Credit Risk Capital for Retail Credit Products:
A Survey of Sound Practices

RMA - The Risk Management Association

December, 2000

Credit Risk Capital for Retail Credit Products[1]

I. Introduction and Summary.

This paper represents RMA's response to informal requests by the U.S. banking agencies for information regarding an appropriate regulatory capital treatment of *retail credit products*. The subject of capital for retail credit products was essentially ignored within the 1999 Consultative Paper on capital issued by the Basel Committee.[2] The Committee did request comment, however, on an "internal ratings-based" approach to capital for *commercial loan products*, and RMA previously has expressed its views on this subject in a March 2000 response to the Consultative Paper.[3] In that document, we argued that the minimum regulatory capital requirements should be based on several of the important, measurable *risk characteristics* that typically are used by advanced-practice institutions as inputs into so-called "economic capital" (for credit risk) models. Further, this risk-characteristic-based process should be viewed as an interim step until a "full-models" approach to regulatory capital for credit risk can be implemented.

In the earlier paper, we provided the results of a survey on internal economic capital allocations, bucketed by important risk characteristics -- estimated expected default frequencies (EDFs) and estimated expected losses-given-default (LGDs) -- for the commercial loan portfolios of our advanced-practice banks. The earlier survey was intended to provide the regulators with information that could be used as the basis for setting specific, minimum capital-for-credit-risk requirements, based on EDF/LGD cells into which an advanced-practice bank would "bucket" its commercial credit assets.

In this paper, we provide similar information for retail credit products. Specifically, Tables 1 and 2 below show how our advanced-practice banks would estimate economic capital at a suggested minimum *confidence interval*. The table shows that, for each type of retail credit product, the economic capital estimates vary widely,

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[1] RMA Retail Capital Working Group. The names of institutions providing data and staff participating in the preparation of this paper can be found in Appendix 1.

[2] See, "A New Capital Adequacy Framework," Basel Committee on Banking Supervision, June, 1999. Only mortgage products were treated within a proposed new "standardized" treatment.

[3] See "Response to the Basel Committee's Consultative Paper on A New Capital Adequacy Framework," RMA (formerly, Robert Morris Associates), March 30, 2000.

depending on the range of estimated EDFs into which a particular asset (account) is slotted. Thus, the survey demonstrates that a "one-size-fits-all" approach to retail credit capital is no more appropriate than such an approach is for commercial products. The paper also provides a broad overview of the processes our banks use for estimating economic capital for retail products, so that regulators and other observers may better understand the range of practice. Among the key conclusions of this paper are the following:

- As in the commercial lending arena, data shortcomings often dictate the choice of analytical device for estimating economic capital.
- While retail products may exhibit higher default frequencies, and higher expected losses, than commercial products, economic capital to cover unexpected losses is often lower for the retail products. This result stems from empirical evidence that suggests that default and loss *correlations* are often lower for retail products than for commercial loan products.
- Within an individual, advanced-practice bank's portfolio for a given retail product, economic capital allocations may rise (fall) dramatically, as the individual account is slotted within a higher (lower) EDF range. However, LGDs for some products tend to fall within narrow ranges, so that a reasonable first-approximation might be to treat a particular retail product as being a proxy for LGD. In effect, the RMA study suggests that a two-dimensional, product/EDF bucketing approach may suffice, at least for some retail products, until a "full-models" approach can be implemented by Basel. That said, the RMA group wishes to reiterate that portfolio composition matters and that no bucketing-based Accord -- an Accord that treats all portfolios, in effect, as subject to the same correlation parameters -- can hope to capture differences in credit risk across institutions.
- As in a risk-characteristic-based approach for commercial loans, it is critical that the supervisory agencies develop sound methods for accrediting a bank's internal processes for slotting retail credit assets into EDF buckets and for estimating internal economic capital for retail products. Banks that do not adopt such sound-practice procedures should not be eligible for a product/EDF-based regulatory capital

treatment of retail products (or an EDF/LGD-based regulatory treatment of commercial loan products).

It is our hope that the Basel Committee will take into account these conclusions, and the results of our retail product capital survey, when designing the next iteration of the Accord. Section II below provides a discussion of the models used to estimate economic capital, including the processes for estimating the parameters used within these credit risk models. Section III provides background on the survey, the results of which are presented in Tables 1 and 2.

II. Estimation of Economic Capital.

As in the commercial lending arena, the credit risk economic capital estimation process involves the implicit or explicit estimation of a loss probability density function (PDF) and the choice of a confidence interval (or, equivalently, the setting of a targeted insolvency probability for the bank holding the portfolio). Economic capital is then defined as the difference between losses at the expected level and losses that occur with the targeted cumulative probability. Thus, if the bank wishes to set its targeted insolvency probability at, say, 5 basis points over a one-year horizon (roughly equal to the frequency with which AA-rated bonds default), its chosen confidence level is 99.95 percent. The bank then measures the loss that would occur in the "bad tail" of the (cumulative) loss distribution at the 99.95 percent probability level (actual losses would be less than this amount 99.95 percent of the time). From this loss amount is subtracted estimated <u>expected losses</u> over the one-year horizon, because such expected losses are covered by the yields imbedded in the (performing) credit assets, while economic capital is needed to cover losses over and above expected losses.[4]

