Evaluating the Adequacy of the Deposit Insurance Fund: A Credit-Risk Modeling Approach

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Abstract

As part of an effort to measure risk effectively, the FDIC hired Oliver, Wyman & Company to develop a credit-risk model for the deposit insurance funds. I apply their credit-risk model to estimate the FDIC's loss distribution; and I perform sensitivity analysis using different assumptions about the parameters of the model. The sensitivity analysis results in a wide range of possible credit ratings associated with the deposit insurance funds. Under one set of assumptions, the deposit insurance funds would not warrant a BBB rating, whereas under another set of assumptions the funds would warrant an A rating. I conclude that the measures of risk derived from the credit-risk model are sensitive to the parameter assumptions, and it is not clear which parameter assumptions are most relevant.

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Introduction

In recent years, an increasing number of financial institutions in the United States and abroad have been using credit-risk models to evaluate the risk of their loan portfolios.[1] In fact, there have been proposals to reform regulatory capital requirements to allow banks to use internal credit-rating models to set capital levels. Banks typically use the output from credit-risk models to estimate the risk-adjusted returns on capital allocated to various banking activities. Managers of those banking activities are then evaluated and compensated on the basis of the profitability of their activities. In addition, some managers use credit-risk models for risk-based loan pricing, to measure the risk-adjusted profitability of the portfolio and to set concentration limits.[2]

Recently the FDIC began to look at credit-risk models similar to those used by large financial institutions, as a means of measuring risk to the insurance funds. As part of this effort, Oliver, Wyman & Company (OWC) developed an application of credit-risk models that explicitly constructs the loss distribution for the FDIC. The OWC model uses a bottom-up approach: it builds the cumulative loss distribution from information on individual institutions insured by the FDIC. In general, credit-risk models can help the

[1] Financial institutions also use internal risk-management models, also known as value-at-risk (VaR) models, to estimate the value at risk in their trading books. See Nuxoll (1999) for more detail.

[2] A survey conducted by the Bank for International Settlements (1999) addressed other applications for credit-risk models. The survey found that financial institutions were using credit-risk models to set concentration and exposure limits, set hold targets on syndicated loans, price loans on a risk basis, improve the risk/return profiles of the portfolio, evaluate the risk-adjusted performance of different business lines or managers, allocate economic capital, and set and value loan-loss reserves.

FDIC measure and manage risk. In one particular application of credit-risk models, the FDIC can use the model developed by OWC to evaluate fund adequacy.[3]

The FDIC should perform a validation of the model before fully incorporating any credit-risk model into its current risk management practice. There are essentially three components of model validation: sensitivity analysis, backtesting, and stress testing. This article focuses on the first component—sensitivity analysis.[4]

Sensitivity analysis involves analyzing the effect of making different assumptions about model parameters on the output from the model. Although by definition parameters are fixed in a model, there is still some uncertainty associated with them. Sensitivity analysis investigates this parameter uncertainty.

The accuracy of the parameter estimates as representations of the future, and the validity of the model assumptions, determine the overall reliability of a credit-risk model. Unfortunately, most financial institutions currently do not conduct sensitivity testing on the parameters or assumptions embedded in their credit-risk models. The few practitioners who have conducted sensitivity analysis observe that the measurement of credit risk in a portfolio typically depends more on the quality of the information used by the model than on the details of the modeling approach. In fact, Koyluoglu and Hickman (1998a, 1998b) and Gordy (2000) demonstrate that alternative credit-risk modeling

[3] The FDIC can also potentially use the model developed by OWC to evaluate alternative risk-based deposit insurance pricing options. Since the model uses a bottom-up approach, it can be used to measure the contribution of an individual institution to the overall risk to the insurance funds, as discussed in Hanweck (2000).

[4] Backtesting entails comparing ex ante estimations with ex post experience. Stress testing involves analyzing the effects of alternative economic scenarios (represented by alternative sets of parameters) on the model output. In contrast to changing many parameters as in stress testing, sensitivity analysis focuses on the effect of changes in one parameter. See BIS (1999) for more information on the validation of credit-risk models.

approaches are essentially equivalent. However, the sensitivity analysis that has been conducted indicates that model outputs are sensitive to changes in model parameters, especially changes in expected default frequencies (EDFs), severity, and default correlations.[5] This article focuses on the sensitivity analysis of these three inputs.

The first section of the article describes credit-risk models and their application to risk evaluation. I compare how credit-risk models are used by financial institutions to how the FDIC can potentially use credit-risk models to evaluate risk to the deposit insurance funds. The next section describes in detail the derivation of the inputs to the model (exposure, expected default frequencies, severity, and default correlation bucketing) and discusses results from a set of baseline simulations. The following three sections discuss the results from the sensitivity analysis performed on three of the inputs: expected default frequencies, severity, and default correlation bucketing. The subsequent section discusses possible areas for further research, and the final section provides concluding remarks.

The Credit-Risk Model

There are two types of credit-risk models: default mode and mark to market. The default-mode models focus on two outcomes—default or no default. The mark-to-market approach models the migration from one credit rating to another. The default mode is the most common approach used to analyze the loan portfolio of a bank and is the type of model used in this analysis.

[5] See BIS (1999).

The primary output of a credit-risk model is a probability density function (PDF) of credit losses. From the PDF, a financial institution can calculate the expected loss and the unexpected loss. The expected loss, which is equivalent to the mean of the PDF, is the amount of loss a bank would expect to experience in its portfolio over the chosen time horizon. The unexpected loss, or the deviation from the expected loss, measures the amount of risk in the portfolio. One measure of risk is the volatility of the potential loss around expected loss, or the standard deviation of the PDF.[6]

Financial institutions use credit-risk models to estimate the economic capital needed to support their credit-risk exposures. The role of loss reserving is to cover expected credit losses.[7] The role of economic capital is to cover unexpected losses. Similarly, the FDIC can look at expected loss generated by a credit-risk model as a measure of the amount of reserves needed to cover these losses over the coming year.[8] The FDIC can also use a credit-risk model to evaluate the adequacy of the deposit insurance funds to cover unexpected losses—analogous to financial institutions setting the appropriate level of economic capital.

Observed distributions of credit losses on loan portfolios are not normally distributed (see Figure 1).[9] The observed distributions are typically skewed toward large losses: for a given mean and standard deviation, the probability of incurring large losses

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[6] To be consistent with the terminology used by Oliver, Wyman & Company, I call the standard deviation of losses the unexpected loss.

[7] Generally Accepted Accounting Principles (GAAP) require reserving for probable and estimable losses. As discussed in Jones and Mingo (1998), the role of reserving policies is to cover expected losses. In the context of this article, expected losses are the product of the probability of incurring a loss multiplied by the estimated loss and are thus both probable and estimable.

[8] The FDIC currently uses an actuarial method to set its contingent loss reserves.

[9] See Jones and Mingo (1999, 1998).

is greater than it would be if the distribution were normal. Similarly, the FDIC faces a skewed distribution of losses: in any given period, there is a high probability of incurring small losses from the failure of a number of small banks but a small probability of incurring large losses from the failure of a large bank and/or the failure of a large number of banks. Since the distribution is skewed, precise estimation of the high quantiles in the distribution is important. The size of the estimation error in this region of the distribution can potentially be large and have a large influence on the shape of the distribution.

Financial institutions typically collapse the estimated PDF into a single measure, such as the amount of economic capital required to meet a certain solvency standard. For example, if the institution is willing to tolerate a 0.03 percent probability that losses will exceed the capital level, or the equivalent of a AA rated corporate bond, it can calculate the amount of capital it needs to achieve that solvency standard. Financial institutions usually choose a capital standard that is consistent with their desired credit rating.[10] Similarly, the FDIC can use the cumulative loss distribution from a credit-risk model to determine what fund balance is required to reach a chosen solvency standard. For example, the FDIC may be willing to accept a minimum of 99.68 percent chance that the fund will not incur losses larger than the fund balance. The solvency standard can also be described in terms of a maximum insolvency probability—0.32 percent in this example. Alternatively, the solvency standard can be described in terms of a credit rating for the insurance fund. In this example, the 99.68 percent solvency standard is approximately

[10] For more detail, see Jones and Mingo (1999, 1998).

equivalent to a BBB- S&P credit rating or a Baa3 Moody's credit rating for a one-year time horizon.[11]

Credit-risk models estimate credit ratings for the deposit insurance funds that are equivalent to a credit rating on a corporate bond. Credit ratings for corporate bonds reflect the risk that a bond will default. However, the FDIC would never default even if the deposit insurance funds became insolvent: the FDIC honors all deposit claims and has the full-faith-and-credit backing of the federal government. For this reason, some may argue that the potential insolvency of the deposit insurance funds is irrelevant. However, funds that are borrowed from the Treasury to cover any insolvency must eventually be repaid. In addition, according to the Federal Deposit Insurance Corporation Improvement Act of 1991 (FDICIA), the deposit insurance funds must be recapitalized through assessments on banks.

Under current law, the FDIC is required to maintain a target level of funds relative to the amount of insured deposits in the industry. The ratio of the size of the fund to insured deposits is the reserve ratio. The target level, or designated reserve ratio (DRR), is constant and set at 1.25. If the insurance funds are above the 1.25 DRR, the FDIC is prohibited from charging insurance premiums to institutions that are well capitalized and well managed.[12] The DRR explicitly links the level of the insurance

[11] The relationship between bond ratings and default probabilities is discussed below. As shown on Table 1, the historical one-year default probability is 0.29 for a bond with a Standard and Poor's rating of BBB-. See Brand and Bahar (2000) for the details of this calculation. As shown on Table 2, the historical one-year default probability is 0.31 for a bond with a Moody's rating of Baa3. See Keenan et al. (2000) for the details of this calculation.

[12] In Section 7(b) of the FDI Act, the FDIC is prohibited from charging assessments in excess of the amount needed to maintain the reserve ratio at the DRR unless an insured depository institution exhibits "financial, operational, or compliance weaknesses ranging from moderately severe to unsatisfactory, or is not well capitalized."

funds to the amount of exposure, measured by total insured deposits. The level of risk to the insurance funds, however, can change even if the reserve ratio is constant.

Evaluating the risk in the deposit insurance funds differs in significant ways from evaluating the risk in a portfolio of loans. Credit-risk models were developed to measure risk in a portfolio of individual loans. Applying credit-risk models to evaluate the risk to the deposit insurance funds requires viewing the funds as a portfolio of risks. The components of the portfolio are not individual loans but exposures to individual insured institutions. The FDIC's exposure to individual banks can be aggregated to arrive at a cumulative loss distribution. Each institution has a small, but non-zero, chance of failing and thereby causing a possible loss to the deposit insurance funds. In general, there is a high probability of a small loss to the insurance fund. There is also a positive probability that the insurance funds will incur large losses either from the failure of a large bank or from the failure of a large number of banks.

Although it seems reasonable to make the analogy between the risk associated with holding a portfolio of loans and the risk associated with insuring a portfolio of banks, clearly the default event is different. The default of a loan means an obligor is unable to make scheduled payments. Although defaults of individual loans usually contribute to the failure of a bank, typically banks fail because of a combination of a wave of individual loan defaults and poor policies, procedures, and management. Another distinction between the default on a loan and the failure of a bank is that the failure of a bank is a regulatory event: only the regulatory authority can close a bank.

One of the difficulties financial institutions have in estimating parameters for their credit-risk models is the lack of data.[13] Few financial institutions have historical records of default rates on credits within their portfolios. The drawbacks of using internal credit-rating systems have been explored extensively in the academic literature.[14] The FDIC is able to avoid some of these drawbacks because the historical data on the frequency of bank failures are much richer than historical data on loan defaults within the portfolio of an institution.[15]

One of the crucial decisions when a credit-risk model is being constructed is the time horizon. There are two approaches to looking at credit risks in the future—through the cycle or point in time. Implementing a through-the-cycle credit-rating philosophy requires estimating the borrower's condition at the worst point in an economic or industry cycle and grading according to the risk posed at that point. Point-in-time approaches base the credit ratings on the current condition of the borrower. Both Moody's and S&P provide through-the-cycle credit ratings.[16] Using a through-the-cycle approach to credit ratings implies that the credit rating for a particular borrower will change much less during an economic cycle than it will if a point-in-time approach is used. Financial institutions commonly use a one-year planning horizon, since this is the period over which they can take actions that will mitigate the risk. Banks typically do not test their

[13] See Jones and Mingo (1998), BIS (1999), and Carey and Hrycay (2001) for discussions of the insufficiency of internal data.

[14] For example, Carey and Hrycay (2001) investigate the methods used to associate a credit-risk rating with each borrower in a loan portfolio. They show that small changes in the method cause the results from a credit-risk model to vary widely.

[15] Although the FDIC has a rich set of data on bank failures, changes in legislation related to bank closings and structural changes in the industry call into question whether the historical data represent default probabilities in the future.

[16] Very weak borrowers, however, are rated primarily according to their current condition.

credit models for sensitivity to the chosen time horizon.[17] In this analysis I, too, adopt a one-year time horizon.[18]

In a default-mode model, the expected dollar losses (EL) are the sum over the portfolio of the individual exposures (EXP_i) times the estimated probability of default (EDF_i) times the expected loss given default, or severity (SEV_i).

$$EL = \sum_{i=1}^{n} EXP_i \times EDF_i \times SEV_i$$

Estimating unexpected losses for the portfolio involves two steps. First, calculate a measure of the unexpected losses for an individual asset in the portfolio (UL_i). One measure of risk is the standard deviation of losses, which I call unexpected losses.[19]

$$UL_i = EXP_i \sqrt{EDF_i \times \sigma^2_{SEV_i} + SEV_i^2 \times EDF_i(1 - EDF_i)}$$

Second, aggregate the volatility of the individual assets into a measure of volatility for the portfolio, taking into account the correlation of default between assets ρ_{ij}, and take the square root.[20]

$$UL = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} \rho_{ij} UL_i UL_j}$$

This simple structure makes it clear that the estimates of all of the parameters EDF_i, EXP_i, SEV_i, and ρ_{ij} play an important role when expected and unexpected losses for the portfolio are estimated. The quality of these estimates can have a material effect on the accuracy of portfolio credit models.

[17] Jones and Mingo (1999, 1998).

[18] BIS (1999) discusses the time horizon typically chosen by financial institutions. The main reason I chose a one-year time horizon was for comparability with results provided in Oliver, Wyman & Company (2000d) and reported by the FDIC (2000).

[19] This calculation assumes exposure (EXP_i) is not stochastic.

[20] For more detail on the derivation of the calculation for unexpected losses, see Ong (1999).

Oliver, Wyman & Company (OWC) developed an application of a credit-risk model for the FDIC to evaluate the risks to the deposit insurance funds.[21] There are three basic types of models that can be used to evaluate either default-mode or mark-to-market credit risks: actuarial, Merton based, and econometric. For example, CreditRisk+ is an actuarial model, CreditMetrics and Portfolio Manager are Merton-based models, and Credit PortfolioView is an econometric model. Koyluoglu and Hickman (1998a, 1998b) show that in theory the three types of credit-risk models are not very different. The results from the different models, provided the input parameters are equivalent, are virtually the same. The model developed by OWC for the FDIC is a combination of the actuarial and Merton approaches.[22] As in the basic framework above, the expected loss for each institution is the product of the expected default frequency (EDF_i), the exposure (EXP_i), and the severity of the loss given default (SEV_i). Expected losses measure the anticipated average annual loss. The total expected loss for the deposit insurance fund is the sum of expected losses for each individual institution insured by the fund. Unexpected loss is the anticipated volatility of loss defined as one standard deviation of loss. The OWC model uses Monte Carlo simulation techniques to generate an empirical distribution of the cumulative losses to the FDIC.

