Capital Ratios and Credit Ratings as Predictors of Bank Failures

Arturo Estrella, Sangkyun Park, and Stavros Peristiani*

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Abstract

We examine the power of various capital ratios — scaled by total assets, risk-weighted assets and gross revenues — to forecast U.S. bank failures. Capital ratios are the centerpiece of the 1988 Basel Accord, and various ratios are currently under consideration in Basel in connection with one of the three "pillars" of a more comprehensive approach to capital adequacy. Using data for the period 1988-1993, which included a relatively large number of failures, we conclude that all three ratios we examine are very significant predictors of failure, and that the simple ratios are about as strong as the more complex risk-weighted measure. Simpler ratios are less costly and may be more broadly applicable than risk-weighted ratios. We also compare the performance of credit ratings as predictors of failure, since credit ratings have a formal role in current regulation, and since the information they provide is correlated with that provided by capital ratios. The number of failed banks with ratings is very small, and evidence in favor of ratings is somewhat mixed.

ARTURO ESTRELLA is a senior vice president in the Capital Markets Function of the Federal Reserve Bank of New York. SANGKYUN PARK is an economist at the Office of Management and Budget. STAVROS PERISTIANI is a research officer in the Capital Markets Function of the Federal Reserve Bank of New York.

*Corresponding author: Federal Reserve Bank of New York, 33 Liberty Street, New York, NY 10045, phone 212-720-7829, e-mail steve.peristiani@ny.frb.org.

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1. Introduction

Capital ratios have long been a valuable tool for bank regulators and supervisors, as well as for bank analysts in general. The history of the informal use of ratios goes back well over a century, as indicated, for instance, by Mitchell (1909). In the United States, minimum capital ratios have been required in banking regulation since 1981, and the Basel Accord has applied capital ratio requirements to banks internationally since 1988. At this moment, the Basel Committee on Banking Supervision (1999) is engaged in an effort to improve the Basel Accord and, once again, capital ratios play an important role in the proposed solution. In this paper, we examine some of the various roles that capital ratios play in bank regulation and we argue that, to be successful in any of those roles, capital ratios should bear a significant negative relationship to the risk of subsequent bank failure. We then present empirical evidence of those relationships.

We focus here on three types of capital ratios – risk-weighted, leverage, and gross revenue ratios. For each ratio, we examine what makes it actually or potentially useful for bank regulation and we ask whether the ratios are indeed significantly related to subsequent bank failure. Perhaps not surprisingly, we find that all three ratios are strongly informative about subsequent failures. Perhaps somewhat surprisingly, we also find that more complex and sophisticated ratios do not necessarily perform better than the simple ones in this context and that the tradeoff between regulatory burden and predictive accuracy may not favor the complex ratios.

Since corporate credit ratings have also been traditionally viewed as indicators of bank failure, we compare the relative performance of credit ratings and capital ratios in the prediction of bank failures. Unfortunately, the proportion of banks with ratings is

relatively small and our data sample for this exercise is not very extensive. The available evidence is somewhat mixed, indicating that ratings sometimes outperform ratios, but that the opposite is also possible.

Before proceeding to the empirical evidence, we develop in the next section the conceptual arguments outlined above. The rest of this paper is organized as follows. In Section 3, we use empirical evidence on U.S. bank failures to evaluate the effectiveness of the three capital ratios in predicting bank failures. Section 4 examines how ratings provided by Standard and Poor's are related to capital ratios and to bank failures. Finally, the main findings of the paper are summarized in the last section.

2. The Role of Capital Ratios in Bank Analysis and Supervision

As noted earlier, bank regulators have relied on capital ratios formally or informally for a very long time. The motivation for their use, however, has not always been the same. For instance, in the days before explicit capital requirements, bank supervisors would use capital ratios as rules of thumb to obtain an independent gauge of the adequacy of the level of capital of an institution. There was no illusion that the simple ratios used (e.g., capital to total assets or deposits) could provide an accurate measure of the appropriate capital level for a bank, but large deviations of actual capital ratios from supervisory benchmarks were cause for further scrutiny.

When capital ratios were introduced formally in regulation in 1981 (see Gilbert, Stone, Trebing 1985), they were applied in a different way. The regulatory requirement set a minimum level of capital that the institution had to hold. Because, then as now, there was substantial diversity among banking institutions, the degree to which the requirement was binding depended significantly on the type of institution. Indeed, several

classes of institutions were initially defined and accorded different treatment by the regulation. Basically, the requirements were most binding for less than a couple of dozen large banks, whereas smaller banks tended to comply more readily with more stringent requirements. Eventually, the size distinctions were eliminated.

The Basel Accord of 1988 attempted to deal with the diversity in institutional activities by applying different credit risk weights to different positions and by including in the base for the capital ratio a measure of the off-balance sheet exposures of the bank. These calibrations notwithstanding, the intent was not to determine an exact appropriate level of capital for the bank, but rather to provide a more flexible way of determining the minimum required level (see Basel Committee on Banking Supervision 1988).

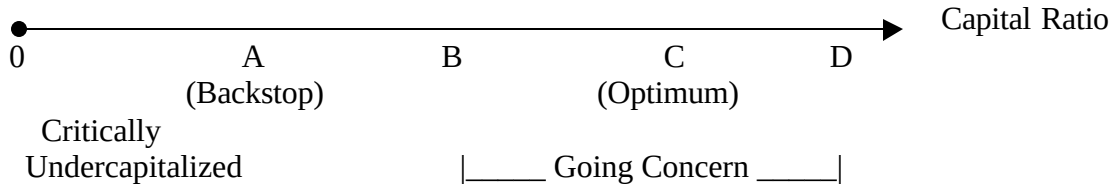
Another significant regulatory development in the U.S. was the Federal Deposit Insurance Corporation Improvement Act of 1991 (FDICIA), which introduced the concept of "prompt corrective action." The degree of supervisory intervention in specific banks is now determined by a formula largely driven by the Basel ratios and by a simple leverage ratio. Banks are now classified as "adequately capitalized" if they meet the Basel requirements, but new distinctions among levels of capital were introduced. For example, a bank is "well capitalized" if it holds a certain buffer above the "adequate" levels.

In contrast, a bank that falls under a specific level, set somewhat below the minimum "adequate" level, is determined to be "critically undercapitalized" and must be shut down by supervisors. This is a different concept of a minimum requirement from the one used in earlier regulation, in that failure to comply results in the closure of the institution. Rather than a minimum safe operating level, which the earlier rules had tried

to identify, the new cutoff point is a backstop level, below which the bank is no longer considered to be viable.

The preceding discussion alludes to a number of distinctions between approaches to benchmarks based on capital ratios, and it may be helpful to spell these out. For example, in some cases a ratio is intended as a minimum acceptable level, whereas in other cases there may be a desire to identify an appropriate level of capital for the bank. This distinction between a minimum and an "optimum" level is discussed in Estrella (1995).

Another distinction is between adequate levels and backstop levels, such as in the 1991 U.S. legislation. In one case, there is a certain level of comfort for bank supervisors, while in the other case the bank is no longer considered viable. Closely related is the distinction between the value of a bank in liquidation and as a going concern. For instance, one of the motivations for the 1991 legislation was that the net value of a bank tends to decrease when it goes from going concern to liquidation mode (see, e.g., Demsetz et al. 1996). Thus, the level of capital that is adequate for regulatory and supervisory purposes may differ between banks operating normally and banks in the process of liquidation. These distinctions are demonstrated in the following simple graph.



The "optimum" level, defined in various ways in economic research (C.f., Estrella 1995, Berger et al. 1995), is shown as point C in the graph. Theoretically, this is the level that

maximizes some objective function for bank owners, but in practice this exact level is very difficult to ascertain with any level of precision. Nevertheless, there is an informal range around this level, say from point B to point D, over which capital may be generally considered adequate for a going concern. That is, capital is high enough (above B) to allow regulators, shareholders, depositors, etc., to sleep at night, but not too high (below D) so that the total cost of capital to the firm is balanced against its benefits. Finally, point A identifies the backstop level at which the bank is no longer viable and must be shut down to prevent losses to depositors and to the public.

A. The Relationship Between Capital Ratios and Bank Failures

The relationship between the level of capital and subsequent failure is clear in the case of a backstop level as defined above. At this level, the bank is either a de facto failure, or is in imminent danger of falling into that category. Therefore, regulators must choose a backstop level that is highly correlated with failure in the very short run or, put differently, the level should be associated with a fairly high probability of failure. For various reasons, regulators will generally wish to select a positive level rather than the level of technical insolvency at which the net worth of the bank is zero.

One reason is that there is always some uncertainty regarding the valuation of the bank. There is no assurance that a bank that is liquidated will be valued at the accounting net worth, although this type of uncertainty could signify that the actual value of the bank could be either higher or lower than the accounting value. A second reason is that, for a going concern, there is generally a “charter value” – an intangible value that disappears with the closure of the institution. Hence, even if the accounting valuation were perfectly

accurate in the first sense, the mere liquidation of the institution could lead to a loss in net value.

This potential loss in the value of the firm in liquidation also helps explain why non-backstop capital levels should be significantly related to bank failure. The charter value of the bank produces a strong incentive to the owners of the bank to manage it as a going concern. If the bank fails, one consequence is the dissipation of charter value, which owners could otherwise capture if the institution were viable by selling their stake. Thus, owners have an interest in maintaining a level of capital that is consistent with a low probability of failure. Needless to say, regulators and supervisors also tend to favor low probabilities of failure.

To summarize, and referring once more to the diagram given above, the backstop level at point A corresponds to a fairly high probability of failure, but represents enough capital to deal with uncertainties with regard to the value of the firm in liquidation. In contrast, values above point B correspond to probabilities of failure that are sufficiently low to satisfy the requirements of owners, regulators, and others.

B. Useful Features of Capital Ratios

A capital ratio is constructed from two components. The numerator is a measure of the capital of the firm and is inversely related to the probability of failure. The denominator is a measure of the scale of the bank, and the taking of the ratio is necessary because one can only gauge whether capital is adequate in relation to some indicator of scale. At a very basic level, a large bank needs a larger amount of capital than a small bank, ceteris paribus. At another level, a riskier bank needs more capital than a less risky bank, ceteris paribus. It is clearly of first-order importance to capture the pure scale – the

size – of the bank in the denominator. It should also be helpful to adjust this pure scale for riskiness, if that can be done accurately. The ratios we examine in this paper represent various approaches to the scaling issue.