Also as in the commercial lending arena, the economic capital estimates for retail credit risk, on a product basis or on a sub-product (risk characteristic) basis, are used for a variety of purposes within the banking organization. These uses include estimation of shareholder-value-added associated with each product or sub-product category, or analogously, the determination of risk-adjusted rates of return on allocated economic capital. Pricing of retail products can also be analyzed by risk-adjusted return on capital (RAROC) calculations. In these analyses, the price (yield) on the retail asset must at least cover all interest and non-interest expenses *plus* an amount to cover expected losses *plus* an amount to cover a required return to the allocated economic capital. Generally, when conducting shareholder-value-added analyses or pricing analyses, the bank uses estimates of economic capital pertaining to all three categories of risk -- credit risk, market risk, and operating risk. This paper discusses only the credit risk capital estimation process.

While there are many similarities between the credit risk economic capital estimation processes in the retail and commercial businesses, some significant differences remain.

a) Many advanced banks use a mark-to-model or mark-to-market (MTM) model for estimating credit risk within the commercial portfolio, but these same banks generally use a Default Mode (DM) model for measuring credit risk within the retail portfolios. That is, within the retail portfolios, "credit losses" generally are measured strictly in relation to losses associated with defaulted loans. In the commercial portfolios, "credit losses" can be defined to include non-default losses (and gains) that may be associated with, for example, the loan receiving a downgrade (upgrade), or because credit spreads for a given loan rating may widen (narrow). In theory, these same types of non-default losses (and gains) are applicable to retail credit portfolios, and a minority of advanced-practice banks are beginning to experiment with MTM credit risk models for retail products (see below).
b) Retail product portfolios exhibit risk characteristics (notably, EDFs, LGDs, and default correlations) that significantly differ from those found within commercial loan portfolios. Specifically, EDFs and LGDs generally are higher for retail loans than for commercial loans (with the notable exception of mortgages), while default correlations generally are lower for retail loans. Thus, yields may be higher (often significantly higher) on retail loans because of higher expected losses (EL = EDFxLGD). But economic capital is

[4] Of course, the bank would estimate expected losses, perhaps through a differing process, for purposes of

determined by the degree to which the loss distribution exhibits a "fat tail", and the shape of the tail of the loss distribution, in turn, is importantly determined by estimated default (loss) correlations. The lower the estimated correlation, all things equal, the less thick is the tail of the distribution and the lower is the estimated economic capital.

c) Contrary to a widely held view, data problems exist for retail products much as they do for commercial loans. Indeed, many advanced practice banks' management information systems permit the tracking of *commercial loan* performance, on an asset by asset basis and according to loan ratings, back through the last recession (to 1989 or earlier). These same banks, however, may have retail product performance data on a sub-product level (e.g., at the individual loan level) in a format that can be used for estimates of loss distributions for only the last 48 months or so. Thus, as in the commercial lending arena, the choice of technique for estimating retail product credit risk (and economic capital for credit risk) may be influenced by severe data limitations.

Perhaps because advanced commercial loan credit risk models were developed in the context of providing support for an active loan trading desk, greater resources have, until now, been devoted to commercial credit risk models than to retail product credit risk models. However, retail credit risk models are rapidly improving in sophistication and in the quality of the associated databases. In broad terms, the type of retail credit risk model used by advanced-practice banks can be divided into the three categories discussed below. Each bank might use a different process for each of several retail products and, often, two or more processes are used as checks against one another when arriving at an economic capital estimate.[5]

1. <u>Estimating loss distribution parameters directly from historical panel-data</u> (combination cross-section/time-series data). This approach, which can be termed a quasi-"top down" approach, relies directly on actual historical performance of segments of the retail credit portfolio. The process begins with the establishment of "buckets" or

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establishing the GAAP allowance for lease and loan losses.

cohorts of each retail product. For example, the mortgage portfolio might be segmented according to Loan to Value (LTV) at origination or, alternatively, estimated Current Loan to Value (CLTV), because LTV is thought to be among the most important of risk characteristics determining default.[6] The segmentation must be undertaken for each historical period in which loan-by-loan data exist in appropriate format. Typically, the management information system of the bank might yield 48-72 months worth of historical data for use in such a process. It is also possible to use industry data rather than internal bank data, if a longer time period can be covered (and if there is reason to believe that the bank's own portfolio of a particular retail product behaves like that of the industry).

Once the historical data are gathered, the analyst computes the mean (annualized) default (or loss) rate for each segment, as well as the standard deviation of losses, over the time series available for that segment. These two parameters -- mean and standard deviation -- are then used as inputs into a loss distribution whose "shape" is assumed to be of a particular nature. For example, the Beta distribution is often used for this technique, because it can be completely characterized by two parameters, each of which is a function of the two statistics measured by the analyst -- mean and standard deviation. Moreover, the Beta distribution is characterized by a thick, skewed "tail", which corresponds to our prior notions of the general nature of credit loss PDFs.