The inputs to the OWC model are the three elements described above (expected default frequency [EDF_i], exposure [EXP_i], severity [SEV_i]) and an additional input: bucketing. To simplify the estimation of the correlation coefficients (ρ_{ij}), the model

[21] All discussion of the OWC model is based on OWC (2000a, 2000b, 2000c, 2000d) and meetings with OWC held at the FDIC in July through September of 2000.

[22] The discussion of the algorithm used in generating the model is based on the limited information that OWC provided to the FDIC. OWC provided a computer model to the FDIC but did not provide descriptions of all of the assumptions embedded in the model, nor did OWC provide the uncompiled source code used to generate the model.

requires that institutions be grouped into buckets. Rather than estimate a correlation coefficient for each combination of individual institutions, the model estimates the correlation coefficients between the buckets of institutions. The model assumes that the defaults of institutions within a particular bucket move together.

More specifically, the model uses the method described here to generate the empirical distribution of cumulative losses to the FDIC. The model computes the average default correlation within the buckets and for the entire portfolio. Given these average default correlations, the model generates asset correlations between any two buckets and uses this correlation matrix to drive a multivariate normal distribution. As in the Merton-based model, the OWC model assumes that asset values follow the multivariate normal distribution and that an individual institution defaults when the asset value falls below a critical point. The OWC model draws from a multivariate normal distribution with the implied asset correlation matrix and determines whether an individual institution defaults or not.[23] For the banks that fail in the simulation, the model calculates the expected loss (EL_i) as the product of exposure (EXP_i) and severity (SEV_i).[24] Then the model sums these individual expected losses to arrive at the expected loss for a simulation. Using Monte Carlo simulation techniques, the model repeats the simulation 50,000 times and generates an empirical distribution. The model then

[23] The OWC model uses principal component analysis to drive the simulation of the normal variates from the asset correlation matrix. Principal component analysis helps to generate simulations when the correlation matrix is known.

[24] The OWC model allows the user to chose whether severity is constant or a random variable. When severity is a random variable, the model assumes that it follows a log-normal distribution. Under this assumption, for each bank that fails the model draws severity from a log-normal distribution with a given mean and standard deviation and uses it to calculate expected losses.

analyzes the sample set of 50,000 cumulative losses to calculate expected and unexpected losses and to evaluate fund adequacy.

Baseline Simulations

To evaluate the adequacy of the deposit insurance funds, I focus on the credit rating that the December 31, 2000, fund balances earn. Since the FDIC does not have a desired credit rating in mind, I report the credit rating the funds would earn. If they fall short of a BBB rating (the lowest rating available from the model output), I report how much additional funding would be required to make the deposit insurance funds the equivalent of a BBB rating.

For all simulations, I investigate fund adequacy for the Bank Insurance Fund (BIF) and for a hypothetical merged fund that includes institutions insured by the BIF and the Savings Association Insurance Fund (SAIF). Currently the BIF and SAIF are two separate insurance funds, and the FDIC calculates and implements separate deposit insurance assessments. However, since the FDIC has long held that the two funds should be merged, I demonstrate the effect of a merger on fund adequacy.

In this analysis, I hold a few elements constant across all simulations. All EDFs are for a one-year horizon, and severity is assumed to be random. Although the OWC model allows for a two-state simulation, I use only the one-state version of the model for all simulations.[25] I assume there are five factors, an assumption implying that the model

[25] The OWC model allows for simulations using either one or two states. A two-state model allows for the definitions of different parameters for a good state and a bad state. The two-state model allows the user to set the percentage of states that are good versus bad.

estimates 25 separate correlation coefficients (ρ_{ij}). I ran all simulations for 50,000 iterations.

The baseline simulations reported in this article mimic the preliminary simulations run by OWC (2000d). Table 3 shows the descriptive statistics for the four inputs to the model: exposure, EDFs, severity, and buckets.[26]

Exposure

In the baseline simulations, exposure for each institution is defined as the total assets of the institution reported on the December 31, 1999, Call Report.[27] One can argue that the FDIC's exposure is significantly less that the total assets of an institution. Some have argued that the FDIC's exposure is limited to the amount of insured deposits. However, using the amount of insured deposits presents data problems. First, the amount of insured deposits reported on the Call Report is an estimate. Second, the measures of severity (discussed below) are available only in terms of total assets. Insured deposits are not measured at the time of closure for all institutions that fail, but only for institutions that are resolved in such a way that the FDIC is required to determine which deposits are insured.[28] Defining exposure as total assets does not distort the results of the model since severity is measured in terms of losses on total assets.[29]

[26] Buckets are numbered from 1 to 25. See below for more detail on the definition of the buckets.

[27] The data used in the analysis are from the Call Report and were retrieved in September 2000. Therefore, they reflect any revisions made between December 1999 and September 2000.

[28] The FDIC estimates insured deposits before the time of failure but does not make a final insurance determination unless such a determination is required for completing the resolution of the failed bank.

[29] The total loss figures measure the loss to the deposit insurance funds and take into account the extent to which losses are smaller because the FDIC shares losses with uninsured domestic depositors.

When I evaluate the BIF separately from the SAIF, the exposure of individual institutions must take into account that some institutions hold both BIF- and SAIF-insured deposits. In all simulations that use an adjustment for this, I allocate exposure (total assets) to the appropriate insurance fund on the basis of the BIF- and SAIF-insured deposit levels in the institution. If, for example, an institution that has the BIF as its primary insurer acquires a SAIF-insured institution, the acquirer must separately report the acquired SAIF-insured deposits for insurance assessment purposes (along with its own BIF-insured deposits). A parallel reporting is required for acquired BIF-insured deposits by SAIF-insured institutions. All acquired deposits are known as Oakar deposits, named after the sponsor of the legislation allowing these types of acquisitions.[30] Under my asset allocation method, if an institution has 25 percent of its domestic deposits as SAIF insured and 75 percent as BIF insured, then 25 percent of its exposure is allocated to the SAIF and 75 percent to the BIF. The FDIC uses this same approach to allocate to the BIF and SAIF the resolution costs that are associated with failed banks.

Expected Default Frequencies

The expected default frequencies used in the baseline simulations are derived from a mix of market information and historical experience. When available, the expected default frequencies are translated from the credit rating on long-term debt. OWC provided the FDIC with a mapping between individual banks and credit ratings for

[30] See the Federal Deposit Insurance Act (12 U.S.C. 1815 Section 5(d)(3)).

146 publicly traded banks and bank holding companies.[31] The source of June 2000 credit rating information was Standard and Poor's (S&P) or, when not available, Moody's. If credit rating information was not available, an unconditional measure of default frequency was used. The unconditional measure is the arithmetic average of historical defaults of FDIC-insured banks from 1934 to 1997.

Market Data

OWC developed a methodology to map S&P and Moody's credit ratings to expected default frequencies (see Table 4).[32] This methodology used information from all industries, not just the financial industry.

Since the EDF is an important input into the credit-risk model, it is essential to investigate the relationship between credit ratings and EDFs. Additional information about this relationship is available from Standard and Poor's and Moody's. Both credit-ratings agencies conduct ongoing research into the default experiences of their rated issuers.[33]

Brand and Bahar (2000) calculated the historical one-year EDF of corporations by Standard and Poor's credit ratings. Their study uses data from 1981 to 1999 for all U.S. and non-U.S. industrials, utilities, insurance companies, banks, other financial institutions, and real estate companies. There are some differences between this study

[31] Many of the bank holding companies hold multiple banks. OWC did not provide the FDIC with details about how it mapped the credit ratings for institutions to the bank certificate number.

[32] OWC did not provide the FDIC with details regarding the methodology it developed to map credit ratings into expected default frequencies.

[33] The definition of default differs slightly across these two rating agencies. Standard and Poor's defines default as the failure to pay any financial obligation. Moody's definition includes not only these defaults, but also the renegotiation of a financial instrument.

and the mapping generated by OWC. First, as shown on Table 1, the historical one-year EDFs are zero for corporations that have AAA, AA+, or AA ratings. In contrast, methodology developed by OWC assigns to institutions with those credit ratings one-year EDFs of 0.01, 0.02, and 0.03 percent, respectively.[34] The OWC methodology assigned significantly higher EDFs for other credit ratings as well: the EDF assigned to institutions rated A+ was more than double the historical EDF, and the EDF assigned to institutions rated A- was triple the historical EDF. The EDFs assigned by OWC were not consistently higher for all of the credit ratings, however. OWC assigned an EDF of 4.46 percent for institutions rated B, compared with an 8.46 percent historical EDF; and OWC assigned an EDF of 7.52 percent for institutions rated B-, compared with a 10.19 percent historical EDF.

Using a proprietary database of ratings and defaults, Moody's calculates historical default rates for industrial and transportation companies, utilities, financial institutions, and sovereigns that have issued long-term debt to the public, including non-U.S. issuers. At the start of 2000, industrial companies represented 39 percent of rated firms, nonbank financials constituted 17 percent of rated firms, and banking institutions were 14 percent.[35] Keenan et al. (2000) calculated the one-year EDFs shown on Table 2 using 1983–1999 data. There were six categories that had zero EDFs according to the historical data; OWC assigned positive EDFs to these categories. As in Table 1, the OWC methodology assigned to some of the credit-rating categories EDFs that were significantly higher. The EDF assigned by the OWC methodology is more than three

[34] The credit-risk model constructed by OWC does not allow for an EDF of zero.

[35] Keenan et al. (2000), 8.

times the historical EDF for institutions with a Baa1 credit rating and more than two times for institutions with a Baa2 credit rating. Most of the remaining EDFs assigned by the OWC methodology were similar to the historical one-year default rates.

The difference between the mapping methods, historical or OWC, may affect the risk measurement and evaluation of fund adequacy generated by the credit-risk model. Of the 146 BIF and SAIF institutions that have credit ratings, about half were rated A, A+, or A- as of June 2000. Two institutions did not have S&P ratings available; one was rated Baa3 and one Ba3 by Moody's. The highest concentration, 21.62 percent of the 148 institutions, had A+ credit ratings, and the OWC methodology assigned a 0.05 percent EDF compared with the historical one-year EDF of 0.02 percent. Similarly for other groups with high concentrations of institutions, the OWC methodology either assigned higher EDFs or, for one group, the same EDF. Using the higher EDFs causes the estimate of the EL to be higher. (See the equation for EL above.) The effect of using the higher EDFs on the UL is not clear, since it will also depend on the correlations between institutions in the buckets. (See the equation for UL above.) Therefore, using the OWC methodology rather than the historical averages from Standard and Poor's and Moody's will result in higher EL but will have an unknown effect on the UL and on overall measures of fund adequacy.

Although the number of institutions (146) that had market information may seem small, the market information represents over one-half of the total for all BIF- and SAIF-insured institutions in terms of total assets, total deposits, and insured deposits. The 146 BIF and SAIF institutions with S&P or Moody's ratings account for approximately 63 percent of total assets, 61 percent of total deposits, and 53 percent of estimated insured deposits of all 9,990 BIF and SAIF institutions in the simulation.

There were 123 BIF-insured institutions that had either S&P or Moody's credit ratings. These 123 institutions account for approximately 65 percent of total assets, 64 percent of total deposits, and 56 percent of insured deposits of the 8,638 BIF institutions included in the baseline simulation.

Historical Bank Default Data

For the institutions that did not have credit ratings available, OWC calculated EDFs using the number of failures from 1934 to 1997 as reported in the FDIC's 1997 Annual Report. There were 8,515 BIF and 1,329 SAIF institutions that were assigned the historical average of 26 basis points.[36]

Severity

When the credit-risk model framework is used to evaluate deposit insurance fund adequacy, severity—also known as loss given default—is the loss incurred when an institution fails. As mentioned above, total assets are the equivalent of "exposure" for all of the simulations. Therefore, severity is expressed as the loss on assets (total losses as a percentage of total assets). As also mentioned above, severity is a random variable in the model developed by OWC. Since the model assumes that severity follows a log-normal distribution, the mean and standard deviation of severity are inputs into the OWC model.

For the baseline simulation, I constructed the mean and standard deviation of severity from a 14-year history of FDIC losses, which is available from the FDIC's

[36] OWC did not provide the FDIC with details of this calculation. I used information from the Annual Reports and the FDIC's internal Failure Transactions Database and arrived at a historical average of 25.42 basis points—close to, but not exactly, the 26 basis points.

Failed Bank Cost Analysis. I split failures into five size groups and calculated the mean and standard deviation of the loss rates on assets. (See Table 5.)[37] In the simulations, each institution was assigned a mean and standard deviation of loss rates on the basis of the size of the institution. Accordingly, the 5,030 BIF-insured institutions in the sample with assets less than $100 million (see Table 6) would be assigned a severity mean of 24.18 percent and a severity standard deviation of 13.78.

<u>Bucketing</u>

As mentioned above, another input into the OWC model is bucketing. The model treats the stochastic properties of the defaults of institutions within each bucket the same. Therefore, it is important to put institutions that are expected to have similar default characteristics in the same bucket. I group borrowers into 25 discrete buckets on the basis of observable characteristics.

For the baseline simulations, institutions were sorted by size, and each of the 20 largest institutions was placed in its own bucket. The remaining institutions were placed

[37] Note that the number of observations in each cell will not match other publicly available data on the number of failed banks. To be consistent with calculations performed by the Division of Finance at the FDIC, I consolidated 202 of the receiverships into the following 13 groups:
1. Banktexas, Inc (11 institutions, failed 1987)
2. First City (59 institutions, failed 1988)
3. First Republic (41 institutions, failed 1988)
4. Alliance (2 institutions, failed 1988)
5. Texas Bank North (2 institutions, failed 1988)
6. Mcorp (20 institutions, failed 1989)
7. Texas American Bancshares (24 institutions, failed 1989)
8. National Bancshares (9 institutions, failed 1990)
9. Bank of New England (3 institutions, failed 1991)
10. Southeast Bank (2 institutions, failed 1991)
11. New Hampshire Banks (7 institutions, failed 1991)
12. First City (20 institutions, failed 1992)
13. Merchants Bank (2 institutions, failed 1992)

in five buckets on the basis of size. These five buckets correspond to the five size categories used for calculating severity.

Simulation Results

Using the baseline assumptions would give the BIF a credit rating worse than BBB. Figure 2 presents three separate simulations. The first simulation allocates assets to the BIF on the basis of the distribution of Oakar deposits. The second is a baseline simulation with all of the assumptions discussed above, except exposure has not been adjusted for Oakar deposits. The third simulation is the results that OWC presented to the FDIC. The bars in the figure indicate the dollar amount needed in the fund to earn the corresponding credit rating. The horizontal line indicates that there was $29.863 billion in the BIF as of December 31, 2000. Correspondingly, the distance between the top of each bar and the horizontal line measures the additional capital that the insurance fund would require in order to earn the corresponding credit rating.

