* this contribution cannot be determined using estimates of a sub-portfolio's stand-alone loss distribution.[5] Stated differently, total economic capital will generally be less than or equal to the sum of economic capital appropriate for each asset or sub-portfolio on a stand-alone basis.

However, there are classes of models which are consistent with an IRB or risk-bucketing approach. In particular, Gordy(2000) has shown that, for a class of one-factor models, portfolio economic capital *will* equal the sum of stand-alone economic capital for individual assets or sub-portfolios. The model underlying the current Basel II is a special case of the Gordy one-factor model and is based on a Merton model with a single normally distributed systematic risk factor.

Assume that a borrower has returns characterized by:

$$X_i = \sqrt{\rho_i}Y + \sqrt{1-\rho_i}\varepsilon_i \tag{4}$$

where $\boldsymbol{Y}$ is a systematic risk factor, ρ_i is the correlation of asset i with the systematic factor, and ε_i is an independent idiosyncratic stochastic factor. We assume X is normally distributed with mean 0 and variance of 1.[6] Let π_i equal borrower i's unconditional probability of default. This implies that borrower i defaults when $X_i < N^{-1}(\pi_i)$. Portfolio losses, conditional on Y, can be written as:

$$L(Y) = \sum_{i=1}^{k} \lambda_i LGD_i \,\mathrm{M_i}\,(\mathrm{Y}, \varepsilon_\mathrm{i}\,, \rho_i) \tag{5}$$

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[5] If the portfolio is sufficiently granular then idiosyncratic components of loss would not enter the calculation.

[6] Once a normal distribution of returns is posited, assuming a standard normal is done without loss of generality.

where λ_i are the dollars of exposure at default in asset i and $M_i(\,)$ is an indicator variable taking on the value 1 if the i^{th} asset defaults and 0 otherwise. To calculate the unconditional expected loss simply replace E $M_i(\,) = \pi_i$ and LGD_i with its expected value.

Borrow i defaults whenever X_i falls below some unobserved threshold - $N^{-1}(\pi_i)$. Conditional on Y, borrower i defaults when:

$$X_i < N^{-1}(\pi_i) \quad or \quad \varepsilon_i < \left(N^{-1}(p_i) - \sqrt{\rho_i}Y\right) / \sqrt{1-\rho_i} \tag{6}$$

For a portfolio that is sufficiently granular, i.e., no individual loan is large relative to the portfolio, the actual loss rate given the realization of Y will asymptotically approach the expected loss rate conditional on Y:[7]

$$L(Y) \cong E[L \mid Y] = \sum_{i=1}^{k} \lambda_i E[LGD_i] N[\left(N^{-1}(\pi_i) - \sqrt{\rho_i}Y\right) / \sqrt{1-\rho_i}\,] \tag{7}$$

To calculate losses at a given confidence level (e.g. 99.95 probability $L < K$), substitute $N^{-1}(\,v\,) = Y$ where v is the chosen confidence level.

$$L(Y_v) = \sum_{i=1}^{k} \lambda_i E[LGD_i] N[\left(N^{-1}(p_i) - \sqrt{\rho_i}N^{-1}(v)\right) / \sqrt{1-\rho_i}\,] \tag{8}$$

Note from the above equation that, in this one-factor model, the tail of the portfolio loss distribution is linear in the tail of the loss distribution for each individual asset. Similarly, if there are sub-portfolios of loans with identical risk parameters including a common asset correlation, then the tail of the portfolio loss distribution will be linear in

[7] See Gordy (2000).

the tails of these homogenous sub-portfolios. Thus the model is compatible with a risk bucketing approach to setting economic capital.[8]

While the one factor model is consistent with a risk bucketing approach, the single factor model is a very restrictive one. In short, portfolio diversification effects are likely to matter. The approach the Basel Committee has taken is to incorporate an industry "average" diversification effect through the correlation parameter entering into equation (8). Regulators have used a combination of statistical estimates based on industry data and comparisons with current industry estimates of economic capital to set correlation parameters. In effect, this creates an average industry diversification discount factor at the product or sub-product level.

In the current Basel II proposal, advanced IRB institutions will provide own estimates for PD and LGD for a particular internal loan rating (for commercial loans) or by "homogenous pools" of retail credits. The correlation parameter is determined by regulators and banks *cannot* use their own internal estimates of asset correlations within a loan rating/pool category, across rating/pool categories or across product types (e.g. correlation between retail exposures and commercial exposures). This decision not to allow banks to use own estimates of correlations is a direct outgrowth of the Basel Committee's view that existing methods for estimating diversification effects for loan portfolios are unreliable.