Once the Beta distribution is estimated, the analyst measures the loss associated with the targeted confidence level (e.g., 99.9 percent), then subtracts the estimated Expected Loss level, resulting in an estimate of Economic Capital.[7] It should be noted that, in terms of the pure theory of credit risk estimation, a "loss distribution" does not refer to the variation in portfolio performance *over time*, but rather to the array of possible outcomes (above and below the expected outcome) over a particular fixed horizon (e.g., one year). Therefore, the historical panel-data approach implicitly rests on the

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[5] See Appendix C of "The Customer Value Imperative," RMA and Oliver Wyman & Co., 1999

[6] CLTV can be estimated, for example, by starting with the original LTV and adjusting it via an MSA-based housing price index (in order to approximate a current house price associated with the loan).

[7] Often, the analyst's work is simplified by assuming that all segments of the product portfolio are subject to the same underlying "shape" to the loss distribution. Then, economic capital can be simply expressed as a constant multiple of each segment's estimated loss standard deviation.

assumption that the inter-asset loss correlations within each segment and between segments, as well as the other parameters such as EDFs and LGDs, remain fixed over the number of years represented by the data used to estimate mean and standard deviation. In other words, the loss distribution's shape remains constant month-to-month and year-to-year, so that variation in outcomes over time can be viewed as legitimate reflections of variations in outcome over any particular fixed horizon. This assumption is not necessary when using the "structural" method described below.

The major benefit of the historical panel-data approach is that it does not require the painstaking estimation of several parameters, including loss correlations, used within structural models. Whether the historical method is "robust", in turn, will depend on the fineness and reasonableness with which the cohorts are defined. For example, suppose research shows that mortgage defaults are importantly determined by both CLTV *and* the obligor's personal creditworthiness (as measured, say, by bureau score). Then, an historical panel-data process in which the product segments are defined along two dimensions is preferred to a process using only one of the two dimensions. In either case, however, the risk analyst is able to make quarterly (or more frequent) adjustments to estimated economic capital for the particular product portfolio. For example, suppose that macro-economic conditions cause a change in many borrowers' credit worthiness (bureau scores in general decline). Then, the portfolio manager will see a "migration" of credits into the higher risk segments, the ones for which higher mean and standard deviation of losses have been estimated. Overall *measured* portfolio risk will increase, as will estimated economic capital for the portfolio.

2. <u>Structural or "bottom-up" credit risk models</u>. Typically, the construction of structural credit risk models within retail credit portfolios is similar to the process used within commercial loan portfolios. Several of our group's members, for example, use a single-equation DM model, common to commercial loan analysis, of the following general form:

(1) Portfolio Loss Standard Deviation $=$ f(EDF, LGD, LGDVOL, ρ, LEQ)

where, measured on an individual asset basis, EDF is the asset's expected default frequency[8]; LGD is the asset's estimated loss given default; LGDVOL is the standard deviation of LGD; ρ is the estimated loss correlation between the particular asset and that of the overall portfolio; and LEQ is the loan-equivalent-exposure.[9] For term consumer loans, the exposure is simply the amount of the loan balance, while for lines of credit the exposure amount is the outstanding balance plus some portion of the unutilized line that is expected to be used just prior to default. This process might be followed for each particular retail product and, in many cases, for each defined segment of a retail product portfolio.

The risk analyst begins by estimating, for individual assets or groups of assets, each of the parameters in equation (1) -- thus, the structural approach is more statistics-intensive than the panel-data approach described above. Once the parameters are estimated to solve for the portfolio loss standard deviation, a particular, thick-tailed distributional form (often, the Beta distribution) is assumed, just as in the panel-data method. Clearly, the robustness of the structural method depends on the quality of the estimated parameters. The reader should note that, as with commercial portfolios, EDF and LGD are two of the most important parameters that must be estimated (and the basis for RMA's insistence that an "internal ratings-based" iteration of the Basel Accord be structured in two or more dimensions such as EDF and LGD). Below, we discuss typical methods for estimating each of the structural model's inputs.

a. <u>EDF</u>. Estimated expected default frequencies tend to be measured *either* by the cohorting process described above under the panel-data approach *or* by some form of statistical scoring process. As an example of the former approach, suppose a bank believes that LTV is the most important determinant of default in a home equity loan. The bank can then use historical data to measure the mean default rates of home equity loans in each of several LTV ranges or buckets. A statistical scoring approach, on the other hand, is a more

[8] In this paper, EDF refers to expected default frequency estimated using any process, while EDF™ refers to an EDF estimated using KMV Corporation's proprietary technology.

[9] For a more complete discussion of DM models see David Jones and John Mingo, "Credit Risk Modeling and Internal Capital Allocation Processes: Implications for a Models-Based Regulatory Bank Capital Standard," Journal of Economics and Business, 1999, vol. 51, pp. 79-108.

formal process in which historical data are used to estimate the parameters of a model that relates defaults to several independent variables. For example, for home equity loans, a default model could include as its independent variables current estimated LTV, current bureau score, current "state" of the account (current, 30-days past due, 60-days, etc.), plus a macro-economic variable. A credit card default model might use a behavioral score as an indicator of default.[10] Each loan can have an EDF associated with it, and the portfolio for a particular retail product can be segmented into accounts that fit within each of several EDF ranges. Tables 1 and 2 in Section III provide an example of an EDF bucketing system (for which our member banks have provided specific estimated economic capital allocations).

