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Capital Ratios as Predictors of Bank Failure

- The current regulatory framework for determining bank capital adequacy is under review by the Basel Committee on Banking Supervision.
- An empirical analysis of the relationships between different capital ratios and bank failure suggests that two simple ratios—the leverage ratio and the ratio of capital to gross revenue—may merit a role in the revised framework.
- The leverage ratio and the gross revenue ratio predict bank failure about as well as more complex risk-weighted ratios over one- or two-year horizons. Risk-weighted ratios tend to perform better over longer horizons.
- The simple ratios are virtually costless to implement and could supplement more sophisticated measures by providing a timely signal of the need for supervisory action.

Capital ratios have long been a valuable tool for assessing the safety and soundness of banks. The informal use of ratios by bank regulators and supervisors goes back well over a century (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. The Basel Committee on Banking Supervision (1999) is currently engaged in an effort to improve the Basel Accord and, once again, capital ratios are being discussed as part of the proposed solution. In this article, we examine some of the roles that capital ratios play in bank regulation and we argue that, to be successful in any of these 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 it is indeed significantly related to subsequent bank failure. Perhaps not surprisingly, we find that all three ratios are strongly informative about subsequent failures. Our analysis suggests that the most complex of the ratios—the risk-weighted ratio—is the most effective predictor of failure over long time horizons. However, perhaps somewhat surprisingly, we also find that the risk-weighted ratio does not consistently outperform the simpler ratios, particularly with short horizons of less than two years. Over the

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shorter time periods, the leverage and gross revenue ratios can play a crucial role as timely backstop thresholds that would trigger regulatory action if breached. They also have the advantage of being less costly to calculate and report. In this context, the trade-off between regulatory burden and predictive accuracy may not favor the risk-based measures.

In the next section, we develop the conceptual arguments in favor of applying capital ratios in bank regulation. We then proceed to use the empirical evidence on U.S. bank failures to evaluate the effectiveness of the ratios in predicting bank failures.

The Role of Capital Ratios in Bank Analysis and Supervision

Although bank regulators have relied on capital ratios formally or informally for a very long time, they have not always used the ratios in the same way. For instance, in the days before explicit capital requirements, bank supervisors would use capital ratios as rules of thumb to gauge the adequacy of an institution's level of capital. There was no illusion that the simple ratios used (for example, capital to total assets or capital to deposits) could provide an accurate measure of the appropriate capital level for a bank, but large deviations of actual capital ratios from supervisory benchmarks suggested the need for further scrutiny.

When capital ratios were introduced formally in regulation in 1981 (see Gilbert, Stone, and Trebing [1985]), they were applied in a different way. The regulatory requirement set a minimum level of capital that the institution had to hold. The degree to which the requirement was binding depended significantly on the type of institution because, then as now, there was substantial diversity among banking institutions. 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 were generally already in compliance with the more stringent requirements.

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. Despite these calibrations, 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 (Basel Committee on Banking Supervision 1988).

Another significant regulatory development in the United States 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 guided by a formula driven largely by the Basel ratios and by a simple leverage ratio. Banks are classified as "adequately capitalized" if they meet the Basel requirements plus a leverage ratio requirement, but additional distinctions are made among levels of capital. For example, a bank is "well capitalized" if it holds a certain buffer above the adequate levels.

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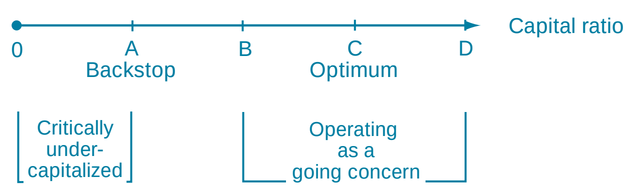
In contrast, a bank that falls under a specific level, set somewhat below the minimum adequate level, is determined to be "critically undercapitalized" and must be shut down by supervisors. This is a different concept of a minimum requirement from the one used in earlier regulation in that failure to 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 June 1999 Basel capital proposal goes beyond the ratios based on accounting data that we have discussed so far. The proposal contemplates (1) the use of external credit ratings as determinants of the weights to be applied to various asset categories, (2) the use, for the same purpose, of internal bank credit ratings based on the firm's own judgment, and (3) the extended recognition of various forms of credit risk mitigation. These features constitute a difference in kind, not simply magnitude, as compared with the accounting-based ratios on which we focus in this article. Ideally, we would like to be able to compute ratios based on the new proposal to examine their power to predict failure, but the required information simply does not exist at this time. We should note, however, that we do not argue here that the ratios that we do examine should substitute for any of the foregoing Basel proposals. Our goal instead is to suggest that some of those ratios contain valuable and virtually costless information, and therefore have a role in an overall framework for regulatory capital.

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. In some cases, a ratio is intended as a minimum acceptable level, whereas in other cases, the ratio may identify an appropriate level of capital for the bank. This distinction between a minimum and an "optimum" level is discussed in detail in Estrella (1995).

Another distinction is between adequate levels and backstop levels, such as in the 1991 FDICIA 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. It is possible that a particular ratio may be more suited for one of these two cases than for the other.

