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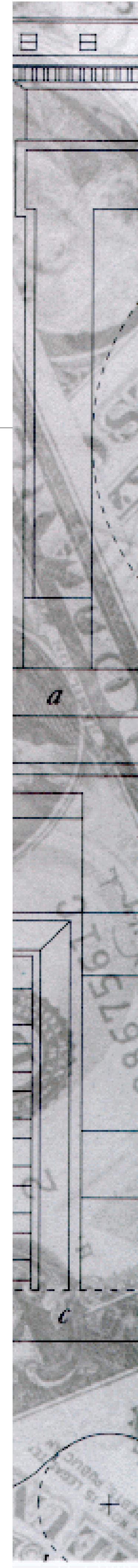

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Deposit Insurance and Risk Management of the U.S. Banking System: How Much? How Safe? Who Pays?

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02-02-B

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The Working Paper Series is made possible by a generous grant from the Alfred P. Sloan Foundation

Deposit Insurance and Risk Management of the U.S. Banking System: How Much? How Safe? Who Pays?[1]

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First Draft: July, 2000
This Draft: April 29, 2002
This Print: April 29, 2002

<u>Abstract</u>: We examine the question of deposit insurance through the lens of risk management by addressing three key issues: 1) how big should the fund be; 2) how should coverage be priced; and 3) who pays in the event of loss. We propose a risk-based premium system that is explicitly based on the loss distribution faced by the FDIC. The loss distribution can be used to determine the appropriate level of fund adequacy and reserving in terms of a stated confidence interval and to identify risk-based pricing options. We explicitly estimate that distribution using two different approaches and find that reserves are sufficient to cover roughly 99.85% of the loss distribution corresponding to about a BBB+ rating. We then identify three risk-sharing alternatives addressing who is responsible for funding losses in different parts of the loss distribution. We show in an example that expected loss based pricing, while appropriately penalizing riskier banks, also penalizes smaller banks. By contrast, unexpected loss contribution based pricing significantly penalizes very large banks because large exposures contribute disproportionately to overall (FDIC) portfolio risk.

Keywords: Deposit insurance pricing, loss distribution, risk-based premiums.

JEL Codes: G210, G280

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[1] We would like to thank Rosalind Bennett, Marc Intrater, Rick Mishkin, Art Murton, Jim Stoker, an anonymous referee and the participants of the Banking Studies Brown Bag at the FRBNY for their insightful comments. We would also like to thank John O'Keefe, Donald Inscoe and Ross Waldrop for providing us with some of the BIF bank-level data, and Sorin Talamba for his excellent research assistance. All remaining errors are ours.

[2] Corresponding author. Any views expressed represent those of the author only and not necessarily those of the Federal Reserve Bank of New York or the Federal Reserve System.

1. Introduction

At the end of 2000, the FDIC Bank Insurance Fund (BIF) had 8571 institutions as members comprising \$6.5tn in assets and about \$2.5tn in insured deposits. The fund had a balance of \$31bn to cover this exposure.[3] Was that enough? What does "enough" mean?

Motivated by similar questions and concerns, the FDIC issued an options paper on regulatory reform in August, 2000, that discussed weaknesses in the present deposit insurance system and offered possible solutions.[4] Whatever the merits or faults of deposit insurance are (and we will discuss these briefly below), any reform needs to address three key issues: 1) how big should the fund be; 2) how should coverage be priced; and 3) who pays in the event of loss. We take a novel approach and argue that the answer to those questions can be found in some of the same risk management techniques used by banks to manage their (mostly asset) risk. After all, the FDIC is managing a portfolio of credit assets, consisting of contingent exposures to the banks it insures. Therefore the risk management problem faced by the FDIC is directly related to the riskiness of the individual banks in its portfolio.

This problem can be broken down into the familiar components of contemporary credit analysis: the probability of an insured bank defaulting (PD), the severity (or loss given default – LGD) of pay-out in the event of a claim, the size of the claim in the event of default (exposure), and the likelihood that several of these adverse events will occur at the same time (default or loss correlation). These factors can be used to estimate the cumulative loss distribution of FDIC insured banks and – critically for policy questions such as pricing of deposit premiums – to frame

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[3] The FDIC has two funds: the BIF and the smaller Savings Association Insurance Fund (SAIF) which at that time had a balance of \$10.9 bn to cover about \$750 bn of insured deposits.

[4] http://www.fdic.gov/deposit/insurance/initiative/OptionPaper.html. See also the commentary on the options paper by Blinder and Wescott (2001).

a discussion about who "owns" which parts of that distribution. We explicitly estimate that distribution for the U.S. banking system using two variations of an options-based approach à la Merton (1974) and include plausible stress scenarios to provide further insight into tail behavior.

In the first application of options theory to deposit insurance pricing, Merton (1977) points out that deposit insurance is much like a loan guarantee and should be priced accordingly. Using Merton's approach, Marcus and Shaked (1984) found that the deposit insurance pricing schedule in effect at that time was far too flat (high risk banks paid similar rates as low risk banks -- still true today), and that the FDIC significantly overpriced deposit insurance.[5] In a theoretical paper, Buser, Chen and Kane (1981) argue the other way, namely that the FDIC intentionally sets premiums too low to induce banks to purchase insurance and submit themselves to FDIC regulatory restrictions. Pennacchi (1987), in an attempt to settle the debate of under vs. overpricing, questions the degree of regulatory control and impact the FDIC really has. By allowing for a range of control, Pennacchi computes pricing bounds, and the actual premiums the FDIC charged at the time were contained within those bounds. Interestingly, under the assumption of low effective regulatory control, the estimates indicate under-pricing of premiums, a prescient result given that his study used data from 1978 – 1983, before the worst of the S&L crisis.

In a recent paper, Pennacchi (2002) develops a risk-based insurance premium pricing model using an insurance valuation approach. His methodology involves treating the insurance guarantee as a moving average of a series of long term insurance contracts. The pricing scheme is stable (i.e. address the procyclicality problem of the existing regime) yet subject to frequent updating. While

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[5] See also Ronn and Verma (1986) for a similar analysis.

Pennacchi provides fair insurance rate estimates for only 42 banks and finds, as do we, that the distribution of those rates is quite skewed.

We find that the BIF reserves are sufficient to cover roughly 99.85% of the loss distribution of the 8571 banks which make up the BIF, corresponding to about a BBB+ rating. This finding is robust across different approaches (asset vs. equity based) and assumptions about loss severity (fixed vs. stochastic). The BBB+ rating is actually quite low – lower, in fact, than most of the large rated institutions covered by the fund, and just slightly above implied average rating for all banks in the system. The implication is that the U.S. government backstop must be quite important in maintaining the confidence that depositors ascribe to the fund. Capital levels commensurate with a AAA rating and / or under stress scenarios, by contrast, are multiples (3 – 10) of current levels. Of course the fund cannot have a better credit rating than that of any single exposure that could render the fund insolvent. Of the five institutions that have an *effective exposure* (severity × exposure) in excess of fund reserves, the lowest has a rating of A-. Of the eight institutions which have *total insured deposits* in excess of the fund reserves, the lowest rated institution has a rating of BBB.

The potential for "catastrophic" losses resulting from a large number of bank failures (or from the failure of large banks) suggests that the FDIC's loss distribution should be thought of as partitioned into two zones: small losses that are covered by reserves (either funded or callable); and excess losses that are covered by reinsurance. A key question under this structure is who should bear the risk of each part of the FDIC's loss distribution?[6] Possible candidates include the government, the banks themselves through a mutual insurance system, and the private capital markets through risk transfer or reinsurance. Each of these alternatives has significant consequences for pricing and policy options. We argue that the most practical and lowest cost solution is the for government to own both zones, a system which can be viewed as a mandatory insurance contract between the government and the banks.

Finally, how can pricing reflect the discrete risk contribution of individual banks to the FDIC? Pricing should be risk-based and, we argue, based specifically on expected losses. This greatly mitigates banks' moral hazard, introduced by the very existence of deposit insurance, and it ensures that the fund is self-financing over time. We show in an example that expected loss based pricing, while appropriately penalizing riskier (higher probability of default) banks also penalizes smaller banks. By contrast, unexpected loss contribution based pricing significantly penalizes very large banks because large exposures contribute disproportionately to overall (FDIC) portfolio risk.

The rest of the paper proceeds as follows. Section 2 provides some background on the theoretical justifications for deposit insurance and a quick history lesson on the U.S. experience; Section 3 describes the economic approach to measuring individual bank and portfolio risk; Section 4 shows empirical results from the estimation of the FDIC's cumulative loss distribution; Section 5 discusses policy options derived from the distribution, including the pricing of premiums; and Section 6 provides some concluding remarks.

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[6] Questions of fund adequacy and risk sharing are complicated by concentration problems arising from the FDIC's exposure to large banks.

2. Deposit Insurance: Theory and Practice

2.1. The Promise of Deposit Insurance

Why might we want deposit insurance? The answer typically given is to prevent bank runs and thereby enhance the stability of the financial system; more formally it is to overcome the asymmetry of information in the banking system (Diamond and Dybvig (1983), Dewatripont and Tirole (1994)). The bank knows more about the riskiness of its activities than do its depositors. A depositor, therefore, is unable to tell a good bank from a bad one. Because banks are highly leveraged institutions, depositors have a strong incentive to show up at the bank first to withdraw their funds in case they doubt the financial health of a particular bank. Those at the end of the line may get nothing. In short, deposit insurance is designed to prevent depositors from overreacting to bad news about banks.[7]

The creation of such a safety net comes at a cost, namely moral hazard. Depositors no longer have an incentive to monitor (or pay to monitor) banks since their deposits are guaranteed up to the coverage limit (currently $100,000 per individual per institution in the U.S.). Banks have an attendant incentive to increase risk. Hence the name of the game in designing a safety net has been to balance the need to prevent bank panics (and other social costs to bank failure such as credit crunches) with the moral hazard brought on by the very presence of the safety net. The regulation of bank capital is often justified to achieve this balance.[8]

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[7] Bank runs and panics were quite real and prevalent in the US in the 19th and early 20th centuries. In the years preceding the creation of the FDIC (i.e. 1930-33), the number of bank failures averaged 2000 per year (Mishkin (1997)).

[8] Santos (2001), in a survey of the bank capital regulation, points out the necessity of jointly considering the problems of deposit insurance pricing, lender of last resort and bank capital standards and regulation. "In general, the optimal regulation encompasses a menu of regulatory instruments, designed to extract information from banks and minimize the cost of 'bribing' the lower quality banks to mimic the higher quality ones." (Santos (2001) p. 59). In short, while the information asymmetry inherent in banking is a real issue, deposit insurance may not be the only solution, and if deposit insurance is chosen, its design matters in determining banking stability and efficiency.