We will define the ratios more precisely in the next section, but we provide here some preliminary discussion of how they deal with scaling. Let us assume, as is the case in our empirical sections, that the numerator is the same measure of capital for all ratios, which allows us to focus on the alternative denominators. In the case of the leverage ratio, the denominator is the total assets of the bank. This measure, which has a long history, assumes implicitly that the capital needs of a bank are directly proportional to its level of assets. For some broad classes of banks, this may not be a bad assumption. However, if we take the example of two banks, only one of which has substantial and risky off-balance sheet activities, the use of the leverage ratio may produce misleading relative results.

A leverage ratio requirement may also affect the asset allocation of banks that are constrained by the requirement. Constrained banks are likely to reduce low-risk assets such as Treasury securities, which are easily marketable, as opposed to less marketable assets such as loans. Nevertheless, a clear advantage of the leverage ratio is simplicity. It is easy to calculate and fairly unambiguous. Thus, the administrative cost is low, and transparency is enhanced.

In 1988, the Basel Accord introduced the concept of risk-weighted assets as the denominator of the capital ratio. This measure contains a component representing off-balance sheet exposures and also adjusts for differentials in credit risk according to type

of counterparty and type of instrument. As such, the Basel ratio represents a well-known example of a risk adjustment to the basic scale of the denominator.

In theory, the risk-weighted ratio should reflect the riskiness of banks better than simple ratios. Inaccuracy is unavoidable, however. Because each loan is unique, it is difficult to evaluate the credit risk of bank assets. In addition, the business of banking is subject to significant sources of risk other than credit risk, such as interest rate risk, operational risk and reputational risk. Weighting assets can weaken the relationship between the capital ratio and these other risks, operational risk in particular.

Furthermore, the financial sector is so dynamic that new products are introduced continuously. Even a well-designed risk-weighting scheme may soon become obsolete as new instruments provide means of economizing on regulatory capital. Considering these difficulties, it is not certain a priori that the risk-based capital ratio is meaningfully superior to simple ratios in capturing the overall risk of banks. Regulatory capital arbitrage under risk-based capital requirements could even produce harmful economic effects. For instance, banks might be induced to reduce lending to risky borrowers who do not have alternative financing sources. Economic activity may contract as a result. Also, it is costly to administer risk-based capital requirements, especially since both monitoring and reporting burdens may be heavy.

Our third ratio uses the gross revenue of the bank as the measure of scale. Like total assets, gross revenue is easily obtainable from the financial statements of the firm. Unlike assets, however, gross revenue includes components associated with off-balance sheet activities. Moreover, gross revenue contains a crude “risk adjustment” in that riskier projects are likely to be undertaken only if they provide larger revenues, at least ex ante.

Thus, gross revenue may reflect the riskiness of bank assets better than total assets, though in principle not as well as risk-weighted assets.

A potential drawback is that gross revenue also captures factors other than risk. For example, banks engaging heavily in fee-generating activities, which may carry only a limited amount of risk, will report large revenue. Gross revenue may also be more sensitive to business cycles than total assets, although this is not entirely clear and is largely an empirical question. This measure has not been subjected to the test of actual usage, but gross revenue seems to be less susceptible to regulatory capital arbitrage than other measures. For instance, it may be difficult for banks to reduce gross revenue without hurting profits or general investor perceptions. As for simplicity, gross revenue is, like assets, a standard accounting concept. Thus, the gross revenue ratio is as simple and transparent as the leverage ratio.

C. Credit Ratings as an Alternative Risk Measure

We close this section with a word about credit ratings. In principle, credit ratings incorporate all risk factors that are perceived to be relevant by rating agencies. Thus, they can be regarded as a comprehensive measure of risk. Since the formula of credit ratings is not public, it seems difficult for banks to manipulate credit ratings. Moreover, credit ratings are simple because they have a one-dimensional scale and, from the perspective of regulators, credit ratings are cost-effective because they already exist for a number of banks. Despite these conceptual merits, the usefulness of credit ratings is unclear. Credit ratings are not entirely transparent. Some information is available, but the methods used for deriving ratings constitute a black box to outsiders. Furthermore, credit ratings may be influenced by the subjective judgements of a few analysts. The practical value of

credit ratings, therefore, is to a large extent an empirical question, to which we turn in a subsequent section.

3. Capital Ratios and The Likelihood of Failure

To analyze the predictive efficacy of capital ratios, our analysis utilizes standard measures defined by the existing capital adequacy rules. In the current regulatory framework, the risk-weighted capital ratio is defined as the ratio of tier 1 capital to risk-weighted assets. The definition of leverage ratio is tier 1 capital divided by total tangible assets (quarterly average). To ensure full compatibility, the gross revenue ratio uses again tier 1 capital in the numerator divided by gross revenue. The measure of tier 1 capital applied in the numerator of all three ratios includes common stock, common stock surplus, retained earnings, and some perpetual preferred stock. Gross revenue is total interest and noninterest income before deducting any expenses.

Our database includes all FDIC-insured commercial banks that failed or were in business between 1989 and 1993. The sample period ends in 1993 because for the most part there were just a handful of bank failures after this period. Because risk-weighted capital measures were not implemented and reported until after 1990, it is difficult to estimate meaningful risk-weighted ratios in the early and mid-1980s. To compute the various capital ratios, we used information from the Consolidated Reports of Condition and Income (Call Reports). The Federal Reserve Board provides a formal algorithm for calculating risk-weighted ratios for years 1991 and after. Risk-weighted capital ratios for years 1988, 1989, and 1990 were estimated based on the *Capital Adequacy Guidelines* published by the Federal Reserve Board.

Table 1 presents summary statistics for the three different measures of capital adequacy for the period 1988-92. Looking at the first panel of the table, we observe that the average and median leverage ratios for our sample of banks during this period are fairly stable around 9 and 8 percent, respectively. Since these statistics are based on unweighted ratios, they are influenced heavily by the large number of small banks that tend to have higher capital ratios. The average capital ratios weighted by assets are lower. The table also helps to highlight that the gross revenue measure varies more widely across years, reflecting its close relationship with economic conditions. Relatively high gross revenue ratios in 1991 and 1992 can be explained by reduced banking revenue caused by an economic downturn. Both the mean and the median of the risk-weighted capital ratio were substantially higher than the required ratio (4 percent). The standard deviation, however, was large, suggesting that many banks had difficulty in meeting the capital requirement.

[insert Table 1 here]

In Table 2, we present measures of correlation for all three capital adequacy ratios. While the Pearson correlation coefficients (top panel) are statistically significant, one may surmise from their magnitude that these capital measures are not consistently correlated over time. However, looking at bottom panel of the table, which shows large and significant rank correlation estimates, we conclude that most of the large fluctuations in the parametric measure of correlation are caused by the presence of outliers. Although the rank correlation is high, these capital ratios are far from perfectly correlated. Thus, each capital ratio may provide some independent information about capital adequacy.

[insert Table 2 here]

A. Distribution of Bank Failures

A good measure of capital adequacy should be related very closely with bank failures. The first phase of our analysis investigates this issue by looking at the distribution of bank failures with respect to the alternative capital ratios. Table 3 presents one-year bank failure rates for various levels of the leverage ratio at the end of the preceding year. The table tabulates all failed and surviving banks during the period of 1989-93. We excluded from the analysis all banks that were acquired during the period because a lot of these mergers involved problem target banks. In its final form, the data set is an unbalanced panel of banks, in which a bank is observed until the time of failure or until the end of 1993. To be specific, a bank that survived between 1989 and 1993 is counted five tines as a nonfailure, and a bank that failed in 1991 is counted twice as a nonfailure (1989 and 1990) and once as a failure (1991). In section 3.B., we will also present a parametric model of survival that gives a more precise account of the conditional distribution of failure.

[insert Table 3 and Table 3a here]

In Panel A, we use an absolute scale to tally failures (observations of banks that failed within a year of the reported capital ratio) and nonfailures (observations of banks that did not fail within a year) for individual capital ratio ranges and cumulatively up to a given cutoff point. For non-cumulative data, each range is bounded above by the cutoff value given in the first column of the panel and bounded below by the cutoff value of the previous row. In contrast, the bottom panel of Table 3 uses a relative scale for the leverage ratio by classifying banks according to percentiles. The absolute scale is helpful for examining the failure experience at specific ranges of the ratio. In contrast, by

dividing the data set in percentile classes of equal size, ranked by the ratio, the relative scale facilitates a uniform comparison of the different capital ratios.

As seen from the fourth column of Panel A, the proportion of failed observations (number of failures divided by the total number of banks in the leverage ratio class) was over 80 percent for institutions with negative leverage ratios. The proportion of failing bank observations decreases monotonically and rapidly with the leverage ratio; the relative frequency drops below 10 percent in the leverage ratio range of 4-5 percent and below 1 percent in the 6-7 percent range. The proportion is quite small (0.1 percent or lower) for bank observations with leverage ratios over 7 percent. In relative terms, Panel B of Table 3 shows that the proportion of failures is very high (74.7 percent) for banks in the lowest one-percentile leverage ratio range but quickly drops below 10 percent in the 3-4 percentile class. The sharp drop-off in the proportion of failures is indicative of a successful measure.

In addition to counting the frequency of failure for specific ranges, Table 3 presents cumulative frequencies. The cumulative proportion of nonfailures (fifth column of the table) represents the number of surviving observations up to that leverage ratio cutoff point, divided by the aggregate number of nonfailing observations. In contrast, the cumulative proportion of failures (last column of the table) represents the total number of failures for bank observations having a leverage ratio greater or equal to the leverage ratio cutoff value, divided by the total number of failures.[1] Looking at the cumulative

[1] Note that the proportions of failures and nonfailures are cumulated in opposite orders. For instance, the cumulative proportion of nonfailures for the leverage ratio class of 2 percent is 0.5 percent. This proportion is the total number of surviving banks up to and including that class (51+62+95=208) divided by the aggregate number of surviving banks (43,643). In contrast, the cumulative proportion of failures for this same leverage ratio

proportion of nonfailures, we find that only 0.5 percent of non-failures would be classified under prompt corrective action as critically undercapitalized (that is, had a leverage ratio less than 2 percent).[2] In comparison, 33 percent of the failures did not fall in the critically undercapitalized region (67 percent did).