In the second simulation (baseline), the expected loss to the BIF is approximately $1.03 billion and the unexpected loss is $2.96 billion (see Table 7). To obtain an A rating for the BIF, the fund would have to grow to $44.73 billion from its balance of $29.863 billion as of December 31, 2000. The baseline simulation indicates that the BIF and SAIF merged fund has an EL of $1.35 billion and a UL of $3.97 billion. There would have to be $55.107 billion in a merged BIF and SAIF fund in order to earn an A credit rating. The balance of $40.591 that existed in the two funds as of December 31, 2000, does earn the merged fund a BBB rating (see Figures 2 and 3). It should be noted that the merged fund is rated higher than the BIF alone, as would be expected from the effects of diversification.

Sensitivity Analysis: Expected Default Frequencies

The specification of the EDFs is important in the simulations, as is evident in the equations for EL and UL.[38] I perform sensitivity analysis on the choice of EDFs, using three alternative sources of EDFs.[39] First, I replace the market information used in the baseline simulation with solely the historical EDFs. Second, I use an econometric model to generate EDFs. Third, I investigate three different sources of market information other than the long-term debt ratings from S&P and Moody's.

Historical Expected Default Frequencies

As mentioned above, the baseline simulation uses two sources of information for EDFs. First, when available, credit ratings are used and mapped to EDFs. Second, the remaining institutions are assigned an EDF of 26 basis points. In the first attempt to measure sensitivity of the model to changes in the EDF, I simply assign the EDF of 26 basis points to all of the institutions. As a comparison of the first and second columns of Table 8 shows, using only the historical EDFs increases both the EL and the UL of the distribution of losses. This simulation indicates that the BIF would have to have a balance of $76.840 billion to receive an A rating and $52.2 billion to receive even a BBB rating (see Figure 4). A BIF and SAIF merged fund would require a balance of $92.763 billion for an A rating and $60.994 billion for a BBB rating (see Figure 5). By performing a rather naive experiment (replacing the market-derived EDFs with the

[38] Carey and Hrycay (2001) emphasize the importance of estimating the default probabilities accurately for use in credit-risk models.

[39] All of the sensitivity analysis for the BIF is performed on the baseline simulations with Oakar adjustments.

historical EDFs), I show that the amount of risk to the insurance fund, as measured by the OWC credit-risk model, has increased dramatically.

Expected Default Frequencies from a Logit Model

A more sophisticated experiment involves generating EDFs from an econometric model. The econometric model I use is a logit model that uses financial ratios to predict the probability of bank failure (EDF). The model assumes that the probability of bank failure takes a logistic functional form and is, by definition, constrained to fall between 0 and 1. The dependent variable, the log of the odds-ratio, is assumed to be linearly related to the explanatory variables (the financial ratios).

The EDFs for all of the BIF- and SAIF-insured institutions are based upon EDF forecasts obtained from a standard "logistic" failure-prediction model. The model states that the likelihood of failure over a 12-month period is determined by the institution's financial condition as of the start of the period. Financial condition is measured by capital adequacy, asset quality, earnings, and safety-and-soundness examination ratings. The data used to estimate the model were year-end condition data and subsequent failures between 1984 and 1997 for commercial and savings banks and thrifts. (Thrift data were available only between 1991 and 1997.) Table 9 shows the estimated relationships. This model is then used to predict EDFs on the basis of December 1999 Call Report and examination data. Exposure is adjusted to account for Oakar deposits (as described above).

The first experiment replaces the EDFs in the baseline simulation with the EDFs generated by the logit model (see column 3 of Table 8). The average EDF produced by the logit model is much lower than the average EDF used in the baseline, but the standard deviation is much higher. The EL for the BIF is much lower than the baseline—$338 million compared with $1.081 billion. Similarly, the UL is much lower—$2.3 billion compared with $3.1 billion. In fact, when the EDFs generated by the logit model are used, the BIF (at the December 31, 2000, balance of $29.863 billion) would earn a rating of BBB+. Similarly, the EL and UL for the BIF and SAIF merged fund decrease, and the merged BIF and SAIF (at the December 31, 2000, balance of $40.591 billion) would earn a rating of BBB+.

Now, instead of replacing all of the baseline EDFs with the EDFs generated by the logit model, I replace only the historical EDFs. The institutions with market information have EDFs from the mapping of credit ratings to EDFs provided by OWC. Again, the average EDF is much lower than the average EDF in the baseline simulation (see Table 8). The mix of market information and EDFs from the logit model shows that the BIF (at the December 31, 2000, balance of $29.863 billion) would earn a BBB+ rating, and the BIF and SAIF merged fund (at a December 31, 2000, balance of $40.591 billion) would earn an A- rating (see Figures 4 and 5).

Overall, using the EDFs generated by a logit model implies that risk to the insurance fund (as measured by the OWC credit-risk model) is lower than in the baseline simulation. The EDFs generated by the logit model are dependent on the financial condition of the insured institution at year-end 1999. Since most insured institutions were in very good financial condition relative to historical periods, it is not surprising that using this model yields lower measures of risk.

<u>Expected Default Frequencies from Market Information</u>

In the baseline simulation, I mapped S&P and Moody's ratings of long-term debt to EDFs using the OWC mapping. I performed a sensitivity analysis that replaced the ratings on long-term debt with ratings on long-term deposits. In addition, I looked to another source, KMV, which publishes EDFs and S&P ratings.

Long-Term Deposit Ratings

Long-term deposit ratings provided by Moody's do not take into account the benefit of deposit insurance schemes that make payments to depositors.[40] When a bank fails, the FDIC reimburses insured depositors and then stands in their place in the receivership. In contrast, debt holders are low in the priority of claimants on the receivership; only stockholders are below them. Thus, the long-term deposit rating produced by Moody's measures risk that more closely mimics the risks incurred by the FDIC than debt ratings do.

I collected credit ratings on long-term deposits from Bloomberg between September 14, 2000, and October 4, 2000. I matched the banks first by name to the list of S&P and Moody's ratings provided to the FDIC by OWC.[41] The sample contained 91 BIF and 106 BIF and SAIF institutions with long-term deposit ratings. Although the number of institutions with long-term deposit ratings is smaller than the number of institutions with ratings in the baseline, institutions in the former group still account for

[40] Long-term deposits are deposits that have a maturity of over one year.

[41] In the data set, I included observations where the names exactly matched, or matches I was able to confirm using additional demographic information about the bank.

more than half of the total assets, total deposits, and total insured deposits in both the BIF alone and the BIF and SAIF merged fund (see Table 10).

The simulation, which uses a combination of the EDFs from the long-term deposit ratings and the historical EDFs, results in slightly higher measured risk. The EL and UL both increase (see Table 11). The BIF (at a December 31, 2000, balance of $29.863 billion) would not earn a BBB rating. The merged fund (at a December 31, 2000, balance of $40.591 billion) would earn a BBB rating (see Figures 6 and 7). Replacing long-term bond ratings with long-term deposit ratings results in a measure of risk that is slightly higher.

Expected Default Frequencies from KMV

KMV developed a model of default probability, Credit Monitor, that uses equity prices and financial statements. The model relates the market value of a firm's assets (which is the sum of the market value of equity plus the market value of debts) to the probability of default.[42] The KMV model is based on two theoretical relationships: (1) the value of equity can be viewed as a call option on the value of a firm's assets, and (2) a link exists between the observable volatility of a firm's equity value and the unobservable volatility of asset values. The model has three steps: (1) estimate the asset value and volatility, (2) calculate the distance to default, and (3) map the distance to default into the default probability. The market value of assets and the volatility of assets are generated by an option pricing model. Credit Monitor uses option pricing theory to derive the asset value and its volatility using the market value of equity, the volatility of

[42] See Crosbie (1997).

equity, and the book value of liabilities. Using the market value of assets, Credit Monitor then determines whether the market value of assets is above or below the default point. The default point—the asset value at which the firm will default—usually lies between total liabilities and short-term liabilities and differs from industry to industry. KMV calculates the distance to default (the market net worth which is the market value of the firm's assets minus the firm's default point divided by the product of the asset value and the asset volatility). The distance to default measures the number of standard deviations the asset value is away from default. KMV then maps the distance to default to the probability of default on the basis of empirical studies of default rates.

Using a mapping between ticker symbols and bank certificate numbers, I assigned KMV EDFs to 119 BIF and SAIF institutions. These institutions account for approximately one-half of the total assets, total deposits, and total insured deposits in the BIF and in the BIF and SAIF merged (see Table 10). When the KMV EDFs are used in combination with the historical average EDF of 26 basis points, the average EDF is not much higher than the baseline (see Table 11). The standard deviation of the EDF, however, is much higher (over four times higher for BIF and three times higher for BIF and SAIF merged).

The risk to the insurance funds, as measured by the OWC credit-risk model, increases dramatically when the KMV EDFs are used. The EL for the BIF increases from the baseline of $1.03 billion to $3.24 billion, and the UL increases from the baseline of $2.96 billion to $8.53 billion. The EL for the BIF and SAIF merged increases from a baseline of $1.35 billion to $4.04 billion; similarly the UL increases from the baseline of $3.97 billion to $10.10 billion. The balances in the BIF and in the BIF and SAIF merged fund are far below the balance required for a BBB credit rating (see Figures 6 and 7).

The KMV EDFs are based on equity prices, which tend to be volatile. The higher standard deviation of the EDFs had a large influence on the amount of risk measured by the OWC model, although the mean of the EDFs was approximately the same.

Credit Ratings from KMV

KMV also publishes credit ratings for long-term debt. I used the same mapping between ticker symbols and bank certificate numbers using June 2000 published data and matched 103 of the BIF and SAIF institutions (see Table 10). Again, these 103 institutions account for more than one-half of the total assets, deposits, and insured deposits in both the BIF and the merged BIF and SAIF. I then mapped these credit ratings into EDFs with the OWC methodology that was used for the baseline simulations.

When the EDFs from the KMV credit ratings and the historical 26 basis point EDF are combined, the mean of the EDF is not much different from the baseline; the standard deviation is slightly lower. The EL and UL increase slightly for both the BIF and the BIF and SAIF merged (see Table 11). The BIF (at the December 31, 2000, balance of $29.863 billion) would not earn a BBB rating. The BIF and SAIF merged fund (at the December 31, 2000, balance of $40.591 billion) would barely earn a BBB rating (see Figures 6 and 7).

Overall, the sensitivity analysis using different methods of deriving EDFs did change the amount of risk measured by the OWC model—in some cases, dramatically. Including EDFs derived from a logit model resulted in lower risk than the baseline; it resulted in a BBB+ rating for the BIF and a BBB rating for the BIF and SAIF merged. When the EDFs from the S&P and Moody's ratings were combined with the EDFs from the logit, the risk measured by the model was even lower—the BIF almost earned a

BBB+ (almost an A-) rating, and the BIF and SAIF merged earned an A- rating. In contrast, measured risk increased slightly when EDFs from long-term deposit ratings were used, and increased dramatically when EDFs from KMV were used.

Sensitivity Analysis: Severity

In the baseline simulation I defined severity as a 14-year weighted average loss rate calculated from the FDIC's *Failed Bank Cost Analysis*.[43] However, losses incurred by the FDIC varied over time during that 14-year period. I performed sensitivity analysis using severity calculated over different time periods. More recently—specifically, between 1990 and 1998—losses were lower than over the entire 14-year period (see Table 12). The first simulation in the severity sensitivity analysis replaces the 14-year average with this more recent loss experience.[44] The remaining simulations for the sensitivity analysis on severity involve averages over relatively low loss rate periods and relatively high loss rate periods. I chose the relatively high loss period, 1986–1989, and the relatively low loss period, 1990–1993, by examining the loss data and grouping the years accordingly.

The first simulation run for sensitivity analysis replaces the 14-year average with a more recent loss experience: an average over 1990-1998. The mean of severity is lower over this period, and the standard deviation is much higher (see Table 13). Using the lower severity figures results in a lower EL and UL. The credit rating for the BIF (at the December 31, 2000, balance of $29.863) improves from below a BBB rating to an A

[43] The weighted average loss rate is calculated as the sum of losses divided by the sum of assets. Thus, the weights used for the average are the total assets of the institution.

[44] The sensitivity analysis for the BIF is performed on the baseline simulation with the Oakar adjustments.

rating (see Figure 8). Similarly, the credit rating for the BIF and SAIF merged fund (at the December 31, 2000, balance of $40.591) improves from BBB for the baseline simulation to A when the 1990–1998 severity figures are used.

When the 14-year averages are replaced by the average severity in the relatively high-loss period, both the mean and the standard deviation of severity increase (see Table 13). The EL and the UL both increase when the 1986–1989 loss rates are used. In this high loss rate scenario, the BIF would have to be $43.806 billion to earn a BBB credit rating, and the BIF and SAIF merged would have to be $49.431 billion, well above the amount currently in the funds (see Figures 8 and 9).

The simulation using the relatively low loss rates results in a lower EL and UL (see Table 13). In this scenario, the mean and standard deviation of severity are both lower than the baseline. At the December 31, 2000, balance ($29.863 billion), the BIF would earn an A credit rating under the low severity scenario; the BIF and SAIF merged ($40.591 balance on December 31, 2000) would also earn an A credit rating (see Figures 8 and 9).

When the low loss rate period (1990–1993) is combined with the high loss rate period (1986–1989), the results are similar to the baseline. The EL and UL are slightly lower than the baseline. As in the baseline, the credit rating for the BIF would be below a BBB; the credit rating for the BIF and SAIF merged would be BBB (see Figure 8 and 9).

As one would expect, when an average severity that is calculated from relatively high loss rate periods is used, the adequacy of the insurance funds drops. Conversely, when an average severity is calculated from a relatively low loss rate period, the adequacy of the insurance funds increases. What is important to note is how drastically the assessment of the adequacy of the insurance funds changes. Simply replacing severity figures that are, on average, only a few percentage points lower, sends both the BIF and the BIF and SAIF merged funds from not earning even a BBB rating to earning an A rating.

Sensitivity Analysis: Bucketing

Bucketing, or grouping institutions into separate buckets, simplifies the estimation of the relationship between defaults of different institutions. Rather than estimating the relationship between defaults for individual institutions, bucketing the model can estimate the relationship between defaults for groups of institutions. This method assumes that institutions within the buckets have the same default correlations with institutions outside the buckets. Therefore, when one constructs buckets, it is best to group institutions that have similar default characteristics.

In the baseline simulation, the 20 largest institutions were put into individual buckets, and five additional buckets group the remaining institutions by size. This bucketing scheme places particular emphasis on the largest institutions—the institutions that present the risk of high losses to the insurance fund at a low probability of occurrence. I conduct sensitivity analysis by grouping institutions, first using a naive grouping scheme and then using common characteristics that might cause them to weaken and fail together.[45]

[45] As above, all sensitivity analysis for the BIF is performed on the baseline simulation including the Oakar adjustments.

Equal Number of Institutions in Each Bucket, by Size

The first simulation takes a naive approach and separates the institutions in the sample into 25 buckets, with an equal number of institutions in each bucket. The institutions are first sorted by size; so, for example, the 346 largest BIF institutions are in the first bucket, the next 346 largest BIF institutions are in the next bucket, and so on. This naive bucketing approach causes the measures of risk (EL and UL) to decrease (see Table 14). The measures of fund adequacy improves—the December 31, 2000, balance of $29.863 billion would earn a BBB rating for the BIF, and the BIF and SAIF merged balance of $40.591 billion would earn a BBB+ rating (see Figures 10 and 11).