Since monitoring difficulty is cited as a primary motivation of bank regulation and deposit insurance, are market mechanisms really unable to perform this task? Berger, Herring and Szegö (1995) and Calomiris (1999), among others, argue that subordinated debt can play a very useful role in market discipline.[9] Flannery and Sorescu (1996) and De Young, Flannery, Lang and Sorescu (2001) find that subordinated debt yields indeed incorporate information about the bank. However, Hancock and Kwast (2001) point to some pitfalls (low liquidity) of using this financial instrument to evaluate the conditions of banks. Swidler and Wilcox (2002) take a different tack; they find that implied volatilities of bank stocks are informative about bank risk. Finally, Morgan (2000) reminds us that monitoring the riskiness of banks is not so easy by showing that bond raters disagree more about banks and insurance companies than about any other kind of firm. Moreover, recent research on corporate bonds indicates that credit (default) risk plays a surprisingly small role in the determination of credit spreads (Elton, Gruber, Agrawal and Mann (2001) and Collin-Dufresne, Goldstein and Martin, (2001)), casting further doubt on the feasibility of bank subordinated debt schemes.

The evidence on the efficacy of deposit insurance in promoting stability is mixed at best. In an important paper, Barth, Caprio and Levine (2001), using data on regulatory and supervisory policies in 107 countries, show that generous deposit insurance schemes have strong adverse effects on bank stability. Demirgüç-Kunt and Huizinga (2000), in a study on multi-country comparison on market discipline and financial safety net design, find that explicit deposit insurance decreases market discipline while private or joint (with government) management of deposit insurance funds increases market discipline.

2.2. A Quick History Lesson of Deposit Insurance in the U.S.[10]

Following an alarming level of bank failures in the 1980s, the FDIC's Bank Insurance Fund (BIF) became depleted to the point where it had negative net worth in 1991. In response to the banking (and savings and loan) crisis, Congress enacted the FDIC Improvement Act (FDICIA) that year. FDICIA re-capitalized the BIF with a loan from the Treasury and allowed the FDIC to raise the deposit insurance rates paid by banks to an average of 23 bp.[11] By 1995, the fund reached a target level of reserves set under FDICIA of 1.25% of insured deposits [12] known as the Designated Reserve Ratio (DRR).[13]

Aside from recapitalizing an otherwise bankrupt fund, FDICIA also allowed the FDIC to introduce risk-based pricing for deposit insurance (Mishkin (1997)). Subsequent legislation, however, tied the level of pricing to the adequacy of reserves in the fund, [14] so that the vast bulk of banks do not pay any premiums when the fund exceeds the DRR. As of year-end 1999, pricing for 93% of FDIC-insured institutions, accounting for 97% of deposits, was in fact zero (FDIC (2000)). The pricing on the remaining 3% of deposits was differentiated for risk somewhat, with five non-zero pricing buckets ranging from 3 bp to 27 bp.[15] But in practical terms there is little meaningful risk differentiation. The roughly 8,000 insured banks falling within the zero premium class surely span enormous differences in risk profile, and in size as well. Yet under the current

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[9] To be sure, Calomiris (1998) is a severe skeptic of deposit insurance; he views FDIC insurance to be "the single most destabilizing influence in the financial system", a view we do not share.

[10] For a more detailed account, see Mishkin (1997) and Benston and Kaufman (1998).

[11] The Financial Institutions Reform, Recovery, and Enforcement Act of 1989 (FIRREA) had allowed an increase in rates from 8.33 bps to 15 bps.

[12] At the end of 2000, the DRR was 1.35%.

[13] In addition to the fund balance, the FDIC has access to a $30 bn line of credit from the Treasury for which it pays nothing (Wilcox (2000)).

[14] Pennacchi (2000) demonstrates in a simulation exercise how the setting of deposit insurance premiums to target a particular insurance fund level leads to distortions in banks' cost of deposit financing.

[15] The premiums are tied to CAMEL ratings. This government risk-based pricing schedule is half as steep (9:1) as the market's as viewed by credit spreads (18:1). For instance, the credit spread ratio of CCC to AA corporate bonds in April, 2002, was 735:40 bp or about 18:1 (1-year maturity). In our sample there is one CCC+ rated bank and several BB+ banks.

structure, a bank with over $100 billion in insured deposits and very complex risk profile may be charged the same amount (zero!) as a small community bank.

The statutory link between the DRR and premiums also introduces cyclicality in pricing. The DRR will drop only at times when the banking industry is weak, requiring then-weakened banks to cough up more in terms of deposit insurance premiums precisely at a time when they can least afford to do so.[16]

Blinder and Wescott (2001), in their comments on the FDIC policy options paper (FDIC (2000)), list three main concerns with the state of deposit insurance in the U.S. today: absence of real risk-based pricing, potential procyclical bias, and determining a fair coverage limit. In this paper we explicitly address the first two, but not the third.

3. The Economic Approach to Measuring Risk in a Credit Portfolio

Our starting point for answering the three key questions (how safe should the fund be? how to price premiums? who pays in the event of loss?) is to construct an explicit model of the FDIC's loss distribution. The loss distribution can then be used to determine the appropriate level of fund adequacy and reserving in terms of a stated confidence interval and to identify risk-based pricing options. In fact, efforts to set capital in relation to an explicit model of a financial institution's risk profile lie at the core of the current proposals for reform of the BIS capital rules (see the BIS (2001), and Jones and Mingo (1998)). Our approach applies the same types of methodologies

[16] Under FDICIA and the Deposit Insurance Funds Act of 1996, pricing would jump (in stages) to as much as 23 bp for banks currently paying zero premiums in the event the DRR falls below 1.25%. This could reduce pre-tax net income of insured institutions by almost $9 billion. See FDIC (2000).

that are under consideration by the BIS Models Task Force to the FDIC's own loss distribution for resolving similar questions of risk and capital management.[17]

3.1. The FDIC is Like a Bank

The conceptual framework used to understand risk and capital for a bank which has a portfolio of credit exposures can also be used to understand risk and capital for the FDIC. The cumulative loss distribution allows the potential for loss to be directly compared with the reserves and other resources available to the insurance funds.[18] This analysis can also be reversed to determine what level of resources – or reserve ratio – is required to reach a chosen *solvency standard*. By creating an explicit link between the potential for loss and reserves, the FDIC can consider the appropriate level of fund adequacy in terms of both a stated confidence interval and market equivalents.[19] For example, just as an individual bank chooses to capitalize according to a desired credit rating, so too can the FDIC choose to capitalize the insurance funds to a desired rating. This approach differs fundamentally from the current system, in which the desired reserve ratio (DRR) is set as a fixed percentage independent of the fund's actual loss profile.

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[17] Our "bottom-up" approach also differs from the "top-down" approach of Sheehan (1998). For a robustness discussion of an earlier version of our approach, see Bennett (2001)

[18] The first resource is the expected income from premiums and interest. In most cases, this will be more than sufficient to cover the losses and the fund will have a gain. The next resource is the current balance of the fund itself. If the losses in any period exceed the funds available, a backstop resource, such as a loan or grant from the Treasury, is required to ensure the payment of all obligations. In fact, by law the Treasury extends a $30bn (repayable) line of credit to the FDIC; however, the FDIC, in stark contract to a private sector institution, does not have to pay for this line of credit. See also Wilcox (2000).

[19] In our analytical discussion of the insurance fund, we will use terms such as capitalization, economic capital and capital charge, despite the fact that the government may not hold capital as an insurer. This is discussed in more detail in Section 5.

3.2. Modeling the Loss Distribution

The first step in analyzing the FDIC's risk profile is to recognize that the deposit insurance funds are portfolios of counterparty risks. These portfolios consist of individual exposures to insured banks and thrifts, each of which has a small but non-zero chance of causing a loss to the fund. Such a portfolio is similar to a bank loan portfolio, although the nature the underlying risks in the FDIC funds raises unique issues. The FDIC portfolio effectively consists of the sum of the "tail" risks of individual banks defaulting.

Expected loss (*EL*) is simply the (unconditional) mean of the loss distribution; its standard deviation is often called unexpected loss (*UL*). We will be interested in tail probabilities, say 99.9% (corresponding to roughly an A- rating), of this loss distribution, and the distance, either from the origin or *EL*, to that critical point. In fact, that distance will be the amount of reserves (funded or callable) needed to insure solvency of the fund. To the extent that there are insufficient funds available to repay insured deposits, then the excess deposit losses will be borne by the FDIC. Put another way, the FDIC assumes the residual "tail" risk of loss to insured deposits.

It is important to recognize that the solvency level will never be 100%. To require 100% solvency means to hold as much capital as insured deposits in the system. Hence the acceptance of a solvency level of less than 100% is tantamount to accepting that, past some level of loss, "all bets are off," even those with the U.S. government and its taxpayers.[20]

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[20] To be sure, solvency levels of funded reserves are not equal to the solvency level implied by the implicit callable reserves of the banking system nor, going yet further out into the tail of the loss distribution, the full faith and credit of the US government. For this (and other) reasons it will be useful to partition the loss distribution when considering policy alternatives, as we will in Section 5.

FIGURE 1 shows the actual historical default frequency of commercial banks covered by the FDIC insurance fund since 1934, with a stylized loss distribution on the right. The chart demonstrates that default frequency can fluctuate widely over time. In 1981, only 0.069% of the insured institutions failed, while just six years later, 1.33% of the institutions failed. The average annual default rate from 1934 to 2000 was 0.26% and its standard deviation is 0.42%.

The derivation of the loss distribution is discussed in detail elsewhere (see Saunders and Allen (2002) and references therein). Hence our exposition will be brief. First we will describe risk at the bank level, then risk at the (FDIC) portfolio level and finally the simulation procedure for building up the loss distribution.

3.2.1. Risk at the Bank Level

Let PD_i = probability of default for bank i over a one-year horizon.[21] Then the expected loss for bank i will the product of PD, exposure (X_i) in the form of insured deposits[22] and the proportion of X_i that will actually be lost, often called severity, S_i:

$$EL_i = PD_i \cdot X_i \cdot S_i \qquad \textbf{3-1}$$

Note that the recovery amount (one minus severity) is typically not known at time of exposure. Hence in addition to PD being stochastic, severity is often treated as random.

Because default is a Bernoulli random variable, its standard deviation is $\sqrt{PD_i\left(1-PD_i\right)}$, and if we make the standard assumption of no correlation between PD_i, S_i and X_i, we obtain the following formulation for unexpected loss, UL_i

[21] The one-year horizon is not required but is typical. Note also that sometimes the term "expected default frequency," or *EDF*, is used instead of *PD*.
[22] The FDIC uses assets as an exposure proxy, as will we. This is discussed in detail in Section 4.1.2.

$$UL_i = \sqrt{\left(PD_i - PD_i^2\right)\mu_{S_i}{}^2 X_i{}^2 + PD_i X_i{}^2 \sigma_{S_i}{}^2} \qquad \textbf{3-2}$$

where $S_i \sim f(\mu_S, \sigma_S)$ and is often taken to be a draw from a beta distribution. The formulation further simplifies when severity is a constant (i.e. $\sigma_{S_i} = 0$):

$$UL_i = \sqrt{\left(PD_i - PD_i^2\right)\mu_{S_i}{}^2 X_i{}^2}$$

The FDIC's exposure to individual banks can be added together to create a cumulative loss distribution. Just as with a bank's credit loss distribution, the FDIC's cumulative loss distribution will reflect the expected loss of the individual insured banks, the size of individual exposures, and the correlation of losses in the portfolio. Typically the distribution will be heavily skewed. There will likely be some "lumpiness" in the distribution which reflects the contribution of individual large banks, each of which imposes a discrete, non-zero probability of a sizeable loss to the fund.