There is an alternative rationale for limiting the scope of internal estimates used in setting regulatory capital. An optimal regulatory capital model may not necessarily be

[8] Typically banks subtract expected losses from their estimates of the tail of the loss distribution when calculating economic capital. However, with the exception of credit card portfolios, the current Basel II formulas use a version of equation (8). Basel II allows for capital requirements related to expected losses

identical to the best internal risk measurement model. Since regulatory capital is enforced externally, an appropriate regulatory model must be either directly verifiable by supervisors or be sufficiently incentive compatible to produce statistically unbiased estimates from the regulated institution.

Estimates of first moments of the loss distribution (probability of default, loss given default, exposure at default) may be more easily verifiable by third parties than estimates of higher moments of the distribution or estimates of asset correlations. For example, if we are estimating parameters from a normal distribution confidence intervals around the mean of the distribution will be functions of the second moment. And, confidence bands around the variance of the distribution will be functions of the fourth moment of the distribution. In addition, estimates of volatility will depend very critically on the timing of losses. Banks have a certain degree of flexibility in the timing of loss recognition to smooth losses and potentially reduce estimates of loss rate volatility.

IV. The Risk Bucketing Approach and Retail Exposures

At first glance, applying the current IRB approach to retail exposures would seem relatively simple. Since institutions rely heavily on statistical models of performance for both making credit decisions and account management, it would seem relatively easy to use those quantitative estimates to supply the relevant risk parameters for retail exposures. In particular, the existence of credit scoring would seem to provide a direct estimate of the probability of default.[9]

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to be covered to a limited extent by loan loss reserves [see Basel Committee on Banking Supervision (2001b)].

[9] There are a wide variety of scoring models used for different purposes (e.g. scoring for determining optimum collection strategies). For ease of exposition, the term scoring model is used here to refer to models commonly used for granting credit or determining the level of credit.

However, the conversion of statistical methods commonly used in managing a retail portfolio into estimates relevant to calculating economic capital is not trivial. Two issues seem of most relevance: estimation of the probability of default, and the determination of "homogenous risk pools" – the retail analog to commercial loan ratings.

Estimating Default Probabilities

Modern credit scoring models apply statistical techniques on the extensive data available on individual borrowers to generate performance forecasts for various types of retail loans. For example, many scoring models use logistic regression to estimate the probability of a loan becoming delinquent or charging off. The output of these models is a direct probability estimate of delinquency or default.

However, there are certain difficulties in directly using these estimates as the PD in an economic capital model. First, the probability estimate is typically not a one-year ahead probability. The typical methodology is to estimate a two-year ahead delinquency probability based on four years of data.[10] Since scoring models are generally not duration models, the forecasted probabilities cannot be adjusted simply to accommodate a shorter time horizon.

More substantially, scoring models are generally built as tools to rank order the performance characteristics of the population, rather than tools to accurately forecast the frequency of particular performance outcomes. This modeling objective effects how the models are constructed, and importantly effects the validation methods for assessing accuracy.

Scoring models are not true forecast models in that they typically do not include the likely state of the economic environment over the forecast period. For example, scoring models based on logistic regression techniques typically do not include actual or predicted values of relevant economic factors among the regressors. Thus, the models are a true "forecast" only if the best prediction of the path of the economy over the next two years is the economy's path over the prior two year period.

The absence of predicted economic variables does not imply that scoring models produce an "unconditional" probability of default -- theoretically the relevant input for PD in the one-factor model of equation (8). Instead, the probability estimate is the probability of default conditional on a replication of recent economic history. While numeric scores are generated to produce the same probability of default over different time periods, a borrower with identical characteristics will have a different score depending on when the scoring model is estimated.

As credit scoring models are typically developed as methods to rank order potential borrowers, the most common method for testing the accuracy of a scoring model is the Kolmogorov-Smirnov Goodness-of-Fit Test (K-S Statistic). The K-S statistic essentially measures whether the performance of lower scored borrowers is substantially worse than the performance of those with higher scores. A model may perform very well using the K-S statistic while producing large prediction errors for any given score band. For example, if the actual performance of borrowers uniformly shifts in a worse or better direction, the K-S statistic will not deteriorate.

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[10] Scoring models generally produce probabilities of various stages of delinquency up to and including default. For ease of exposition, we refer to the output of the scoring model as a "probability of default" estimate.