b. LGD. For non-mortgage consumer loans, LGDs tend to be higher than in the commercial arena. Often, the bank assigns a single LGD estimate on a product basis (as in Table 1), rather than by segmenting the product portfolio according to LGD. In other cases, research indicates that LGD is functionally related to measurable facility characteristics. For example, LGDs on home mortgages may be importantly determined by LTV or CLTV.

c. LGDVOL. In some instances the bank may assume that the volatility of LGD is zero (this would be the case, for example, when a very high or 100% LGD is assumed). For other products, research may show significant variation in LGD that may be explained by the application of LGD "scoring" models (i.e., statistical models that relate recoveries to characteristics of the facility or the obligor). For example, best practice institutions may use statistical models to direct the efforts of workout (collection) staff. To the extent that such statistical models relate LGD to one or more explanatory variables, the LGD estimation process may have embedded within it estimates of LGD volatility (i.e., the error terms in regression equations). At a minimum, the existence

[10] A behavior score is an internal predictor of default or other bad "state" of the loan over a given horizon. The scores are produced for existing accounts (post-origination) and are based on a variety of account-specific attributes. For example, a credit card behavior score might be based on the current (external) bureau score, along with internal account data such as credit line, cash line, credit utilization, cash utilization, delinquency history, and geographic location.

and scope of LGD volatility can be examined via the cohorting process described under the panel-data method.

d. Correlations (ρ). The correlation parameter plugged into equation (1) can simply be assumed (for example, if the bank measures average correlations within the commercial portfolio at 0.30 percent, it might choose 0.25 percent as the average correlation within its retail portfolios). More rigorous methods fall into two broad categories.

   1) Estimation of correlations from historical panel-data on defaults. For large numbers of obligors (as is typical in retail portfolios), the average default correlation can be shown to be a function of the mean and standard deviation of defaults, as well as N, the number of obligors.[11] Therefore, ρ can be estimated from the same panel data used within the first, non-structural method for estimating economic capital. Of course, if all the parameters of the structural equation were estimated directly from the historical panel data, the structural approach would become identical to the historical approach. In practice, however, the parameters of equation (1), *other than* the correlation parameter, are estimated by devices such as statistical scoring models.

   2) Estimation of correlations from formal factor models. Such models are in common use within commercial loan portfolios, but are just now being introduced into the measurement of credit risk within retail portfolios. A factor model is aimed at explaining the correlation between any two obligors' performance in relation to a set of common factors such as (for commercial loans) industrial sector, country, or macro-economic conditions.

e. Exposure (LEQ). The issue of exposure arises in home equity lines (HELOCs) and credit cards. Generally, the risk analyst uses internal historical data on defaults (which are usually sufficiently large in number for retail portfolios) to estimate the average amount of the line that is used at default.

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[11] See CreditMetrics™ - Technical Document, 1998, Chapter 8, p. 83.

> For example, one bank in our group estimates that HELOCs are more than 90% used at default, and therefore, for economic capital purposes, sets the exposure conservatively at the full amount of the line.

While the Default Mode structural model is the most widely used within our banks' retail portfolio, some institutions are beginning to work with risk-analytic consultants to develop true Mark-to-Market credit risk models for retail products. In these models, losses (and gains) can occur as retail assets migrate into different "value-buckets" which can be related to EDF or payment status.

3. Non-parametric methods for estimating retail credit loss distributions. A few advanced-practice banks are beginning to experiment with purely non-parametric approaches to estimating loss distributions, based on Monte Carlo simulations. In this procedure, historical data at the individual loan level are used to sequentially "draw" hypothetical portfolios of retail loans that satisfy the current composition of the portfolio. For example, each retail product portfolio can be segmented according to estimated EDF (using, say, bureau scores), payment status (current, 30-day past due, etc.), vintage (loan seasoning), etc. From the historical panel data, a hypothetical portfolio is constructed by randomly drawing loans until each risk-characteristic segment is "filled" to the level represented in the actual portfolio. This process is repeated by computer, say, 10,000 times, thus producing 10,000 possible portfolio outcomes over the one-year horizon. If, the analyst wishes to measure losses at, say, the 99.9 percent confidence interval, she simply reads off the portfolio loss that is the 10th worst out of the 10,000 simulated portfolio outcomes.[12] While this approach can be machine-intensive, it obviates the need to measure correlations, because these are imbedded within the simulated loss distribution obtained by the random drawing process.

No matter which of the above processes the bank uses to estimate economic capital for retail credits, the risk analyst must wrestle with several associated problems.

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[12] See Mark Carey, "Credit Risk in Private Debt Portfolios." Journal of Finance, 1998, 53:4, 1363-1387. Of course, numerical simulations are also used in structural models for which no closed-form solution exists (e.g., KMV's PortfolioManager™).

Aggregation (diversification). If economic capital for credit risk is measured for each retail product, then simply adding up the results would overstate economic capital. That is, inter-product loss correlation is not perfect (correlations between portfolios are less than 1.0). Moreover, the loss correlations between the retail portfolios and the commercial portfolio are each less than 1.0 (an increase in losses on the retail side is not perfectly correlated with an increase in commercial loan losses). Therefore, the analyst must find some method for aggregating economic capital estimations across the entire credit portfolio, while accounting for the effect of diversification on overall economic capital.

