



A guide to choosing absolute bank capital requirements

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Abstract

Resampling implementation of a stress-scenario approach to estimating portfolio default loss distributions is proposed as the basis for estimates of the appropriate absolute level of economic capital allocations for portfolio credit risk. Estimates are presented for stress scenarios of varying severity and implications of different time horizons are analyzed. Results for a numeraire portfolio are quite sensitive to such variations. Although the analysis is framed in terms of recent proposals to revise regulatory capital requirements for banks, the arguments and results are also relevant for bankers making capital structure decisions. Published by Elsevier Science B.V.

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1. Introduction

The internal ratings-based (IRB) approach recently proposed by the Basel Committee on Banking Supervision (BCBS) seeks to make bank regulatory capital requirements for credit risk approximate economic capital requirements (Basel Committee on Banking Supervision, 2001). That is, under certain assumptions (Gordy, 2000b), IRB capital requirements would vary across banks according to the riskiness of their portfolios in a manner that would make the estimated likelihood of insolvency due to credit losses approximately the same for all banks that are at the regulatory minimum. Required capital would be larger for banks with portfolios posing greater risks of large losses and vice versa.

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The IRB capital formula for credit risk takes as inputs loan and portfolio characteristics and produces capital requirements. Designing such a formula involves decisions about (1) the *dimensions* of credit risk to be included, that is, which loan and portfolio characteristics should appear as variables in the formula; (2) the *relative* variations in capital requirements as loan and portfolio characteristics vary from those of a reference or numeraire loan or portfolio; and (3) the *absolute level* of capital required for the numeraire portfolio. Carey (2001) examines the dimensions of credit risk and Basel Committee on Banking Supervision (2001) examines issues of relative variation.

This paper focuses on the absolute level of capital for credit risk. Taking the numeraire to be a portfolio of fully drawn loans each with a one-year probability of default (PD) of 1%, a loss given default (LGD) of 50%, and a remaining time to maturity of three years, the Basel Committee on Banking Supervision (2001) proposal suggests that the absolute dollar amount of capital required for such a portfolio should be 10% of the amount of the loan. Basel Committee on Banking Supervision (2001) is not clear about the basis for this calibration, but two methods of calibration have been suggested by various observers, a bottom-up and a top-down method. In the bottom-up method, an economic analysis of the relationship between portfolio risk and PDs, LGDs, etc. is conducted. Debate focuses on the assumptions of the analysis and on the choice of a portfolio credit loss distribution percentile. In the top-down method, policymakers make a judgmental choice of a target capital ratio for the banking system as a whole. Given the characteristics of bank portfolios, the parameters of the IRB formula are calibrated to hit the systemic target. Unfortunately, results of the top-down method can be difficult to relate to basic policy objectives, such as likely bank insolvency rates.

A drawback of extant bottom-up analyses is that validity of many of the supporting assumptions is difficult to assess. Most importantly, assumptions about the sensitivity of credit losses to systematic risk factors are hard to evaluate because such sensitivities usually cannot be estimated with confidence. Such assumptions can have a major impact on estimates of absolute capital requirements produced by conventional credit value at risk (VaR) models.

This paper presents a bottom-up analysis of the appropriate absolute level of capital in which key assumptions are relatively transparent and easy to relate to the objectives of bank regulators and bank managers. The paper makes three contributions. First, portfolio credit loss distributions are estimated using a non-parametric, stress-scenario approach (see Kupiec (1998) and Shephard-Walwyn and Rohner (2000) for other stress-scenario approaches and Jorion (2001) for a general discussion of stress testing). Frequency distributions of loss rates are computed by simulating losses on a large number of portfolios. Loss rates for each simulated portfolio are computed by sampling with replacement from populations based on particular years of Moody's database of defaulting and non-defaulting bond issuers, with realistically random loan sizes and LGDs.

If loan sizes and LGDs were fixed instead of random, the estimated portfolio loss distributions would approximate transformed binomial distributions in which an aggregate annual borrower default rate is the key parameter, so I describe this paper's

approach as involving modified binomial loss distributions. Because aggregate default rates can be related to the severity of economic downturns and (in this paper's setup) loss distribution percentiles represent bank survival rates, policymakers may set capital to limit bank failures to some acceptable estimated rate in an economic scenario of intuitively specified severity.

The use of modified binomial distributions flows from assumptions that differ from those of conventional credit VaR modeling (such as the CreditMetrics model of Gupton et al. (1997)) in two important respects. First, as noted, each estimate of required capital is conditional on a fixed stress scenario that is characterized by an aggregate default rate. Second, banks' portfolio investments are modeled as a series of independent draws from the aggregate pool of loans. Such independence is motivated by an assumption that, *ex ante*, neither banks nor regulators can measure portfolio exposure to factors that predict systematic credit losses. Without estimates of systematic factor loadings, portfolio credit risk diversification cannot be fine-tuned by variations in the identity of portfolio borrowers. The independence assumption is arguably more realistic than the common credit VaR modeling assumption that exposures to systematic factors are measured without error.¹

A second contribution is that VaR estimates are presented for one, two, and three-year time horizons. Conventional credit VaR analysis uses a one-year horizon. Given a goal that banks remain solvent indefinitely, use of a one-year horizon involves an implicit assumption that a bank that experiences large credit losses during a year will recapitalize by the end of that year. To accomplish this, one or both of a troubled bank and its regulator must move very rapidly to effect recapitalization, which may be unrealistic.

Third, the existing definition of regulatory capital used by the BCBS is inconsistent with portfolio credit risk analysis that focuses on bank solvency as a policy goal. Such inconsistency causes substantial practical problems of implementation. An alternative definition of regulatory capital is proposed.

To use this paper's estimates to set absolute capital allocations, bankers and policymakers must choose a loss distribution percentile. Two popular methods of making the choice are explained. The preferred method, which focuses on projected bank failure rates, can be applied using this paper's alternative VaR measures but not when representative-bank models are used (in those models, if one bank fails, all fail).

Results imply that required capital is quite sensitive to the severity of stress scenarios and to the time horizon of the analysis. For example, required capital implied by a Great Depression scenario is more than half again as large as that implied by US experience during 1989–91. Similarly, using a two year horizon increases estimated bad-tail losses by more than 50% relative to results for a one-year horizon. The choice of acceptable bank insolvency rate is also important, but the allowable insolvency rate must be increased by roughly a factor of ten to reduce capital by one-quarter to one-third.

¹ As described further below, the practical assumption is not that banks cannot diversify, but rather that differences in bank diversification strategies amount to noise.

No specific recommendations about the appropriate level of absolute capital are made. Reasonable people may differ about acceptable bank failure rates, about the severity of the economic downturn in which preservation of bank solvency is desired, and about the likely speed of bank and supervisory responses to large credit losses. The paper is intended to provide conceptual clarifications and empirical estimates that can aid bankers and regulatory policymakers in translating their views about such matters into decisions about regulatory requirements and capital structure.