We may interpret these cumulative proportions using simple statistical hypothesis-testing terminology. In this context, the null or testable hypothesis is that the bank will fail within one year versus the alternative hypothesis that bank will not fail over the same period. Acceptance of the null hypothesis, in turn, would be associated with some appropriate action on the part of the supervisory authority, for instance, closure of the bank. Accepting the null hypothesis when it is actually false (known as Type II error) is equivalent to closing a bank that would have survived beyond one year, which in the table corresponds to the proportion of nonfailed bank observations. Similarly, the cumulative proportion of failures is analogous to the so-called Type I error, that is, the choice of not closing an institution that failed within one year. Consider, for example, the 2 percent closure rule for critically undercapitalized banks, using the figures reported in the previous paragraph. The Type II error is only 0.5 percent (0.5 percent of non-failures were statistically misclassified). In contrast, the Type I error for observations with a leverage ratio greater than 2 percent is 33 percent (that is, 33 percent of the failures were

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class is 33.0 percent. This value is equal to the cumulative number bank failures for all banks with a leverage greater than 2 percent (76+45+31+25+17+8+3+2=131) divided by 628, the total number of failures.

[2] Technically, the criterion for critically undercapitalized banks uses tangible equity as a measure of capital, instead of tier 1 as in the leverage ratio. To economize on data reporting and to make results more comparable within the paper, we base our illustrations on table 3, which is based on the leverage ratio. Tangible equity ratios produce similar results.

statistically misclassified). Note that there is a tradeoff in general between the probabilities of Type I and Type II errors. It is impossible to reduce both simultaneously by shifting the cutoff ratio.

Although it would be difficult for bank supervisors to frame any practical regulatory goals based solely on these statistical errors, sound regulatory policies should help to promote some balance between these cumulative proportion errors of failure and nonfailure. As seen from Panel B, the two cumulative ratios are approximately equal around the seventh percentile cutoff, which is equivalent to the 5.75 percent leverage ratio cutoff point.[3] Also it is interesting to note that current FDICIA capital adequacy guidelines for well-capitalized banks, which require a 5 percent leverage ratio, would have generated Type I and Type II errors of 3.2 percent and 8.8 percent, respectively.

Bank failures are correlated about as strongly with gross revenue ratios as with leverage ratios (Table 4). As in the case of leverage ratios, the table shows that the proportion of failing observations declines quite rapidly with the gross-revenue ratio and that failures are highly concentrated at low gross revenue ratios. Panel A may be somewhat difficult to interpret because the levels of the gross revenue ratio tend to be less familiar than levels of standard capital ratios. Nonetheless, our results illustrate that the likelihood of failure is quite small for depository institutions that maintain a gross revenue ratio greater than 60 percent. Interestingly, Panel B reveals that the cumulative proportion of failed banks (Type I error) is approximately equal to the cumulative proportion of nonfailures (Type II error) around the 60 percent gross revenue ratio

[3] Equality of Type I and II errors in an interesting illustrative benchmark, but regulators can clearly choose different levels of this tradeoff to suit their goals and preferences.

threshold. Based on the comparison between the Panel B of Table 4 and that of Table 3, the gross revenue appears to classify failures and nonfailures about as accurately as the leverage ratios. The two panels show very similar failure rates, Type I errors, and Type II errors in each percentile class.

[insert Table 4 and Table 4a here]

Finally, Table 5 tabulates the distribution of bank failures for the tier 1 risk-weighted ratio. In general, the distribution of failures against tier 1 risk-weighted ratios is comparable with the other capital ratios. However, the table also reveals a number of small differences between the tier 1 risk-based measure and the leverage ratio. Current FDICIA rules specify that a well-capitalized bank must maintain, at a minimum, a 6 percent tier 1 risk-weighted capital ratio, a 10 percent total (tier 1 plus tier 2) risk-weighted capital ratio, and a 5 percent leverage capital ratio. Note that the failure rate at the 6 to 7 percent tier 1 capital range is 5.2 percent. In comparison, the failure rate for well-capitalized banks with 5 to 6 percent leverage ratios is only 1.4 percent (Table 3). This pair-wise comparison suggests that the 5 percent leverage ratio threshold is more binding than the 6 percent tier 1 risk-based requirement. Having said that, however, we should note that the stringency in the risk-weighted ratios is best captured by the total (tier 1 plus tier 2) ratio. Although the distribution table for the total risk-weight measure is not included in the paper, we find that the failure rate at the 10 to 11 percent range is only 0.4 percent, suggesting that the total risk-based measure may be the most binding of all the FDICIA capital adequacy ratios.

[insert Table 5 and Table 5a here]

As expected, the performance of capital ratios deteriorates somewhat when we move from a one-year horizon to focus on the second year, that is, on failures occurring between one and two years after the capital ratio is observed. Tables 3a-5a, which follow tables 3-5, respectively, summarize the second-year failure rates and cumulative distribution of second-year failures and nonfailures, for firms that survive the first year. The capital ratio still provides a fairly clear signal, as evidenced by the sharp drop in the failure rates for individual ranges as the ratio increases. However, the failure rates for adequately capitalized bank observations are now considerably greater. In particular, the failure rate for observations in the 4 to 5 percent leverage ratio class is 13.9 percent, as compared with the 4.7 percent one-year rate. Similarly, the failure rate is now 21.4 percent for observations in the 4 to 5 percent risk-weighted ratio range, as compared with a one-year rate of 14.7 percent. Overall, in the metric of a second-year horizon, the three capital ratios stack up against each other quite similarly, although the likelihood of failure is somewhat harder to estimate than in the case of a one-year horizon.[4]

B. Qualitative Forecasts and the Probability of Failure

To examine more rigorously the relationship between likelihood of failure and capital ratios, we utilize a discrete choice logit model. The primary objective of this qualitative choice model is to evaluate how well these alternative capital ratios predict failure. In this framework, the dependent variable is the probability of failure and the explanatory variables are the leverage ratio, the gross revenue ratio, and the risk-weighted ratio. Although many other balance sheet and income statement explanatory variables are

[4] If p is the estimated proportion (failure rate), a measure of the variance of the estimate is given by $p(1-p)/n$, where n is the number of observations. This variance is larger with p closer to ½ and with n smaller, both of which apply in the case of second-year rates as

relevant in predicting bank failure, we focus on the three capital ratios because our main purpose is not to build a failure-prediction model but instead to compare the effectiveness of various capital ratios.[5]

Table 6 reports the results of the logit regressions. All three alternative capital ratios predict fairly well failures occurring within one year (panel A). When each capital ratio is entered separately in the regression, it is statistically significant at the one-percent level. Looking at the concordance ratios, we observe that the logit models based solely on capital ratios can accurately predict failures.[6] Among the three capital ratios, the leverage ratio achieves the highest pseudo R-square and concordance ratio.[7] The difference in this forecasting efficiency measure, however, is very small. In Model 4, which includes all three capital ratios, the gross-revenue ratio shows the highest significance. Because the competing capital ratios are highly collinear, we are unable to draw any strong conclusions from this model.

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compared with one-year rates.

[5] Early warning models use various balance sheet and income-statement variables to predict bank failure (e.g., Cole et al. 1995, Cole and Gunther 1995, Thompson 1991). Capital adequacy is highly significant in those models. Nevertheless, high correlation among variables reflecting financial strength makes it difficult to infer the significance of individual variables.

[6] The concordance ratio is calculated based on the pair-wise comparison of failure probabilities estimated by a logit model. The estimated probability for each failure is compared with those of nonfailures (m·(n-m) pairs when there are m failures out of n observations). A pair is counted as concordant if the estimated probability is higher for the failed one and discordant in the opposite case. Thus, a high concordance ratio indicates that the logit model accurately classifies failures and nonfailures.

[7] The pseudo R-square is defined as in Estrella (1998) by $(1-\log L_u/\log L_c)^{-2\log L_c/n}$, where L_u is the value of the unconstrained likelihood, L_c is the value of the likelihood with only a constant term in the model, and n is the number of observations.

[insert Table 6 here]

The relative performance of the risk-weighted ratio improves when the time horizon is extended to between one and two years (Panel B Table 6). As a result, the pseudo R-square and the concordance ratio are higher in Model 3 than those in Models 1 and 2. The performance gap, however, is very small in this case as well. When all three ratios are included in the logit regression simultaneously (Model 4), the gross revenue and risk-weighted ratios exhibit similar statistical significance.

We also experimented with a more narrowly defined predictive horizon (Panel C in Table 6), in which observations correspond to the fourth quarter after the ratio is observed, as opposed to the first or the second year as in panels A and B. The results for regressions that use the narrower window appear to be a mixture of those shown in Panels A and B. This outcome is not surprising because the average time to failure in this case (about ten and half months) is close to the average of the previous two cases (about six months and eighteen months, respectively). Independently, the leverage ratio and the risk-weighted ratio show about the same Pseudo R-square and concordance ratio. When all variables are entered together in the regression, the statistical significance is highest for the gross-revenue ratio.

Based on these regression results, simple capital ratios (leverage ratio and gross-revenue ratio) appear to predict bank failure as well as the risk-weighted ratio, especially in short time horizons. A noteworthy finding is the strong performance of the gross-revenue ratio in regressions that include all three variables. One explanation for the strong significance of the gross revenue measure may be that it contains more independent information than the other balance-sheet-based capital ratios. This regression

finding provides evidence that the gross revenue ratio can effectively supplement more complicated capital ratios.

Again we should expect that the efficacy of these regulatory capital ratios might deteriorate if we evaluate the forecasting ability of these measures beyond the two-year horizon. Peek and Rosengren (1997) find that most banks that failed during the New England banking crisis of 1989-1993 were well-capitalized two years before failure. Similarly, Jones and King (1995) argue that during 1984-1989 most troubled banks would have not been classified as undercapitalized under the FDICIA rules. Those studies concluded that prompt corrective action rules mandated by FDICIA would have been ineffective in dealing with banking problems during those periods.

In the context of our data set, regulatory ratios seem to be fairly good predictors of failure even in longer time horizons. For instance, we find that failing banks begin to show signs of weakness (become undercapitalized) 2 to 3 years before are closed by supervisors. Figure 1 presents the time-profile of the three capital ratios for failed banks, plotted according to the number of quarters before failure. The figure also includes analogous data for a control sample of non-failed banks. The control group consists of randomly chosen banks located in the same state and having a similar asset size as the banks in the failed group.