Closely related is the distinction between the value of a bank in liquidation and the value of a bank 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 the bank ceases to be a going concern and moves into liquidation mode (see, for example, Demsetz, Saidenberg, and Strahan [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 (see discussions in Estrella [1995] and Berger, Herring, and Szegö [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 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 to allow regulators, shareholders, and depositors to sleep at night, but not so high that the total cost of capital to the firm outweighs 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.

The Relationship between Capital Ratios and Bank Failure

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; that is, the level should be associated with a fairly high probability of failure. Regulators will generally select a positive level for the backstop rather than the level of technical insolvency at which the net worth of the bank is zero. One reason is that the valuation of the bank is not known precisely until liquidation. There is no assurance that a liquidated bank 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.

Regulators must choose a backstop level that is highly correlated with failure in the very short run; that is, the level should be associated with a fairly high probability of failure.

This potential loss in the value of the firm in liquidation also helps explain why capital levels in general 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—value that the owners could capture by selling their stakes if the institution were viable. 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, with reference once more to the graph, the backstop level at point A corresponds to a fairly high probability of failure but represents enough capital to deal with uncertainties relating 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.

Useful Features of Capital Ratios

A capital ratio is constructed from two components. The numerator is a measure of the absolute amount (for example, the dollar value) of capital of the firm and is inversely related to the probability of failure. The denominator is a proxy for the absolute level of risk of the bank. By taking the ratio we are able to gauge whether the absolute amount of capital is adequate in relation to some indicator of absolute risk. Basically, a large bank needs a larger amount of capital than a small bank, ceteris paribus, and a riskier bank needs more capital than a less risky bank, ceteris paribus. Absolute risk is probably roughly proportional to scale, so that measures of scale are generally good proxies for absolute risk. The three ratios we examine in this paper represent various approaches to measuring scale and absolute risk.

We will define the ratios more precisely in the next section, but we provide here some preliminary discussion of how each deals with scale and risk. 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 virtually costless to administer and very transparent.

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.

Risk weighting effectively requires financial institutions to charge more capital for riskier assets, discouraging them from holding risky assets. By responding to the risk-reducing incentives, banks can increase the risk-weighted ratio without raising capital. On the other hand, failure to respond would result in a low risk-weighted ratio. Thus, if risk weights accurately reflect the riskiness of assets, the risk-weighted ratio should better distinguish between risky and safe banks and should be a more effective predictor of bank failure 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.

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.

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, since lending to risky borrowers belongs in the highest risk-weight category, the incentive to economize capital might induce banks to reduce lending to those borrowers that do not have alternative financing sources.[1] Economic activity may contract as a result. In addition, it is costly to administer risk-based capital requirements, especially since both monitoring and reporting burdens may be heavy.

Our third ratio—not currently part of the regulatory framework but suggested, for example, by Shepheard-Walwyn and Litterman (1998)—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 and thus is virtually costless to administer. 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.

Capital Ratios and the Likelihood of Failure

To assess the predictive efficacy of capital ratios, our analysis utilizes standard measures defined by the existing capital adequacy rules. The measure of capital applied in the numerator of all three ratios is *tier 1 capital*, defined to include common stock, common stock surplus, retained earnings, and some perpetual preferred stock. The *risk-weighted capital ratio* is defined as the ratio of tier 1 capital to risk-weighted assets. The definition of the *leverage ratio* is tier 1 capital divided by total tangible assets (quarterly average). The *gross revenue ratio* is tier 1 capital divided by total interest and noninterest income before the deduction of 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) produced by the Federal Financial Institutions Examination Council. The Federal Reserve Board provides a formal algorithm for calculating risk-weighted ratios for 1991 and subsequent years. Risk-weighted capital ratios for 1988, 1989, and 1990 were estimated based on the *Capital Adequacy Guidelines* published by the Board of Governors of the Federal Reserve System.

Table 1 presents summary statistics for the three different measures of capital adequacy for the period 1988-92. Looking at the top panel of the table, we observe that the mean and median leverage ratios for our sample of banks during this period are fairly stable at around 9 and 8 percent, respectively. Since these statistics are based on unweighted data, 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 (not shown in table) are lower. The table also helps to highlight that the gross revenue measure (middle panel) 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 (bottom panel) 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.

Table 1

Summary Statistics

Year	Number of Observations	Mean	Median	Standard Deviation	Minimum	Maximum
			Leverage Ratio			
1988	13,299	0.094	0.082	0.077	-0.512	0.998
1989	12,903	0.096	0.083	0.076	-0.440	0.995
1990	12,388	0.094	0.082	0.072	-0.549	0.998
1991	11,941	0.094	0.082	0.070	-0.438	0.998
1992	11,473	0.096	0.085	0.068	-1.663	0.997
Total	62,004	0.095	0.083	0.073	-1.663	0.998
			Gross Revenue Ratio			
1988	13,299	1.146	0.866	3.712	-4.938	300.110
1989	12,903	1.228	0.816	13.192	-4.228	1,345.000
1990	12,388	1.032	0.819	2.239	-4.124	135.240
1991	11,941	1.211	0.864	15.051	-1.088	1,601.330
1992	11,473	1.253	1.004	6.683	-0.729	679.500
Total	62,004	1.173	0.871	9.595	-4.938	1,601.330
			Risk-Weighted Capital Ratio			
1988	13,299	0.186	0.142	0.264	-0.607	12.383
1989	12,903	0.195	0.144	0.608	-0.739	52.089
1990	12,388	0.179	0.136	0.298	-0.524	9.534
1991	11,941	0.208	0.139	3.040	-0.439	330.902
1992	11,473	0.193	0.147	0.487	-1.584	34.249
Total	62,004	0.192	0.141	1.390	-1.584	330.902