3.2.2. Risk at the Portfolio Level

Because expected loss is unaffected by correlation, portfolio *EL* is a summation of *N* individual institution *EL*'s, just as the expected return on an equity portfolio is a simple weighted average of returns to the individual holdings in a portfolio:

$$EL_p = \sum_{i=1}^{N} EL_i$$

This is especially useful when we consider expected loss pricing. By charging individual institutions expected loss pricing, the additivity of the individual *EL*'s implies that the FDIC is charging for its overall expected loss.

Calculating portfolio unexpected loss must consider the correlation between individual losses, ρ_{ij}. For a portfolio with *N* institutions, portfolio unexpected loss, UL_p, is:

$$UL_p = \left[\sum_{i=1}^{N} UL_i^2 + \sum_{i=1}^{N} \sum_{j=1}^{N} \rho_{ij} UL_i UL_j \right]^{1/2} \qquad \textbf{3-3}$$

Portfolio *UL* may also be written as the sum of *contributory* unexpected losses, ULC_i, from each of the *N* elements (i.e. *N* banks) in the portfolio: $UL_p = \sum_{i=1}^{N} ULC_i$, where $ULC_i = \frac{\partial UL_p}{\partial X_i} X_i$.

The risk to FDIC's portfolio of the i^{th} bank does not depend on its expected loss – after all, we *expect* it and hence should account (price) for it. Instead portfolio risk depends on the contribution of the i^{th} bank to portfolio volatility, or contributory unexpected loss ULC_i, which is driven by two things: the volatility of bank *i*'s losses, which in turn is driven by its *PD* and exposure (i.e. size), and its correlation with the rest of the portfolio. What impact this may have on insurance premiums under strict contributory risk-based pricing will be discussed in Section 5.1.

3.2.3. Building up the Loss Distribution

The loss distribution is really a characterization of the loss experience over the very long run, or in all states of the world. We need a way to link default (and loss) to changes in states of the world. Consider, therefore, the probability of default, PD_i, as determined by a function of systematic or macro variables **M**, shared by all banks, and a bank-specific idiosyncratic stochastic component ε_i

$$PD_i = f(\mathbf{M}, \varepsilon_i) \qquad \textbf{3-4}$$

Thus default correlation enters via **M**, but of course not all elements of **M** affect all banks in the same way. All credit portfolio models share this linkage of systematic risk factors, e.g. the economy, to default and loss. They differ in specifically how they are linked.

Broadly there are three approaches. The first is an options-based approach, often called the Merton approach after Merton (1974), which we will follow in this paper. This approach is used by industry models such as by CreditMetrics as well as KMV's PortfolioManager. The second is an econometric approach where PD_i is estimated via logit with macro-variables entering the regression directly (Wilson (1997)). The third is an actuarial approach employed by CSFB's CreditRisk+ where the key risk driver is the variable mean default rate in the economy. For detailed comparisons, see Koyluoglu and Hickman (1998), Saunders and Allen (2002) and Gordy (2000).

3.2.4. The Merton Option-Based Model of Firm Default

We consider a simple structural approach to modeling changes in the credit quality of a firm. The basic premise is that the underlying asset value evolves over time (e.g. through a simple diffusion process), and that default is triggered by a drop in firm's asset value below the value of its callable liabilities. Following Merton (1974), the shareholders effectively hold a put option on the firm, while the debtholders hold a call option. If the value of the firm falls below a certain threshold, the shareholders will put the firm to the debtholders. The concept is shown schematically Figure 2.

The Merton model defines default as when the value of an institution's assets declines to below the value of its liabilities. In standard implementations of Merton's approach, asset returns are taken to be normally distributed. Credit portfolio management models such as CreditMetrics adjust the asset returns to be standard normally distributed. Moreover, this class of models places a specific interpretation on credit ratings from rating agencies, namely as a distance to default metric,[23] where the default probability can be expressed as the probability of a standard normal variable falling below some critical value. Similarly, thresholds can be established for transitions to other rating states (see Figure 3).

Employing the empirically estimated probability of default (PD) for a specific initial rating class, the asset return threshold for the default state can be derived by the following relationship

$$PD = \Phi(Z_D)$$
$$Z_D = \Phi^{-1}(PD), \qquad \textbf{3-5}$$

where $\Phi(\cdot)$ denotes the cumulative standard normal distribution.[24] In other words, the critical value matches the probability of an adverse change in asset values with the expected default probability. An assets return less than Z_D will result in default.

The assumption of normality is carried to higher dimensions. In the case of two banks, the joint normal distribution of their assets will characterize their joint likelihood of default. It should now be clear how correlation will enter the picture: correlation of losses will derive from correlation of assets. Moreover, those default correlations should be much lower than asset correlation. For example, if PD_A= 0.10% (corresponding to about a A- rating) and PD_B = 0.20% (corresponding about a BBB rating) and their asset correlation is 40%, their implied default correlation would be about 3.3%.

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[23] See also Saunders and Allen (2002).
[24] See the Appendix for a mapping from credit grades to *PD*s.

3.2.5. Conditional Loss

Building up the loss distribution by simulating states of the world (economy) is done by integrating the state-conditional losses over all states.[25] Recall that an individual loan will default when its asset return z_i is less than the critical value Z_D:

$$z_i \le Z_D = \Phi^{-1}\left(PD_i\right)$$

Following (3-4), asset returns can be decomposed into a set of k orthogonal systematic factors, $\mathbf{M} = (m_1, m_2, \ldots, m_k)$, and an idiosyncratic shock ε_i

$$z_i = \sum_{j=1}^{k} \beta_{i,j} m_j + \left(1 - \sum_{j=1}^{k} \beta_{i,j}^2\right)^{1/2} \varepsilon_i \qquad \textbf{3-6}$$

where both the k systematic factors and the idiosyncratic shock are standard normal, and $\beta_{i,j}$ are the factor loadings. Consequently $z_i \sim N(0,1)$. For the case of a single borrower or a homogeneous portfolio, we can collapse the systematic factors into one, m:

$$z_i = \alpha m + \delta \varepsilon_i \qquad \textbf{3-7}$$

We can determine the constants α and δ from the asset correlation between two loans in this portfolio, $\mathrm{E}[z_i z_j] = \rho_{ij} = \alpha$. Hence $\alpha = \sqrt{\rho_{ij}}$ and $\delta = \sqrt{1 - \rho_{ij}}$.[26]

The sensitivity to the common factor exactly reflects the asset correlations. For a homogeneous portfolio, $\rho_{ij} = \rho$. Following (3-6), we can express the portfolio asset correlation in terms of the factor loadings as $\rho = \sum_{j=1}^{k} \beta_j^2$. Then (3-7) can be rewritten as:

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[25] See also Finger (1999).

[26]

$$\begin{aligned}\mathrm{E}(z_i z_j) &= \mathrm{E}\left(\alpha^2 m^2 + \delta^2 \varepsilon_i \varepsilon_j + \delta\alpha m \varepsilon_i + \delta\alpha m \varepsilon_j\right)\\ &= \alpha^2 \mathrm{E}(m^2) + \delta^2 \mathrm{E}(\varepsilon_i \varepsilon_j) + \delta\alpha \mathrm{E}(m\varepsilon_i) + \delta\alpha \mathrm{E}(m\varepsilon_j)\\ &= \alpha^2\end{aligned}$$

$$\begin{aligned}\mathrm{E}(z_i^2) &= \mathrm{E}\left(\alpha^2 m^2 + \delta^2 \varepsilon_i^2 + 2\delta\alpha m \varepsilon_i\right)\\ &= \alpha^2 \mathrm{E}(m^2) + \delta^2 \mathrm{E}(\varepsilon_i^2) + 2\delta\alpha \mathrm{E}(m\varepsilon_i)\\ &= \alpha^2 + \delta^2\\ \delta &= \sqrt{1 - \rho_{ij}}\end{aligned}$$

$$z_i = \sqrt{\rho} \cdot m + \sqrt{1-\rho} \cdot \varepsilon_{\mathrm{i}} \qquad \textbf{3-8}$$

The bank will be in default when

$$\sqrt{\rho} \cdot m + \sqrt{1-\rho} \cdot \varepsilon_i \le \Phi^{-1}(PD_i)$$

$$\varepsilon_i \le \frac{\Phi^{-1}(PD_i) - \sqrt{\rho} \cdot m}{\sqrt{1-\rho}}$$

This means for a given value of *m* the probability that an individual bank will default is:

$$PD_i\big|_m \le \Phi\left[\frac{\Phi^{-1}(PD_i) - \sqrt{\rho} m}{\sqrt{1-\rho}}\right] \qquad \textbf{3-9}$$

Conditional on *m*, we draw a standard normal variate ε_i, and check whether or not the institution defaults. This is characterized by an indicator function:

$$\mathrm{I}\left\{\varepsilon_i \le \frac{\Phi^{-1}(PD_i) - \sqrt{\rho} m}{\sqrt{1-\rho}}\right\} = \begin{cases} 1 \text{ if true} \\ 0 \text{ if false} \end{cases} \qquad \textbf{3-10}$$

Then, for a given draw from state *m*, *m(r)*, and draw ε_i, $\varepsilon_i(r)$, the loss to bank *i* is

$$\mathrm{Loss}_i\big|_{m(r)} = \mathrm{I}\left\{\varepsilon_i(r) \le \frac{\Phi^{-1}(PD_i) - \sqrt{\rho} m}{\sqrt{1-\rho}}\right\} \cdot X_i \cdot S_i \qquad \textbf{3-11}$$

it's expected loss is

$$\mathrm{E}\big|_m\left(Loss_i\right) = \frac{1}{R}\sum_{r=1}^{R}\left(\mathrm{I}\left\{\varepsilon_i(r) \le \frac{\Phi^{-1}(PD_i) - \sqrt{\rho} m}{\sqrt{1-\rho}}\right\} \cdot X_i \cdot S_i\right)$$

and the portfolio loss conditional on the state draw *m(r)* is

$$\mathrm{Loss}_p\big|_{m(r)} = \sum_{i=1}^{N} \mathrm{Loss}_i\big|_{m(r)} \qquad \textbf{3-12}$$

4. The Loss Distribution Faced By The FDIC

4.1. The Data

As of year-end 2000, the FDIC insured deposits at nearly 10,000 financial institutions nationwide. The vast majority – over 8500 – of these institutions are commercial banks, whose deposits are insured through the Bank Insurance Fund, or BIF. The remainder of the institutions are Savings and Loans institutions, the deposits of which are presently insured by the Savings Association Insurance Fund, or SAIF. For simplicity we estimate the cumulative loss distribution for the BIF only.

4.1.1. Probabilities Of Default

There are several sources of default frequency information. At the aggregate level there is the time series of defaults since the inception of the FDIC over 65 years ago. This consists of the number of failures as well as the number of institutions present in each year, resulting in the default frequency for each year in the sample. In Section 3.2 we saw that the historical default rate from 1934 to 2000 was 0.26% per year.

The second source for *PD*'s is a credit scoring model which generates a credit score or rating as a function of firm observables, typically using balance sheet or capital market information as discussed in Chava and Jarrow (2001).[27] For the purpose of our loss distribution estimates we did not separately generate a credit scoring model. However, the FDIC does have such a model and uses it for just this purpose.