As seen from Figure 1, the median capital ratios for the group of failed banks are consistently lower than the median ratios of the control sample of surviving banks. The shaded area in each panel of the figure represents the critical region for a one-sided test of equality. When the median capital ratio of the control group (dashed line) is in the shaded area, we cannot reject the hypothesis that the median capital ratios for the two groups are

different from each other. For the most part, the median capital ratio for the control of non-failed banks is outside the shaded critical region, suggesting that all three capital ratios are fairly good predictors of failure even as far back as 2-3 years.

[insert Figure 1 here]

4. Bank Credit Ratings and Capital Ratios

We have shown that regulatory capital ratios can be quite useful in evaluating the safety and soundness of depository institutions. In this section, we shift the focus to private credit ratings of banks. Like regulatory ratios, private debt ratings offer an indication of the soundness of depository institutions. Investors, including banks, rely routinely on private rating agencies to assess the investment quality of some credits. Debt ratings are indicative of the likelihood that the firm will default on its debt obligations within a particular time horizon and of the potential loss to creditors in the event of default. For instance, bond ratings are designed to assess the long-term credit risk of the institutions. Rating agencies analyze a firm's financial health based on its current condition and on its estimated future performance under various economic scenarios.

In some ways, the concerns of private credit ratings are quite similar to those of the capital adequacy standards imposed by the Basel Accord and FDICIA. Both regulators and rating agencies focus on the likelihood of firm failure and have a preference to minimize unexpected losses to creditors and depositors. In the case of insured deposits, minimizing losses to the safety net is equivalent to minimizing depositors' losses. Recognizing this similarity in concerns, some have argued that regulatory agencies can contribute to existing regulatory standards by having large rated banks meet some minimum investment-grade criterion.

Given the focus of private credit rating agencies, one would expect a strong relationship between credit ratings and capital ratios. An analysis of historical default rates by Moody's Investor Services (see Keenan et al. (1998)) illustrates a strong relationship between default rates and credit ratings. For example, the study reports that 3.27 percent of speculative-grade issues have defaulted within one year of the assignment of the rating over the 1920-1997 period compared with only 0.17 percent of investment-grade issuers. The study also shows that the overall one-year-weighted average default rate for corporate issues during this period is less than 0.01 percent for the highest rated firms.

In this section, we focus on the relationship between regulatory capital ratios and private debt ratings and examine their relationship to bank failures. We attempt to make our analysis as consistent as possible with the analysis of the capital ratios in the previous section. In particular, we analyze Standard and Poor's ratings for bank holding companies operating in the United States. Note that the focus has shifted from commercial banks to bank holding companies in this section, since public securities are mostly issued at the holding company level. Our sample includes quarterly information on the S&P senior bond rating on 84 publicly traded bank holding companies over the period of 1986 to 1994.

The sample is small for two principal reasons. The first is that only a small proportion of the large number of banking institutions in the United States issue publicly traded securities that can be rated by the credit rating agencies. The second reason is that the sample includes only those firms for which there is complete information with regard to credit ratings and capital ratios. Clearly, the binding constraint is the existence of a

credit rating. Although the sample consists of a limited number of large institutions, it accounts for a substantial proportion of the banking assets in United States

Table 7 shows the relationship between S&P bond ratings and regulatory capital ratios. Most banks are rated as investment-grade (that is, have a BBB- or better credit rating). For the most part, the table shows a positive association between regulatory capital ratios and credit ratings, as lower rated (below investment-grade) institutions are more likely to fail to meet capital adequacy standards.[8] At the same time, however, this cross-tabulation reveals some small but important discrepancies between credit ratings and the leverage ratio. For instance, 27 banks rated BBB- or higher, ratings presumably higher than the "minimum acceptable" investment-grade standard, are not adequately-capitalized (leverage ratio below 4 percent) according to existing U.S. bank regulation.

[insert Table 7 here]

As seen from Figure 2, the relationship between capital ratios and credit ratings is not monotonic. Banks rated AA+ or AA have, on average, a lower leverage ratio and gross revenue ratio than institutions rated between A and BB+. In fact, the average gross revenue ratio for banks rated B is around 75 percent compared with only 45 percent for AA+ institutions. This pattern may result partly from the inclination of rating agencies to give large institutions higher ratings. Ratings increase consistently with asset size (bottom panel of Figure 2). The precise reasons why credit agencies view large banks as safer issuers are beyond the scope of our study, but the size bias may reflect the degree of asset diversification and other quality assessments that are related to bank size (see, e.g.,

[8] Because of difficulties in estimating tier 1 capital for bank holding companies in the mid-1980s, both the leverage and gross revenue ratio were based on equity capital as reported in the Y-9C reports, which is very close to tier 1 capital.

Demsetz and Strahan (1997)). Rating agencies may also conjecture that regulatory authorities have implicitly a "too big to fail" policy. Thus, credit ratings could be essentially adjusting for the lower likelihood of default by large institutions.

[insert Figure 2 here]

Figure 3 presents the relationship between the credit rating and bank asset size before and after 1992. After 1992, FDICIA's prompt corrective action provisions made capital adequacy levels the centerpiece of regulatory oversight, forcing regulatory authorities to close a bank when its leverage ratio fell below two percent of assets irrespective of asset size. The last two panels of Figure 3 show what appears to be a breakdown in the importance of size among top-rated banks (for instance, A-rated institutions are bigger than AA-rated banks in the third panel), perhaps also reflecting a perceived declining emphasis on "too big to fail."

[insert Figure 3 here]

One drawback of the S&P ratings database is that only six of the rated banks failed during 1986-1994. As a result of the small sample of failures, it is not feasible to compute meaningful distributions for surviving and failing banks. Despite the paucity of data, it may be useful to examine the six bank holding company failures individually, comparing the behavior of the capital ratio and the credit ratings in the period leading to failure. Such case studies are a useful supplement to the statistical analysis of capital ratios in Section 3. Thus, the six panels in Figure 4 compare the leverage ratio and the S&P rating in the period leading to the failure of six particular failed banks of various sizes, ranging from $400 million to $33 billion in assets at the time of failure. The panels are arranged according to date of failure, starting from the case of First Republic Bank

Corporation, which failed in 1988.Q3 and ending with First City Bank Corporation, which failed in 1992.Q2.

[insert Figure 4 here]

Generally, the leverage ratio and credit rating behave in a similar manner in the last few quarters of each panel, rapidly declining as the bank approaches failure. In one case (First Republic Bank Corp) the senior debt rating was upgraded to above investment-grade about one year before failure. In this case, the credit ratings may have provided a misleading signal on the impending default. A similar pattern is observed in the case of First City BankCorp, but in that case the upgrading occurred about three years before failure. In general, these cases appear to be exceptions, rather than the rule, since in all other cases credit ratings fall in the last two years before failure. The first three failures reveal the dangers of delaying the recognition of failure of an institution, as all three banks had negative net worth at the time of failure. However, in the last three cases, which occurred in the early 1990s, failing banks are actually technically solvent (have positive net worth) at the time of failure. With the enactment of FDICIA, which established prompt corrective action rules, regulators appear to have been more proactive in closing failing banks in the early 1990s, even before the law went fully into effect. Figure 5 has the same format as Figure 4, but traces the path of the gross revenue ratio against the S&P ratings. In each case, the gross revenue produces a signal that is almost identical to that of the leverage ratio.

[insert Figure 5 here]

5. Summary

This paper compares the effectiveness of simple and risk-weighted capital ratios in predicting bank failures, and also examines how credit ratings are related to capital ratios and bank failures. An important result of our study is that simple ratios predict bank failures about as well as the more complex risk-weighted ratio. This finding suggests that bank regulators may derive substantial benefits from the use of simple ratios, possibly as a supplementary requirement, even when more complex measures such as risk-weighted ratios are used to formulate the primary requirements. Moreover, we find that credit ratings may also provide useful information, though the small sample of failures for rated banks prevents us from drawing any strong conclusions.

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Table 1. Summary Statistics

Leverage Ratio

Year	N	Mean	Median	STD	Minimum	Maximum
1988	13299	0.0941	0.0817	0.0769	-0.5120	0.9977
1989	12903	0.0955	0.0827	0.0760	-0.4404	0.9953
1990	12388	0.0937	0.0818	0.0716	-0.5490	0.9984
1991	11941	0.0936	0.0821	0.0695	-0.4383	0.9978
1992	11473	0.0964	0.0850	0.0680	-1.6625	0.9970
Total	62004	0.095	0.083	0.073	-1.663	0.998

Gross Revenue Ratio

1988	13299	1.146	0.866	3.712	-4.938	300.110
1989	12903	1.228	0.816	13.192	-4.228	1345.000
1990	12388	1.032	0.819	2.239	-4.124	135.240
1991	11941	1.211	0.864	15.051	-1.088	1601.330
1992	11473	1.253	1.004	6.683	-0.729	679.500
Total	62004	1.173	0.871	9.595	-4.938	1601.330

Tier 1 Capital Ratio

1988	13299	0.186	0.142	0.264	-0.607	12.383
1989	12903	0.195	0.144	0.608	-0.739	52.089
1990	12388	0.179	0.136	0.298	-0.524	9.534
1991	11941	0.208	0.139	3.040	-0.439	330.902
1992	11473	0.193	0.147	0.487	-1.584	34.249
Total	62004	0.192	0.141	1.390	-1.584	330.902

Table 2. Measures of Correlation

Pearson Correlation Coefficient

Year	Leverage Ratio - Gross Revenue Ratio	Leverage Ratio - Tier 1 Capital Ratio	Gross Revenue Ratio - Tier 1 Capital Ratio
1988	0.410	0.749	0.284
1989	0.216	0.442	0.179
1990	0.496	0.740	0.344
1991	0.151	0.179	0.020
1992	0.221	0.537	0.567
Total	0.194	0.210	0.069

Spearman's Rank Correlation

1988	0.930	0.825	0.840
1989	0.932	0.849	0.865
1990	0.921	0.849	0.859
1991	0.911	0.824	0.833
1992	0.874	0.783	0.788
Total	0.917	0.830	0.841