However, as an example, the results imply that the proposed 10% requirement for the Basel numeraire portfolio is consistent with an estimated failure rate of approximately one IRB bank in 200 during an episode similar to the 1989–91 period of US debt distress (this presumes that, in the future, supervisors will be reasonably effective at forcing rapid recapitalization of troubled banks, that no bank experiences both large non-credit losses and large credit losses at the same time, and that subordinated debt comprises 25% of banks' Total Capital as defined by the BCBS). An 8% requirement for the numeraire would be consistent with a failure rate near five banks in 100. Other assumptions would yield different conclusions about likely failure rates. It is important to emphasize that estimates in this paper are for the specified numeraire portfolio, not the typical bank portfolio, and thus are not directly comparable to the "8%" requirement of the 1988 Accord.

Although this paper is phrased in terms of Basel Accord policy decisions, it is relevant to decision-making by bank managers and directors. Such individuals must make decisions about capital structure. The difficulty of interpretation of results of conventional VaR analyses is problematic for them as well as for regulators.

A number of caveats apply. First, this paper focuses only on capital for credit risk, but other kinds of risk (market, operational, etc.) are material. Moreover, like the IRB approach itself in many cases, this paper does not consider the impact of structured portfolio hedging strategies on capital requirements, such as first-to-default credit derivatives.

The implications of geographic and industry concentrations of credit risk are not analyzed here (data limitations would make such analysis difficult). I suspect that modest variations in the geographic and industry composition of the loan portfolios of very large banks' have little effect on required capital, but this is a subject for future research.

Only losses associated with defaults are incorporated in this paper's analysis, not losses associated with non-default changes in the market value of portfolio assets. A "default-mode" setup is largely for simplicity. If the analysis were done on a mark-to-market (MTM) basis, estimated capital requirements probably would be higher.

Although US loss experience data is the basis for many choices of parameter values in this paper, the results are general in that the key parameters are generic (peak default rate relative to average default rate, choice of loss distribution percentile, and time horizon of analysis). A few auxiliary parameters that I set to be representative of US experience might have different values in other countries, but the main lessons of the paper are robust to variations in the auxiliary parameters.

Finally, for simplicity, many details of the IRB approaches proposed in Basel Committee on Banking Supervision (2001) are ignored. For example, differences between the Foundation and Advanced IRB approaches are ignored, as are elements of the proposal like maturity and granularity adjustments. Such aspects of Basel Committee on Banking Supervision (2001) may reflect important determinants of portfolio risk but are not of primary importance for this paper's purposes.

Section 2 provides background about conventional credit VaR analysis and motivates this paper's approach to estimates of credit loss distributions. Section 3 briefly describes current regulatory capital measures and proposes a more appropriate alternative. Such details of capital measurement are important background for interpreting results. Section 4 describes the data and some details of estimation, while Section 5 presents results. Section 6 discusses the importance of assumptions about VaR time horizons and provides illustrative results. Section 7 describes common ways of choosing VaR percentiles and argues for a focus on projected bank failure rates. Section 8 offers a summary and concluding remarks.

2. Model setup

2.1. Background: Portfolio risk, soundness, and capital

Portfolio credit risk modeling is typically a partial equilibrium analysis in which capital is a buffer that can absorb losses (Berger et al. (1995) survey the role of capital more generally). Capital regulation seeks to ensure that the buffer is large enough to preserve the soundness of individual banks or banking systems. Differences of opinion exist about the proper definition of "soundness," but at this time, most policymakers seem to view a low rate of bank insolvencies (especially for systemically important banks) as a central component of "soundness." One operational statement of this goal is: Soundness requires that the estimated probability of insolvency of each bank be smaller than a small threshold level. A somewhat different goal would be that, with high probability, bank insolvency rates remain smaller than some threshold level. The relationship between individual insolvency probabilities and aggregate insolvency rates depends on the extent to which different banks' portfolios have common exposures to systematic risk factors.²

A VaR-style risk-sensitive capital regulation focused on bank solvency requires (1) estimated probability distributions of portfolio loss rates that are reasonably accurate, or that at least are consistent across portfolios, and (2) a choice of loss distribution percentile, that is, a choice of the threshold or maximum level of individual bank insolvency probability or the bank insolvency rate that policymakers are willing to tolerate. The capital requirement for any given bank is the loss rate at

² Some other definitions of soundness require only that costs of resolving bank insolvencies borne by national governments be small. Overall, the debate about the definition regulators should use is in its infancy. This paper uses an insolvency-focused definition of soundness for simplicity.

the chosen percentile of that bank's estimated portfolio loss distribution. See Jorion (2001) and Ong (1999) for background about VaR modeling.³

2.2. Difficulty of interpretation of conventional credit VaR analysis

Gordy's (2000a) representation of a default-mode version of the CreditMetrics model introduced by Gupton et al. (1997) provides a convenient notation for summarizing key aspects of conventional default-mode credit VaR models. Estimated losses L for a portfolio are

$$L = \sum_i D_i \lambda X_i \quad (1)$$

where D_i is an estimated default indicator variable for obligor i , λ is the LGD (constant for simplicity), and X_i is the dollar amount of exposure to obligor i . Default by obligor i is estimated to occur if $y_i < C_{g(i)}$, where C is a cut-off value which varies by rating grade g and $C_{g(i)}$ is the cutoff for the grade to which borrower i is assigned. C_g is calibrated so that the estimated unconditional default probability for borrowers in grade g is p_g . y_i is a latent random variable given by

$$y_i = xw_i + \eta_i \varepsilon_i \quad (2)$$

where x is a vector of normally distributed systematic risk factors and w_i a vector of weights that express the influence of the factors on obligor i 's repayment behavior. ε_i is an idiosyncratic shock and η_i expresses the relative importance of idiosyncratic and systematic factors for i . Although the elements of x may covary, normalizations make the marginal distribution of each element of x $N(0, 1)$ and the ε_i are assumed to be iid $N(0, 1)$. For large portfolios, the estimated loss distribution is determined by an appropriate average of the w_i (idiosyncratic shocks wash out, and large values of a given element of w_i for one borrower are less important than the overall exposure of the portfolio to each systematic risk factor).⁴

A primary drawback of conventional VaR analysis for calibration of absolute capital is the difficulty of estimating values of w_i and of relating w_i to commonly understood economic concepts. The broad intuition is clear enough: Conventional portfolio theory implies that, for sufficiently large and fine-grained portfolios, loss rates should be driven by the sensitivity to systematic economic factors of borrowers' ability to repay and by the frequency and severity of bad systematic events. However, the transformations that provide convenient distributions for x and ε_i cause the w_i to incorporate assumptions about the volatility of systematic economic factor realizations as well as about the sensitivity of repayments to factor realizations. As a

³ Estimated loss distributions for banks with riskier portfolios have longer, fatter bad tails. Thus, even though the chosen percentile is the same across banks, the loss rate (capital requirement) at which the percentile falls varies across banks.