Size and Region

During the banking crisis of the 1980s and early 1990s, bank failures tended to be concentrated by region.[46] I separate institutions into buckets according to the five size categories used for the severity calculations and according to location in five regions of the United States: Northeast, Southeast, Central and Midwest, Southwest and West (see Table 15). The EL and UL again are smaller than in the baseline simulation (see Table 14). Under this scenario, fund adequacy improves: at the December 31, 2000, fund balances, the BIF is rated BBB, and the BIF and SAIF merged fund is rated BBB+.

[46] Regional concentration may not be the case in the future, since the law now permits interstate banking. Thus, institutions may now diversify risk across regions.

CAMELS Rating Group and Region

Institutions with similar supervisory ratings have similar default characteristics. In this simulation, I group banks by supervisory rating and by region. Supervisory, or CAMELS, ratings range from 1 to 5 (1 being the best). Each of the six components--capital (C), asset quality (A), management (M), equity (E), liquidity (L), and sensitivity to market risk (S)—is rated separately; in addition, supervisors rate the overall health of the institution in a composite rating. Regulatory agencies consider institutions with composite ratings of 4 or 5 to be problem institutions. A component rating of 4 or 5 indicates that the institution is having a severe problem in that particular component of its business. As of December 1999, most institutions had a composite rating of 1 or 2.

Since most institutions are concentrated in composite ratings 1 and 2, I am unable to place institutions in 25 separate buckets using solely the information from the composite rating. Therefore, I create five CAMELS groups using information from the composite ratings and from the capital and asset component ratings. The five CAMELS groups are

- CAMELS 1: Institutions with composite CAMELS ratings of 1.
- Strong 2: Institutions with a composite CAMELS rating of 2 and a capital or asset component rating of 1 or 2.
- Weak 2: Institutions with a composite CAMELS rating of 2 and a capital or asset component rating of 3, 4, or 5.
- Strong 3: Institutions with a composite CAMELS rating of 3 and a capital or asset component rating of 1 or 2.

- Weak 3, 4 and 5: Institutions with a composite CAMELS rating of 3 and a capital or asset component rating of 3, 4, or 5, and institutions with composite CAMELS ratings of 4 or 5.

Combining the five CAMELS groups with the five regions results in 25 buckets (see Table 16). Including CAMELS groups instead of size buckets leads to slightly lower measures of risk (a lower EL and a lower UL) (see Table 14). Accordingly, the fund adequacy measures improve. The December 31, 2000, balance of the BIF would earn a BBB rating, and the merged BIF and SAIF would earn an A- rating (see Figures 10 and 11).

CAMELS Rating Group and Size

If I combine the CAMELS rating groups and size buckets, I am not able to populate all 25 buckets required by the OWC model. However, if I modify the two largest size categories to be \$1 billion to \$3 billion and over \$3 billion, I am able to populate the buckets, but only for the BIF and SAIF merged fund (see Table 17).

Combining the CAMELS groups with size rather than region results in slightly higher measures of risk (the EL and UL are higher) (see Table 14). Accordingly, the measures of fund adequacy are lower. The December 31, 2000, balance of the BIF and SAIF merged earns an A- rating.

Specialized Lender and Region

Banks with exposures to similar types of lending or banks with similar business lines are likely to experience difficulties at the same time. For example, if a drought occurs, I would expect agricultural banks to begin having difficulties. Accordingly, I group banks into specialized lending groups, as follows:[47]

- Agricultural Bank: Agricultural loans and agricultural real estate loans represent more than 25 percent of total loans.
- Consumer Lender: This category includes both credit-card lenders and other consumer lenders. Consumer lenders are lenders whose residential real estate and consumer loans are more than 50 percent of total assets. Credit-card lenders are lenders whose credit-card loans plus securitized credit-card loans sold are greater than 50 percent of total loans plus securitized credit-card loans sold and whose total loans plus securitized credit-card loans sold are greater than 50 percent of the sum of total assets plus securitized credit-card loans sold.
- Commercial Lender: Commercial and industrial loans, construction loans, multiple family real estate loans, and nonresidential real estate loans are greater than 25 percent of total assets.
- Mortgage Lender: Residential real estate loans and mortgage-backed securities are greater than 50 percent of total assets.
- Multinational Bank: Total assets are greater than $10 billion, and more than 25 percent of total assets are held in foreign offices.
- Other Large: Total assets are greater than $1 billion and the institution is not placed in one of the categories above.
- Other Small Specialized: Total assets are less than or equal to $1 billion, and total loans are less than 40 percent of total assets.

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[47] Ross Waldrop of the Division of Research and Statistics, FDIC, created these groupings.

- Other Small: Total assets are less than or equal to $1 billion, and the institution is not placed in one of the categories above.

When I combine five of the specialized lenders (agricultural, consumer, commercial, mortgage, and multinational) with the regions, three buckets do not have any institutions in them (see Table 18). The remaining institutions are put into the three remaining groups by type: other large, other small specialized, and other small institutions. The measures of risk (EL and UL) are lower than in the simulations that use size or CAMELS groups with region groupings (see Table 14). Fund adequacy appears slightly worse in this scenario. At the December 31, 2000, balances, the BIF earns an A- rating and the BIF and SAIF merged fund earns a BBB+ rating.

Overall, sensitivity analysis conducted using changes in bucketing results in fund adequacy measures that fluctuate less widely than measures when other inputs are changed. The December 31, 2000, BIF balance is rated BBB for three of the four scenarios and BBB+ for the remaining scenario (specialized lender and region). The December 31, 2000, balance of the BIF and SAIF merged fund is rated BBB+ for four of the five scenarios and A- for the remaining scenario (region and CAMELS group).

Further Research

One area for further research is whether small and large banks should be segregated into separate risk portfolios. Small and large banks pose two very different types of risk to the FDIC. Small banks as a group pose a high probability of low losses, whereas large banks pose a small probability of high losses. In addition, the quality of data available to construct inputs that relate to the very large banks is lower than the quality of data available for small banks. For example, the historical data on losses incurred from failures does not include information for any institution larger than $33 billion. (The 25 largest institutions as of December 31, 1999, had an average of $159 billion in total assets.) It may be possible to construct some ad hoc measure of how much a large bank would cost the FDIC to close, but such a measure would be just that—ad hoc. Another issue is the systemic-risk exception: some of the large banks in the portfolio may very well fall under the systemic-risk exception to the Least-Cost Test as spelled out by FDICIA. Since this exception has never been invoked, it is difficult to figure out how to measure severity in this scenario.

Another area for future research relates to the application of these mappings between credit ratings and EDFs. First, is it appropriate to use the average default rate for each credit rating? If it is appropriate, should data from all industries be used to calculate the EDFs and then the resulting EDFs applied just to banks?

The mapping of credit ratings to EDFs makes the implicit assumption that all institutions with the same credit rating have the same probability of failing and that this probability of failing is equal to the historical average default rate. Kealhofer et al. (1998) show that the actual default rate can differ significantly from the historical average default rate. Within a rating grade, the range of default rates is substantial, and the mean default rate can significantly exceed the median default rate (the mean may be almost twice the median). They conclude that the historical average default rate is a noisy estimate of the actual mean. As such, the historical EDF is a noisy estimate of the probability of default for any given institution.

If the given institution is a bank, an additional issue arises when historical EDFs are used from all industries. Using these mappings of credit ratings to expected default frequency may not be appropriate for the banking sector. If banks have systematically different default risks than other corporate borrowers that are assigned the same credit rating, the mapping may introduce bias in the assignment of expected default frequencies. There is reason to believe that this is the case, since banking is a regulated industry. In contrast to most other industries, bank default is a regulatory event: the chartering authority closes a bank. And creditors of a bank are given a different priority to receive payment from the receivership than creditors of a corporation that goes into bankruptcy.

Evidence presented by Nickell, Perraudin, and Varotto (2000) shows that banks have less stable ratings than industrials. BIS (2000) adds further doubt that the EDFs from other industrial sectors should be applied to the banking sector. The BIS study suggests that U.S. banks experience a higher default rate than U.S. industrial firms for a given Moody's rating in a given year. Since this suggests that the true relationship between credit ratings and expected default frequencies may be different for banks than for other corporate entities, it would be useful to construct a mapping for the banking industry alone.[48]

Certainly I have not exhausted the possibilities for sensitivity analysis. I could use more information, such as financial ratios, to form buckets. And, I have conducted sensitivity analysis of the OWC model only under the following conditions: random severity, one state, with five factors. Any of these assumptions can be changed for a more thorough investigation of the model's sensitivity to inputs.

I also see some areas in which the model can be extended that may prove useful to the FDIC for risk assessment. As it currently stands, the OWC model is a static model

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[48] Of course, this study would also encounter problems. The amount of data available is much smaller for defaults in an individual industry than for defaults in a group of industries. The lack of data may be so severe as to make the study unreliable. Another problem this type of study would face is controlling for legislative changes to bank closing procedures, especially the changes made by FDICIA in 1991.

evaluating fund adequacy for only one period. However, there are dynamic implications to fund adequacy (see Sheehan [1998] and Oshinsky [1999]). The model's response to multiyear simulations over the cycle and to stress testing also provides interesting research possibilities.

Another extension would address the issue of large fluctuations in insured deposits. Since data limitations allow me to measure exposure only in terms of total assets, I ignore this effect. Recently, investment companies have been able to convert some of their customer accounts very quickly into FDIC-insured accounts. This implies that insured deposits, and thus the exposure of the insurance funds, can change. Unfortunately, the OWC model is unable to take this into consideration. However, there may be a way to extend the model, using more complicated techniques that are analogous to how credit-related optionality (loan commitments and lines of credit) is treated in other credit models.

Another extension of the model that might be useful to the FDIC is to look at multistate credit-risk models. These models look at migration of credits across credit classes. The analogy for the FDIC would be to look at the migration of banks across different risk categories. This would enable the FDIC to track the source of the shifts in risk.

In an early version of documentation for CreditMetrics, J. P. Morgan stated, "…almost any risk measurement system is better at stating relative rather than absolute risk."[49] Given the amount of uncertainty in the model parameters, it would not be prudent to use the models for any application that required an absolute measure. Credit-

[49] J. P. Morgan (1997), 15. This quotation is from an early version of the document and is no longer included in the current version available on J. P. Morgan's web site.

risk models, however, are useful for measuring both the relative riskiness of portfolios under differing circumstances and the contribution of individual credits to the overall riskiness of the portfolio.

Conclusions

As measured by the OWC credit-risk model, the credit rating of the FDIC is very sensitive to different assumptions about the expected default frequencies and the severity of losses. Under one set of assumptions the FDIC would not warrant a BBB rating, whereas under another set the FDIC would warrant an A rating.

The OWC model is sensitive to changes in the EDFs. When six different sets of EDFs were used, the credit rating for the December 31, 2000, BIF balance ranged from requiring $54.163 billion in additional capital to earn a BBB rating to earning an A- rating with no additional capital. The credit rating for the December 31, 2000, BIF and SAIF balances ranged from requiring $58.862 billion to earn a BBB rating to earning an A- rating at current capital levels.

The model was most sensitive to changes in severity. When average severity from recent periods and periods of low loss rates was used, the BIF and the BIF and SAIF merged funds were both rated A. When average severity from high loss rate periods was used both the BIF and the BIF and SAIF merged funds would not be investment grade. In the latter case, the BIF and the BIF and SAIF merged required $13.943 billion and $8.841 billion, respectively, to be rated BBB.

The OWC model was less sensitive to changes in alternative bucketing techniques. Fund adequacy measures for the BIF did not change much: the BIF was rated BBB in all but one scenario, where it earned BBB- (specialized lender and region bucketing). The bucketing scheme had more of an effect on the fund adequacy measures for BIF and SAIF merged: the BIF and SAIF merged fund was rated BBB+ under all but one scenario, where it was rated 'A-' (region and CAMELS group).

The model developed by OWC for the FDIC provides useful quantitative information about the risks faced by the deposit insurance funds and the adequacy of the funds. As part of the deposit insurance reform debate, there have been recommendations to eliminate the 1.25 designated reserve ratio and replace it with a wider band of accepted level of capitalization in the deposit insurance funds. Results from the model may be useful information to incorporate into a determination of acceptable levels of capitalization. However, this information must be used with caution because, as I have demonstrated with the sensitivity analysis, the model results can fluctuate rather dramatically under different reasonable assumptions.

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Table 1

Comparison of Rating Calibrations with Standard and Poor's Historical Default Rates

Standard and Poor's Rating	Historical One-Year Default Rates, 1981–1999	Oliver, Wyman & Company One-Year Default Probability
AAA	0.00%	0.01%
AA+	0.00	0.02
AA	0.00	0.03
AA-	0.03	0.04
A+	0.02	0.05
A	0.05	0.07
A-	0.03	0.09
BBB+	0.13	0.13
BBB	0.22	0.18
BBB-	0.29	0.31
BB+	0.57	0.53
BB	0.89	0.93
BB-	1.14	1.57
B+	2.66	2.64
B	8.46	4.46
B-	10.19	7.52

Sources: Historical one-year default rates, 1981–1999, are from Brand and Bahar (2000), 15; Oliver, Wyman & Company one-year default probabilities from FDIC (2000), 29.

Table 2

Comparison of Rating Calibrations with Moody's Historical Default Rates

Moody's Rating	Historical One-Year Default Rates, 1983–1999	Oliver, Wyman & Company One-Year Default Probability
Aaa	0.00%	0.01%
Aa1	0.00	0.02
Aa2	0.00	0.03
Aa3	0.07	0.04
A1	0.00	0.05
A2	0.00	0.07
A3	0.00	0.09
Baa1	0.04	0.13
Baa2	0.07	0.18
Baa3	0.31	0.34
Ba1	0.62	0.63
Ba2	0.53	1.21
Ba3	2.52	2.25
B1	3.46	4.21
B2	6.88	7.86
B3	12.23	12.95

Sources: Historical one-year default rates, 1983-1999, are from Keenan et al. (2000), 27; Oliver, Wyman & Company one-year default probabilities from FDIC (2000), 29.

Table 3

Descriptive Statistics for Baseline Simulations

Mean and Standard Deviation

Simulation	Number of Institutions	Exposure (Total Assets) (000 omitted)	Expected Default Frequency (EDF)	Severity	Bucket
BIF	8,638	$687,856	0.2575%	22.67%	24.41
		(9,207,674)	(0.00022)	(0.0302)	(1.10)
BIF with Oakar Adjustment	8,638	$637,120	0.2575	22.67	24.41
		(8,625,601)	(0.00022)	(0.0302)	(1.10)
BIF and SAIF Merged	9,990	$683,657	0.2581	22.57	24.37
		(8,733,580)	(0.00031)	(0.0311)	(1.08)

Note: Buckets are numbered 1 through 25.

Table 4

Rating Calibrations

Standard & Poor's Credit Rating	One-Year Default Probability	Moody's Credit Rating	One-Year Default Probability
AAA	0.01%	Aaa	0.01%
AA+	0.02	Aa1	0.02
AA	0.03	Aa2	0.03
AA-	0.04	Aa3	0.04
A+	0.05	A1	0.05
A	0.07	A2	0.07
A-	0.09	A3	0.09
BBB+	0.13	Baa1	0.13
BBB	0.18	Baa2	0.18
BBB-	0.31	Baa3	0.34
BB+	0.53	Ba1	0.63
BB	0.93	Ba2	1.21
BB-	1.57	Ba3	2.25
B+	2.64	B1	4.21
B	4.46	B2	7.86
B-	7.52	B3	12.95

Source: FDIC (2000), 29.
Note: The one-year default probabilities reflect the methodology of Oliver, Wyman & Company.