Advanced-practice banks use several, alternative methods to handle cross-portfolio diversification.[13] One method is to assume a degree of loss correlation across portfolios, thereby allowing, in effect, a crude estimation of a bank-wide credit loss distribution. Economic capital is measured for this bank-wide distribution at the desired soundness level (say, at the 99.95 percent confidence level). Then, the bank-wide economic capital is compared with the simple sum of the economic capital amounts measured for each of the product portfolios. The percentage difference between the fully-diversified estimate of capital and the simple aggregation of product capital allocations is then applied to each product capital allocation. Typically, this results in a 25-30 percent reduction in the economic capital allocated at the product level. Equivalently, the bank may use the bank-wide, fully diversified estimate of economic capital as a benchmark for lowering the confidence level applied at the individual product level. For example, the bank may find that by applying, say, a 99.6 percent confidence level at the product level, then summing up the results, the aggregate capital level is approximately equal to the capital estimated by applying a 99.95 percent confidence level to the crude, bank-wide credit loss distribution.

Several advanced-practice banks are beginning to handle bank-wide credit risk diversification within the context of well-known commercial lending portfolio models such as CreditMetrics™ or PortfolioManager™. In this process, retail products and/or segments of each retail product portfolio can be treated as homogenous sub-portfolios of

[13] See "The Customer Value Imperative", ibid., p. 51-52.

the commercial loan portfolio. Inter-product correlations can be estimated, as discussed above, by factor models or other devices, then the overall portfolio model can be run to generate a bank-wide loss distribution. A potentially useful by-product of this type of research is that the contribution to the bank-wide loss distribution of retail products can be evaluated in the context of a mark-to-market model rather than a default-mode model.[14] Research into this arena can best be described as in a nascent stage.

Macro-economic events. Another issue facing the credit risk analyst in the retail arena is how to handle the prospect of a macro-economic downturn. Since, typically, the available data do not go back through the 1990-91 recession, a concern is that the economic capital estimates are biased downward. Often, this problem is handled by incorporating within a structural credit risk model a correlation parameter that is *higher* than that implied by the late 1990's credit loss experience. That is, the impact of the recession can be viewed as increasing the number of accounts that jointly default over any horizon. The exact amount by which the bank raises the correlation parameter (over that observed in the database) to account for the chance of a recession is often a matter of subjectivity.

Of course, during a recession, more accounts will migrate into higher EDF categories (as, for example, bureau scores deteriorate). To some extent, therefore, a bank might use (within the credit risk model) a higher EDF than observed over the database years (i.e., the bank might use a somewhat "cycle-neutral" EDF estimate). However, credit spreads can be adjusted upward as the economy enters a recession (as is seen in the market for corporate bonds and other traded instruments), effectively covering higher expected losses. Estimated economic capital to cover unexpected losses should also rise, however, because of both higher EDFs and higher correlations. The process by which the bank incorporates the probability of a recession into the credit risk model, and therefore into the economic capital estimate, is often subjective in nature.

[14] Note that switching from a DM model to an MTM model does not necessarily drive up economic capital estimates. For example, a recession does not automatically drive down the MTM value of the portfolio. As EDFs (and observed charge-offs) rise, having a deleterious effect on economic capital requirements in a DM model, many (performing) cardholders increase their line usage, having a positive effect on value in an MTM model. Also, related fee income (in the form of late fees) on performing accounts rise. See "The Customer Value Imperative," ibid., p. 17.

Embedded options. A final issue that must be addressed within the context of retail credit risk models is the treatment of prepayment options within retail products. These arise mostly for mortgage products and the treatment, for purposes of estimating economic capital, varies across institutions. Some banks treat prepayment risk as a form of credit risk, others treat it as a market risk. In either case, the total economic capital attribution for the retail product might include a computation of the joint probability that an account would prepay *and* that the funds cannot be reinvested at the contractual spread embedded in the retail account.

III. A survey of credit risk capital allocations for retail products.

The current survey was conducted in the same spirit as our March, 2000 survey of commercial credit economic capital allocations. That is, our intent is to show economic capital allocations at a common confidence level (or, equivalently, at a common soundness standard). Most of the group's members measure economic capital in a fashion consistent with maintaining a double-A or single-A insolvency probability -- roughly equivalent to a 3 to 10 basis point insolvency probability (99.90 to 99.97 percent confidence interval) over a one-year horizon. Since regulatory capital standards are properly viewed as *minimums* (i.e., banks should hold greater than required regulatory capital), we have suggested previously that the regulatory standard be set to be consistent with a soundness standard that represents the dividing line between investment grade and non-investment grade (or roughly a 0.5 percent insolvency probability over a one-year horizon). Therefore, the economic capital calculations presented in Tables 1 and 2 are computed at the 99.5 percent confidence level.[15]

The survey is intended to provide information to regulators in crafting the next iteration of the Accord as an "internal-ratings-based" system. As indicated earlier, we are hopeful that such an IRB system translates into what we might term a "risk-characteristic-based" system along two key dimensions -- EDF and LGD. In that regard, the group's members believe that retail *product-type*, at least for some products, is a reasonable proxy for LGD. Indeed, for many retail products, most of our members currently assign a single

LGD estimate for the product category. Thus, initially the RMA survey was crafted to show internal economic capital for credit risk allocations, for a set of EDF ranges, for 8 separate retail products. The 8 product classes were chosen to provide meaningful distinctions in terms of effective capital allocations, without being too cumbersome.