⁴ Estimation of credit loss distributions is often by simulation. A large number of values of x are drawn and a value of L is computed for each x . The frequency distribution of the L form the estimate of the portfolio loss distribution.

practical matter, because general economic recessions are the most important systematic events, the key conventional VaR model parameters embed estimates of the likelihood and severity of recessions as well as estimates of the exposure of individual firms to recessions. Currently available data do not support confident estimation of values of w_i . Portfolio credit risk model parameters are usually set by adjusting statistical estimates so that model results are reasonable in the eyes of the analyst. Moreover, parameter values are usually assumed to be measured without error (Nickell et al. (1999) offer evidence that typical ex ante parameter estimates may result in substantial ex post capital shortfalls).⁵

Given such subjectivity and parameter uncertainty, most senior bankers and regulatory policymakers want to form their own opinion of the reasonableness of model-builders' judgments, but the difficulty of attaching clear economic interpretations to transformed model parameters makes that difficult. Thus, although portfolio credit risk model results increasingly influence risk-adjusted resource allocations within financial institutions, model results continue to have relatively little influence on absolute capital, that is, on capital structure decisions for the whole institution.

Bank failure rates also are difficult to analyze in conventional representative-bank credit VaR setups. Gordy (2000b) shows that a portfolio model fully consistent with the Basel Committee on Banking Supervision (2001) IRB approaches can have only a single systematic risk factor (x must be scalar) and that portfolios with the same mix of borrower PDs must be similarly exposed to the single factor. Under such assumptions, if all banks are exactly in compliance with IRB minimum capital requirements, then there is a critical threshold value of the systematic factor such that for worse draws all banks fail and for better draws all banks survive. For purposes of modeling and interpreting absolute capital requirements, such all-or-nothing model behavior is inconvenient.⁶

2.3. A modified binomial approach

This paper's estimates of portfolio loss distributions are driven by parameter choices that are more intuitively understandable. Two changes in the terms of the portfolio credit modeling problem support this convenience. First, instead of requiring decision-makers to take a position about the volatility of realizations of

⁵ Parameter estimation and interpretation are also problematic for other portfolio credit risk models, such as CreditRisk+ or KMV CreditMonitor, but the details of model structure and estimation differ. Depending on the structure of the model under consideration, discussions of the analogs of w_i may be in terms of "factor loadings," "asset correlations," or "default correlations." The concepts are related because Merton (1974) implies that firms with assets the values of which are highly correlated with systematic economic factors will tend to default at the same time to a greater degree than firms with asset values largely driven by idiosyncratic factors.

⁶ In my opinion, the difficulty of estimating and interpreting values of w_i is a primary reason for the focus of the BCBS on top-down approaches to setting absolute regulatory capital requirements. Such approaches have objectives that are understandable, such as maintaining the banking system's current aggregate amount of capital, but it is not clear that current capital regulations achieve adequate soundness (Jackson et al. (2002) and Nickell and Perraudin (1999) provide some indicative evidence).

the (pre-normalization) systematic factors, they must take a position about a maximum relevant realization of the aggregate default rate. Thus, this paper implements a variant of stress-scenario approaches. Second, portfolio managers are assumed to construct their portfolios by independent draws of individual loans from the available pool of loans. Portfolios are not identical, but are equally diversified apart from a kind of sampling error. The resulting conditional independence of portfolio outcomes allows loss distribution percentiles to be interpreted as bank survival rates as well as bank survival probabilities.

Expressing these assumptions in terms of the representation given in (2), an estimated loss distribution is conditional on an assumed (non-random) value of x rather than on a fixed estimate of w_i . Conversely, w_i is assumed to be a random variable the value of which is neither observable nor estimable. The distribution of values of the w_i in any given loan portfolio is equivalent to the population distribution except for the sampling error associated with an investment policy that consists of independent draws. Thus, the number of defaults experienced by any given portfolio departs from the population value (conditional on x) only by a binomial sampling error.

If λ and X_i are fixed and equal for all loans, and for a given scenario, the inverse of the probability distribution for portfolio loss rates L is given by λX_i times the inverse of a binomial distribution with parameters equal to the number of portfolio obligors and the specified aggregate default rate. That is, under the given assumptions, a closed-form solution for required capital is available.⁷

I describe this paper's estimates as being from a "modified" binomial distribution because I allow λ and X_i to be random variables and I impose certain other restrictions for realism, as described further below. Thus, estimates are produced by Monte Carlo methods rather than from a closed form solution.

The remainder of this subsection motivates the key assumptions that support the modified binomial approach. A focus on stress scenarios in which the aggregate default rate is the key parameter makes estimates conditional on something that is easy to understand. A limitation is that the impact of default rates worse than that of the chosen stress scenario is not modeled. However, a policymaker can obtain a practical idea of such impact by examining the sensitivity of results to variations in the stress scenario.

The assumption that investment decisions are equivalent to independent draws is motivated by three supporting assumptions: (1) multiple systematic factors influence borrowers' ability to repay, exposure to each such factor differs across borrowers, and such factors are not perfectly correlated; (2) neither banks nor regulators can estimate systematic factor loadings for individual borrowers; (3) a long-run average default probability (PD) for each borrower can be estimated, that is, an unconditional PD.

These assumptions imply that any two portfolios of straight debt which differ in the identities of borrowers, but which have the same distributions of borrower PDs,

⁷ The distribution is binomial if loans are "drawn" into portfolios with replacement. It is hypergeometric if draws are without replacement. Although the latter seems more realistic, for large portfolios, the binomial and hypergeometric distributions are almost identical.

have no *predictable* differences in estimated portfolio loss distributions. This does not mean that loss outcomes will be the same for all such portfolios but merely that, *ex ante*, any two such portfolios are observationally equivalent with respect to estimated portfolio loss rate distributions. *Ex post*, portfolios with greater exposures to those systematic factors for which realizations are bad in a given year will experience larger losses in that year. Some banks will be lucky and “draw” relatively few borrowers that end up in default and some will be unlucky and lend to relatively many defaulters. For those unlucky banks in the bad tail of the loss distribution, the absolute size of their losses is determined by the overall default rate for the year (by the binomial parameter value). The worse the overall rate (the worse the stress scenario), the larger the dollar losses in the tail.⁸

It follows that, conditional on PD mix, all diversification strategies are the same *ex ante*. Thus, random selection of portfolio exposures is an economically sensible policy. Moreover, I assume that investment policies that may be intended to produce different degrees of diversification do not actually do so (except to the extent that portfolio sizes or the distribution of loan sizes differ).