Table 3. Distribution of Bank Failures by Leverage Ratios

A. Absolute Scale

Cutoff Point	Failures 1989-1993	Non-Failures 1989-1993	Failure Rate For row (percent)	Cum. Proportion Non-Failures (Type II Error) (percent)	Cum. Proportion Failures (Type I Error) (percent)
0	231	51	81.9	0.1	63.2
1.0	100	62	61.7	0.3	47.3
2.0	90	95	48.6	0.5	33.0
3.0	76	194	28.1	0.9	20.9
4.0	45	367	10.9	1.8	13.7
5.0	31	628	4.7	3.2	8.8
6.0	25	1799	1.4	7.3	4.8
7.0	17	5136	0.3	19.1	2.1
8.0	8	8175	0.1	37.8	0.8
9.0	0	7767	0.0	55.6	0.8
10.0	3	5858	0.1	69.0	0.3
11.0	0	3940	0.0	78.1	0.3
12.0	0	2702	0.0	84.3	0.3
Infinity	2	6869	0.0	100.0	0.0

B. Relative Scale

Cutoff Percentile	Cutoff Point	Failures 1989-1993	Non-Failures 1989-1993	Failure Rate For row (percent)	Cum. Proportion Non-Failures (Type II Error) (percent)	Cum. Proportion Failures (Type I Error) (percent)
1	0.97	330	112	74.7	0.3	47.5
2	2.95	166	277	37.5	0.9	21.0
3	4.03	46	397	10.4	1.8	13.7
4	4.78	22	420	5.0	2.8	10.2
5	5.20	13	430	2.9	3.7	8.1
6	5.51	7	436	1.6	4.7	7.0
7	5.75	8	435	1.8	5.7	5.7
8	5.92	3	439	0.7	6.8	5.3
9	6.06	3	440	0.7	7.8	4.8
10	6.18	2	441	0.5	8.8	4.5
25	7.22	18	6180	0.3	22.9	1.6
50	8.55	5	11063	0.0	48.3	0.8
75	10.46	3	11065	0.0	73.6	0.3
100	Infinity	2	11508	0.0	100.0	0.0

NOTE: Non-cumulative data are for range defined by cutoffs in current & previous row. Cumulative data are aggregated up to cutoff point.

Table 3a. Distribution of Bank Failures by Leverage Ratios (2-year Failure Horizon)

A. Absolute Scale

Cutoff Point	Failures 1989-1993	Non-Failures 1989-1993	Failure Rate For row (percent)	Cum. Proportion Non-Failures (Type II Error) (percent)	Cum. Proportion Failures (Type I Error) (percent)
0	24	15	61.5	0.0	94.8
1.0	28	19	59.6	0.1	88.8
2.0	43	36	54.4	0.2	79.6
3.0	44	107	29.1	0.5	70.1
4.0	60	227	20.9	1.2	57.2
5.0	69	428	13.9	2.4	42.4
6.0	71	1391	4.9	6.4	27.1
7.0	57	4001	1.4	17.9	14.8
8.0	32	6627	0.5	37.0	8.0
9.0	9	6285	0.1	55.1	6.0
10.0	6	4714	0.1	68.6	4.7
11.0	6	3242	0.2	78.0	3.4
12.0	5	2190	0.2	84.3	2.4
Infinity	11	5462	0.2	100.0	0.0

B. Relative Scale

Cutoff Percentile	Cutoff Point	Failures 1989-1993	Non-Failures 1989-1993	Failure Rate For row (percent)	Cum. Proportion Non-Failures (Type II Error) (percent)	Cum. Proportion Failures (Type I Error) (percent)
1	3.11	154	198	43.8	0.6	66.9
2	4.22	63	289	17.9	1.4	53.3
3	4.93	44	308	12.5	2.3	43.9
4	5.31	25	327	7.1	3.2	38.5
5	5.59	23	329	6.5	4.2	33.5
6	5.80	14	338	4.0	5.1	30.5
7	5.97	13	339	3.7	6.1	27.7
8	6.10	10	342	2.8	7.1	25.6
9	6.22	10	342	2.8	8.1	23.4
10	6.33	8	344	2.3	9.1	21.7
25	7.29	39	4891	0.8	23.2	13.3
50	8.60	31	8771	0.4	48.4	6.7
75	10.49	12	8791	0.1	73.7	4.1
100	Infinity	19	9135	0.2	100.0	0.0

NOTE: Non-cumulative data are for range defined by cutoffs in current & previous row. Cumulative data are aggregated up to cutoff point.

T

Table 4. Distribution of Bank Failures by Gross-Revenue Ratios

A. Absolute Scale

Cutoff Point	Failures 1989-1993	Non-Failures 1989-1993	Failure Rate For row (percent)	Cum. Proportion Non-Failures (Type II Error) (percent)	Cum. Proportion Failures (Type I Error) (percent)
0	231	51	81.9	0.1	63.2
10	102	76	57.3	0.3	47.0
20	93	160	36.8	0.7	32.2
30	75	299	20.1	1.3	20.2
40	42	488	7.9	2.5	13.5
50	36	772	4.5	4.2	7.8
60	13	1755	0.7	8.3	5.7
70	14	3634	0.4	16.6	3.5
80	13	5431	0.2	29.0	1.4
90	5	5945	0.1	42.6	0.6
100	1	5431	0.0	55.1	0.5
110	2	4526	0.0	65.5	0.2
120	0	3499	0.0	73.5	0.2
Infinity	1	11576	0.0	100.0	0.0

B. Relative Scale

Cutoff Percentile	Cutoff Point	Failures 1989-1993	Non-Failures 1989-1993	Failure Rate For row (percent)	Cum. Proportion Non-Failures (Type II Error) (percent)	Cum. Proportion Failures (Type I Error) (percent)
1	8.85	323	119	73.1	0.3	48.6
2	25.17	148	295	33.4	0.9	25.0
3	34.56	60	383	13.5	1.8	15.4
4	42.61	24	418	5.4	2.8	11.6
5	47.93	20	423	4.5	3.8	8.4
6	51.97	7	436	1.6	4.8	7.3
7	54.83	4	439	0.9	5.8	6.7
8	57.16	3	439	0.7	6.8	6.2
9	59.09	3	440	0.7	7.8	5.7
10	60.87	2	441	0.5	8.8	5.4
25	75.30	19	6179	0.3	22.9	2.4
50	94.27	11	11057	0.1	48.3	0.6
75	120.24	3	11065	0.0	73.6	0.2
100	Infinity	1	11509	0.0	100.0	0.0

NOTE: Non-cumulative data are for range defined by cutoffs in current & previous row. Cumulative data are aggregated up to cutoff point.

Table 4a. Distribution of Bank Failures by Gross-Revenue Ratios (2-year Failure Horizon)

A. Absolute Scale

Cutoff Point	Failures 1989-1993	Non-Failures 1989-1993	Failure Rate For row (percent)	Cum. Proportion Non-Failures (Type II Error) (percent)	Cum. Proportion Failures (Type I Error) (percent)
0	24	15	61.5	0.0	94.8
10	30	25	54.5	0.1	88.4
20	51	82	38.3	0.4	77.4
30	50	183	21.5	0.9	66.7
40	65	311	17.3	1.8	52.7
50	69	494	12.3	3.2	37.8
60	64	1183	5.1	6.6	24.1
70	49	2545	1.9	13.9	13.5
80	25	3998	0.6	25.4	8.2
90	10	4628	0.2	38.8	6.0
100	5	4429	0.1	51.5	4.9
110	3	3840	0.1	62.6	4.3
120	3	2988	0.1	71.2	3.7
Infinity	17	10023	0.2	100.0	0.0

B. Relative Scale

Cutoff Percentile	Cutoff Point	Failures 1989-1993	Non-Failures 1989-1993	Failure Rate For row (percent)	Cum. Proportion Non-Failures (Type II Error) (percent)	Cum. Proportion Failures (Type I Error) (percent)
1	26.19	130	222	36.9	0.6	72.0
2	36.63	69	283	19.6	1.5	57.2
3	44.64	58	294	16.5	2.3	44.7
4	50.08	32	320	9.1	3.2	37.8
5	53.72	21	331	6.0	4.2	33.3
6	56.48	24	328	6.8	5.1	28.2
7	58.90	10	342	2.8	6.1	26.0
8	60.93	15	337	4.3	7.1	22.8
9	62.56	6	346	1.7	8.1	21.5
10	63.99	8	344	2.3	9.1	19.8
25	78.24	49	4881	1.0	23.1	9.2
50	97.39	19	8783	0.2	48.4	5.2
75	123.78	8	8795	0.1	73.7	3.4
100	Infinity	16	9138	0.2	100.0	0.0

NOTE: Non-cumulative data are for range defined by cutoffs in current & previous row. Cumulative data are aggregated up to cutoff point.

Table 5. Distribution of Bank Failures by Risk-Weighted Ratios

A. Absolute Scale

Cutoff Point	Failures 1989-1993	Non-Failures 1989-1993	Failure Rate For row (percent)	Cum. Proportion Non-Failures (Type II Error) (percent)	Cum. Proportion Failures (Type I Error) (percent)
0	231	52	81.6	0.1	63.2
1.0	69	39	63.9	0.2	52.2
2.0	59	46	56.2	0.3	42.8
3.0	60	73	45.1	0.5	33.3
4.0	55	140	28.2	0.8	24.5
5.0	35	203	14.7	1.3	18.9
6.0	33	261	11.2	1.9	13.7
7.0	25	454	5.2	2.9	9.7
8.0	17	775	2.1	4.7	7.0
9.0	7	1251	0.6	7.5	5.9
10.0	10	2217	0.4	12.6	4.3
11.0	5	3061	0.2	19.6	3.5
12.0	8	3492	0.2	27.6	2.2
Infinity	14	31579	0.0	100.0	0.0

B. Relative Scale

Cutoff Percentile	Cutoff Point	Failures 1989-1993	Non-Failures 1989-1993	Failure Rate For row (percent)	Cum. Proportion Non-Failures (Type II Error) (percent)	Cum. Proportion Failures (Type I Error) (percent)
1	1.50	330	112	74.7	0.3	47.5
2	4.31	158	285	35.7	0.9	22.3
3	5.89	51	392	11.5	1.8	14.2
4	6.87	27	415	6.1	2.8	9.9
5	7.55	10	433	2.3	3.8	8.3
6	8.03	8	435	1.8	4.7	7.0
7	8.44	2	441	0.5	5.8	6.7
8	8.77	4	438	0.9	6.8	6.1
9	9.05	1	442	0.2	7.8	5.9
10	9.28	5	438	1.1	8.8	5.1
25	11.42	15	6183	0.2	22.9	2.7
50	14.66	10	11058	0.1	48.3	1.1
75	19.86	2	11066	0.0	73.6	0.8
100	Infinity	5	11505	0.0	100.0	0.0

NOTE: Non-cumulative data are for range defined by cutoffs in current & previous row. Cumulative data are aggregated up to cutoff point.