The reliance on the rank ordering properties of a credit scoring model reflects the business methods used for managing risk in retail portfolios. Historically, the retail market was characterized by lenders making offers of credit at a single interest rate and then either accepting or rejecting borrowers based on an assessment of likely performance. Lenders needed only to establish a single margin separating the two pools of accepted and rejected applicants. The probabilities of performance for non-marginal applicants would affect actual earnings results, but generally would not effect the decision to extend credit for applicants well above or well below the credit score cutoff.

Probability estimates would still be critical for making decisions about marginal borrowers. However, a retail lender's approach to handling prediction error uncertainty was typically to rely on monitoring actual performance and adjusting relevant score cutoffs based on recent performance history. This approach to risk management determined when scoring models needed to be reestimated. Generally, a credit scoring model was only reestimated if its rank ordering properties deteriorated, but it was not typically discarded if it rank orders properly but substantially misforecasts the conditional probability of default. To some extent, this explains the reluctance of credit risk modelers to use directly the probability estimates derived from credit scoring models as PD's in their economic capital models.

There have been and continue to be substantial market changes taking place that will likely lead to improved direct estimates of probability of default using scoring models in the near future. Among other factors, the revolution in information and communications technology has led to much greater degrees of risk-based pricing and targeted marketing in retail lending.[11] In this environment, a greater premium is placed on a lender's ability to accurately differentiate the credit quality of borrowers and to understand the contributions of particular sub-portfolios to the overall level of risk. This inevitably leads to a greater emphasis on scoring models for predicting profitability outcomes of particular business decisions rather than merely establishing reject/accept cut-offs. Accurate forecasts of profitability require improvements in methodologies for more accurate forecasts of actual default frequencies.

While there are weaknesses in using the direct probability estimates derived from scoring models, the rank ordering properties of scoring models can be an important input into estimates of the probability of default, nonetheless. Some banks use internal data to estimate the *ex post* one-year ahead default behavior using credit scores and other risk factors, such as loan seasoning, delinquency status, loan-to-value ratios, as conditioning variables. However, two related empirical issues arise when using this approach to estimate PD:

- Should models use "origination" or "refreshed" scores?
- Should recent history be weighed more heavily in the analysis?

Refreshed scores represent the most up-to-date information about borrower quality and therefore provide the most appropriate predictor of performance of the particular loans in the portfolio.[12] However, refreshed scores will be significantly affected by the

[11] A lender compares any gain from increasing price discrimination to the costs of the increased information necessary for more finely differentiating potential borrowers.

[12] Theoretically, refreshed scores could be a worse short-run predictor of performance since the models do not include optimal predictions of future economic factors. However, empirically the variations in individual characteristics should generally dominate variations generated by misforecasts of future economic factors. Moreover, since economic factors tend to be highly autoregressive, the implicit economic predictions in the refreshed score should be either identical (scoring model estimated over the same period) or better (scoring model estimated over more recent period) than the predictions implicit in the origination score.

state of the economy. That is, in a bad economic environment all scores will generally shift down for two reasons. First, it is more likely that measured borrower characteristics will have deteriorated (e.g. more late payments, higher unemployment) during economic downturns. Second, scores will generally shift down for a given set of initial borrower characteristics since borrowers with the same initial conditions over the estimation period are more likely to suffer similar negative economic shocks.

While origination scores will not provide the optimum performance forecast over the next year, origination scores will reflect a smoother distribution of cyclical effects since loans in the portfolio will be originated at different time periods. In short, a model based on the most current information about borrowers will produce more accurate short-run loss predictions, but those predictions will have a greater pro-cyclical component.

A second related issue is the sample period over which the relationship should be estimated. A general way to think about this issue is whether recent observations should receive greater weight in forecasts relative to earlier observations.[13] A longer history would be an appropriate estimate of the "long run" one year default probability if the relationship between score and performance are stationary. However, if there are permanent shifts in the relationship, then greater weight should be given to more recent history.[14] Moreover, greater weight should be given to more recent history if the objective of regulatory capital minimums is to ensure adequate coverage for short-run risks. Setting regulatory capital minimums to cover short-run risks produces a more pro-

[13] At the extremes the alternatives are to estimate the relationship over a long period of time giving each period equal weight or to truncate the sample and only estimate the relationship over recent time periods.
[14] Kim and Santomero (1993) discuss this issue in relationship to establishing loan loss reserve requirements.

capital requirement, and this approach has been rejected by the Basel Committee largely due to concerns over creating an excessively pro-cyclical capital requirement.

Resolving this issue is an empirical matter. Unfortunately, current practice in this area is largely driven by data availability considerations. In the past, most banks did not make a systematic effort to maintain extensive internal historical data at the individual account level. While account level data generally exists in archived systems, retrieving the data and generating consistent data elements is usually very costly for large banks. This problem is particularly acute for institutions that have participated in multiple mergers among banks with incompatible information systems.