It is important to note that the assumptions of this paper do *not* imply that modern portfolio credit risk models are useless. As noted, the “factor loadings” of such models typically embed assumptions about portfolio exposure to risk factors and about the volatility of factor realizations. The latter enters this paper’s analysis by virtue of inclusion of a range of stress scenarios. Moreover, as a practical matter, this paper’s assumption of non-estimable exposures to factors does not require that banks know nothing about such exposures. The effects of any common component of banks’ diversification strategies, such as imposing loan limits related to borrower geography, industry, etc., will be reflected in the makeup of the measurable available pool of loans (that is, in the contents of default loss experience databases). Thus, the practical assumption is not that bank diversification strategies have no effect, but rather that cross-bank *differences* in diversification strategies amount to noise. This is reasonable because the risk information sets available to banks are largely common and trade associations and consultants act to rapidly propagate advances in risk measurement techniques. Moreover, extant analysis of absolute capital requirements for the Basel Committee on Banking Supervision (2001) IRB approaches has largely focused on analysis of a representative portfolio, which implicitly assumes away all differences across banks in exposures to systematic risk factors. Such an assumption is stronger than this paper’s assumption of random differences in such exposures.

The modified binomial approach has several virtues. First, the problem of setting absolute capital requirements is largely reduced to one of specifying a maximum tolerable bank insolvency rate (equivalent to a loss distribution percentile) and the severity of the bad times in which capital should be adequate to limit insolvencies to the tolerable rate. Such severity is expressed in terms of the realized economy-wide

⁸ As noted, loss rates are also importantly influenced by the mix of borrower PDs. Among others, Zhou (1997) shows that, for given systematic factor loadings, borrowers with higher PDs contribute more to overall portfolio credit risk than do borrowers with low PDs.

bad-year default rates for borrowers in each PD bucket. Such default rates can be loosely related to severities of general economic recessions. Thus, policymakers can form their preferences about the binomial parameter intuitively by thinking in terms of recession severity.

Because different banks' portfolios are assumed to be composed by conditionally independent draws, any given percentile of the portfolio loss distribution gives not only the estimated capital needed for an individual bank to remain solvent (with the percentile probability) but also the estimated bank survival rate (1-failure rate) for all banks with the same mix of PDs. In essence, each simulated portfolio can be thought of as representing the experience of a different bank. This is more convenient than the all-or-nothing failure behavior of representative-bank models because policymakers can choose VaR percentiles by reference to either failure rates or individual bank failure probabilities.

Finally, the Basel Committee on Banking Supervision (2001) IRB approach's equal treatment of portfolios that differ in composition but that have the same mix of PDs is consistent with the modified binomial model. Gordy's (2000b) argument that such equal treatment requires an assumption of a single systematic risk factor implicitly assumes that factor loadings are measurable *ex ante*. In this paper, the single-factor assumption is relaxed, but equal treatment remains appropriate because investments are conditionally independent draws.

As a specific example, suppose a policymaker is willing to tolerate the insolvency of one bank out of every hundred during a fairly severe recession, and further suppose that "severe" means that actual default rates are three times larger than the portfolio long-run average PD (and the long-run average portfolio default rate). If all bank loan portfolios have a long-run average PD of 1% and a fixed LGD of 50%, this implies a bad-year default rate of 3%. In the specified bad year, the average bank will lose 1.5% of assets (3 times the 50% LGD). However, the 99th percentile of the appropriate binomial distribution is near a 5% default rate. Thus, a 2.5% capital requirement would be sufficient to support the survival of all but one in one hundred just-adequately-capitalized banks. Of course, in an even worse recession, the bank failure rate would be higher.

This paper's way of defining and modeling VaR loss distributions is related to existing stress-test methods of capital allocation (see Jorion, 2001; Kupiec, 1998; Shephard-Walwyn and Rohner, 2000). However, a typical credit stress-test analysis specifies default rates for each line of business, or for firms in each geographic region or industry. Estimates in this paper are conditional on specifications of stress scenarios in terms of aggregate default rates, but the independence assumption and the resulting modified binomial structure for loss distributions is new.

3. Economic versus regulatory capital: A proposal

Proper interpretation of results that follow necessitates discussion of the components of capital. A bank's regulatory capital requirement must be compared against its actual available capital in order to determine whether it is in compliance. This

implies that the components of measured actual capital must be consistent with the economic intent of the requirements. Unfortunately, the existing Basel Accord's main regulatory capital measure, "Total Capital," is inconsistent with a soundness standard that focuses on solvency.⁹ "Total Capital" consists of Tier 1 capital (mainly the book value of equity) plus Tier 2 capital (the unallocated loan loss reserve, subordinated debt, and a number of other items ignored here for simplicity). The Accord limits the share of Total Capital that each element of Tier 2 capital can represent.

Equity and loan loss reserves can absorb credit losses. However, subordinated debt does not provide an additional buffer that preserves solvency. Once a bank experiences and writes off credit losses large enough to exhaust equity plus the loan loss reserve, any further writeoffs will lead to book-value insolvency even if subordinated debt is among the bank's liabilities. Of course, the bank's cash flow may be such that it is able to continue making payments on its subordinated debt even if it is book-value insolvent but, as a practical matter, public pressure on the regulators of a book-value-insolvent bank may force them to put the bank into receivership even if its liquidity is adequate. Thus, to the extent that banks satisfy default-mode IRB capital requirements with regulatory capital that includes significant amounts of subordinated debt, the achieved degree of solvency protection may be substantially less than intended by policymakers.

Subordinated debt is useful as a buffer that protects national governments from liquidation losses in the event of bank insolvencies. Under a MTM or partial MTM approach to estimating IRB capital requirements, subordinated debt could be a buffer to absorb losses to a deposit insurer flowing from increases in credit spreads since a failed bank's loans were originated ("spread risk") or declines in the credit quality of non-defaulting loans ("rating transition risk") (Kiesel et al. (1999) find that such sources of risk are quite important, especially for high-quality debt). That is, regulatory capital measures might include a Tier A category composed of equity plus the unallocated loan loss reserve, and also a Tier B category including subordinated debt and perhaps other liabilities that protect national governments from losses associated with liquidating failed-bank portfolios at values less than par. Tier A values would be compared against requirements that specify the capital needed to protect against default losses. Tier B values would be compared against requirements that specify the capital needed to protect against transition and/or spread risk. This would require separate modeling and specification of default and non-default MTM losses.¹⁰

Subordinated debt is a much less costly form of finance for banks than is equity, and thus such a Tier A, Tier B architecture would permit regulators to achieve

⁹ Shephard-Walwyn and Rohner (2000), and Risk Management Association (2001) also note such inconsistencies. They propose alternative compositions of regulatory capital that differ somewhat from this paper's proposal.

¹⁰ Because Tier B is not useful in preserving soundness, no Total Capital measure that sums Tier A and Tier B would make sense. However, equity and loan loss reserves are useful as buffers against liquidation losses as well as in preserving solvency. Thus, any surplus of Tier A capital beyond that required as a buffer against default losses could be added to Tier B capital for comparison with the Tier B requirement.

solvency soundness targets and liquidation-loss targets more efficiently than in either a pure default-mode approach or in a MTM approach in which subordinated debt is not counted as regulatory capital.