Table 5a. Distribution of Bank Failures by Risk-Weighted Ratios (2-year Failure Horizon)

A. Absolute Scale

Cutoff Point	Failures 1989-1993	Non-Failures 1989-1993	Failure Rate For row (percent)	Cum. Proportion Non-Failures (Type II Error) (percent)	Cum. Proportion Failures (Type I Error) (percent)
0	24	16	60.0	0.0	94.8
1.0	18	10	64.3	0.1	91.0
2.0	22	11	66.7	0.1	86.2
3.0	32	27	54.2	0.2	79.4
4.0	39	68	36.4	0.4	71.0
5.0	34	125	21.4	0.7	63.7
6.0	49	156	23.9	1.2	53.1
7.0	46	306	13.1	2.1	43.2
8.0	58	546	9.6	3.6	30.8
9.0	38	974	3.8	6.4	22.6
10.0	37	1784	2.0	11.6	14.6
11.0	15	2533	0.6	18.9	11.4
12.0	10	2880	0.3	27.2	9.2
Infinity	43	25308	0.2	100.0	0.0

B. Relative Scale

Cutoff Percentile	Cutoff Point	Failures 1989-1993	Non-Failures 1989-1993	Failure Rate For row (percent)	Cum. Proportion Non-Failures (Type II Error) (percent)	Cum. Proportion Failures (Type I Error) (percent)
1	4.62	150	202	42.6	0.6	67.7
2	6.30	80	272	22.7	1.4	50.5
3	7.15	41	311	11.6	2.3	41.7
4	7.73	34	318	9.7	3.2	34.4
5	8.22	25	327	7.1	4.1	29.0
6	8.58	14	338	4.0	5.1	26.0
7	8.88	14	338	4.0	6.1	23.0
8	9.15	10	342	2.8	7.0	20.9
9	9.35	10	342	2.8	8.0	18.7
10	9.55	7	345	2.0	9.0	17.2
25	11.52	32	4898	0.6	23.1	10.3
50	14.66	28	8774	0.3	48.4	4.3
75	19.73	12	8791	0.1	73.7	1.7
100	Infinity	8	9146	0.1	100.0	0.0

NOTE: Non-cumulative data are for range defined by cutoffs in current & previous row. Cumulative data are aggregated up to cutoff point.

Table 6. Logit Regressions

A. Failures in Less than 1 Year

	Model 1	Model 2	Model 3	Model 4
Intercept	-0.2984	-0.3362	-0.4761	-0.2881
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Leverage Ratio	-75.4425			-3.0368
	(0.0001)			(0.3484)
Gross-Revenue Ratio		-7.6882		-7.0513
		(0.0001)		(0.0001)
Risk-Weighted Ratio			-45.9838	-2.1878
(Tier 1)			(0.0001)	(0.1742)
Pseudo R-Square	0.0835	0.0790	0.0773	0.0795
Concodant	97.4%	96.3%	96.1%	96.6%
Discodant	1.7%	2.0%	2.2%	1.9%
Tie	0.9%	1.7%	1.7%	1.6%
Failures	634			
Non-Failures	63627			

B. Failures in between 1 and 2 Years

Intercept	-1.0317	-1.0580	-1.0667	-0.9414
	(-0.0001)	(0.0001)	(0.0001)	(0.0001)
Leverage Ratio	-53.1015			2.0074
	(0.0001)			(0.0001)
Gross-Revenue Ratio		-5.3647		-2.2675
		(0.0001)		(0.0001)
Risk-Weighted Ratio			-33.5477	-21.4743
(Tier 1)			(0.0001)	(0.0001)
Pseudo R-Square	0.0203	0.0230	0.0245	0.0252
Concodant	85.9%	86.5%	88.6%	88.2%
Discodant	10.6%	9.9%	8.5%	8.6%
Tie	3.6%	3.6%	2.9%	3.2%
Failures	454			
Non-Failures	51221			

C. Failures in 4 Quarters

Intercept	-2.8797	-1.8823	-2.6260	-1.8705
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Leverage Ratio	-41.8547			3.0538
	(0.0001)			(0.0005)
Gross-Revenue Ratio		-6.2133		-6.1901
		(0.0001)		(0.0001)
Risk-Weighted Ratio			-29.2866	-2.1220
(Tier 1)			(0.0001)	(0.0067)
Pseudo R-Square	0.0105	0.0125	0.0107	0.0126
Concodant	92.0%	90.3%	92.1%	90.3%
Discodant	3.3%	3.4%	3.7%	3.4%
Tie	4.7%	6.3%	4.3%	6.3%
Failures	582			
Non-Failures	215492			

*Note: Numbers in parentheses are p-values.

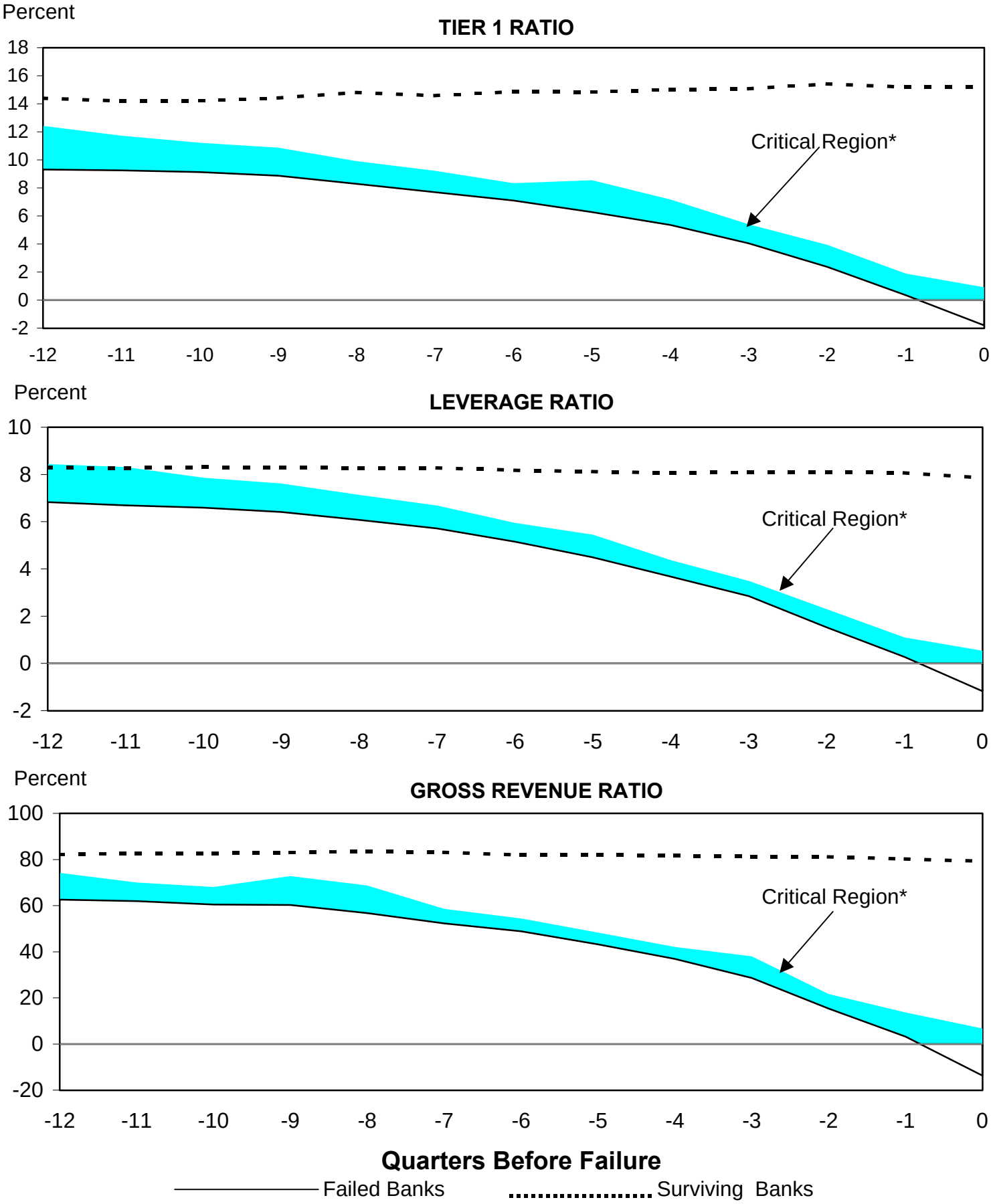
Table 7. Frequency Distribution of Leverage Ratio by S&P Senior Debt Ratings

(1986 - 1995)

	Ranges of Leverage Ratios in Percent							
Rating	<0	0-2	2-4	4-6	6-8	8-10	>10	Total
AA+ to AA-	0	0	7	142	138	27	0	314
	(0.00)	(0.00)	(2.23)	(45.22)	(43.95)	(8.60)	(0.00)	
A+ to A-	0	0	9	210	676	192	19	1106
	(0.00)	(0.00)	(0.81)	(18.99)	(61.12)	(17.36)	(1.72)	
BBB+ to BBB-	0	0	11	108	247	88	5	459
	(0.00)	(0.00)	(2.40)	(23.53)	(53.81)	(19.17)	(1.09)	
BB+ to BB-	0	5	14	38	62	17	1	137
	(0.00)	(3.65)	(10.22)	(27.74)	(45.26)	(12.41)	(0.73)	
B+ to B-	0	2	13	11	15	3	0	44
	(0.00)	(4.55)	(29.55)	(25.00)	(34.09)	(6.82)	(0.00)	
CCC+ to CCC-	2	3	8	4	1	0	0	18
	(11.11)	(16.67)	(44.44)	(22.22)	(5.56)	(0.00)	(0.00)	
D	15	0	1	0	6	0	0	22
	(68.18)	(0.00)	(4.55)	(0.00)	(27.27)	(0.00)	(0,00)	
NR	38	22	131	829	2565	2239	842	6666
	(0.57)	(0.33)	(1.97)	(12.44)	(38.48)	(33.59)	(12.63)	
Total	55	32	194	1342	3710	2566	867	8766
	0.63	0.37	2.21	15.31	42.32	29.27	9.89	100.00

Note: Pooled sample of quarterly observations: Number in the Parenthesis = (Number of banks in the specific leverage ratio range / total number of banks in the same debt-rating range) X 100.