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[27] The first such model was Altman's Z-score model (Altman (1968)).

Third, there are public sources of risk ratings, such as from Standard & Poor's or Moody's. Both of these rating agencies give solvency standards for the rated institutions in the form of a credit grade, which may then be converted to a probability of default, *PD*. We use *PD*s implied by credit ratings for 178 institutions at year-end 2000,[28] comprising 75% of all assets and 62% of all deposits in the BIF member institutions. For the remaining banks we simply use the average historical default probability of 0.256% which corresponds roughly to a BBB rating.

4.1.2. Exposure And Severity

The FDIC uses assets for its own estimates of potential exposure for the simple reason that historical losses have to date been measured in terms of assets, not insured deposits. Moreover, the FDIC has not always paid out only the insured deposit amounts. When compounded with the rough estimates which are available for insured deposits for each bank insured today, using assets turns out to be a more reliable measure of exposure. To be sure, this results in some peculiarities when deciding which banks are "big." For example, State Street is the 16th largest bank in the BIF on a pure asset basis with $64.6bn in assets (qualifying as "big"), yet its deposit base is tiny in relation at $476mm. How to deal with this in the loss distribution estimation will be discussed below.

Severity can be treated in two ways: fixed or stochastic. We provide results using both methods. Severity parameters were chosen based on FDIC results of its Failed Bank Cost Analysis as summarized in Bennett (2001), the details of which are discussed in the next section.

James (1991), in a study of losses realized from bank failures using FDIC data from 1985 - 1988, finds that these losses average 30% of the failed bank's assets, one-third of that coming from

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[28] See FDIC (2000), Table 6, reproduced in Appendix B.

direct expenses such as administrative and legal costs. James finds some economies of scale in these costs but not in the recovery of poor assets, the other two-thirds. Note that not all bank failures result in an FDIC payoff to the depositors of the failed bank. Of the 412 failed banks analyzed by James, only 96 (about 23%) result in a payoff.[29] The most common resolution of bank failures is the auctioning of part or all of the bank's assets, the so-called purchase and assumption (P&A) transaction.[30] In the 1990s, of 925 failed institutions, only 68 (~7%) resulted in a payoff.

For random severity, we want to draw a value from a bounded distribution. We choose a beta distribution which has the advantage of being bounded and easily parameterizable. The beta distribution has two-parameters which together govern shape and dispersion.[31] The parameters can be expressed in terms of mean and variance.

4.2. Simulation

4.2.1. Asset Returns

Asset returns are hard to observe directly. However, for publicly traded banks we do have equity return information as a proxy.[32] For these banks we may estimate their return correlation matrix and generate synthetic returns to build up the loss distribution. Unfortunately less than 10% of the banks in the BIF are publicly traded, although they hold about two-thirds of all insured deposits. We thus perform two simulations, each with a different compromise.

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[29] James (1991), Table 1.

[30] See http://www.fdic.gov/hsob/. For a recent discussion of disposing of failed bank assets, see Spiegel (2001).

[31] Strictly speaking there are four parameters including the two endpoints which are typically 0 and 1. See Mood, Graybill and Boes (1974).

[32] Arguably equity returns are even preferred since they allow for non-constant liabilities within the Merton framework.

4.2.2. Equity Return Based Approach

Our first approach takes the 30 largest banks and their state bank subsidiaries, all of which are publicly traded. These 30 institutions comprise 57% of total bank assets in the BIF and 44% of the estimated insured deposits) and are listed in Table 1.

Estimates of the loss distribution are obtained through simulation. We estimate the correlation matrix from monthly cum dividend returns obtained from Datastream from January 1996 to December 2000 and use that to generate correlated standard normal returns, check for each iteration if the bank default threshold has been passed, and if yes, compute a loss given default as described in Section 4.1.2. Returns are generated directly without needing to separate them into a systematic and idiosyncratic component.[33] While we are able to obtain a reasonably good estimate of the correlation structure between the 30 largest banks, a key driver for the loss distribution, we cannot do so for the entire portfolio.

4.2.3. Implied Asset Return Based Approach

The second approach includes all 8500+ banks in the BIF in the loss simulation. If the BIF portfolio were homogeneous, we know from (3-8) that the average asset correlation will drive the asset return process. Knowing PD_i, we may then build up the loss distribution through the generation of synthetic draws from m, the systematic factor, and ε_i, bank i's idiosyncratic shock.

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[33] This is not unlike the regulatory capital requirement for general and specific market risk. A separate specific risk charge is assigned only if the (internal risk) model is not sufficiently granular. This might occur if, for instance, all equities in a broad portfolio are represented by only one risk factor, say the S&P500, rather than, in the limit, each firm being its own risk factor in the value-at-risk model.

There are two problems: 1) assuming that the whole portfolio is homogeneous is troublesome, and 2) we do not have an estimate of the average asset correlation. The solution to the first problem is achieved by grouping or bucketing. If the assumption of homogeneity for the whole portfolio is unreasonable, it is less so for properly constructed subsets. This is described in detail in Section 4.2.4, but the basic idea is to homogenize on size.

Let's now turn to the second issue, asset correlations. In Section 4.1.2 we discussed bank mean losses and loss volatility. Isolating just the default component, each bank has a default variance given by the variance of a Bernoulli trial.

$$\text{var}(\text{default}_i) = \sigma^2_{def} = PD_i\,(1\text{-}PD_i)$$

For a homogeneous portfolio, the portfolio variance approaches[34]

$$\sigma^2_{def} \approx \overline{PD}(1-\overline{PD})\rho_{def}$$

where $\overline{PD}$ is the portfolio mean default rate and ρ_{def} is the default correlation. We can express the unobservable default correlation in terms of observable average default rates as well as its volatility from FDIC loss rate data spanning 1934 - 2000.

$$\rho_{def} \approx \frac{\sigma^2_{def}}{\overline{PD}(1-\overline{PD})} \qquad \textbf{4-1}$$

At the aggregate level, $\widehat{\overline{PD}}$ = 0.26% and $\hat{\sigma}_{def}$ = 0.42%, implying ρ_{def} = 0.69%. We will make one further modification to (4-1) for the simulation by incorporating average default estimates from each (homogeneous) bucket. For each of the $q = 1,\ldots, Q$ groups[35] we can compute an average group-level default rate, $\overline{PD}_q$, which will yield group-level estimates of default correlation

[34] See JP Morgan (1997) and Koyluoglu and Hickman (1998).
[35] Q = 25 in our simulation.

$$\rho_{def,q} \approx \frac{\sigma_{def}^2}{\overline{PD}_q(1-\overline{PD}_q)}$$

The Merton model yields a one-to-one mapping between default and asset correlations which can be used to generate group-level asset correlations.

With this asset correlation implied by the homogeneous default correlation structure, we now have a simple way of generating simulated asset returns that will determine default based on each institution's probability of default. We draw a set of standardized normal pseudo-random variates from a multivariate normal distribution with the specified $Q \times Q$ correlation matrix. Each of these draws will determine whether an institution defaults or not, and by construction these defaults have the appropriate default correlation.

4.2.4. Bank Grouping

We group the institutions according to asset size, where the 20 largest institutions are in their own 'bucket' but the remainder of the institutions are categorized by size in five different buckets. Each bucket receives one *PD* value and one loss given default (*LGD*) value which allows for the asset correlation matrix to be computed at the group level. The *LGD* of bucket q equals the severity for that bucket times the sum of the assets for all institutions in that bucket. The design is summarized in Table 2.

We closely follow the bucketing approach used by the FDIC for its own severity estimates which, in turn, are based on FDIC's Failed Bank Cost Analysis data covering 1986 – 1998.[36] They found the mean loss rate to be a decreasing function of bank size in roughly the breakdown described by

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[36] See Bennett (2001).

these buckets. We reproduce their findings in Appendix C as a reference. Our grouping differs slightly in that we increased granularity at the top (large asset) end and lumped the last two of their buckets together.[37] The motivation is simple: the loss distribution is driven very heavily by large, lumpy exposures, indicating that modeling effort should be concentrated there at the expense of the (much) smaller exposures of the small banks.

To be sure, bucket 21 is somewhat special. It includes a number of banks which, ranked purely on asset, should be in the top 20. However, because their deposit base is so small, including them in the top 20 would have excluded others more relevant from a perspective of exposure to the FDIC. These banks are listed in Table 3.

For comparison, the largest bank in the BIF is Bank of America with \$584.3bn in assets and \$217.8bn in estimated insured deposits. The number 20 bank, Mellon, had \$42.0bn in assets and \$12.9bn in estimated insured deposits at year-end 2000.

Because of this property of the correlation matrix, we use principal component analysis (PCA) to drive the simulation of normal variates from the asset correlation matrix, as opposed to the more standard Cholesky decomposition approach.[38] PCA simply allows us to compute the coefficients on the market factors m_j, and ε_i, the idiosyncratic factors, subject to the constraint of intra-group correlations being less than one. An illustrative example is given in Appendix A.

[37] The severity mean and standard deviation for our smallest bucket is just the average of their last two buckets.

[38] Note that if each group were comprised of a single institution, the diagonal of the correlation matrix would contain all ones, and we could proceed with standard Cholesky decomposition.

4.3. Results

We present simulation results for the two approaches: equity correlation based for the 30 largest banks and implied asset correlation based for the entire BIF fund of 8571 banks. In each case we ran the simulation with either fixed or random severity. We consider several percentiles implied by credit ratings all the way out to AAA, a benchmark thought to be useful by Blinder and Wescott (2001): "We were also attracted to the idea […] of targeting the DI [deposit insurance] fund to have the rough equivalent of a Standard & Poor's AAA rating – that is, having an annual probability of default of about 0.01 percent."[39]

4.3.1. Equity Correlation Based Loss Distribution For 30 Largest Banks

Results are summarized in Table 4 employing unconditional estimates of correlations using monthly returns spanning 1996 to 2000. It provides the capital levels needed to insure the 30 largest banks to four different confidence levels. The loss distribution is highly right-skewed. Losses go up dramatically as we move further out into the tails. For two of the simulation runs, no losses were observed at all 1% of the time.

Using random as opposed to fixed severity seems to have only a modest influence. For instance, taking the most replication intensive results (# of replications = 100,000), we see that the 99.9% confidence level, corresponding to a 10bp tail region (implying a 0.10% chance of fund insolvency), would require about $40bn of capital under the fixed severity and $45bn under the random severity scenario. The BIF is capitalized at $31bn (year-end 2000), implying a 99.85% confidence level, analogous to about a BBB+ rating. The Blinder and Wescott benchmark

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[39] Blinder and Wescott (2001), p. 10.

suggests a funding level in excess of \$100bn -- \$156bn for the more realistic random severity case (# of replications = 100,000), five times the current level!

We repeated the exercise using instead a simple conditional model of correlations. Specifically we made use of the method popularized by RiskMetrics: exponentially weighted moving average (EWMA), a special case of an IGARCH model.[40] Very briefly, covariances are assumed to evolve dynamically according to:

$$\sigma_{i,j,t} = \lambda\sigma_{i,j,t-1} + (1-\lambda)r_{i,t}r_{j,t}$$

where $r_{i,t}$ is the return for bank i from time $t-1$ to t, and $0 < \lambda < 1$ is a decay weight. For monthly data the value of λ used by RiskMetrics is 0.93; we use this value as well. A simple interpretation the EWMA model is as an information updating model: new information receives weight $(1-\lambda)$; thus the decay rate of information is λ^t. We initialize the dynamic process with the unconditional estimate using 24 months of data prior to January 1996.