Table 5

Severity and the Standard Deviation of Severity

1986–1998

Asset Size	Number of Observations	Mean of Severity[a]	Standard Deviation of Severity[a]
Less than $100 million	967	24.18%	13.78
$100 million–$500 million	120	22.39	12.97
$500 million–$1 billion	15	16.46	10.60
$1–5 billion	22	12.79	8.45
Larger than $5 billion	9	8.75	6.93

Source: FDIC, *Failed Bank Cost Analysis*, 1986–1998, and consolidation of receiverships as performed by the FDIC Division of Finance.

[a] The mean and standard deviation of the loss as a percentage of assets for individual institutions within the asset size group.

Table 6

Size Distribution of BIF and SAIF Institutions in Sample

as of December 31, 1999

Asset Size	BIF	SAIF	Total
Less than $100 million	5,030	584	5,614
$100 million–$500 million	2,854	567	3,421
$500 million–$1 billion	334	89	423
$1–5 billion	283	87	370
Larger than $5 billion	137	25	162
Total	**8,638**	**1,352**	**9,990**

Table 7

Results from Baseline Simulations

BIF Only
(000 omitted)

	Baseline	**Baseline without Oakar Adjustment**	**Oliver, Wyman & Company Results[a]**
Expected Loss (EL)	$1,029,281	$1,081,123	$1,100,000
Unexpected Loss (UL)	$2,964,964	$3,122,898	$3,240,000
Solvency ($30 Billion)	99.82%	99.80%	99.81%
Solvency ($40 Billion)	99.91%	99.89%	n.a.
A Rating Solvency	$44,730,822	$47,679,389	$46,840,000
A- Rating Solvency	$40,281,094	$42,809,475	$42,760,000
BBB+ Rating Solvency	$33,966,694	$35,607,379	$35,210,000
BBB Rating Solvency	$30,126,141	$31,343,388	$30,840,000
BIF Balance 12/31/2000	$29,863,000	$29,863,000	$29,863,000

BIF and SAIF Merged
(000 omitted)

	Baseline	**Oliver, Wyman & Company Results[a]**
Expected Loss (EL)	$1,348,092	$1,360,000
Unexpected Loss (UL)	$3,967,074	$3,610,000
Solvency ($30 Billion)	99.74%	n.a.
Solvency ($40 Billion)	99.85%	99.87%
A Rating Solvency	$55,106,919	$51,320,000
A- Rating Solvency	$50,532,935	$45,560,000
BBB+ Rating Solvency	$42,725,025	$40,320,000
BBB Rating Solvency	$35,584,250	$35,270,000
BIF and SAIF Balance 12/31/2000	$40,591,000	$40,591,000

[a] A*nalyzing Policy Options for Deposit Insurance Reform: Phase II* (Oliver, Wyman & Company, LLC, September 2000), 16.

Table 8

Comparison of Expected Default Frequencies

BIF Only				
	Baseline	**Historical EDFs**	**Logit EDFs Only**	**S&P and Logit EDFs**
Expected Loss (EL)	$1,029,281	$1,639,147	$338,418	$347,866
Unexpected Loss (UL)	$2,964,964	$5,130,944	$2,317,682	$2,130,876
Solvency ($30 Billion)	99.82%	99.44%	99.87%	99.91%
Solvency ($40 Billion)	99.91%	99.67%	99.92%	99.95%
A Rating Solvency	$44,730,823	$76,840,452	$41,828,549	$35,811,218
A- Rating Solvency	$40,281,094	$71,624,047	$36,347,644	$30,155,487
BBB+ Rating Solvency	$33,966,695	$61,482,048	$29,501,005	$25,852,732
BBB Rating Solvency	$30,126,141	$52,226,188	$25,262,962	$20,920,374
BIF Balance 12/31/2000	$29,863,000	$29,863,000	$29,863,000	$29,863,000
Mean of EDF	0.2575%	0.2600%	0.0589%	0.0594%
Standard Deviation of EDF	0.00022	n.a.	0.000033	0.000033

BIF and SAIF Merged				
	Baseline	**Historical EDFs**	**Logit EDFs Only**	**S&P and Logit EDFs**
Expected Loss (EL)	$1,348,092	$2,033,287	$484,328	$527,947
Unexpected Loss (UL)	$3,967,074	$6,187,109	$3,214,885	$3,021,281
Solvency ($30 Billion)	99.74%	99.25%	99.82%	99.85%
Solvency ($40 Billion)	99.85%	99.56%	99.88%	99.91%
A Rating Solvency	$55,106,919	$92,763,008	$51,669,367	$43,733,125
A- Rating Solvency	$50,532,935	$83,345,074	$46,162,110	$38,577,392
BBB+ Rating Solvency	$42,725,025	$71,136,979	$36,902,057	$32,917,347
BBB Rating Solvency	$35,584,250	$60,994,320	$29,650,221	$26,548,098
BIF and SAIF Balance 12/31/2000	$40,591,000	$40,591,000	$40,591,000	$40,591,000
Mean of EDF	0.2581%	0.2600%	0.0708%	0.0717%
Standard Deviation of EDF	0.00031	n.a.	0.000125	0.000125

Table 9
Logistic Regression of the Incidence of Failure One Year Following Condition Measurement
(1984–1997 year-end Call Data)

Explanatory Variable	Coefficient Estimate (Standard Error)
Intercept	-6.6763 (0.2352)*
Equity plus loss reserves	-0.3847 (0.0140)*
Loans past due 30–89 days	0.1321 (0.0152)*
Loans past due 90 days or more	0.1224 (0.0070)*
Gross loan charge-offs	-0.0507 (0.0121)*
Net income	-0.1961 (0.0097)*
Capital rating	0.1814 (0.0670)*
Asset rating	0.2492 (0.0658)*
Management rating	0.3406 (0.0558)*
Earnings rating	0.0084 (0.0587)
Liquidity rating	0.3802 (0.0463)*
"Age" of examination data	0.6644 (0.0354)*
Pseudo R Squared = 57%	
Somers' D = 0.953	

* Significant at the 1% confidence level.

Table 10

Coverage of Market Data

BIF Only

	Total	S&P and Moody's Baseline	Long-Term Deposit Ratings	KMV EDFs	KMV S&P Ratings
Number	8,638	123	92	107	91
Total Oakar Adjusted Assets (000 omitted)	$5,941,700,000				
Percent of Total Oakar Adjusted Assets		65.46%	55.13%	55.07%	52.72%
Total Deposits (000 omitted)	$3,964,400,000				
Percent of Total Deposits		63.99%	53.75%	53.24%	56.06%
Total Insured Deposits (000 omitted)	$2,361,800,000				
Percent of Total Insured Deposits		55.85%	47.87%	51.15%	48.40%

BIF and SAIF Merged

	Total	S&P and Moody's Baseline	Long-Term Deposit Ratings	KMV EDFs	KMV S&P Ratings
Number	9,990	146	106	119	103
Total Assets (000 omitted)	$6,829,700,000				
Percent of Total Assets		63.35%	51.23%	51.94%	54.30%
Total Deposits (000 omitted)	$4,506,300,000				
Percent of Total Deposits		61.36%	50.00%	50.06%	52.54%
Total Insured Deposits (000 omitted)	$2,849,000,000				
Percent of Total Insured Deposits		53.42%	43.45%	47.00%	44.73%

Table 11

Comparison of Market Information

BIF Only				
	Baseline	**EDFS from Deposit Ratings**	**EDFs from KMV**	**KMV S&P Ratings**
Expected Loss (EL)	$1,029,281	$1,130,759	$3,241,537	$1,135,890
Unexpected Loss (UL)	$2,964,964	$3,469,460	$8,531,030	$3,178,776
Solvency ($30 Billion)	99.82%	99.71%	98.43%	99.80%
Solvency ($40 Billion)	99.91%	99.84%	99.04%	99.90%
A Rating Solvency	$44,730,823	$52,669,028	$117,729,928	$48,847,790
A- Rating Solvency	$40,281,094	$50,391,163	$106,984,102	$43,513,512
BBB+ Rating Solvency	$33,966,695	$43,999,126	$93,874,997	$35,844,012
BBB Rating Solvency	$30,126,141	$37,368,571	$84,026,021	$31,238,261
BIF Balance 12/31/2000	$29,863,000	$29,863,000	$29,863,000	$29,863,000
Mean of EDF	0.2575%	0.2581%	0.2680%	0.2583%
Standard Deviation of EDF	0.00022	0.00019	0.00095	0.00018

BIF and SAIF Merged				
	Baseline	**EDFs from Deposit Ratings**	**EDFs from KMV**	**KMV S&P Ratings**
Expected Loss (EL)	$1,348,092	$1,422,982	$4,036,797	$1,478,630
Unexpected Loss (UL)	$3,967,074	$4,216,838	$10,095,162	$4,229,332
Solvency ($30 Billion)	99.74%	99.66%	97.85%	99.71%
Solvency ($40 Billion)	99.85%	99.84%	98.66%	99.83%
A Rating Solvency	$55,106,919	$57,845,132	$133,540,821.19	$57,571,691
A- Rating Solvency	$50,532,935	$52,406,777	$127,289,519.36	$52,606,527
BBB+ Rating Solvency	$42,725,025	$44,213,931	$111,200,218.98	$46,444,241
BBB Rating Solvency	$35,584,250	$38,751,914	$99,452,835.69	$39,008,221
BIF and SAIF Balance 12/31/2000	$40,591,000	$40,591,000	$40,591,000	$40,591,000
Mean of EDF	0.2581%	0.2584%	0.2677%	0.2586%
Standard Deviation of EDF	0.00031	0.00032	0.00093	0.00019

Table 12

Severity

Mean, Standard Deviation, and Number of Observations

Asset Size Group	1986–1998	1990–1998	1986–1989	1990–1993	1986–1989 and 1990–1993
Less than $100 Million	24.18%	20.30%	26.28%	20.37%	24.28%
	(13.78)	(12.17)	(14.15)	(12.21)	(13.81)
	n = 967	n = 339	n = 628	n = 322	n = 950
$100 Mil.–$500 Mil.	22.39%	20.23%	26.70%	20.67%	22.89%
	(12.97)	(12.33)	(13.29)	(12.21)	(12.85)
	n = 120	n = 80	n = 40	n = 69	n = 109
$500 Mil.–$1 Bil.	16.46%	17.96%	14.21%	17.96%	16.46%
	(10.59)	(10.18)	(11.76)	(10.18)	(10.59)
	n = 15	n = 9	n = 6	n = 9	n = 15
$1–$5 Billion	12.79%	12.20%	14.81%	12.20%	12.79%
	(8.45)	(8.19)	(10.02)	(8.19)	(8.45)
	n = 22	n = 17	n = 5	n = 17	n = 22
Larger than $5 Billion	8.75%	4.43%	14.15%	4.43%	8.75%
	(6.93)	(4.91)	(5.10)	(4.91)	(6.93)
	n = 9	n = 5	n = 4	n = 5	n = 9
All Size Groups	23.55%	19.75%	26.05%	19.85%	23.68%
	(13.71)	(12.15)	(14.11)	(12.16)	(13.73)
	n = 1,133	n = 450	n = 683	n = 422	n = 1,105

Source: FDIC, *Failed Bank Cost Analysis*, 1986–1998.
Note: Severity is defined as the loss to the FDIC as a percentage of total assets at failure.

Table 13

Comparison of Severity

BIF Only

	Baseline	1990–1998 FBCA Loss	1986–1989 FBCA Loss	1990–1993 FBCA Loss	1986–1989, 1990–1993 FBCA
Expected Loss (EL)	$1,029,281	$831,740	$1,304,806	$838,685	$1,037,303
Unexpected Loss (UL)	$2,964,964	$2,043,576	$4,097,239	$2,054,773	$2,976,544
Solvency ($30 Billion)	99.82%	99.94%	99.63%	99.93%	99.81%
Solvency ($40 Billion)	99.91%	99.98%	99.78%	99.98%	99.91%
A Rating Solvency	$44,730,823	$29,088,866	$68,411,002	$29,267,814	$44,890,290
A- Rating Solvency	$40,281,094	$26,273,941	$61,286,866	$26,469,106	$40,302,622
BBB+ Rating Solvency	$33,966,695	$22,930,585	$51,332,350	$23,005,923	$34,148,599
BBB Rating Solvency	$30,126,141	$19,322,538	$43,805,777	$19,489,892	$30,189,626
BIF Balance 12/31/2000	$29,893,000	$29,893,000	$29,893,000	$29,893,000	$29,893,000
Mean of Severity	22.67%	19.67%	25.38%	19.86%	22.90%
Standard Deviation of Severity	0.0302	0.0244	0.0340	0.0249	0.0304

BIF and SAIF Merged

	Baseline	1990–1998 FBCA Loss Rates	1986–1989 FBCA Loss Rates	1990–1993 FBCA Loss Rates	1986–1989, 1990–1993 FBCA Loss Rates
Expected Loss (EL)	$1,348,092	$1,088,398	$1,698,828	$1,096,962	$1,357,969
Unexpected Loss (UL)	$3,967,074	$2,770,582	$5,185,556	$2,783,737	$3,980,995
Solvency ($30 Billion)	99.74%	99.89%	99.52%	99.89%	99.74%
Solvency ($40 Billion)	99.85%	99.94%	99.71%	99.94%	99.85%
A Rating Solvency	$55,106,919	$36,864,877	$80,947,302	$37,071,417.38	$55,197,745
A- Rating Solvency	$50,532,935	$33,439,131	$67,808,472	$33,504,511.09	$50,812,284
BBB+ Rating Solvency	$42,725,025	$28,069,456	$57,599,839	$28,284,784.95	$42,855,240
BBB Rating Solvency	$35,584,250	$24,261,820	$49,431,794	$24,403,095.26	$35,650,181
BIF and SAIF Balance 12/31/2000	$40,591,000	$40,591,000	$40,591,000	$40,591,000	$40,591,000
Mean of Severity	22.57%	19.62%	25.29%	19.81%	22.80%
Standard Deviation of Severity	0.0312	0.0251	0.0354	0.0256	0.0318