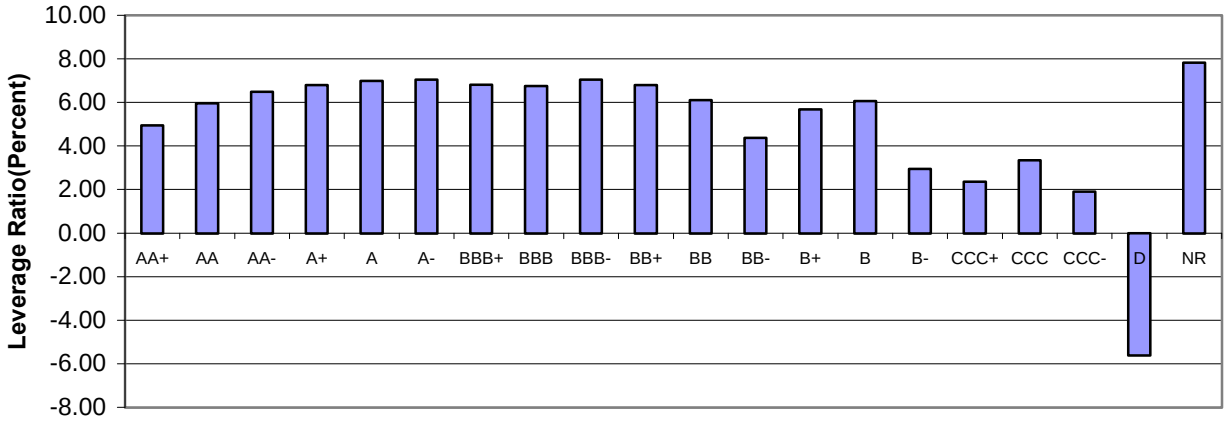
Figure 1. Capital Ratios Before Failure



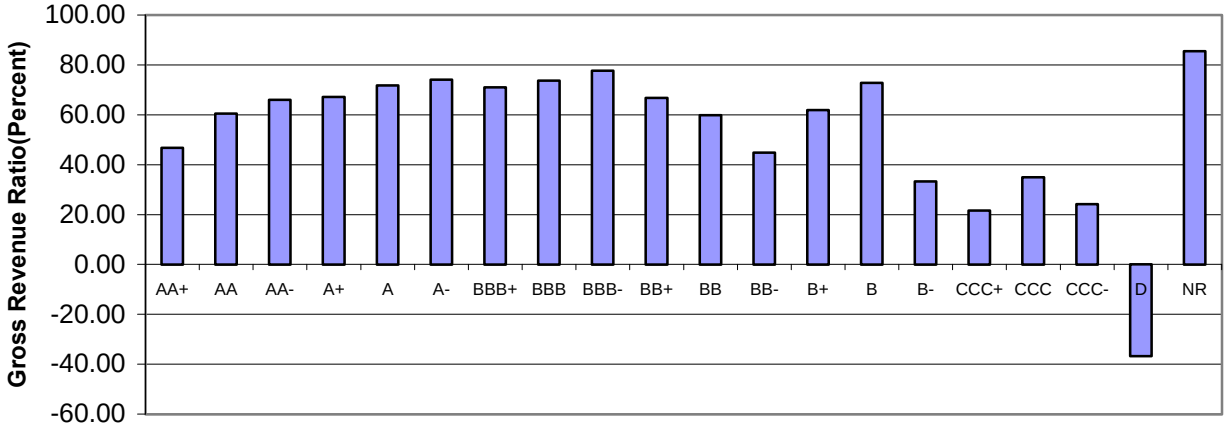
* A one-percent critical region of equality for failed and surviving banks. When the dashed line is outside the shaded area, the population median of surviving banks is statistically greater than the population median of failed banks.

Figure 2. Distribution by Credit Rating

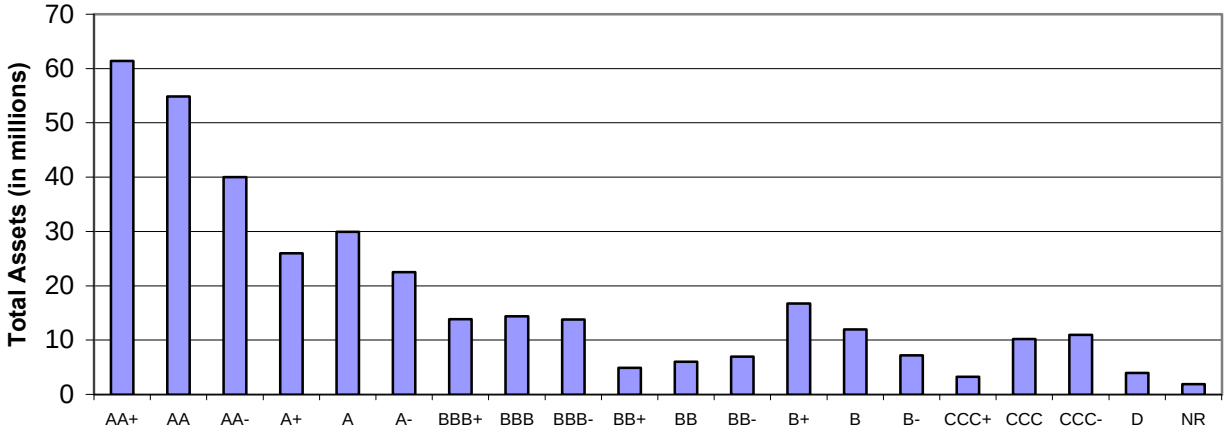
Leverage Ratio



Gross Revenue Ratio



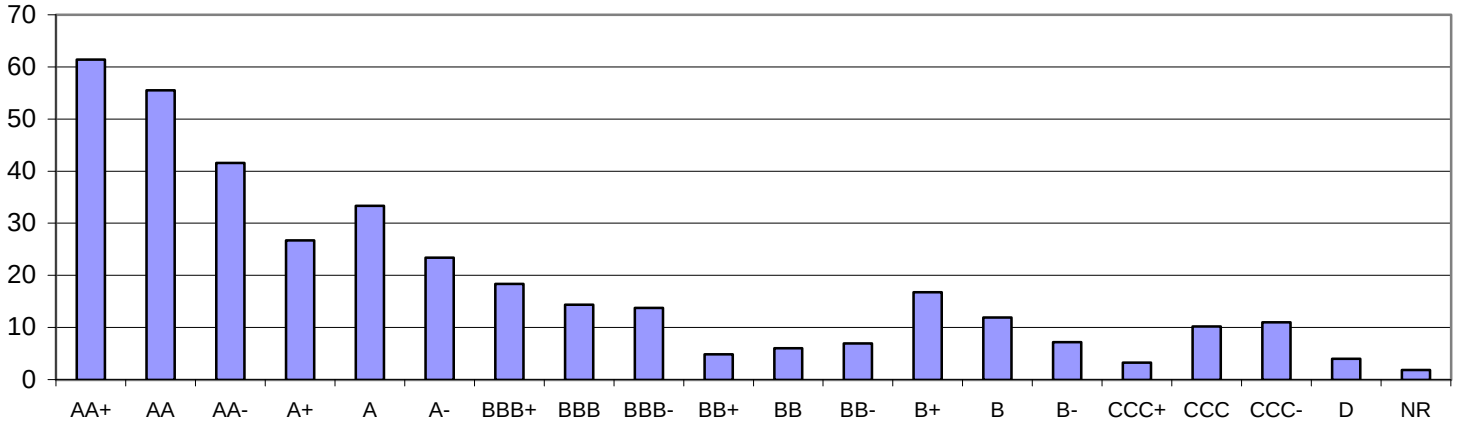
Asset Size



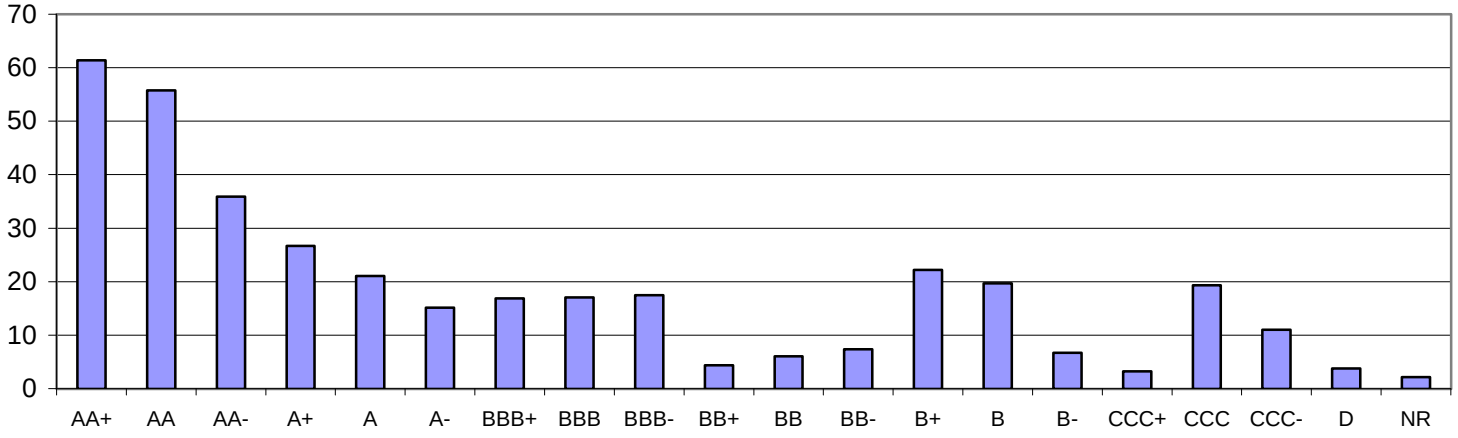
S&P Senior Debt

Figure 3. Distribution of Asset Size, 1986-1995.