As noted previously, in this paper, all estimated capital requirements are based on modeling of default losses alone (“default mode”), and thus are labeled as Tier A requirements. It seems unlikely that the Basel Committee on Banking Supervision will change the definition of regulatory capital in the near future. Thus, readers who wish to apply this paper’s evidence to calibration of Basel IRB capital requirements should presume that IRB requirements will be satisfied by Total Capital measures that include some subordinated debt. Such readers should inflate the numbers in this paper by a factor equal to one plus their estimate of the share of subordinated debt in Total Capital in order to get absolute levels of required capital that will achieve the stated levels of soundness. Unfortunately, the subordinated debt share varies substantially across nations and across banks within nations, and thus I can provide no good estimate of the appropriate multiplier beyond the fact that it lies between one and two. Moreover, banks’ incentives to substitute Tier 2 components for Tier 1 components may cause the share to change over time.

4. Resampling implementation, data, and parameters of the base case

Closed-form modeling of absolute capital requirements using binomial distributions is impractical because loss given default (LGD; λ) and the dollar size of exposures (X_i) are variable. A bank may experience unusually large credit losses not only by experiencing more than the expected number of defaults, but also by experiencing recoveries on those defaults that are worse than average or by finding that the dollar amount of exposures to defaulting borrowers represents a disproportionate share of total portfolio exposure. Moreover, modeling of the effect of different portfolio loss horizons, loan-to-one-industry limits, and other factors is desirable.

The resampling method of Carey (1998, 2001) embeds the binomial model of portfolio loss rates as a special case and can generalize it to handle variable LGDs, exposures, and other considerations. This bootstrap-like method simulates the likely range of loss experience of a portfolio manager who randomly selects assets from those available for investment while at the same time causing the portfolio to conform to specified targets and limits. For each exercise (set of portfolio parameters), 20 000 simulated portfolios are composed. For each portfolio, loans are drawn randomly from the loss experience database until the specified portfolio size is reached. Drawn assets are rejected for inclusion if they fail to satisfy the parameters for the given exercise. For example, each exercise specifies a target percentage of the portfolio to fall in each Moody’s obligor rating category. A Baa-rated asset would be rejected for inclusion if sufficient assets with that rating had already been drawn, even if the total simulated portfolio was not yet filled. Looking across simulated portfolios, all have the same set of specified characteristics, but by chance some include many defaulting assets and others few. Loss rates are computed for each sim-

ulated portfolio and the frequency distribution of such losses forms an estimate of the loss distribution for portfolios with the specified characteristics.¹¹

A key determinant of results of a resampling exercise is the aggregate default rate in each year in the database of loans available for investment. If the analysis time horizon is one year and all loans are drawn from a single database year, the aggregate default rate for that year is essentially the binomial parameter for the exercise. Varying the default rate embedded in the data corresponds to varying the stress scenario that characterizes the exercise.

The resampling method can also produce estimates that more closely resemble conventional credit VaR model results by tracing out the loss distribution using simulated portfolios drawn from each of many years. In that case, the estimated distribution represents a mixture of modified binomial distributions, one for each database year included in the exercise. Most estimates in Carey (1998, 2001) are of this form. However, because the focus of this paper is on results for different stress scenarios, here draws are from only a few years of loss experience data.

4.1. Data

In principle, the loss experience database could be entirely artificial. However, to add realism to some of the auxiliary aspects of the modeling (like loan-to-one-industry limits) and to provide real-world stress scenarios, I use Moody's database of bond ratings and defaults during 1970–98 to represent the universe of possible investments available to the simulated portfolio manager. The Moody's database is a complete history of their long-term rating assignments for US and non-US financial and non-financial firms and sovereigns (no commercial paper ratings, municipal bond ratings, or ratings of asset-backed-securities are included). In addition to the ratings of individual bonds and loans, Moody's provides a table of issuer ratings, that is, the actual or likely rating on senior unsecured debt for each issuer for each date the issuer had any rated debt outstanding. In this paper, all analysis is done at the issuer level and is restricted to US non-financial issuers (the number of non-US issuers became material only in recent years).¹²

¹¹ Draws for any single simulated portfolio are without replacement. For any given simulated portfolio (iteration), the draw is in two stages: (1) one of the experience years in the set of years used in the exercise is drawn, and (2) individual loans exposed during that year are drawn until the simulated portfolio is filled. Using experience from multiple years for a given simulated portfolio would tend to understate tail loss rates because the results of different realizations of systematic economic risk factors would be unrealistically combined.

Because draws are without replacement, for fixed LGD and exposure sizes the resampling method produces estimates of a hypergeometric distribution of portfolio loss rates rather than a binomial. However, the two distributions are very similar for the portfolio sizes used in this paper.

¹² A loss experience record is constructed for each issuer and year in which the issuer was rated at the start of the year. Those cases where the issuer defaulted during the year are exposed-and-defaulting records, whereas those where no default occurred are counted as exposed but not defaulting. Similar to the methods of Moody's annual study of default rates by grade, the default rate for any year and grade is the number of defaults divided by the total number of exposures. Cases where an issuer's rating is withdrawn during the experience year are counted as half a unit of exposure unless the issuer defaults.

Table 1
Parameters of the base case

Parameter	Value	Comment
Experience years included	1989–91	Equally weighted
Loss horizon	Two years	
Loan maturities	All equal to loss horizon	
Portfolio size criterion	Dollar limit of \$5 billion	
Loan sizes	Mimic an actual bank's distribution	Mean is near \$10 million
Number of portfolio loans	Floats	But close to 500
Loan to one borrower limit	3% of portfolio size	
Loan to one industry limit	5% of portfolio size	
Included credit events	Only actual defaults	
LGD specification	Mimic Society of Actuaries (1998) distribution for loans	But adjust to achieve mean LGD of 50%
Fraction rated A or better	0%	This mixture of Baa and Ba assets produces a one-year average default rate of 1% over 1970–98
Fraction rated Baa	20%	
Fraction rated Ba	80%	
Fraction rated B	0%	

Simulated portfolios and resampling exercises have the characteristics described in this table for the base case, and for all other cases unless otherwise noted.

Most results in this paper are based on data only from the years 1989–91, which represents the worst three-year period of default rates for agency-rated US non-financial obligors. I use data from three years rather than a single year to permit modeling at a three-year horizon. For exercises involving a one-year horizon, one-third of simulated portfolios are drawn from each of the three years to promote comparability with results for longer horizons.