Table 14

Comparison of Bucketing Techniques

BIF Only					
	Baseline	**25 Equal-Sized Buckets**	**Size and Region Buckets**	**Region and CAMELS Group**	**Size and CAMELS Group**
Expected Loss (EL)	$1,029,281	$1,022,313	$1,021,277	$1,018,609	n.a.
Unexpected Loss (UL)	$2,964,964	$2,850,705	$2,904,048	$2,672,266	n.a.
Solvency ($30 Billion)	99.82%	99.85%	99.85%	99.86%	n.a.
Solvency ($40 Billion)	99.91%	99.94%	99.92%	99.94%	n.a.
A Rating Solvency	$44,730,823	$37,928,519	$41,120,109	$38,270,777	n.a.
A- Rating Solvency	$40,281,094	$34,607,657	$37,073,875	$36,126,245	n.a.
BBB+ Rating Solvency	$33,966,695	$31,726,703	$32,072,389	$30,502,680	n.a.
BBB Rating Solvency	$30,126,141	$27,567,381	$28,096,159	$26,438,022	n.a.
BIF Balance 12/31/2000	$29,863,000	$29,863,000	$29,863,000	$29,863,000	$29,863,000
BIF and SAIF Merged					
	Baseline	**25 Equal-Sized Buckets**	**Size and Region Buckets**	**Region and CAMELS Group**	**Size and CAMELS Group**
Expected Loss (EL)	$1,348,092	$1,358,606	$1,318,140	$1,322,520	$1,340,016
Unexpected Loss (UL)	$3,967,074	$4,112,536	$3,332,633	$3,147,276	$3,487,437
Solvency ($30 Billion)	99.74%	99.81%	99.82%	99.83%	99.77%
Solvency ($40 Billion)	99.85%	99.90%	99.91%	99.92%	99.87%
A Rating Solvency	$55,106,919	$50,094,404	$43,968,687	$42,337,006	$50,223,083
A- Rating Solvency	$50,532,935	$41,029,174	$41,190,330	$38,340,234	$45,683,066
BBB+ Rating Solvency	$42,725,025	$35,556,210	$34,266,907	$33,966,022	$39,383,483
BBB Rating Solvency	$35,584,250	$30,349,565	$30,445,176	$29,523,589	$33,645,466
BIF and SAIF Balance 12/31/2000	$40,591,000	$40,591,000	$40,591,000	$40,591,000	$40,591,000

Table 14 (continued)

Comparison of Bucketing Techniques

BIF Only

	Baseline	**Specialized Lender and Region**
Expected Loss (EL)	$1,029,281	$1,011,899
Unexpected Loss (UL)	$2,964,964	$2,669,365
Solvency ($30 Billion)	99.82%	99.88%
Solvency ($40 Billion)	99.91%	99.93%
A Rating Solvency	$44,730,823	$39,197,578
A- Rating Solvency	$40,281,094	$33,656,518
BBB+ Rating Solvency	$33,966,695	$28,535,282
BBB Rating Solvency	$30,126,141	$25,375,685
BIF Balance 12/31/2000	$29,863,000	$29,863,000

BIF and SAIF Merged

	Baseline	**Specialized Lender and Region**
Expected Loss (EL)	$1,348,092	$1,342,231
Unexpected Loss (UL)	$3,967,074	$3,425,842
Solvency ($30 Billion)	99.74%	99.79%
Solvency ($40 Billion)	99.85%	99.89%
A Rating Solvency	$55,106,919	$46,895,982
A- Rating Solvency	$50,532,935	$42,561,018
BBB+ Rating Solvency	$42,725,025	$37,820,884
BBB Rating Solvency	$35,584,250	$33,177,356
BIF and SAIF Balance 12/31/2000	$40,591,000	$40,591,000

Table 15

Size and Region Buckets

BIF Institutions

	Northeast	Southeast	Central and Midwest	Southwest	West	Total
Less than $100 Million	213	673	2,757	944	443	**5,030**
$100–$500 Million	490	565	1,045	422	332	**2,854**
$500 Mil.–$1 Billion	92	49	111	37	45	**334**
$1–$5 Billion	97	45	65	21	55	**283**
More than $5 Billion	45	27	37	10	18	**137**
Total	**937**	**1,359**	**4,015**	**1,434**	**893**	**8,638**

BIF and SAIF Institutions

	Northeast	Southeast	Central and Midwest	Southwest	West	Total
Less than $100 Million	341	777	3,027	1,003	466	**5,614**
$100–$500 Million	641	666	1,275	460	379	**3,421**
$500 Mil.–$1 Billion	115	67	138	42	61	**423**
$1–$5 Billion	120	60	91	29	70	**370**
More than $5 Billion	47	29	46	13	27	**162**
Total	**1,264**	**1,599**	**4,577**	**1,547**	**1,003**	**9,990**

Note: The Northeast region includes the following states: Connecticut, Delaware, District of Columbia, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont. The Southeast region includes the following states: Alabama, Florida, Georgia, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia. The Central and Midwest region includes the following states: Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. The Southwest region includes the following states: Arkansas, Louisiana, New Mexico, Oklahoma, and Texas. The West includes the following states: Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, Nevada, Oregon, Utah, Washington, and Wyoming.

Table 16

CAMELS Group and Region Buckets

BIF Institutions

	Northeast	Southeast	Central and Midwest	Southwest	West	Total
CAMELS 1s	433	498	1,837	713	280	**3,761**
Strong 2s	406	699	1,804	562	470	**3,941**
Weak 2s	51	81	214	63	72	**481**
Strong 3s	30	56	123	62	50	**321**
Weak 3s, 4s and 5s	17	25	37	34	21	**134**
Total	**937**	**1,359**	**4,015**	**1,434**	**893**	**8,638**

BIF and SAIF Institutions

	Northeast	Southeast	Central and Midwest	Southwest	West	Total
CAMELS 1s	556	584	2,072	754	308	**4,274**
Strong 2s	567	814	2,047	617	529	**4,574**
Weak 2s	72	97	248	65	78	**560**
Strong 3s	47	71	161	70	63	**412**
Weak 3s, 4s and 5s	22	33	49	41	25	**170**
Total	**1,264**	**1,599**	**4,577**	**1,547**	**1,003**	**9,990**

Table 17

CAMELS Group and Size Buckets

BIF and SAIF Institutions						
	Less than $100 Million	**$100 Mill– $500 Mill**	**$500 Mill– $1 Bill**	**$1 Bill– $3 Bill**	**More than $3 Bill**	**Total**
CAMELS 1s	2,208	1,603	219	143	101	**4,274**
Strong 2s	2,671	1,482	176	134	111	**4,574**
Weak 2s	352	174	15	15	4	**560**
Strong 3s	263	124	7	11	7	**412**
Weak 3s, 4s and 5s	120	38	6	5	1	**170**
Total	**5,614**	**3,421**	**423**	**308**	**224**	9,990

Table 18

Asset Concentration and Region Buckets

BIF Institutions						
	Northeast	Southeast	Central and Midwest	Southwest	West	Total
Agricultural Bank	1	55	1,608	304	125	2,093
Consumer Lender	48	72	139	25	33	317
Commercial Lender	361	774	1,199	491	588	3,413
Mortgage Lender	246	28	86	26	27	413
Multinational Bank	7	n.a.	1	n.a.	n.a.	8
Other Large Lenders	n.a.	n.a.	n.a.	n.a.	n.a.	80
Other Small Specialized Lenders	n.a.	n.a.	n.a.	n.a.	n.a.	464
Other Small Institutions	n.a.	n.a.	n.a.	n.a.	n.a.	1,850

BIF and SAIF Institutions						
	Northeast	Southeast	Central and Midwest	Southwest	West	Total
Agricultural Bank	1	55	1,613	307	125	2,101
Consumer Lender	54	81	156	32	37	360
Commercial Lender	392	845	1,297	512	638	3,684
Mortgage Lender	509	166	493	96	78	1,342
Multinational Bank	7	n.a.	1	n.a.	n.a.	8
Other Large Lenders	n.a.	n.a.	n.a.	n.a.	n.a.	86
Other Small Specialized Lenders	n.a.	n.a.	n.a.	n.a.	n.a.	487
Other Small Institutions	n.a.	n.a.	n.a.	n.a.	n.a.	1,922