One approach employed by many banks is to create an internal historical database from the historical scores on their own customers obtained from the credit bureaus. In addition, some large institutions are undertaking major efforts to create consistent historical internal data series. While this is partly in response to the Basel II proposals, it is mainly a recognition of the competitive value of improving internal analytics. One potential unintended beneficial externality that may result from an IRB capital standard is that it will produce relatively consistent standards for data maintenance at large banks. Going forward, this could substantially reduce some of the difficulties of creating consistent historical data when large institutions merge.

Defining "Homogenous Risk Pools"

The Basel II risk-bucketing approach requires that estimation of PD and LGD be done for sub-portfolios of homogenous exposures.[15] For the commercial loan portfolio, the relevant sub-portfolios will be internal ratings categories.[16] While the methods for grouping commercial loans into internal ratings categories are not identical across banking organizations, there is a degree of consistency due to the typical practice at large banks of mapping internal loan grades to equivalent bond ratings. There are no similar benchmark criteria for grouping retail exposures by homogenous risk characteristics.

At first glance, the problem of creating homogenous risk pools for retail exposures appears to be relatively simple. Since retail lenders use fairly standard quantitative measures of credit quality in managing a retail portfolio, it is relatively straightforward to group retail exposures by a set of objective criteria. This contrasts with the commercial loan process where subjective and idiosyncratic factors play a more significant role in rating assignment.

However, while "bucketing loans" using objective criteria is relatively straight forward once criteria are established, there is no standard industry practice for setting criteria and no benchmark analogous to bond ratings for commercial loans. Moreover, segments used for internal bank management typically span a wide spectrum of credit risk. For example, credit card issuers commonly track performance by segments defined by mailing programs aimed at a particular client base (e.g. student cards), by affinity card programs (e.g. university affiliation), or co-branded cards (e.g. airline card).

[15] In the Merton one-factor model economic capital for the portfolio is a weighted sum of the economic capital for individual assets. One cannot substitute the average risk parameter for a portfolio or sub-portfolio made up of non-homogenous assets.
[16] The regulatory standards for advanced IRB institutions will require banks to have a minimum number of ratings categories.

Retail portfolio risk managers do track information on various types of credit scores and other risk metrics, and this information is used in various ways. However, there are no standard methods for grouping credits into risk buckets for analytical purposes. For products with a very large customer base, risk bucketing could in principle be done at a very fine level for measuring probability of default. The two main constraints are ensuring adequate sample sizes for estimation and obtaining historical data consistent with the risk segmentation adopted.

Using the current Basel one-factor model to set required capital will create an incentive for bank's to use more finely defined risk pools for calculating capital. In the one factor model described above, capital factors are concave in PD for given LGD. Since bank's are likely to have estimates of PD on a much finer level then information on LGD (information on LGD's are generally not tracked at the account level), then overall required capital will be lower if PD's are estimated at a finer level of segmentation. Thus, the one-factor model creates incentives for bank's to generate reliable information at a more granular level.

Note that this is exactly opposite to the results from using measures of volatility. Since the sum of sub-portfolio volatilities will generally be greater than the volatility of the entire portfolio, capital requirements based on volatility measures will be higher the finer the degree of segmentation. Thus, use of direct measures of historical volatility without correcting for diversification effects (or more generally the effects of segment composition) could create disincentives for measuring risk parameters on more granular sub-portfolios.

V. Summary

Current retail credit risk modeling at U.S. banking institutions has been relatively slow in development and is characterized by a wide divergence in approaches. In addition, few banks have maintained historical databases with consistent data to enable estimating of detailed risk characteristics of the components of their portfolio.

Nevertheless, there are significant inherent advantages to credit risk modeling in the retail area compared to modeling commercial loan portfolios. In particular, the wide scale use of very sophisticated credit scoring models and the associated extensive data mined to produce scores provides excellent raw material for sophisticated portfolio risk measurement techniques.

Many institutions with large retail portfolios are recognizing the value of credit risk modeling for a wide variety of business purposes including allocation of economic capital. This recognition, along with the desire to qualify as advanced IRB banks in the Basel II framework, is generating substantial efforts to improve retail banks information systems and modeling sophistication. It is likely, given the inherent advantages of quantitative tools for credit risk modeling of retail exposures, that advances in this field will move rapidly and that the direction will be toward portfolio modeling based on measuring performance characteristics for detailed segments of the retail portfolio.

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