The 8 product classes chosen were first mortgages, home equity loans, home equity lines (HELOCs), credit cards, retail leases, *unguaranteed* student loans, other secured loans, and other unsecured loans. The results of pre-survey work showed that, for 6 of these 8 product categories -- first mortgages, credit cards, retail leases, unguaranteed student loans, other secured loans, and other unsecured loans -- the ranges of LGDs used by the group's members were fairly narrow. This suggests that, for these 6 product categories, a two-dimensional bucketing approach -- "product" and EDF range -- would suffice when designing a first-iteration, bucket-based Basel Accord. However, for the other 2 product categories – home equity loans (second mortgages) and HELOCs -- LGDs estimated by the participating banks varied all over the map, suggesting that the "product" definitions were too broad. Indeed, just as the LGDs on these product categories varied widely across banks, so did credit risk capital estimates in the pre-survey work.

Second mortgages can have widely varying effective LGDs depending on the size of the second mortgage relative to the value of the house (the underlying collateral). Home equity loans and lines can be thought of in much the same way one views a subordinated tranche in a securization. The "wider" the tranche, the lower the LGD on the tranche if, in fact, there is a default on the tranche. Thus, a second mortgage constituting 10 percent of the home's value will be assigned a significantly lower LGD than a second mortgage constituting 5 percent of the home's value. For this reason, the RMA group decided to break second mortgages into two broad LGD categories – a "high LGD" category in which the responding banks used the actual estimated LGD within their portfolio of mostly "high LGD" home equity loans, and a "low LGD" category in which a common 30% LGD assumption was used by the banks wishing to provide economic capital estimates for such "low LGD" loans. Table 2 shows the median credit-risk

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[15] Due to the aggregation (diversification) effect, actual minimum economic capital levels *at the product*

economic capital estimates from the participating banks (at the 99.5% confidence level), for each of the two “product” categories for second mortgages, within each of the EDF ranges chosen by the group.

For purposes of showing economic capital estimates in Tables 1 and 2, the group decided to use an array of EDF ranges similar to that used in the commercial loan survey.[16] A key exception is that EDFs for retail products tend to be higher than those for commercial loan facilities and, in particular, few retail products exhibit estimated EDFs that are found in the first two EDF ranges (0-0.04% and 0.04-0.08%) used for the commercial portfolio. Conversely, in the higher EDF ranges, it was felt that the fairly wide EDF ranges used to "bucket" the commercial portfolio needed to be more finely divided in order to generate the full range of capital allocations that occur for retail products. Thus, in Tables 1 and 2 there are 12 EDF ranges, excluding "Default", compared with 13 ranges including Default in the commercial loan survey. In general, since LGDs are quite high for retail products (with the exception of mortgage instruments), there is little in the way of unexpected losses (stemming from recovery uncertainty) associated with a defaulted instrument. For this reason, or because measured LGD volatility is low, many of our group's members do not attribute economic capital for credit risk for defaulted retail loans.

Table 1 below shows the median economic capital (at the 99.5% confidence level) for credit risk allocations, by EDF range, for each of the 6 products for which the banks estimated fairly narrow LGD ranges. Eight (8) of the 11 banks constituting the RMA Retail Capital Working Group provided data for the matrix. However, some of the 8 banks did not calculate economic capital within each of the 12 EDF cells for each product, either because within the bank's portfolio there are no observations of loans in that cell, or because the bank did not choose to contribute data for a particular product. Therefore, for most cells in the matrix there are 5 to 7 observations (numbers of banks

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level might be estimated at lower than the 99.5 percent confidence level.

[16] See "Response to the Basel Committee's Consultative Paper on A New Capital Adequacy Framework," ibid., Table 2.

providing capital allocations). Due to the low number of observations, quartile breakpoints are not meaningful and are not provided.