Figure 1
Credit Loss Distribution

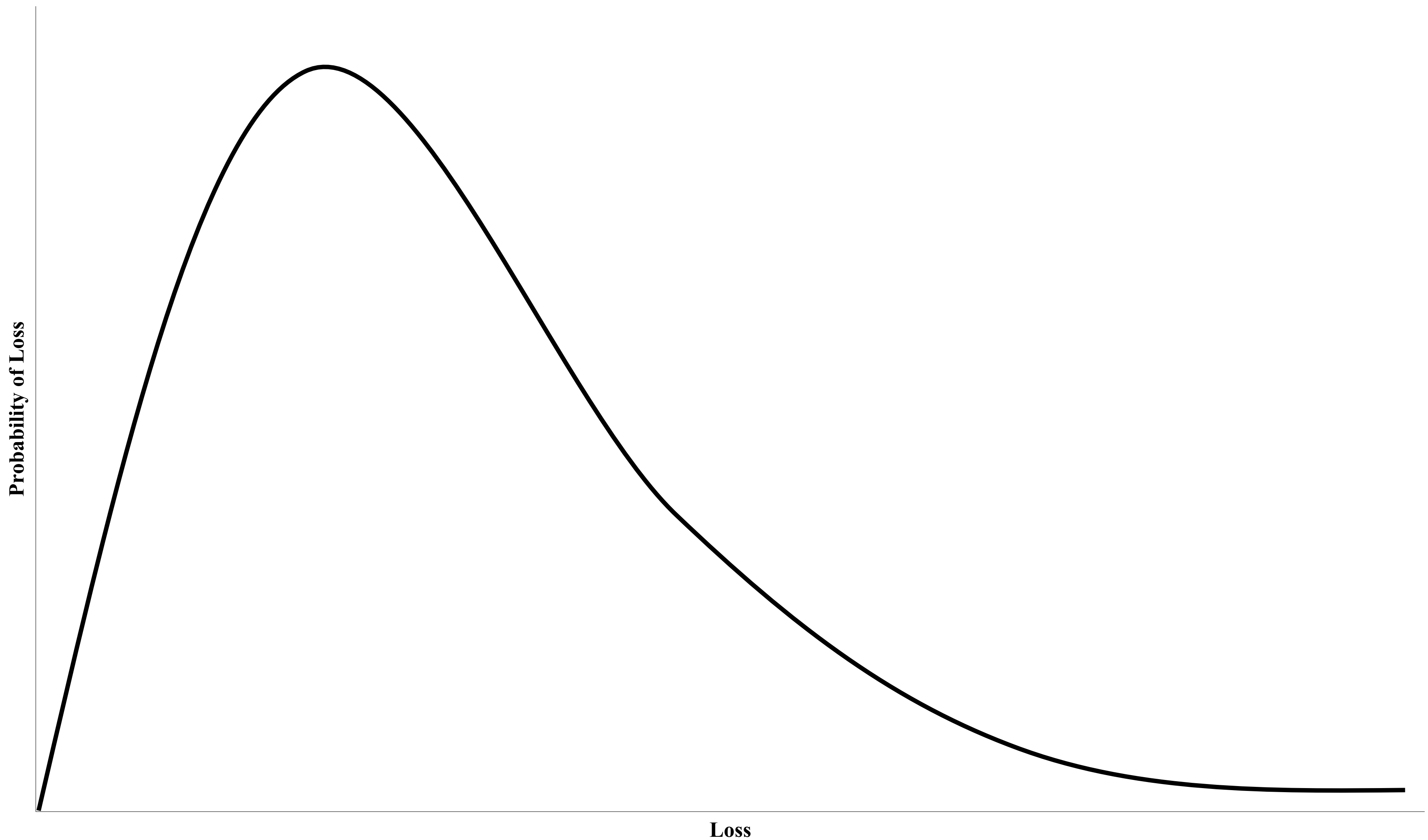

Figure 2
Baseline Simulations
BIF

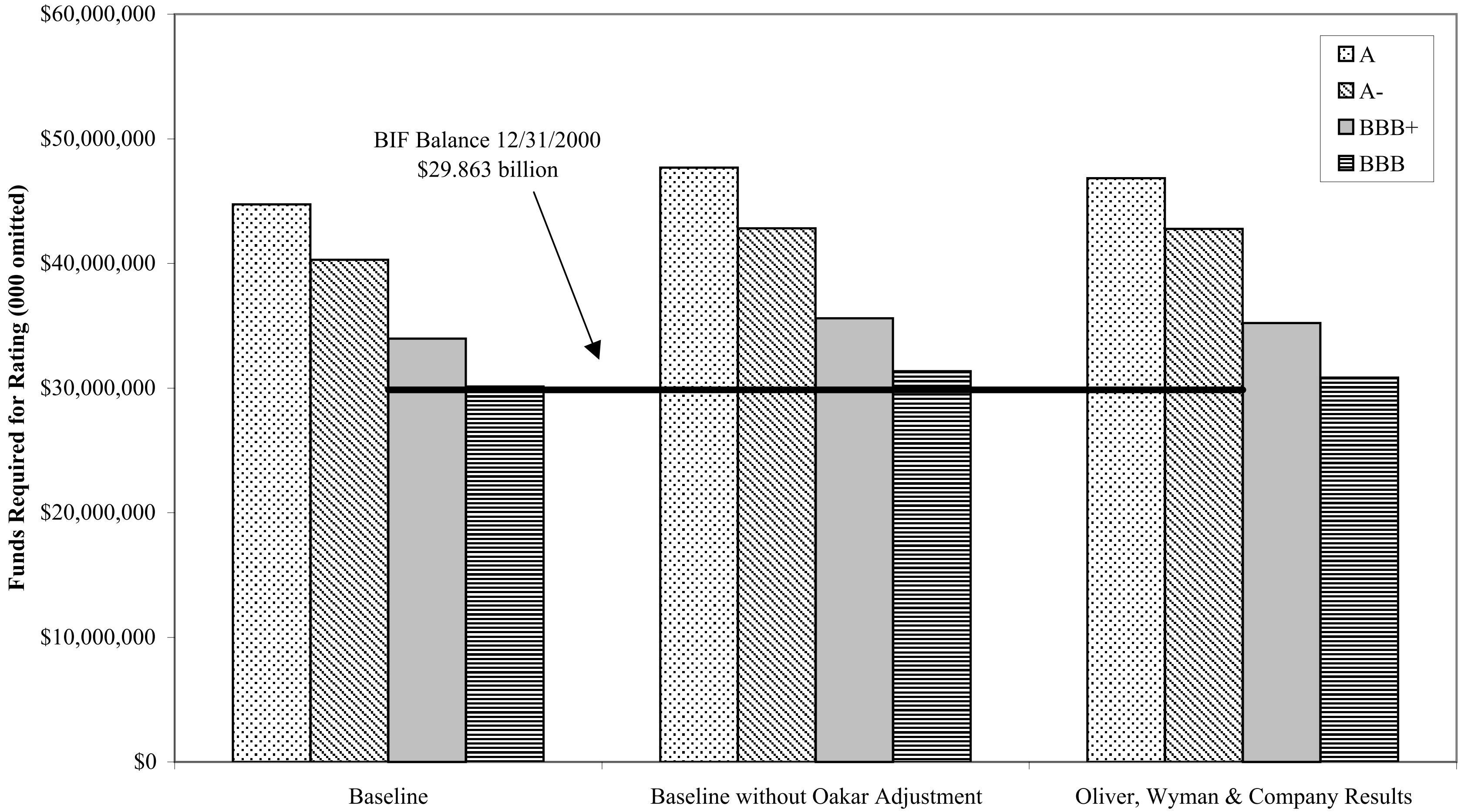

Figure 3
Baseline Simulations
BIF and SAIF Merged

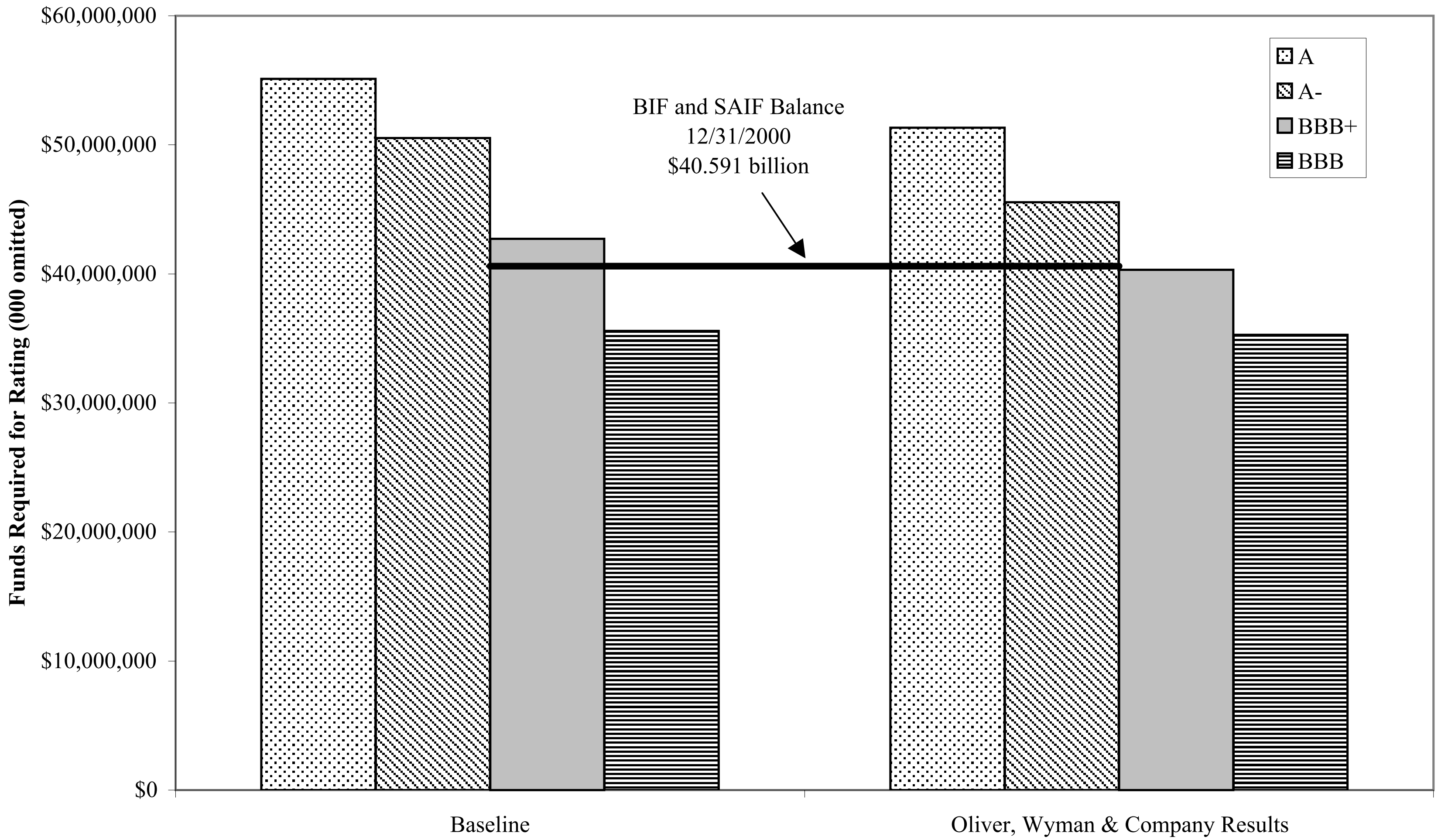

Figure 4
Sensitivity Analysis: Expected Default Frequencies
BIF

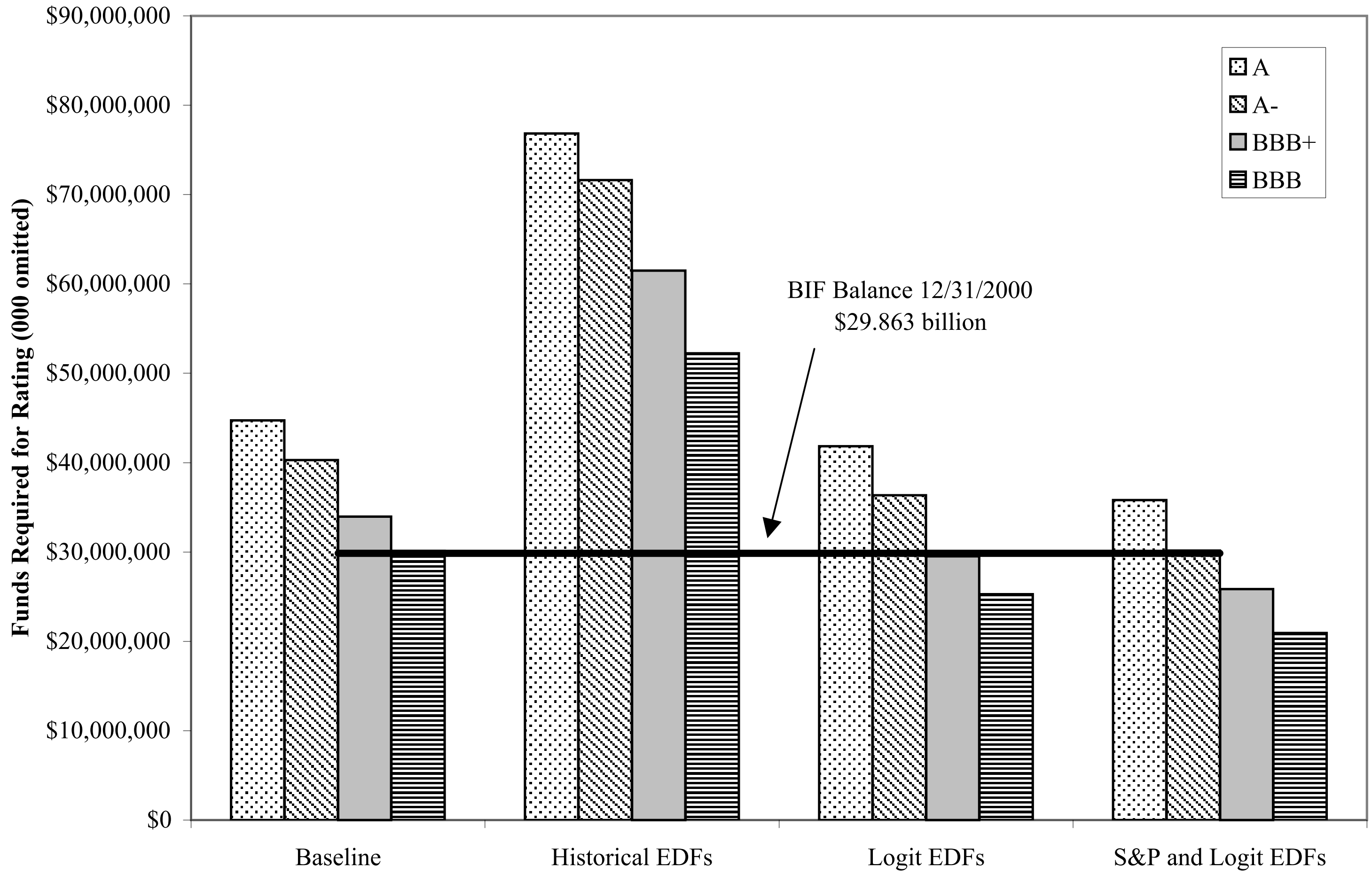

Figure 5
Sensitivity Analysis: Expected Default Frequencies
BIF and SAIF Merged

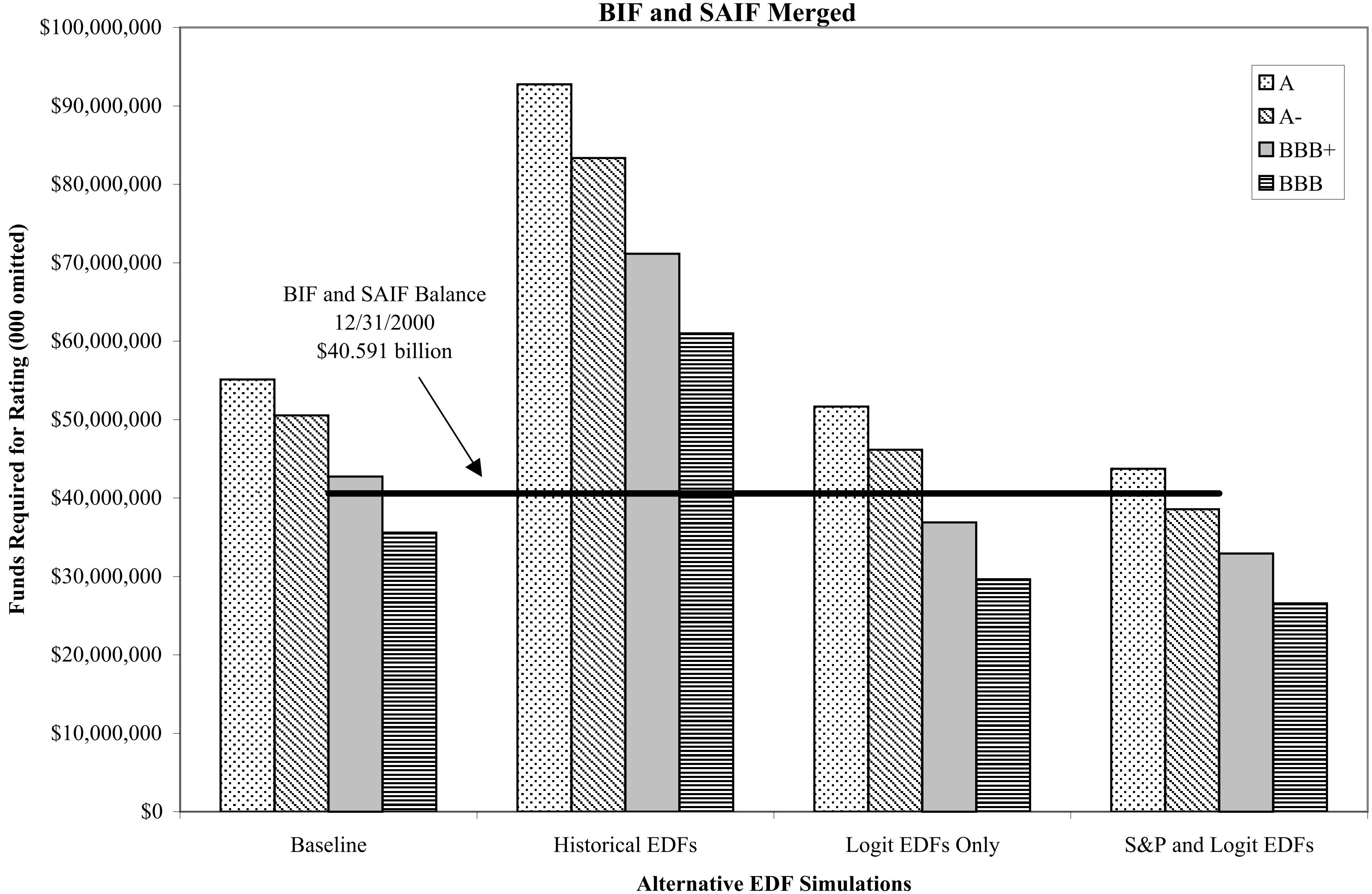

Figure 6
Sensitivity Analysis: EDFs from Market Information