We present two sets of results. The first is the EWMA correlation matrix at the end of our sample period, namely December 2000. For the second set we chose that month over the five-year sample range where the average correlation was the highest. That turns out to be August 1998, the month of the Russian bond crisis. The motivation is a simple stress test: how would the loss distribution for the 30 largest banks change if the FDIC faced that correlation structure which existed at a particularly stressful time within the last five years? For simplicity we present only the random severity results as the fixed severity results are very similar. The results are presented in Table 5.

[40] See JP Morgan (1995) for details.

The results are not markedly different from the fixed unconditional correlation results except in the tails. Especially the August 1998 scenario generates very high capital requirements at the AAA level – nearly $200bn. In addition the distribution seems to have become more skewed. Comparing the unconditional with the EWMA-based correlations (Aug. 1998), skewness increased from 37.0 to 46.6.

4.3.2. Implied Asset Correlation Based Loss Distribution For All BIF Banks

Results are summarized in Table 6 below. It provides the capital levels needed to insure the portfolio of the 8571 banks in the BIF at year-end 2000. As with the equity based correlations, we report results for four different confidence levels. For simplicity we report only the results for 50,000 replications.

Stochastic severity results in significantly higher capital levels in the tails of the loss distribution: $104 bn vs. $72 bn for fixed severity at the AAA level. In addition, to illustrate the general shape of the loss distribution, Figure 4 shows a histogram of the fixed severity case while Figure 5 is a kernel density plot of only the tail region: just those losses >$20bn, representing the largest 170 losses (out of 50,000 runs). The asset based results yield a significantly less skewed loss distribution. For fixed severity, the skewness is 13.4 in contrast to values around 40 for the equity correlation based results.

4.4. Discussion

From the perspective of the simulation results, the major difference between the two approaches can be traced to the underlying correlations. Most values in the asset correlation matrix, which forms the basis of the multivariate Gaussian draws for the simulation, have values around 0.25, whereas for the equity correlation based results we see correlations typically ranging from 0.4 to 0.6.[41]

In either case, the results point to an implied capitalization to about the 99.85% confidence level, corresponding roughly to a BBB+ rating. As seen in Table 7, the results are quite consistent across the different approaches. The $31bn capitalization level occurs over a narrow range of 12 and 17 bp under our different approaches. This is not wide enough to affect the implied solvency level rating for the BIF of BBB+. One has to go out much further into the tail to detect larger differences. Table 8 compares the 0.10%, 0.05% and 0.01% tail regions, corresponding to A-, A+ and AAA ratings respectively.

Of course the fund cannot have a better credit rating than that of any single exposure that could render the fund insolvent. Of the five institutions that have an *effective exposure* (severity $\times$ exposure)[42] in excess of the fund reserves, the lowest has a rating of A-. Of the eight institutions which have *total insured deposits* in excess of the fund reserves, the lowest rated institution has a rating of BBB.

The higher correlations of the equity-based approach, and within that approach the higher correlations from the conditional crisis matrix (Aug. 1998), bear fruit in the far tail by producing higher losses. One needs several large institutions failing in the same year (note that each replications simulates a loss-year) in order to obtain losses at such levels. Thus even the asset-based results, despite containing all 8571 BIF banks, are driven in the tails by the largest institutions. In short, differences in tail behavior are driven largely by differences in correlations.

[41] Calem and Rob (1999) use a single factor model to generate a loss distribution with asset correlations assumed to be 25%.

On a cautionary note, there is reason to believe that the severity estimates from FDIC used here are (possibly very) conservative. For one, there has been no observed failure for an institution with assets exceeding \$33bn.[43] At the end of 2000 more than 20 institutions exceeded this level. Second, it is easier to dispose of assets when the market for distressed assets is not flooded with such. In the event that the FDIC has to deal with multiple bank failures at once, actual severity will likely be higher. Both Frye (2000) and Altman, Resti and Sironi (2001) document significantly lower recoveries (higher loss severities) during periods of high aggregate default rates, in Frye's case nearly doubling. The stochastic severity approach is an attempt at simulating this situation. To explore this speculation, we reran some of the equity-based simulations by doubling both the mean and standard deviation of severity draws from μ_S = 8.75% to 17.5% and σ_S = 6.93% to 13.86%. The results are summarized in Table 9 for the unconditional and August 1998 conditional covariance matrices.

All of the capital requirements nearly double at each of the three critical points relative to the standard severity parameter assumptions, though even at the most extreme specification (stressed severities, crisis correlation matrix, AAA implied rating level) the losses barely exceed \$300bn, about 3% of U.S. GDP.[44]

Finally, recognizing that tail behavior is driven by dependence of asset returns across institutions, there is exciting new research in extreme event clustering and tail dependence which suggests that

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[42] We take a conservative measure of assets × (avg. severity + 2 × (std. dev. of severity)) to be effective exposure.
[43] That was Continental Illinois, the ninth largest bank at the time. It would take triple that amount to get into the largest ten today.
[44] While loss estimates due to banking crises are notoriously difficult to arrive at, this 3% of GDP would place near the bottom of the sample studied by Caprio and Klingebiel (1996).

brute force simulation of models formed from the dense part of historical distribution may not be very informative about tail behavior. Authors such as Embrechts, McNeil and Straumann (1999) remind us that correlation does not equal dependence, and falsely assuming otherwise can lead to underestimation of tail risk.

5. Policy Discussion: How much? How safe? Who pays?

5.1. Bank-Level Pricing

There is little argument about the merits of risk-based pricing for banks participating in the deposit insurance fund. At a minimum, premiums should cover expected losses, much like banks price their loans to their borrowers. Expected loss pricing has two key benefits: at the systemic level, setting the price for each bank equal to its expected loss ensures that the premium inflows to the fund are ultimately equal to average long-term loss, making the fund self-financing over time. Additionally, risk based pricing helps to relieve moral hazard problems: banks that try to use the availability of insured deposits to increase risk will be penalized through higher premiums.

Expected loss based pricing at least controls for default level risk; however, very large exposures are underpriced. After all, from the FDIC portfolio perspective, it is contributory risk which really matters as that effects the loss distribution. Contributory risk, or unexpected loss contribution (*ULC*), is a function of expected loss, correlation effects and exposure. Pricing for (risk-based) economic capital consumption would require incorporating *ULC*. For a bank this would simply be the expected loss for exposure *i* plus the unexpected loss contribution times the hurdle rate *h* [45]

[45] For simplicity, we leave out overhead costs.

$$P_i = EL_i + h \cdot ULC_i \qquad \textbf{5-1}$$

Computing the hurdle rate for a firm is straightforward, but what does it mean for a government deposit insurance fund? A lower bound is likely the risk-free rate which we shall use.[46]

To empirically estimate *ULC* is not so straightforward, reason enough to be skeptical of its practical usefulness for policy. One approach is to compute the increase in portfolio *UL*, UL_P, from increasing $ exposure to a given bank. Alternatively one could leave out that bank entirely and compute the difference in UL_P, before and after, again by simulation. Generally large banks will require a substantially higher economic capital charge because they contribute disproportionately to the volatility of losses in the insurance fund. This can make a big difference.

As an illustration, in Table 10 we present results using the leave-one-out method for two banks: the first, with assets of over $500bn, is representative of one of the 20 largest bank, while the second, with assets of about $250mm, is typical of a Bucket 25 bank in the asset correlation based approach (Bucket 25, recall, is defined as banks with assets <$500MM).[47] We present *EL* and *ULC* in percentage terms. Note that these figures are based on the impact on a loss distribution computed via simulation, assuming asset-based exposure with stochastic severity.

Two things are striking about these results. 1) *EL*-based pricing will penalize riskier banks, as defined by having a higher *PD* or a lower rating, and smaller banks since they are assigned higher severities. 2) Moving from *EL* to *ULC*-based pricing significantly penalizes very large banks. Their premiums would increase by nearly 60% while the premium for a small bank would

[46] Specifically we use a rate of 2.5%.
[47] The $ increase in exposure approach yielded very similar results.

scarcely budge. This is largely reflective of large exposures contributing disproportionately to overall (FDIC) portfolio risk.

5.2. Risk Sharing Alternatives

A fundamental question in evaluating policy options for reform of the deposit insurance fund is who should bear the relevant parts of the FDIC's loss distribution. The answer helps determine the approach for setting the solvency standard for the fund; the level of required pricing, both for the fund overall and for individual banks; the impact of the "big bank" problem; and the need for dynamic adjustments, including both rebates and re-capitalization.

The FDIC loss distribution can be thought of as being partitioned into two zones: Zone A, consisting of small losses which are covered by reserves or callable premiums; and Zone B, consisting of large or "catastrophic" losses, which are covered by loss reinsurance. The two zones are separated by the risk sharing point. The "fund" is deemed responsible for losses to the left of the risk sharing point, while a reinsurer is deemed responsible for excess losses to the right of the point (see Figure 6).[48] This structure mirrors the loss distribution of insured banks: losses are covered by the banks' shareholders up to the capitalization level, and beyond that, losses are borne by deposit insurance and uninsured creditors.

As implied by the loss partitioning, the Zone A and Zone B risks need not be held by the same party. In principle, there are three groups that can hold either the Zone A or Zone B risks: the Government; the banks themselves through a mutual insurance system; or the private capital or

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[48] How large should Zone A be? Conceptually it should be large enough to provide the correct incentives for the banks which will be discussed in more detail below. There is a question of how to treat the very largest banks that could by themselves wipe out Zone A. The complex issues around too-big-to-fail are beyond the scope of this paper, however. For a recent treatment, see, for instance, Freixas (1999).

reinsurance markets. We examine three viable combinations. At one extreme is a government system, in which the government, through the FDIC and the Treasury, is viewed to hold both the Zone A (small) and Zone B (catastrophe) risks. At the other extreme is a private system, in which the banks mutually reinsure small losses and transfer large, catastrophic risk to the private capital markets. In between these two cases is a quasi-mutual system, in which banks mutually insure small losses in Zone A, but the government reinsures catastrophic losses in Zone B. Each of these systems is described below, with policy implications for fund adequacy, pricing, and dynamic adjustments.

5.2.1. Government System

The government system can be viewed as a mandatory insurance contract between the government and the banks. Under this system, the government assumes both parts of the risk distribution: the Zone A losses, which are booked against a reserve fund administered by the FDIC; and the Zone B losses, which are reinsured by the Treasury. In return for providing insurance protection, the government charges each bank an insurance premium discussed in more detail below.

5.2.1.1. Fund Adequacy

Since the government ultimately bears both parts of the risk distribution, the division of risk between the FDIC and the Treasury is somewhat arbitrary. As long as the government is solvent, the fund will be solvent, whether or not there is money specifically set aside to cover claims in the FDIC. Under this system, Congress may still choose to maintain a funded reserve: Such a reserve would provide a pool of readily available money to pay off depositors in case of bank failures. It would also create incentives for the FDIC to monitor the banking system, as losses greater than the size of the fund would require the FDIC to go hat-in-hand to the Treasury. But in economic terms, the pool from which small and large claims are paid is strictly a government accounting entry.