Table 1

Economic Capital for Credit Risk

Median allocations, at 99.5 percent confidence level*

	Retail Product											
EDF range	1st Mort.		Cards		Leasing		Student		Other Secured		Other Unsecured	
0-0.16%	0.27%	(4)	0.79%	(6)	0.62%	(6)	0.97%	(3)	0.63%	(6)	0.90%	(6)
0.16-0.32	0.46%	(4)	1.36%	(6)	1.07%	(6)	1.67%	(3)	1.09%	(6)	1.55%	(6)
0.32-0.64	0.65%	(4)	1.84%	(6)	1.51%	(6)	2.36%	(3)	1.54%	(6)	2.19%	(6)
0.64-1.28	0.94%	(4)	2.38%	(6)	2.13%	(6)	3.33%	(3)	2.17%	(6)	3.09%	(6)
1.28-1.92	1.33%	(4)	3.04%	(6)	2.74%	(6)	4.19%	(3)	2.31%	(7)	3.67%	(6)
1.92-2.56	1.59%	(4)	3.57%	(6)	3.23%	(6)	4.49%	(3)	3.29%	(6)	4.53%	(6)
2.56-3.84	1.13%	(6)	3.95%	(7)	3.85%	(6)	4.87%	(3)	3.24%	(7)	5.14%	(6)
3.84-5.12	2.21%	(4)	4.76%	(6)	4.53%	(6)	5.21%	(3)	4.32%	(6)	5.78%	(6)
5.12-7.68	2.68%	(4)	5.47%	(6)	5.15%	(6)	5.54%	(3)	4.50%	(7)	6.30%	(8)
7.68-10.0	3.97%	(5)	6.32%	(6)	5.76%	(6)	5.91%	(3)	5.35%	(6)	6.26%	(7)
10.0-20.0	4.07%	(4)	7.71%	(7)	6.36%	(6)	6.46%	(3)	6.29%	(6)	9.75%	(8)
>20.0%	5.42%	(2)	10.47%	(4)	9.79%	(5)	9.33%	(3)	8.41%	(4)	12.35%	(4)
LGD Range	10-20%		84-96%		71-78%		80-83%		50-77%		79-90%	
% excess of internal EC**	35.00%		15.03%		35.00%		n.a.		35.00%		14.92%	

* Numbers in parentheses represent the number of observations (banks reporting data in each cell).

** [Economic capital at the internal soundness standard / economic capital at 99.5%] minus 1.0 = the percentage amount by which internal EC exceeds EC at the minimum suggested regulatory soundness standard.

Note that there are some anomalies in the table associated with the fact that, for certain product/EDF cells, a differing set of banks provided capital data than for other cells. Therefore, the median capital allocations may not increase monotonically as EDF increases. This occurs in the middle EDF ranges for "first mortgages" and “other secured,” and in the lower EDF ranges for "other unsecured."

The median capital allocations shown in Table 1 do not include capital for prepayment risk (in home mortgages). A few of the participating banks provided rough estimates of capital for these risks, which is on the order of 2.0% of balances. Even this rough estimate should be regarded with caution, however, because of the low numbers of banks providing estimates and because of the possible significant differences across these banks in prepayment options and in portfolio construction.

The last two rows in Table 1 provide some additional information on two important issues facing the regulator -- the estimated LGDs associated with each of the product categories, and the differences between economic capital for credit risk at the regulatory soundness level versus economic capital at the (generally higher) internal soundness target of the bank.

The next to last row in Table 1 shows the range of LGDs assigned to each product category. These numbers are the ranges of *weighted average* LGDs provided by several of our banks. In each case, the bank may or may not assign a single LGD to a product category. Thus, when a product category contains multiple LGDs, the bank has measured the product category's average LGD, weighted by the balances of each LGD bucket. Table 1 shows that LGDs are much higher for retail products than for commercial loans (except for first mortgages).

Differences in average weighted LGDs across banks for each product category may be due to differences in a) marketing strategies; b) underwriting criteria; c) regional economics; and d) workout strategies. The effect on LGD of differing workout strategies is straightforward. With respect to the other bank-by-bank differences, however, the impact on LGDs may be subtle. For example, suppose that, within a given region, high-end houses have a greater likelihood that LTV (at default) will be lower (higher) than original LTV. Then, average LGDs for such mortgages might be higher (lower) than for mortgages on lower-priced homes. A bank that has a higher percentage of its mortgage portfolio in high-end loans will show a higher (lower) average weighted LGD than other banks. In a similar vein, in regions with faster growth, higher house price appreciation in general may reduce average LGD. Demographics in some regions may affect LGDs. For example, if the population is less transient in a particular region then lower loss severities might be expected (as principal payments reduce loan-to-value). These factors will influence the calculation of economic capital for credit risk, and that is one reason why the capital allocations in the product/EDF cells in Table 1 will differ across advanced-practice banks.

The last row in Table 1 shows the median percentage amount by which the actual internal economic capital allocation differs from the minimum economic capital allocated for a particular product. That is, in the product/EDF cells in Table 1, each bank has shown the economic capital it would allocate if the bank were using a 99.5% confidence interval over a one-year horizon. However, most (but not all) of our banks actually use a higher confidence level for internal purposes. The last line in Table 1 shows the median percentage difference between the actual internal capital calculation and the "minimum" capital allocation as represented in the EDF/product cells. Note that internal economic capital varies between 15 percent and 35 percent higher than minimum economic capital, depending on the product. For these retail products, the percentage differences between internal economic capital and "minimum" economic capital generally are lower than for commercial loans. This is still another manifestation of the fact that, for many retail products, loss correlations are estimated to be lower than for commercial loan products. In other words, the bad "tails" of the loss distributions for retail products generally are thinner than those estimated for commercial loans. The thinner the bad tail, the less of an increase in capital is required to go from the 99.5 percent confidence level to, say, the 99.9 percent confidence level.

In Table 2 below are shown the median economic capital allocations (at the 99.5% confidence level) for second mortgages. The EDF ranges are the same as in Table 1, but in Table 2 each of the two “products” – home equity loans and HELOCs – are broken down into a “high LGD” product and a “low LGD” product. Note that only 3 of our banks provided economic capital data for low-LGD second mortgages. In calculating economic capital in Table 2, a common, fixed LGD of 30% was used within the credit risk models of the 3 participating banks for “low-LGD” second mortgages.