4.2. Base case parameters

Table 1 presents the parameters of a base case. Subsequent exercises vary the time horizon or the stress scenario while holding other parameters constant at base-case values unless otherwise noted. The base portfolio has \$5 billion of commercial loans with sizes that vary in a manner similar to that of an actual large US bank. The number of loans in the portfolio is not fixed, but the parameterization of the loan size distribution keeps the number close to 500 (results are qualitatively similar regardless of whether numbers or dollars of loans are fixed). I enforce a loan-to-one-borrower limit of 3% of portfolio dollar size and a loan-to-one-industry limit of 5% of portfolio size. The latter is implemented using a judgmentally developed 39-industry classification scheme (see Carey, 2001).¹³

¹³ In principle, the industry limit might cause estimated capital requirements to be biased downward if industry is a good proxy for important systematic risk factors and if banks or regulators do not consistently impose similar limits. In practice, results of simulations for varied limits are qualitatively similar (not shown in tables). Intuitively, this is because defaults are spread widely across industries in a general economic recession, so tight industry limits do not prevent a bank from experiencing large volumes of defaults.

Three parameters of the base case are different than those frequently seen in analyses of US loan portfolio risk. First, the time horizon over which credit losses are cumulated is two years instead of the more conventional one year. The reasons for this choice are described below. Second, the percentage lost on each default (LGD) is not fixed, but is drawn randomly for each defaulting loan such that the distribution of LGDs matches the distribution for loan default LGDs in Society of Actuaries, 1998. However, instead of adjusting the distribution to produce mean LGDs in the range 20–30% (which would be realistic for US C&I loans), for convenience of comparison with the Basel Committee on Banking Supervision (2001) IRB numeraire portfolio, the distribution is adjusted such that the mean LGD in this paper is 50%.¹⁴

Third, the mix of each simulated portfolio's borrowers falling in each Moody's rating grade includes 80% Ba-rated borrowers and 20% Baa-rated borrowers (such a mixture is not typical of the average US large-bank portfolio, which would have a larger fraction rated investment grade (Treacy and Carey, 1998)). An 80–20 mix of ratings produces an average measured one-year default rate of 1% using all the years 1970–98. If probabilities of default are estimated using unconditional average default rates, as appears to be recommended in Basel Committee on Banking Supervision (2001), the simulated portfolios can be characterized as having a 1% PD.

It is important to note that actual default rates for the specified mix of rating grades are much higher than 1% during 1989–91 (2.4%, 2.7%, and 4.4%, respectively). Such higher default rates qualify those years as a stress scenario. As described further below, I create other stress scenarios by removing or adding defaults to the data to achieve lower or higher aggregate default rates.

5. Results

The middle row of Table 2 presents results for the base case for various percentiles of the estimated portfolio credit loss distribution. The results imply that the mean cumulative loss over a two year period during years similar to 1989–91 is 3.58%, whereas the loss at the 99.5th percentile is 7.63%.¹⁵ (I focus discussion on the 99.5th percentile for convenience. Results at other percentiles are also of interest.) An average LGD of 25%, which as noted previously is more realistic for US commercial loans, would yield loss rates about half as large as those shown.¹⁶ For

¹⁴ All extant empirical studies of average US commercial loan LGDs find values well below the average corporate bond LGD of around 50%. The largest values for loans are found by Society of Actuaries (1998) and Asarnow and Edwards (1995), but the samples in those studies include some subordinated debt, and such debt very rarely appears in US bank loan portfolios today. Carty et al. (1998) estimate the average LGD for senior unsecured loans to be 21%.

¹⁵ Mechanically, the distribution is an equal mixture of simulated portfolios drawn from 1989–90 and from 1990–91.

¹⁶ The percentile loss rates shown in all tables in this paper incorporate both “expected” and “unexpected losses”. That is, the loss rates at the high percentiles give the “Tier A” capital ratio required to protect solvency, as discussed previously. As noted, the rates in Table 2 are not directly comparable to either the current Basel Accord's Total Capital minimum ratio of 8% nor to its auxiliary Tier 1 minimum of 4%.

Table 2
Average and bad-tail loss rates for various stress scenarios, two-year analysis horizon

Variant	Simulated loss rates (%)					
	Mean	Tier A capital required at loss distribution percentiles				
		95	98.5	99	99.5	99.9
Non-stress case (aggregate default rates = 1%)	1.00	2.37	3.05	3.25	3.60	4.44
“Mild” stress: between non-stress and base cases	2.53	4.55	5.40	5.61	6.02	6.96
Base case: from 1989–91 actual data	3.58	5.97	6.89	7.17	7.63	8.80
“Very bad” stress: between 89–91 & depression	5.34	8.27	9.34	9.65	10.18	11.20
“Great Depression” case	7.07	10.43	11.52	11.86	12.50	13.51

The third row reports loss rates at different loss distribution percentiles for a base case, the parameters of which are specified in Table 1, and which is based on aggregate default rates during the 1989–91 period of US debt distress. Results in the remaining rows vary the degree of stress by varying the underlying aggregate default rates.

example, a Tier A capital allocation near 4% would be appropriate for 1%-PD US commercial loan (conditional on the two-year horizon and the base case stress scenario being appropriate).¹⁷

The first row of Table 2 shows the estimated loss distribution in a benchmark non-stress case in which the actual default rate in each year is engineered to be 1%. I created this scenario by randomly changing defaulting exposures in the data to non-defaulting exposures in quantities sufficient to bring annual default rates down to 1%. Given a 50% LGD and a horizon of two years over which losses are cumulated, this results in a 1% mean cumulative loss rate, as shown. At the 99.5th percentile the loss rate is 3.6%, implying that the amount of capital needed to protect solvency during “normal” economic times is far less than during stress periods. Similarly, the estimates predict that while Tier A capital ratios of 3.6% would be consistent with a bank failure rate of one in 200 during “normal” times, such a level of absolute capital would be consistent with the projected failure of half of all banks during a period similar to 1989–91 (since the mean loss rate for the base case is near 3.6%). As described further below, such assertions about failure rates presume that a two-year horizon is appropriate for analysis of likely failure rates. I also assume that banks fail when their Tier A capital reaches zero (in contrast, current US regulations mandate closure when a bank’s equity-to-assets ratio falls below 0.02).

Reasonable people may differ about the severity of the general economic recession in which capital must be adequate to protect solvency with high probability. The second, fourth and fifth rows of Table 2 present results for other stress scenarios. The

¹⁷ For reference, using the average distribution of loans by agency grade at large US banks reported in Treacy and Carey (1998), and long-run average default rates by grade from Moody’s or S&P’s annual studies, the mean PD for commercial loan portfolios at large US banks is arguably somewhere between 1 and 1.5%.

second row is for a case of “mild” stress in which realized aggregate default rates are simulated to be roughly halfway between those underlying the no-stress case of the first row and the actual 1989–91 rates from the base case.

The fifth row reports estimates for a simulated Great Depression scenario. Moody’s Investors Service (2000) annual default study shows the all-corporate one-year default rate peaking at around 9% during the early 1930s (the trough of the Great Depression in the US), which is about twice the peak rate during 1989–91. I simulate the capital needed to survive a Great-Depression-like event by randomly adding simulated default events to the Moody’s database such that the resulting total number of defaults in each year and grade is about twice as large as in the actual data. The fourth row of Table 2 is a “very bad” stress scenario based on aggregate default rates halfway between those of the base case and the Great Depression scenario.