Significantly, given that the entire risk distribution is borne by the government, the solvency standard for the FDIC's portion of losses is not strictly relevant. This means that the fund can be managed (and premiums can be priced) independently of the impact of large bank exposures. Similarly, the solvency standard in the fund can be allowed to fluctuate with the business cycle, eliminating the need for dynamic adjustment mechanisms such as rebates and re-capitalization.

5.2.1.2. Pricing

If the government assumes the risk in both Zones A and B, it follows that the government bears the full cost of deposit insurance. The price for deposit insurance should be equal to an actuarial charge for expected loss plus a charge for the economic capital needed to absorb loss volatility. An argument can be made, however, that the government does not need to hold any incremental capital to absorb loss volatility from bank failures. Provided that the size of the government balance sheet (or its risk-free borrowing capacity) is sufficiently large relative to bank-related claims, then the government has a near-infinite ability to diversify bank losses with other government claims.[49] This means that the economic capital charge to the government is effectively zero. Assuming the government prices deposit insurance at cost, the deposit premium should be set simply at the level of expected loss.

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[49] This point is arguable. The United States government ultimately has a finite borrowing capacity, at least at a given cost of funds. Nevertheless, it seems safe to say that the government should be relatively indifferent to the timing of losses in the fund.

Pricing below the private sector is the defining feature of the government system. The very size of the government allows it to "produce" insurance at a lower cost than the market and transfer these savings to the banks. This is not a subsidy to the banking system. Rather it can be viewed as a form of public good, where the government can provide deposit insurance more efficiently than private markets.

Unlike current practice, expected loss pricing also implies non-zero marginal pricing for all banks, as even well-capitalized institutions have expected losses greater than zero. This would align price with the cost of coverage and so eliminate the free rider problem manifest in the existing system. Of course as expected loss changes, the premium will change as well, and this change is not a function of the past losses of the system.

Pennacchi (2002) cautions against procyclical effects resulting from conditional (frequently updated) risk-based pricing schemes. Our view of expected loss based pricing is more consistent with a low frequency updating process. A death spiral effect of a bank being "downgraded" (be it by rating agencies or bank supervisors' own assessment) during a recession requiring expensive recapitalization and thus possible further downgrading should be controlled via supervisory prompt corrective action (PCA) provisions.[50] Some support for this view is provided by Calem and Rob (1999). They find that bank risk-taking is U-shaped in capital. Risk based insurance premiums exhibit no deterrent effects (in risk-taking behavior) on well-capitalized nor on severely undercapitalized banks. Hence they question the effectiveness of capital-based deposit insurance premiums but cast PCA into a favorable light. Specifically, they stress the value of PCA for severely undercapitalized banks, akin to the "death spiral" case.

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[50] Mishkin (1997) views PCA as arguably the most important policy step in FDICIA.

5.2.1.3. Dynamic Effects

In the government system, there is no link between reserves and current pricing. As long as the government correctly sets (annual) prices at the level of (annual) expected loss, the system will be self-funding over the business cycle. As a result, there is no need for rebates or re-capitalizations. The deposit insurance premiums paid by banks are similar to auto insurance premiums paid by individuals – if a driver doesn't have an accident, the premium is lost forever; if she does, the claims are paid up to the full amount insured. Either way, the premiums are unaffected by the current level of reserves.

5.2.2. Private System

A private sector alternative to a closed governmental system is for losses to be shared between the banks and the capital and reinsurance markets. In this system, the banks would mutually insure the losses in Zone A, but would reinsure or transfer the losses in Zone B to the capital markets. Here the FDIC could be viewed as a government-sponsored mutual insurance system operated on behalf of the banks. It would administer a "small claims" fund for Zone A losses and would contract with the private markets for stop-loss reinsurance beyond the risk transfer point.

5.2.2.1. Fund Adequacy

In a private system, the solvency standard would be of genuine importance. The FDIC, on behalf of the banks, would need to judge the point at which it would become efficient to reinsure or distribute losses beyond the banking system. The efficient risk transfer point would be a function of the callable reserves within the banking system and the benefits that could be obtained by distributing risk outside the system.

A practical consequence of a private system is that the banks in Zone A, and the re-insurers and/or capital markets in Zone B, would bear the impact of large bank losses. Recall that the largest insured bank currently has insured deposits in excess of $200bn, relative to funded reserves (in the bank fund) of roughly $30bn. This means that, to reach the solvency standard of the fund's biggest bank, the system as a whole would need to hold, or have access to, sufficient capital to absorb losses at a multiple of current funded reserves.

5.2.2.2. Pricing

Because a private system would need to hold capital to cover large losses, pricing would have to reflect both a charge for expected loss and a volatility premium for the capital held to absorb loss volatility. This would necessarily imply a higher price than in the closed government system.

The split of pricing between the banks and the re-insurers would depend on the risk transfer point. Total pricing, however, would be unaffected by the division of losses between Zone A and Zone B. At an individual bank level, the impact of the economic capital charge would not be spread evenly among banks (i.e., in proportion to expected loss), but would be borne disproportionately by large banks. This is because large banks impose a much greater need to hold incremental economic capital. A specific example is given in Section 5.1. Under such a pricing regime, it may not be efficient for large bank depositors to seek deposit insurance coverage. They might wind up paying 3-4 bp of insurance premium to protect against 1 bp of expected loss.

5.2.2.3. Dynamic Effects

Since the solvency standard matters in a private system, the fund would have to be insulated from cyclical fluctuations. During expansions, the system would tend to accumulate reserves beyond the target solvency standard. To the extent that the excess reserves accumulate within the mutual system in Zone A, then the excess should be rebated to member banks – otherwise, the mutual system would be overcapitalized. To the extent that the excess reserves arise from unclaimed reinsurance coverage in Zone B, then there is no rationale for a rebate. The "excess" reserves are profits to the reinsurers resulting from fairly priced premiums. Conversely, when reserves in the mutual system fall below the target solvency standard, there will be a converse need to recapitalize the fund. In practice, this is problematic, as recapitalizations are likely to be necessary at the trough of the business cycle.

5.2.2.4. Other Observations

Although in theory a private system should allow for efficient pricing of deposit insurance and create positive incentive effects, we are skeptical that in practice private markets would be able to play a major role in insuring bank deposits. There are at least two reasons for this: first, the $3.5 trillion of insured deposits[51] is extremely large relative to the size of both the banking industry and the insurance markets. By way of comparison, total Tier 1 capital in the banking industry is $550 bn and the total policyholders' surplus of U.S. P&C insurers is $420 bn (*Best's Aggregates and Averages* (1999)). Relative to the available capital resources, the failure of even a single large bank could impose huge claims.[52]

Second, by transferring risk to private markets, FDIC systemic risk would be converted to off-balance sheet counterparty risk. Yet no counterparty would have a solvency standard significantly better than that of the largest and best capitalized banks in the FDIC system, let

[51] $2.5tn from the BIF and $0.75tn from the SAIF.
[52] Relative to catastrophe claims, a large bank loss could impose huge claims as well. The largest catastrophe loss event, Hurricane Andrew (1992), resulted in approximately $16 BN in losses. See *The Insurance Information Institute Insurance Fact Book 2000*.

alone equal to the government's. As a result, it is unclear that depositors would gain significant value in the protection afforded by a private insurance system. In the end, the limited risk absorption capacity of private markets implies an ongoing government responsibility for losses at the far right tail.

5.2.3. Quasi-Mutual System

The quasi-mutual system entails an explicit division of the loss distribution between the banking system and the government. Accordingly, the policy implications lie somewhere between a closed governmental system and a purely private system.

5.2.3.1. Fund Adequacy

In the quasi-mutual system, the banks mutually insure the Zone A losses, while the government reinsures Zone B losses. As a result, the overall solvency standard of the system is equal to that of the government. The risk sharing point between the banks and the government, however, determines the amount of risk that the banks will bear themselves. This point influences the level of funded or callable reserves the banks need to supply, with implications for pricing and dynamic adjustments.

5.2.3.2. Pricing

In a quasi-mutual system, pricing is best seen as separated into two components – premiums charged by the mutual insurance system and premiums charged by the government. The rationale for the government premiums is the same in the quasi-mutual system as it is in a closed government system: the government should charge the banking system expected loss for the excess loss reinsurance. The total cost will depend on the risk sharing point. If the government is only insuring extreme catastrophe losses, the year-by-year payment from the banking industry to the government would be very small.

The price of mutually insuring small bank losses is more complex and depends on where the risk sharing point is between the government and the banks. If the Zone A losses were insured by the private market, the price would be based on expected loss plus an economic capital charge for loss volatility up to the risk sharing point. To the extent that Zone A is small and covers only small losses, required pricing will be close to expected loss. To the extent that Zone A also covers large losses, the impact of the economic capital charge could become significant.

Even if an economic capital charge is theoretically required in a quasi-mutual system, practical considerations may argue for adopting expected loss pricing. Expected loss pricing would simplify the requirements for calculating risk-based premiums at the individual bank level. The alternative would be to estimate the marginal risk contribution of individual banks up to the risk sharing point – a difficult analytical exercise that will require a number of simplifying assumptions. More importantly, the introduction of an economic capital charge would penalize large banks disproportionately.[53] Here again, it may not be efficient for large bank depositors to pay the full marginal cost of deposit insurance protection, although the banks are mandated to purchase such protection on their behalf by the government. A better solution might be to price the mutual insurance at expected loss, even if this meant that small banks would, to a certain extent, be subsidizing large banks. Given the complexities associated with a positive economic capital charge, this may be a small price to pay.

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[53] See the pricing example in Section 5.1.

5.2.3.3. Dynamic Effects

The dynamic effects in the quasi-mutual system would be similar to those in the private system. The reserves held by the mutual system to protect against Zone A losses will fluctuate over the business cycle. As in the private system, this could lead to a build-up of "excess" reserves above the target solvency standard (or conversely, the need to re-capitalize the fund if reserves dip below the solvency standard.) In such a case, rebates (re-capitalizations) would be appropriate and should be determined separately from current pricing so that marginal pricing always reflects expected loss.

6. Concluding Remarks

In this paper we argue that a constructive approach to addressing some of the core questions of deposit insurance (How much? How safe? Who pays?) can be found in the toolkit of modern risk measurement and management. Specifically, the risk management problem faced by the FDIC is directly related to the riskiness of the individual banks in its portfolio. This problem can be broken down into the familiar components of contemporary credit analysis and used to estimate the cumulative loss distribution of FDIC insured banks.

We find that the BIF reserves are sufficient to cover roughly 99.85% of the loss distribution of the 8571 banks which make up the BIF, corresponding to about a BBB+ rating. This finding is robust across different approaches (asset vs. equity based) and assumptions about severity (fixed vs. stochastic). A BBB+ rating is actually quite low – lower, in fact, than most of the large rated institutions[54] covered by the fund, and just slightly above implied average rating for all banks in the system. The implication is that the U.S. government backstop must be quite important in maintaining the confidence that depositors ascribe to the fund. A capitalization level required for a much higher implied rating of AAA is quite a bit larger: multiples of three to ten of the current reserve levels.