Note that for the 3 banks providing data for low-LGD second mortgages, the economic capital calculations for home equity loans and HELOCs are the same. The implicit assumption is that the line tends to be fully used at default and prior to default. That is, the economic capital allocations are expressed as percentages of current balances – therefore, for the capital allocations to be the same for loans and lines implies that, for this type of product, the line tends to be fully or nearly fully used. This same assumption was used for the economic capital data provided by some of the banks with respect to high-LGD second mortgages. Also note that, while the 3 banks provided economic capital data for low-LGD second mortgages, this does not necessarily mean that such mortgages constitute any significant part of the banks’ actual mortgage portfolios.

In the case of the high-LGD mortgages, it should be repeated that the LGDs used by the banks were the actual average weighted LGDs for such mortgages.[17] For the 5 or 6 banks providing economic capital calculations for high-LGD second mortgages, capital for lines tends to be higher than capital for loans – suggesting that, for some of these banks, home equity lines are not fully used but that usage rises just prior to default. Finally, it should be noted that, for second mortgages our banks did not generally provide information on the difference between economic capital at the 99.5% confidence level and the actual (higher) economic capital levels used by the banks for internal purposes.

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[17] In some cases, the reporting bank used a single LGD for each product; this LGD, therefore *is* the average-weighted LGD for the product. In other cases, the banks used LGDs that vary according to LTV, CLTV, etc. (i.e., LGDs vary by account). In such cases, it is the average-weighted LGD for the product that is effectively the basis on which the economic capital figures are reported within each EDF range.

Table 2

Economic Capital for Credit Risk

Median allocations, at 99.5 percent confidence level*

	Retail Product							
EDF range	Home Equity low LGD		Home Equity high LGD		HELOC low LGD		HELOC high LGD	
0-0.16%	0.45%	(3)	0.73%	(5)	0.45%	(3)	1.33%	(5)
0.16-0.32	0.77%	(3)	1.27%	(5)	0.77%	(3)	2.12%	(5)
0.32-0.64	1.06%	(3)	1.80%	(5)	1.06%	(3)	2.71%	(5)
0.64-1.28	1.33%	(3)	2.54%	(5)	1.33%	(3)	3.40%	(5)
1.28-1.92	1.52%	(3)	3.27%	(5)	1.52%	(3)	3.87%	(5)
1.92-2.56	1.63%	(3)	3.86%	(5)	1.63%	(3)	4.15%	(5)
2.56-3.84	1.87%	(3)	4.60%	(5)	1.87%	(3)	5.00%	(5)
3.84-5.12	2.34%	(3)	5.42%	(5)	2.34%	(3)	6.25%	(5)
5.12-7.68	2.93%	(3)	6.43%	(5)	2.93%	(3)	7.80%	(5)
7.68-10.0	3.53%	(3)	7.49%	(5)	3.53%	(3)	9.41%	(5)
10.0-20.0	4.60%	(3)	9.55%	(5)	4.60%	(3)	9.42%	(6)
>20.0%	5.75%	(2)	12.16%	(3)	5.75%	(2)	12.16%	(3)
LGD Range	30%		71-79%		30%		77-82%	

* Numbers in parentheses represent the number of observations (banks reporting data in each cell).

Economic capital allocations are only as good as the bank's processes for estimating the parameters of credit risk models and constructing such models in reasonable fashion. Advanced practices include appropriate validation procedures for estimating risk parameters, as well as tests in which measured risk parameters are stressed to estimate their impact on the shape of the tail of the loss distribution. Further, as these advanced practices continue to evolve, it is important that banks be rewarded for migrating toward advanced-practice status. One such reward would constitute eligibility for a risk-characteristic-based version of the Accord, rather than a (revised) "standardized" Accord. However, the RMA Retail Capital Working Group believes that a risk-characteristic-based Accord cannot work unless the supervisory agencies develop appropriate methods for "accrediting" the procedures banks use for measuring risk characteristics and "slotting" assets according to those measured characteristics. In a forthcoming paper, we expect to outline our views of how such an accreditation practice might be structured. In the meantime, we are hopeful that the survey information provided in this paper will assist the Basel Committee in constructing a risk-characteristic-based iteration of the Accord, both for commercial credit products and retail credit products.

Appendix 1:

Staff participating in the drafting of this paper (and banks providing data for Table 1):

Bank of America: John Walter, Richard Swenson and David Staufenberger.
Bank of Montreal: Stuart Brannan and Wendy Millar.
Bank One: Rantch Isquith, Justin Zhang, Joel Brodsky, and Ronald Cathcart.
Citigroup: Bruce Fletcher and Scott Powell.
First Union: Rhea Thornton and Chris Livingston.
FleetBoston Financial: Ranga Rangarajan, Thomas E. Freeman, and James N. Papadonis.
KeyCorp: Ashish K. Dev and Robert Kula.
PNC Financial Services Group: Terry Jewell.
Royal Bank of Canada: Lyn McGowan, Chitra Muralikrishnan, and Paul Stathopoulos.
Union Bank of California: Paul C. Ross and John Chittenden.
Wells Fargo: George Wick.
RMA - The Risk Management Association: Pamela Martin and Mark Zmiewski.
Mingo & Co., John Mingo.