BIF

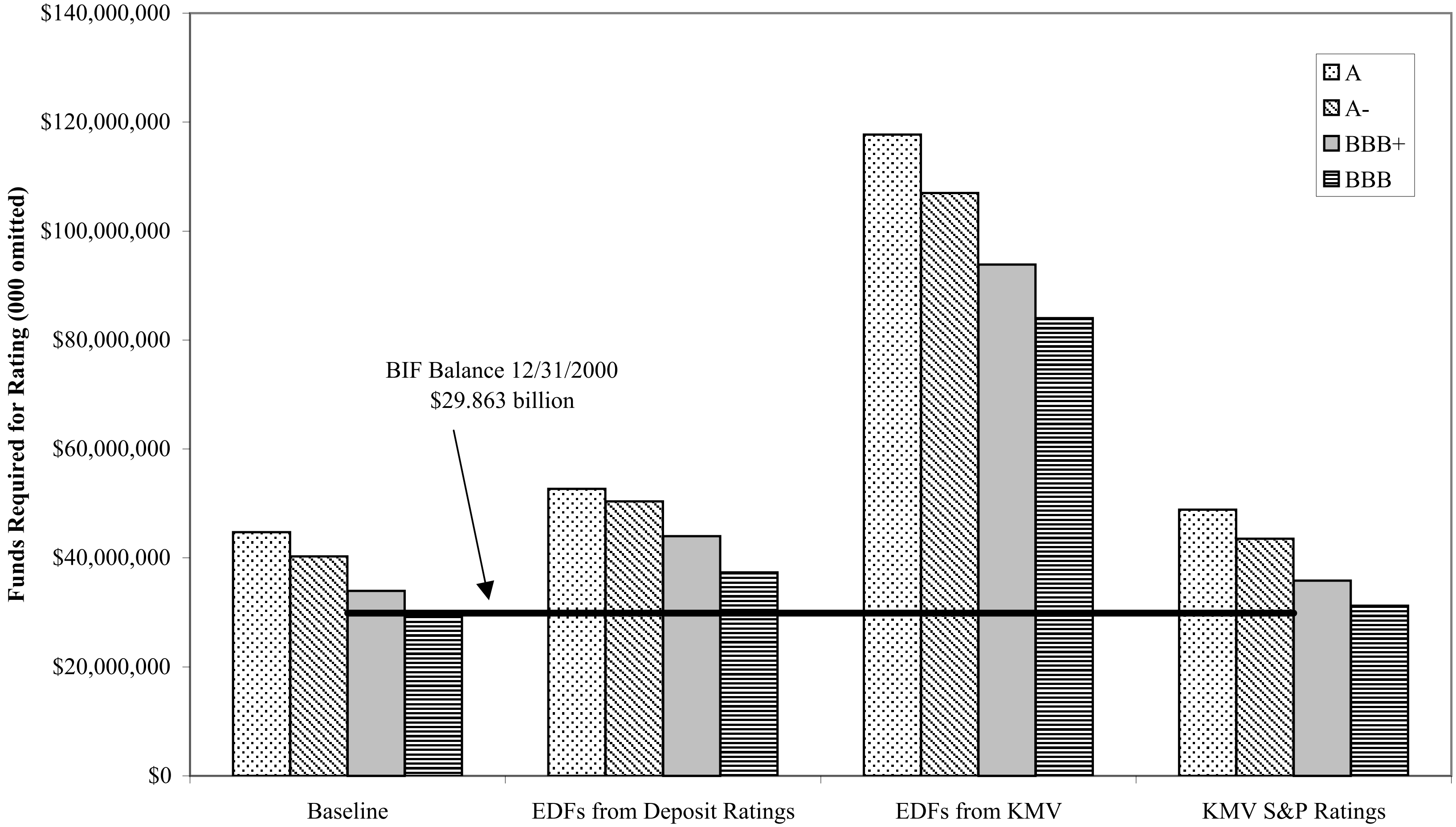

Figure 7
Sensitivity Analysis: EDFs from Market Information
BIF and SAIF Merged

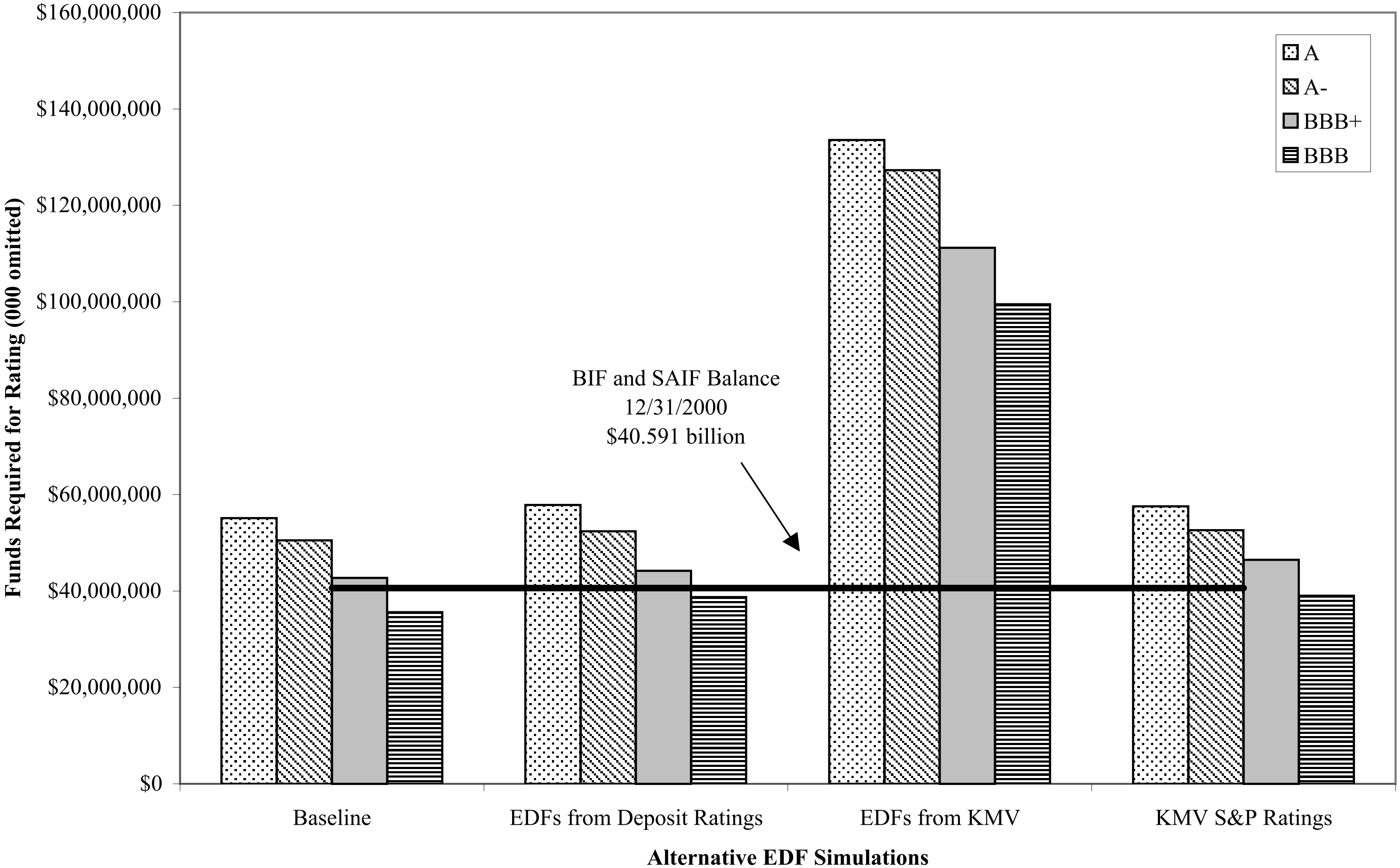

Figure 8
Sensitivity Analysis: Severity
BIF

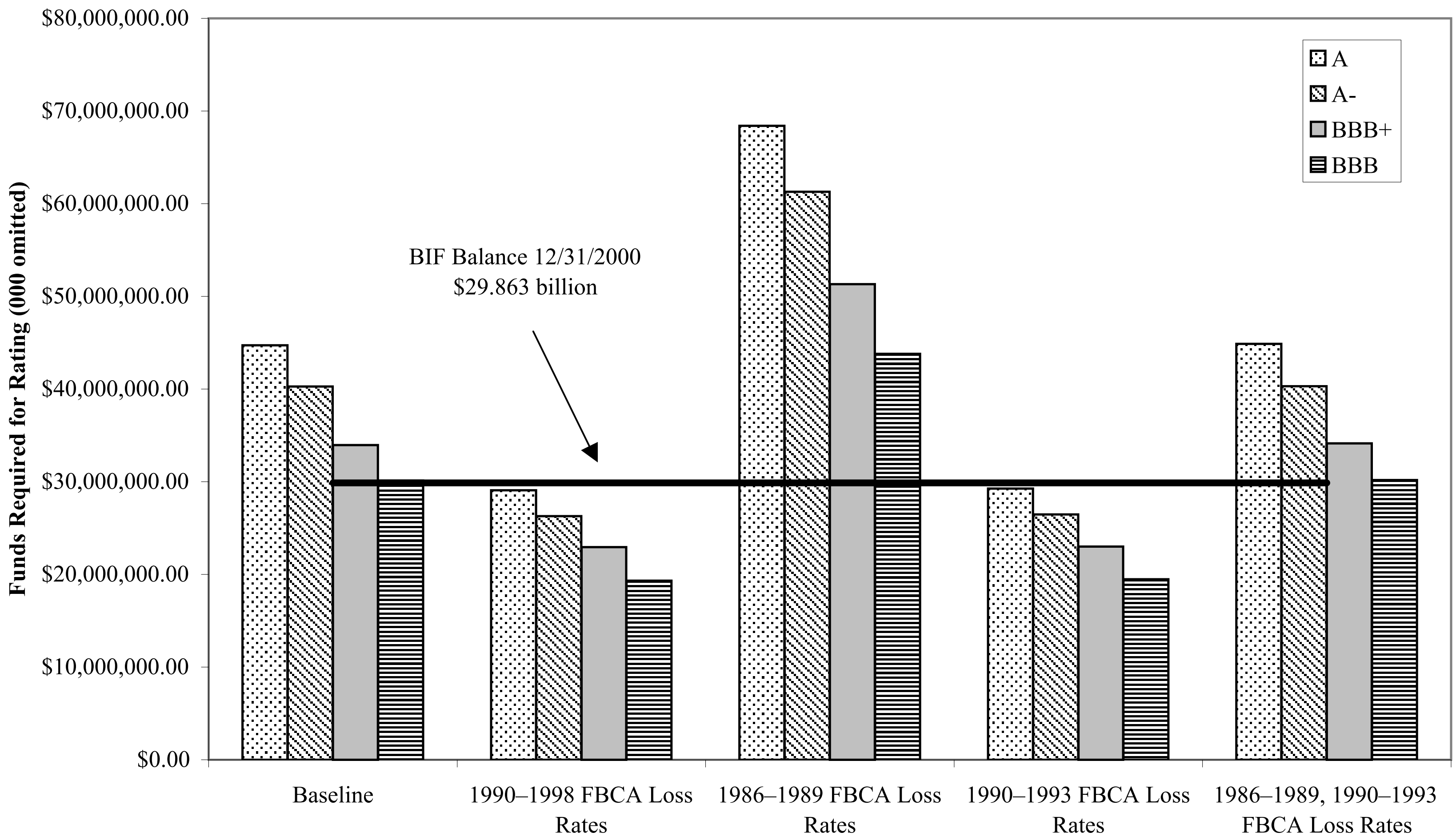

Figure 9
Sensitivity Analysis: Severity
BIF and SAIF Merged

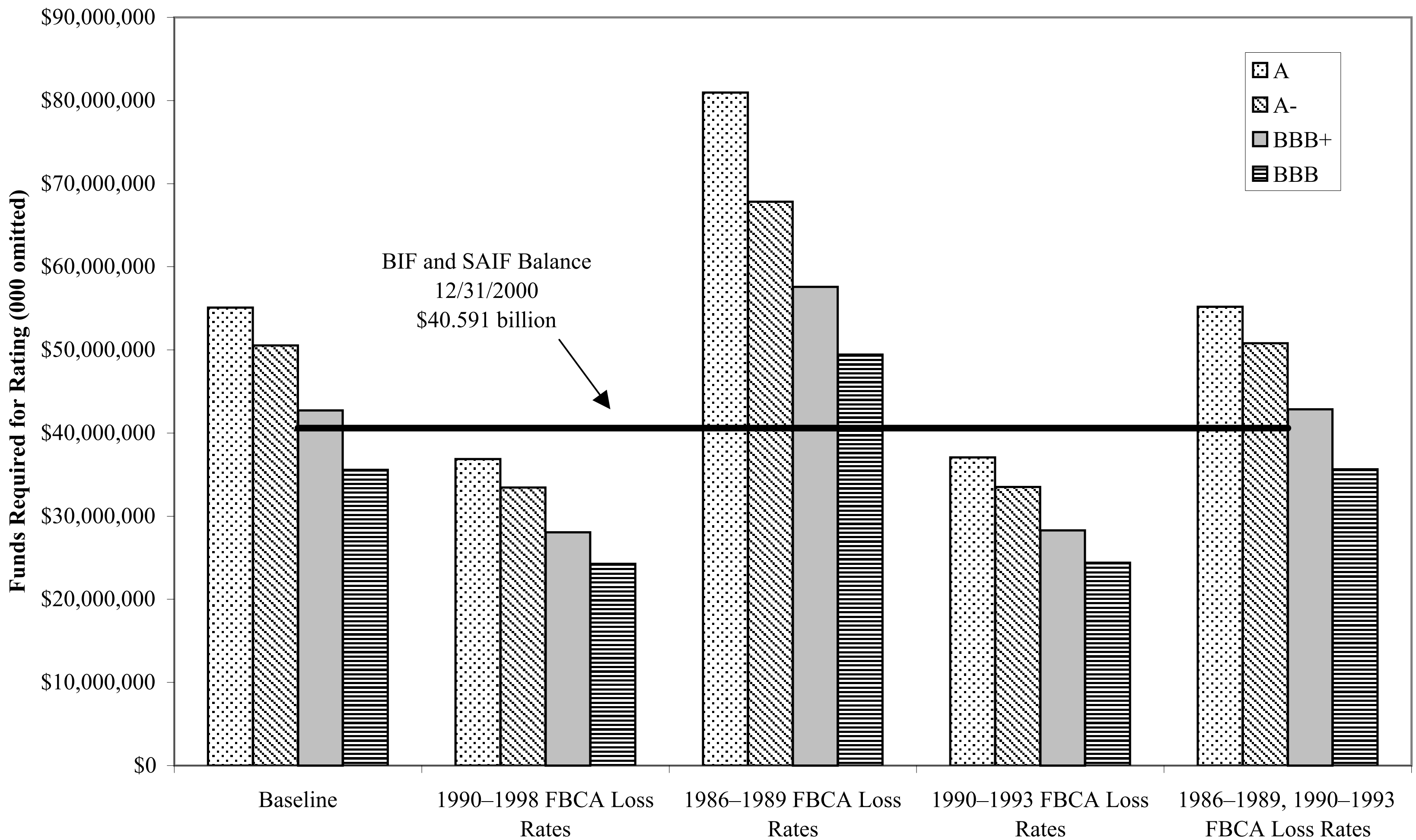

Figure 10
Sensitivity Analysis: Bucketing
BIF

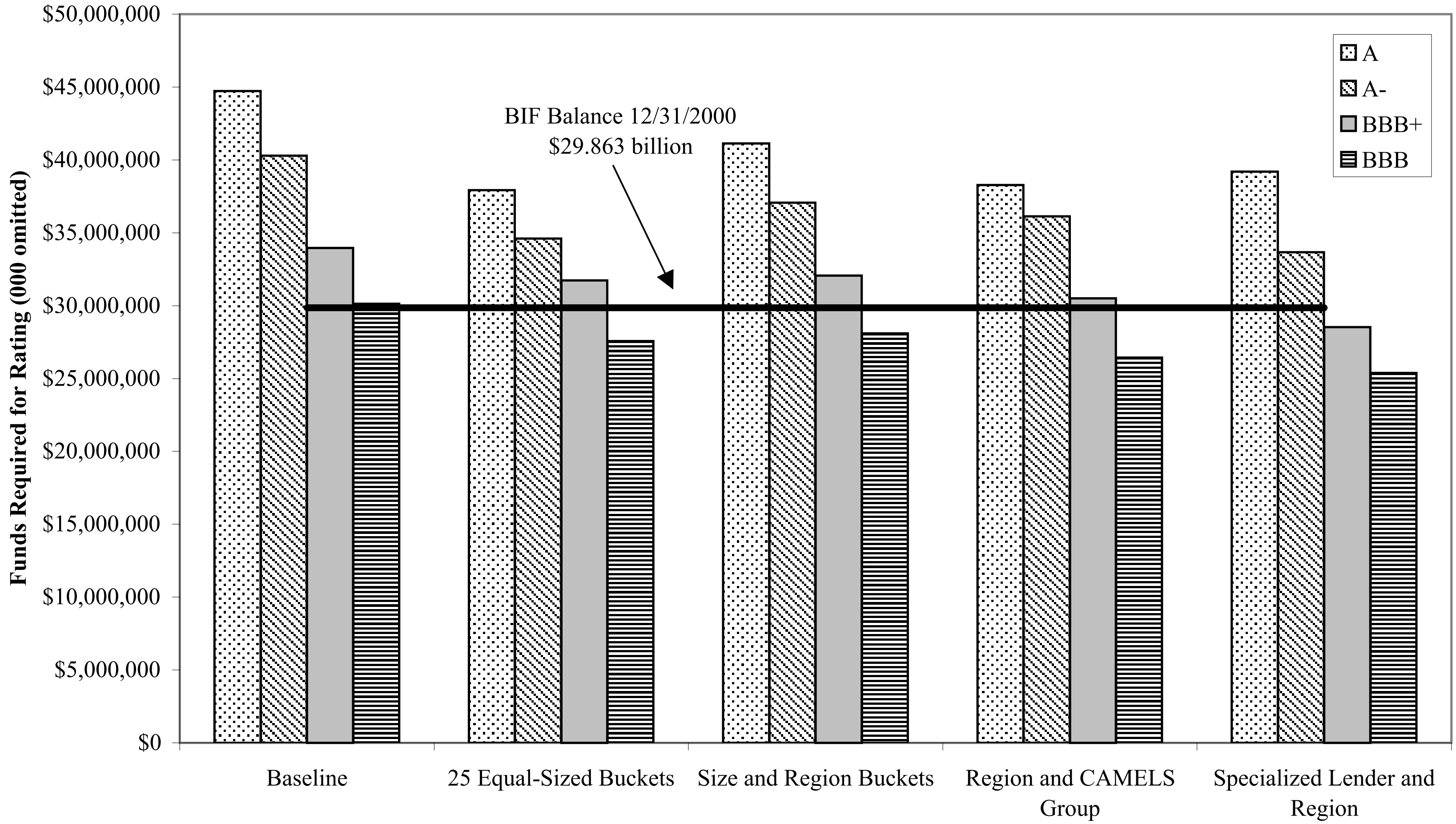

Figure 11
Sensitivity Analysis: Bucketing
BIF and SAIF Merged