The potential for "catastrophic" losses resulting from a large number of bank failures (or from the failure of large banks) suggests that the FDIC's loss distribution should be thought of as partitioned into two zones: small losses that are covered by reserves (either funded or callable); and excess losses that are covered by reinsurance. A key question under this structure is who should bear the risk of each part of the FDIC's loss distribution, and how does the partition point influence pricing?

The FDIC's portfolio of banks is highly heterogeneous which complicates matters. Importantly, there are significant concentrations: the top 1% of institutions by insured deposits account for just over half of the insured deposits in the United States. These banks contribute disproportionately to the risk borne by the FDIC: the tail of the loss distribution is driven by multiple failures of large banks. If deposit insurance premiums were based on contributory risk, large banks would bear a significant burden. However, under such a pricing regime, it may not be efficient for large bank depositors to seek deposit insurance coverage. They might wind up paying 3-4 bp of insurance premium to protect against 1 bp of expected loss.

We therefore argue that the most practical and lowest cost solution is for the government to own both parts of the loss distribution. This can be viewed as a mandatory insurance contract between the government and the banks. Pricing should be risk-based and based specifically on expected losses. This greatly mitigates banks' moral hazard, introduced by the very existence of deposit insurance, and it ensures that the fund is self-financing over time.

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[54] Of the 30 largest banks, only two have a rating lower than A-.

While several important questions remain unanswered, one certainly is the cost to taxpayers for this insurance provision. One way to think of this issue it to treat the backstop provided by U.S. government to the FDIC as CAT (catastrophic) insurance or a CAT bond. How might this bond be priced, and how would that price be influenced by the chosen level of solvency of the fun (i.e. the level of reserves)? Might the size of the fund influence the probability of systemic risk? We look tackle these questions in subsequent research.

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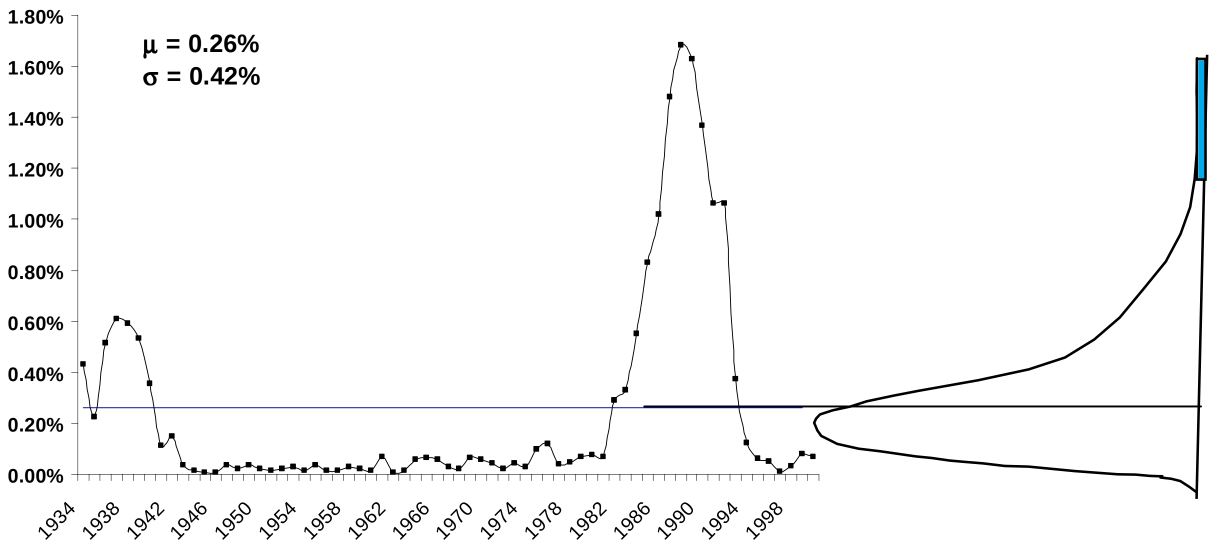
Figures

Figure 1: FDIC Default History 1934-2000



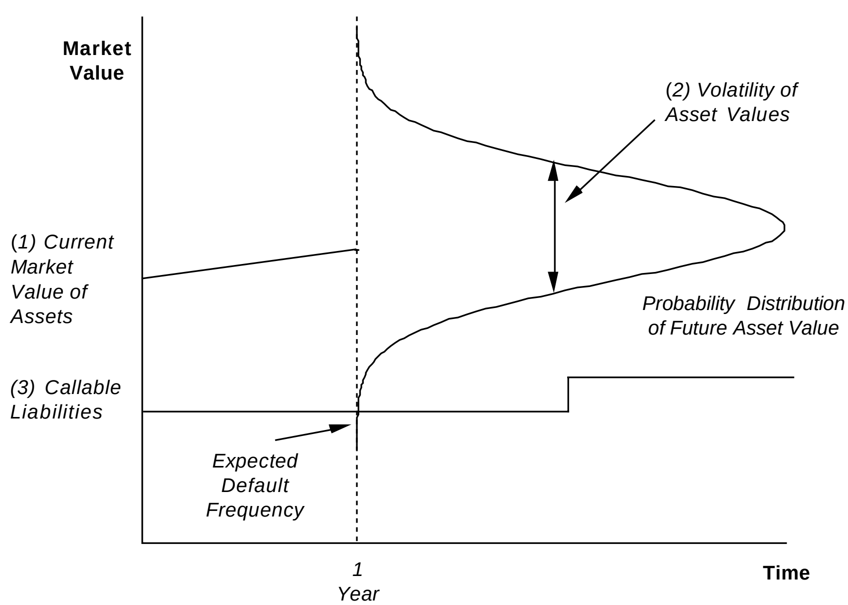


Figure 2: Distribution of Future Asset Values and Expected Default Frequency

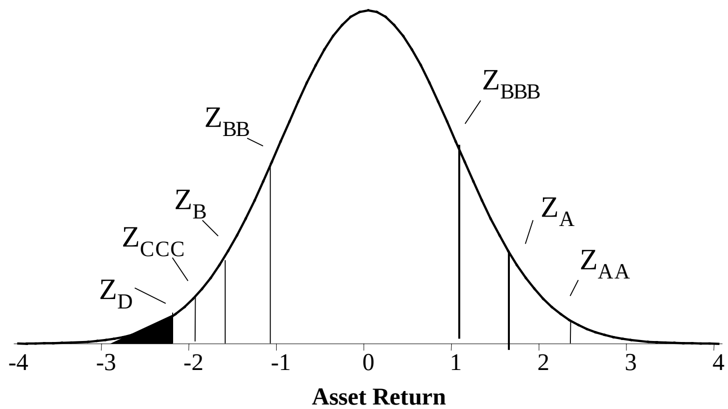


Figure 3: Asset Return Distribution for BBB+ Borrower with Rating Thresholds

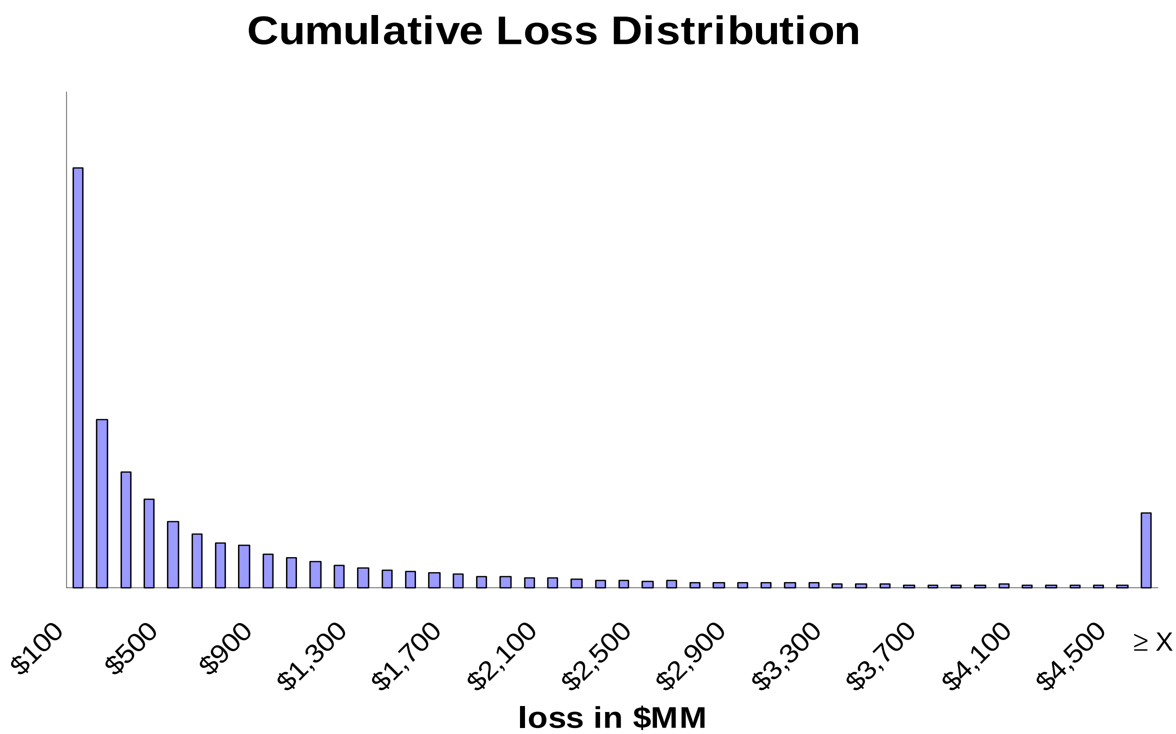


Figure 4: Loss distribution, asset-based, fixed severity

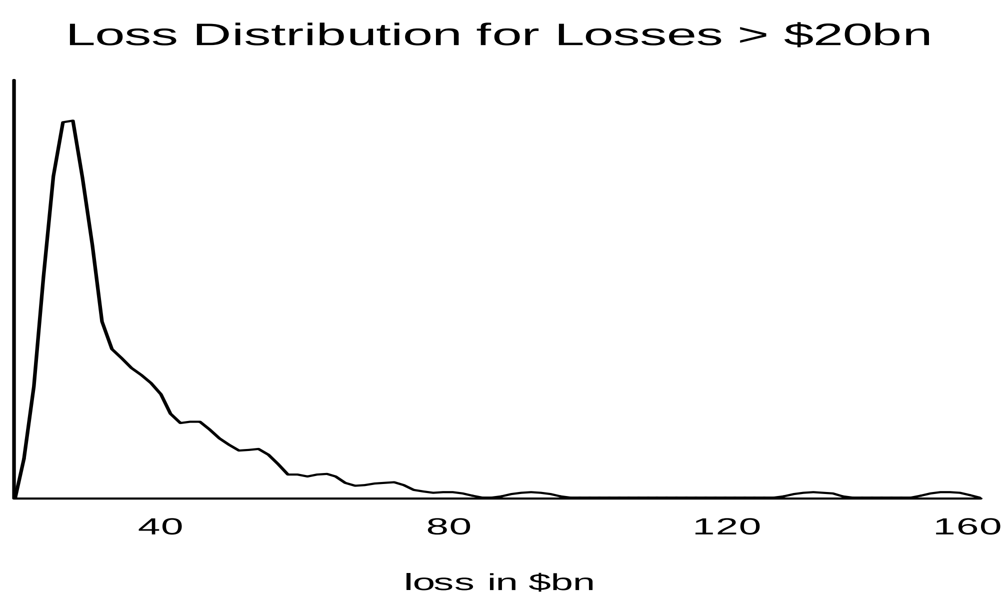


Figure 5: Tail of loss distribution: largest 170 (of 50,000) events[55]

[55] As this is portion of the whole loss distribution, the line should start high up on the y-axis. That it doesn't is an unfortunate effect of the density plotting software.