It is important to note that because the high default rates that characterize the “very bad” and Great Depression scenarios do not appear in Moody’s 1970–98 database, these scenarios are in a sense inconsistent with the maintained hypothesis of an unconditional one-year PD of 1% for the simulated portfolios. If such scenarios were in the data for 1970–98, the mix of Baa and Ba borrowers needed to obtain a 1% estimated long-run average PD would be different. However, measured PDs that do not incorporate effects of very bad stress events are likely to be commonly used in practice. Thus, these scenarios may be thought of as representing economic events that may be out-of-sample with respect to PD estimation but that have been observed over the course of recorded history.

Unsurprisingly, the results in Table 2 imply that the worse the stress scenario, the higher the required capital at all percentiles of the loss distribution. A comparison of the Great Depression case with the base case yields an impression somewhat analogous to the comparison of the base case with the non-stress case. Capital adequate to achieve the 99th percentile in the base case (a 7.17% Tier A ratio) is close to the mean loss rate in the Great Depression scenario, implying that capitalization rates adequate for reasonable protection of banking systems in a “normal” stress case may be quite inadequate in an extraordinarily severe case. This is consistent with the near-insolvency of entire national banking systems that has been observed during the last ten or fifteen years in countries which have experienced extraordinarily severe macroeconomic crises.

Overall, it is obvious that policymakers’ preferences about the severity of economic distress in which bank insolvency rates should remain low without government support are likely to be a major determinant of opinions about appropriate levels of absolute capital.

6. Time horizon for loss cumulation

Implicit in the insolvency-focused approach to capital requirements is an assumption that if large losses (short of insolvency) are experienced during the analysis period, a bank will take actions such that its probability of remaining solvent during the following period will remain high. Such actions include raising new equity to

replace that which has been lost or rebalancing to a safer portfolio such that the remaining equity is adequate to preserve solvency with the specified probability. For bank loan portfolios, substantial rebalancing is usually difficult to accomplish quickly, especially during the periods of general economic distress that are typically associated with large losses. Thus, unless a bank is able to raise new equity by the end of the analysis period, it will begin the next period with a larger-than-desired probability of insolvency.

The conventional loss horizon in most credit risk modeling is one year. However, I am not aware of evidence supporting the one-year horizon for loan portfolios. The one-year convention may have arisen largely because, until recently, default rates and rating transition matrices were most easily available at a one-year horizon, and such data are key inputs to conventional portfolio credit risk models.

Barakova and Carey (2002) present evidence that a one-year loss horizon may be too short. They examine the behavior of US banks that experienced losses large enough to make them seriously undercapitalized anytime during the period 1984–99, but that ultimately recapitalized and survived. Equity infusions were a key component of such banks’ recoveries, but only about half of such banks recovered within one year of becoming undercapitalized. About 70% recovered within two years, and about 85% within three years. Moreover, in Barakova and Carey (2002), the measured onset of distress occurs *after* large losses have been experienced, whereas the starting date of a VaR analysis horizon is the beginning of the period in which losses are experienced.

Tables 3 and 4 display results for each stress scenario for one-year and three-year loss horizons, respectively. The effect of horizon on loss distribution percentile values is substantial. At the 99.5th percentile, the loss rate for a one-year horizon is 4.72% for the base case versus 7.63% for the two-year-horizon base case and 10.30% for a

Table 3
Average and bad-tail loss rates for various stress scenarios, one-year analysis horizon

Variant	Simulated loss rates (%)					
	Mean	Tier A capital required at loss distribution percentiles				
		95	98.5	99	99.5	99.9
Non-stress case (aggregate default rates = 1%)	0.50	1.35	1.85	2.04	2.40	3.07
“Mild” stress: between non-stress and base cases	1.07	2.34	3.01	3.21	3.55	4.50
Base case: from 1989–91 actual data	1.50	3.12	3.83	4.05	4.46	5.41
“Very bad” stress: between 89–91 & depression	2.34	4.45	5.34	5.58	6.05	7.09
“Great Depression” case	3.12	5.66	6.69	6.92	7.44	8.48

The third row reports loss rates at different loss distribution percentiles for a base case, the parameters of which are specified in Table 1 (except the time horizon is one year), and which is based on aggregate default rates during the 1989–91 period of US debt distress. Results in the remaining rows vary the degree of stress by varying the underlying aggregate default rates.

Table 4
Average and bad-tail loss rates for various stress scenarios, three-year analysis horizon

Variant	Simulated loss rates (%)					
	Mean	Tier A capital required at loss distribution percentiles				
		95	98.5	99	99.5	99.9
Non-stress case (aggregate default rates = 1%)	1.50	3.31	4.08	4.32	4.72	5.52
“Mild” stress: between non-stress and base cases	3.66	6.24	7.23	7.56	8.11	9.40
Base case: from 1989–91 actual data	5.20	8.39	9.49	9.80	10.30	11.29
“Very bad” stress: between 89–91 & depression	7.50	11.48	12.72	13.10	13.73	14.86
“Great Depression” case	10.02	14.91	16.31	16.75	17.38	18.70

The third row reports loss rates at different loss distribution percentiles for a base case, the parameters of which are specified in Table 1 (except the time horizon is three years), and which is based on aggregate default rates during the 1989–91 period of US debt distress. Results in the remaining rows vary the degree of stress by varying the underlying aggregate default rates.

three-year horizon. Thus, while rarely debated, the choice between a one-year and two-year horizon has about the same proportional impact on required capital as the choice between the base-case stress scenario and the Great Depression scenario.

For default-mode credit VaR models, regulators’ views about the proper analysis horizon should be related to views about the speed with which bank supervisors will detect large losses and with which they will force troubled banks to recapitalize. In Barakova and Carey’s (2002) data, most of the banks that got into trouble did so before the current US laws concerning Prompt Corrective Action by regulators were implemented. Thus, in the future, at least in the US, banks may recover more quickly than in the past because regulators may react more quickly to initial losses. The question is, how much more quickly? I focus most of this paper’s discussion on results using a two-year horizon because, given the limited available evidence, it seems prudent to assume that banks will require more than one year to recapitalize in the wake of large losses.

7. The level of soundness

Choosing absolute capital requirements using bottom-up methods requires not only a specification of time horizon and of the severity of the recession in which capital must be adequate, but also a choice of portfolio loss distribution percentile. Under this paper’s assumptions, loss distribution percentiles may be interpreted as one minus the estimated bank failure rate in an economic downturn of the specified severity for banks with capital equal to the estimated loss rate at the percentile (because different banks’ portfolios have conditionally independent loss rates). For example, for purposes of calibrating absolute capital, choosing the 99th percentile

and a one-year horizon is equivalent to accepting an annual bank insolvency rate of 1% during the specified stress scenario (the insolvency rate during good years would be much less).