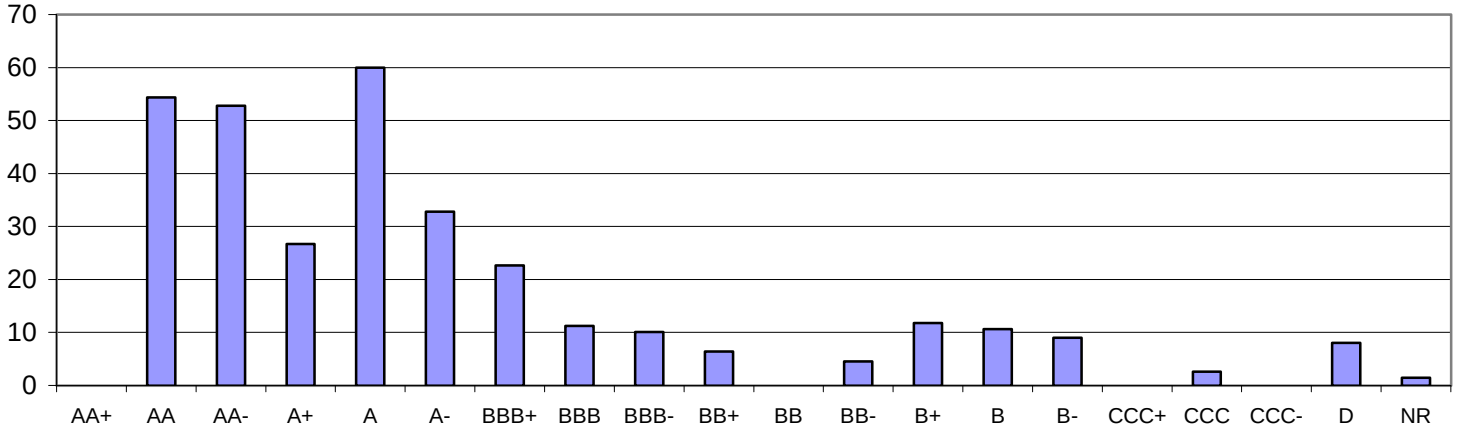
Period: 1986-1995



Period: 1986-1991

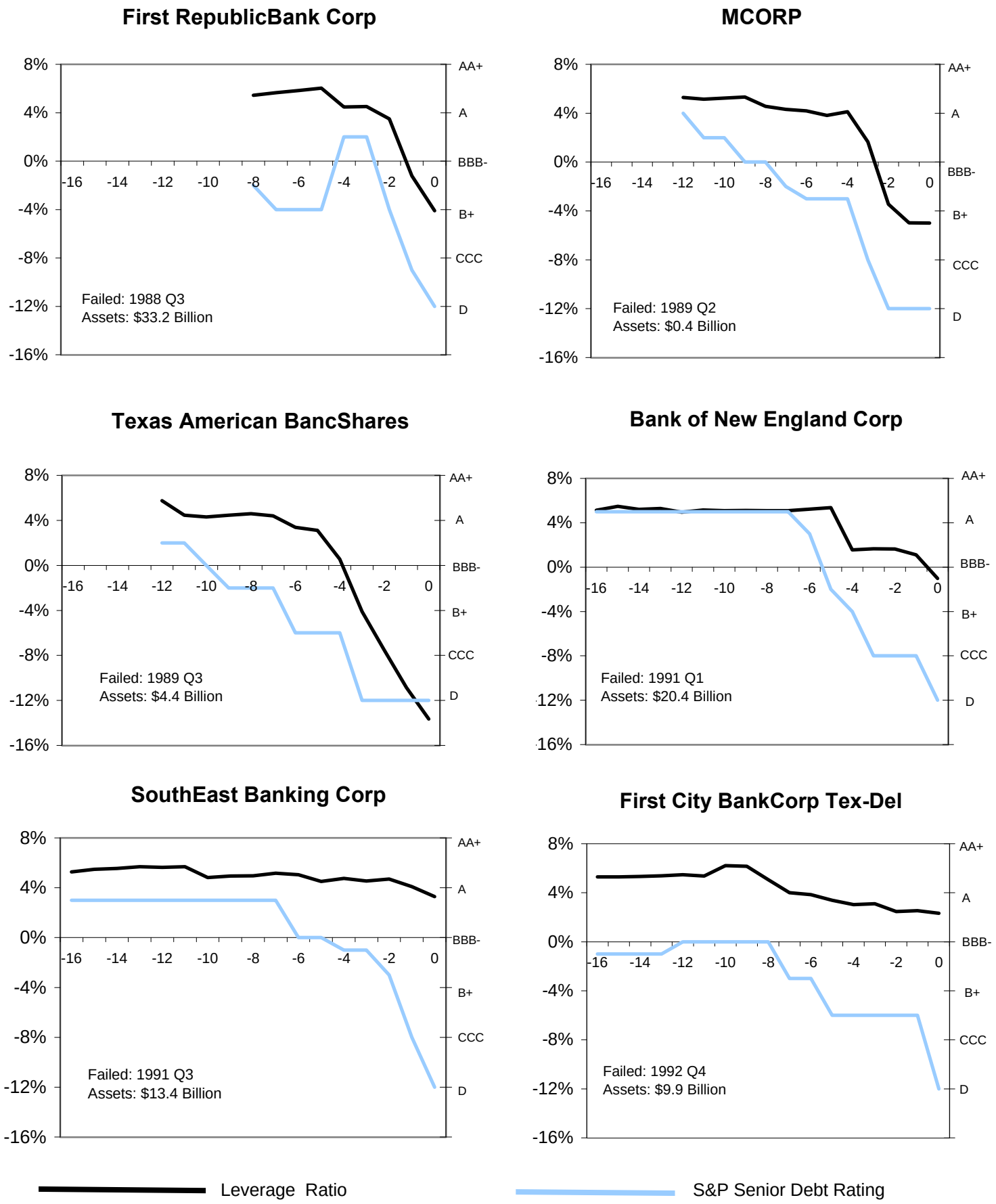


Period: 1992-1995



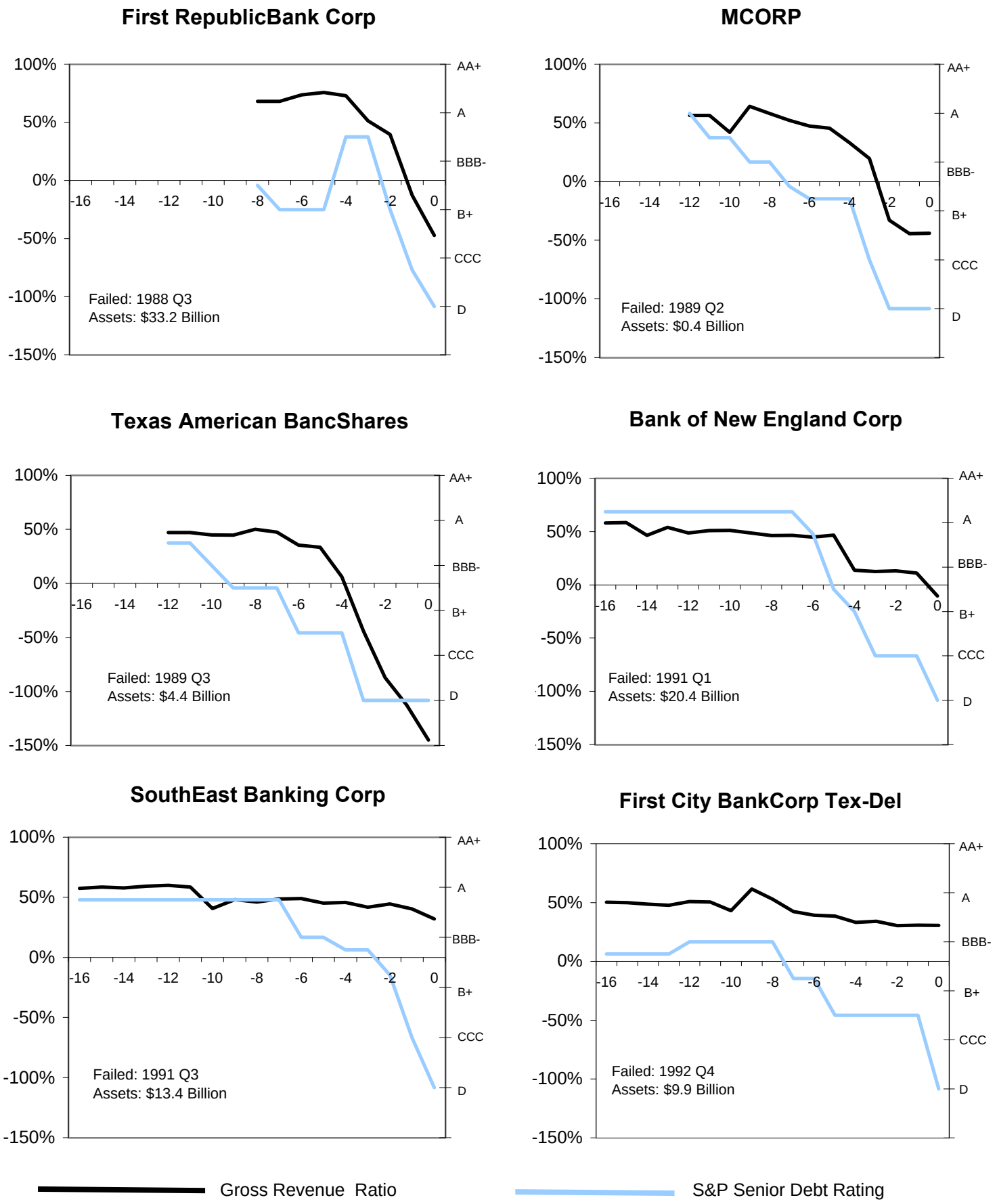
*Note: Y-axis denotes the total assets in billions.

Figure 4. Leverage Ratios and S&P Senior Debt Ratings Before Failure



*Note: Numbers on the horizontal axis denote quarters before failure; Left vertical axis is Leverage Ratio and right vertical axis is S&P Senior Debt Rating.

Figure 5. Gross Revenue Ratios and S&P Senior Debt Ratings Before Failure



*Note: Numbers on the horizontal axis denote quarters before failure; Left vertical axis is Gross Revenue Ratio and right vertical axis is S&P Senior Debt Rating.