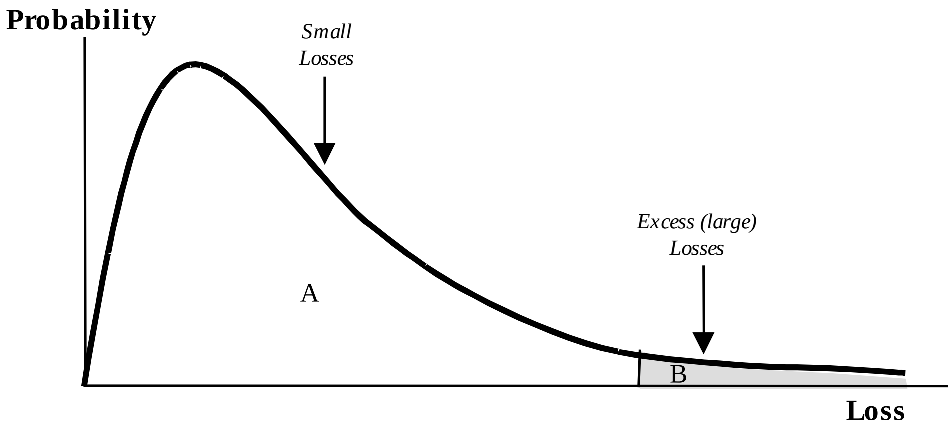


Figure 6: Risk-sharing

Tables

Bank of America	Keybank	Bank of New York
Citibank	Wachovia	State Street
JP Morgan Chase	PNC	Amsouth
First Union	World Savings[56]	National City
FleetBoston	LaSalle Bank (ABN Amro)	Washington Mutual
Wells Fargo	BB&T	Union Planters
Bank One	Southrust	Summit Bank
Suntrust	Regions Bank	Comerica
US Bank (w/ Firstar)	Merrill Lynch	Fifth Third
HSBC	Mellon Bank	Huntington Bank

Table 1: 30 Largest Banks

Bucket (and # of banks in bucket)	Asset Threshold	Severity (mean)	Severity (std. dev.)	Bucket PD
1 - 20	--	8.75%	6.93%	Bank specific
21 (33)	≥ $15bn	8.75%	6.93%	0.13%
22 (66)	$5 - $15bn	8.75%	6.93%	0.18%
23 (268)	$1 - $5bn	12.79%	8.54%	0.25%
24 (340)	$500mm - $1bn	16.46%	10.60%	0.26%
25 (7804)	≤ $500 mm	23.29%	13.38%	0.26%

Table 2: Bank Bucketing Parameters

Bank	Assets ($1000s)	Estimated Insured Deposits ($1000s)
Bank of New York	74,266,429	12,134,756
State Street	64,643,911	476,527
Bankers Trust (Deutsche Bank)	44,324,000	3,276,100

Table 3: Some Bucket 21 Banks[57]

[56] Owned by Golden West Financial.

[57] This is not a complete list of Bucket 21 banks, but rather only those banks which would have been in the top 20 (in assets) but have a very small deposit base.

	# of reps.	*EL* (*UL*) in $ MM	$ MMs Needed at Confidence Interval (Implied Credit Rating)			
			99.7% (BBB)	99.9% (A-)	99.95% (A+)	99.99% (AAA)
Fixed Severity	50,000	$162 ($2,862)	$13,529	$49,252	$71,411	$91,871
	100,000	$159 ($2,704)	$13,599	$40,439	$53,526	$116,650
Random Severity	50,000	$163 ($3,132)	$13,443	$43,982	$68,413	$114,490
	100,000	$171 ($3,345)	$14,355	$44,921	$69,320	$156,110

Table 4: Capital Levels Needed to Insure 30 Largest Banks (Unconditional Correlations)

	# of reps.	*EL* (*UL*) in $ MM	$ MMs Needed at Confidence Interval (Implied Credit Rating)			
			99.7% (BBB)	99.9% (A-)	99.95% (A+)	99.99% (AAA)
Dec. 2000	50,000	$166 ($3,052)	$12,571	$43,850	$66,654	$125,470
	100,000	$170 ($3,249)	$14,354	$43,524	$67,916	$139,070
Aug. 1998	50,000	$162 ($3,992)	$10,746	$34,375	$73,008	$197,060
	100,000	$158 ($3,367)	$11,999	$39,545	$67,313	$172,270

Table 5: Capital Levels Needed to Insure 30 Largest Banks (EWMA Correlations)

Severity	# of Reps.	*EL* (*UL*) in $ MM	$ MMs Needed at Confidence Interval (Implied Credit Rating)			
			99.7% (BBB)	99.9% (A-)	99.95% (A+)	99.99% (AAA)
Fixed	50,000	$1,095 ($2,912)	$21,223	$35,476	$46,722	$72,976
Random	50,000	$1,107 ($3,396)	$22,228	$37,089	$60,317	$103,824

Table 6: Capital Levels Needed to Insure All BIF Banks

Approach		Severity Assumption	Tail Area at $31bn	Implied Solvency Level at $31bn
Equity-Based	Unconditional Correlation	Fixed	0.17%	BBB+
		Random	0.15%	BBB+
	EWMA correlation (Aug. 1998)	Fixed	0.13%	BBB+
		Random	0.12%	BBB+
Asset-Based		Fixed	0.13%	BBB+
		Random	0.14%	BBB+

Table 7: Comparing Solvency Standard Across Approaches for Nrep = 50,000

Approach		Severity	Reserve Requirement for A- (0.10%)	Reserve Requirement for A+ (0.05%)	Reserve Requirement for AAA (0.01%)
Equity -Based	Unconditional Correlation	Fixed	$49,252	$71,411	$91,871
		Random	$43,982	$68,413	$114,490
	EWMA correlation (Aug. 1998)	Fixed	$42,143	$64,519	$164,400
		Random	$34,375	$73,008	$197,060
Asset-Based		Fixed	$35,476	$46,722	$72,976
		Random	$37,089	$60,317	$103,824

Table 8: Comparing Far Tail Regions Across Approaches for Nrep = 50,000

Correlation Matrix	*EL* (*UL*) in $ MM	$ MMs Needed at Confidence Interval (Implied Credit Rating)		
		99.90% (A-)	99.95% (A+)	99.99% (AAA)
Unconditional	$320 ($6,012)	$85,538	$123,980	$261,580
EWMA (Aug. 1998)	$320 ($7,371)	$74,250	$144,620	$321,410

Table 9: Severity Stress Test for Largest 30 banks(Nrep = 100,000)

	Big Bank	**Small Bank**
PD (implied rating)	0.04% (AA-)	0.26% (BBB)
Severity (mean): μ_{SEV}	8.75%	22.39%
$EL = PD \cdot \mu_{SEV}$ (in %)	0.0035%	0.0573%
ULC (in %)	0.0056%	0.0596%
% increase from *EL* to *ULC*	**59.3%**	**4.1%**

Table 10: EL / ULC pricing comparison

Appendix A

Drawing on (3-8), consider the following illustrative example for two market factors, two groups and three banks.

- m_1, m_2, ε_1, ε_2, ε_3 are *iid* N(0,1)
- Banks in Group A and Group B have intra-group correlations of ρ_A and ρ_B, respectively, and an inter-group correlation of ρ_{AB}
- $\rho_A = \rho_{A1} + \rho_{A2}$
- $\rho_B = \rho_{B1} + \rho_{B2}$
- $\rho_{AB} = \sqrt{\rho_{A1}\rho_{B1}} + \sqrt{\rho_{A2}\rho_{B2}}$

We can then draw asset returns for two institutions within Group A as follows:

$$A_1 = \sqrt{\rho_{A1}} \cdot m_1 + \sqrt{\rho_{A2}} \cdot m_2 + \sqrt{1 - \rho_{A1} - \rho_{A2}} \cdot \varepsilon_1$$
$$A_2 = \sqrt{\rho_{A1}} \cdot m_1 + \sqrt{\rho_{A2}} \cdot m_2 + \sqrt{1 - \rho_{A1} - \rho_{A2}} \cdot \varepsilon_2$$

It is straightforward to show that the two asset returns have a correlation of ρ_A. We can draw for an institution in Group B as follows:

$$B_1 = \sqrt{\rho_{B1}} \cdot m_1 + \sqrt{\rho_{B2}} \cdot m_2 + \sqrt{1 - \rho_{B1} - \rho_{B2}} \cdot \varepsilon_3$$

It is easily shown that the inter-group correlation with either of the assets in Group A is ρ_{AB}.

Appendix B

Default Probabilities[58]

S&P Rating	Default Prob. (in bp)
AAA	1
AA+	2
AA	3
AA-	4
A+	5
A	7
A-	9
BBB+	13
BBB	22
BBB-	39
BB+	67
BB	117
BB-	203
B+	351
B	608
B-	1054
CCC	1827

Bank	Assets (1000s)	Estimated Insured Deposits (1000s)
Bank of America	584,284,000	217,795,700
Citibank	382,106,000	26,678,900
Chase Manhattan (w/o JP Morgan)	377,116,000	58,285,900
First Union	231,837,000	89,110,500
FleetBoston	166,281,000	52,469,400
Wells Fargo (w/o Norwest)	115,539,000	50,040,900
Bank One	101,228,538	12,545,509
Suntrust	99,528,008	41,337,046
US Bank (w/o Firstar)	82,023,123	34,112,057
HSBC	80,057,987	24,870,410
Keybank	77,760,463	27,361,035
Wachovia	69,187,160	29,810,683
PNC	63,185,903	30,302,874
World Savings (Golden West Finl.)	55,737,371	29,289,836
LaSalle Bank	48,852,837	17,713,282
BB&T	46,991,799	18,585,193
Southrust	45,170,172	18,096,433
Regions Bank	43,528,061	21,231,341
Merrill Lynch	43,171,125	29,235,608
Mellon Bank	41,974,315	12,880,690

Table 11: The 20 Largest Banks[59]

Appendix C

Asset Threshold	Number of Observed Failures	Weighted Avg. Loss Rate[60]	Severity (mean)[61]	Severity (std. dev.)
< $100mm	967	24%	24.18%	13.78%
$100mm - $500mm	120	23%	22.39%	12.97%
$500mm - $1bn	15	17%	16.46%	10.60%
$1 - $5bn	22	12%	12.79%	8.54%
$5 – $33bn	9	8%	8.75%	6.93%

Table 12: FDIC Severity Buckets

[58] Using S&P ratings data from 1981 – 1998. Table 6 in FDIC (2000).
[59] Source: www.fdic.gov
[60] Sum of all losses for all institutions in the asset size group divided by the sum of all assets for all institutions in the asset size group.
[61] The mean and standard deviation of the loss as a percent of assets for individual institutions within the asset size group.