Results in Tables 2–4 imply that the choice of percentile is important, but perhaps not as important as the choice of analysis horizon or of severity of stress scenario. Focusing on the base case, the difference between the 99.5th and the 99.9th percentile in Table 2 is a bit more than 1 percentage point of capital, whereas varying the time horizon by one year changes required capital by about 3 percentage points and going from the base case to the “very bad” stress scenario results in about a 2.5 percentage point change.

Choosing a VaR percentile by choosing an acceptable failure rate appears to be a method that is directly relevant for regulatory policymakers because it is relatively easy to relate to basic regulatory objectives like systemic stability and macro-economic impact of bank failures. However, it is not the most commonly applied method. Instead, many people prefer to make the choice in terms of Moody’s or S&P ratings, for two reasons. First, as noted, results of conventional VaR analysis are usually difficult to translate into bank failure rates. Second, ratings provide a way to appraise the soundness demanded of banks in the marketplace. Bank regulators often express reluctance about imposing capital requirements that are higher than the capital ratios chosen voluntarily by highly rated banks. Conventional wisdom holds that most banks prefer to be rated A or better, implying that the chosen level of minimum regulatory soundness should be consistent with a rating no safer than A.

How much riskier than A depends on the decision-maker’s tolerance for individual bank insolvency risk. Table 5 displays long-run average default rates for both Moody’s and S&P’s grades Ba/BB, Baa/BBB, and A/A, taken from studies each agency published in 1995 and 2000, for both one-year and three-year horizons. Measured default rates differ somewhat when computed for different periods but, focus-

Table 5
Historical issuer default rates by grade, one-year and three-year horizons (%)

Grade	Moody’s ratings and studies				S&P’s ratings and studies			
	1970–94 study		1970–99 study		1981–94 study		1981–99 study	
	One-year	Three-year	One-year	Three-year	One-year	Three-year	One-year	Three-year
A/A	0.0	0.3	0.01	0.15	0.07	0.30	0.04	0.21
Baa/BBB	0.2	0.9	0.13	0.78	0.25	0.95	0.22	0.88
Ba/BB	1.7	6.5	1.34	6.30	1.17	6.58	1.01	6.28

Source: Moody’s Investors Service, “Corporate Bond Defaults and Default Rates 1970–94” (published January 1995) and 1920–99 computed using Moody’s Credit Risk Calculator, US obligors only. See also “Historical Default Rates of Corporate Bond Issuers, 1920–99” (published January 2000), which reports average one-year rates for 1920–99 of 0.08%, 0.30%, and 1.43% for A, Baa, and Ba, respectively. Standard & Poor’s, “Special report: Corporate Defaults Level Off in 1994” (published May 1995) and “Ratings Performance 1999” (published February 2000).

ing on the one-year horizon, for the A grade are $<0.1\%$, for Baa/BBB are $<0.3\%$, and for Ba/BB are generally $<1.5\%$. Using the studies published in 2000, average default rates for Baa3 and Ba1 are 0.31% and 0.62% respectively, and for BBB– and BB+ are 0.29% and 0.57% , respectively (not shown in the table). Because Baa3 and Ba1 (and BBB– and BB+) bracket the dividing line between investment-grade and “junk” ratings, these numbers suggest that equating “adequately capitalized” with “barely investment grade” is equivalent to specifying a maximum one-year insolvency probability of about 0.5% as a soundness standard.

When the loss horizon is greater than one year, followers of the target-rating approach to soundness choose a percentile by looking at cumulate agency-grade default rates over periods of the same duration as the horizon. For example, Moody’s average cumulative two-year default rates for Baa3 and Ba1 are 0.81% and 2.13% , respectively, and cumulative three-year default rates are 1.34% and 3.86% , respectively. Thus, if the criterion for bank soundness is “at least investment grade,” the proper percentile in Table 2 is the 99th or perhaps the 98.5th; in Table 3 it is the 99.5th; and in Table 4 it is perhaps the 97.5th (not reported in the table, but the loss rate is 9.07% for the base case).

If it is true that banks generally wish to maintain a rating of A or better, and if banks use a one-year loss horizon, results for the 99.9th percentile may be representative of the capital ratios that banks would themselves choose to hold, assuming their credit risk modeling assumptions are similar to those made in this paper. At a two year horizon, the 99.75th percentile is about right (the loss rate is 8.11% for the two-year horizon base case (not shown in the table)).

Ultimately, ratings are helpful in choosing a percentile mainly in the case where they are good indicators of the probability that a bank will remain solvent by virtue of its own resources alone. In that case, the rating-focused manner of choosing loss distribution percentiles is simply an indirect way of taking a position about acceptable insolvency probabilities or rates. However, actual ratings may be better than those implied by stand-alone insolvency probabilities due to the possibility of government support in a crisis. In that case, the ratings observed in the marketplace might provide distorted guidance about soundness standards. For bankers, the importance of ratings per se to competitive position may make the rating-based approach convenient and relevant even where the likelihood of government support is substantial. However, for regulatory policymakers, who presumably focus on issues of systemic stability and the likelihood they will need to provide direct support to banks, it would seem that the direct focus on likely bank insolvency rates that this paper’s methods can offer would be more convenient.

8. Concluding remarks

This paper suggests and implements a resampling method of estimating default-mode portfolio credit loss distributions that is equivalent to use of transformed modified binomial distributions. Key differences from conventional credit VaR models that motivate this paper’s approach include a focus on stress scenarios and an

assumption that bank investment decisions are equivalent to independent draws from the available pool of loans. The latter is motivated by an assumption that the impact of systematic risk factors on individual borrowers' repayment behavior cannot be estimated. The modified binomial model is convenient because its results can be related intuitively to variables of central concern to bankers and regulatory policymakers, such as the severity of general economic distress in which continued bank solvency is desired or acceptable rates of bank failures.

In addition, the paper examines the impact of reasonable variations in VaR analysis horizons and stress scenario severity and compares a popular method for selecting loss distribution percentiles with a more direct method that focuses on insolvency probabilities and bank failure rates. This paper's estimates imply that bankers' and policymakers' decisions about analysis horizon and severity of stress scenario have a major impact on estimated absolute capital requirements. Decisions about loss distribution percentiles, while important, have a somewhat smaller impact on estimated capital requirements. It is not clear that the relative importance of these modeling decisions has been widely recognized.

I regard conventional methods of credit VaR estimation and this paper's methods as complementary. Conventional methods are more convenient for estimating relative variations in portfolio risk as PDs vary and are a necessity for evaluating the impact on portfolio risk of structured instruments like first-to-default credit derivatives. This paper's methods provide a convenient and intuitive basis for decision-making about absolute levels of capital needed to support bank solvency and systemic stability.

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