Sources: Federal Financial Institutions Examination Council, Consolidated Reports of Condition and Income; authors' calculations.

Table 2

Measures of Correlation

Year	Leverage Ratio–Gross Revenue Ratio	Leverage Ratio–Risk-Weighted Capital Ratio	Gross Revenue Ratio–Risk-Weighted Capital Ratio
	Pearson Correlation Coefficient		
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

Sources: Federal Financial Institutions Examination Council, Consolidated Reports of Condition and Income; authors' calculations.

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 the 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.

Distribution of Bank Failure

A good measure of capital adequacy should be related very closely to bank failure. 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 covers all failed and surviving banks during the period 1989-93. We excluded from the analysis all banks that were acquired during the period because many 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 times 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 the next subsection, we will also present a parametric model of survival that gives a more precise account of the conditional distribution of failure.

In the top panel of Table 3, 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 noncumulative data, each range is bounded above by the cutoff point of the row and bounded below by the cutoff point of the previous row. 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 into percentile classes of equal size, ranked by the ratio, the relative scale facilitates a uniform comparison of the different capital ratios.

A good measure of capital adequacy should be related very closely to bank failure. . . . Our analysis investigates this issue by looking at the distribution of bank failures with respect to the alternative capital ratios.

As the column headed "Failure Rate for Row" indicates, the proportion of failed observations (number of failures divided by the total number of banks in the leverage ratio class) on an absolute scale (top panel) was more than 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 to 5 percent and below 1 percent in the 6 to 7 percent range. The proportion is quite small (0.1 percent or lower) for bank observations with leverage ratios higher than 7 percent. In relative terms, the bottom panel of Table 3 shows that the proportion of failures is very high (74.7 percent) for banks in the lowest 1 percentile leverage ratio range but quickly drops below 10 percent in the 3 to 4 percentile class. The sharp drop-off in the proportion of failures is indicative of a successful measure.

Table 3

Distribution of Bank Failures by Leverage Ratios

Cutoff Percentile	Cutoff Point	Failures 1989-93	Nonfailures 1989-93	Failure Rate for Row (Percent)	Cumulative Proportion of Nonfailures (Type II Error) (Percent)	Cumulative Proportion of Failures (Type I Error) (Percent)
	Absolute Scale					
—	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	1,799	1.4	7.3	4.8
—	7.0	17	5,136	0.3	19.1	2.1
—	8.0	8	8,175	0.1	37.8	0.8
—	9.0	0	7,767	0.0	55.6	0.8
—	10.0	3	5,858	0.1	69.0	0.3
—	11.0	0	3,940	0.0	78.1	0.3
—	12.0	0	2,702	0.0	84.3	0.3
—	Infinity	2	6,869	0.0	100.0	0.0
	Relative Scale					
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	6,180	0.3	22.9	1.6
50	8.55	5	11,063	0.0	48.3	0.8
75	10.46	3	11,065	0.0	73.6	0.3
100	Infinity	2	11,508	0.0	100.0	0.0

Sources: Federal Financial Institutions Examination Council, Consolidated Reports of Condition and Income; Board of Governors of the Federal Reserve System, National Information Center database; authors' calculations.

Notes: Noncumulative data are for the range defined by cutoffs in the current and the previous row. Cumulative data are aggregated up to the cutoff point.

In addition to reporting the frequency of failure for specific ranges, Table 3 presents cumulative frequencies. The cumulative proportion of nonfailures 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 represents the total number of failures for bank observations having a leverage ratio greater than or equal to the leverage ratio cutoff value, divided by the total number of failures.[2] Looking at the cumulative proportion of nonfailures, we find that only 0.5 percent of nonfailures would be classified under prompt corrective action as critically undercapitalized (that is, showing a leverage ratio of less than 2 percent).[3] 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; the alternative hypothesis is that the 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 Table 3 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 decision not to close 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 nonfailures 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 statistically misclassified). Note that there is a trade-off in general between the probabilities of Type I and Type II errors. It is impossible to reduce both simultaneously by shifting the cutoff ratio.

The gross revenue ratio classifies failures and nonfailures about as accurately as the leverage 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 the lower panel of Table 3 suggests, the two cumulative ratios are approximately equal around the seventh percentile cutoff, which is equivalent to the 5.75 percent leverage ratio cutoff point.[4] In addition, 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 proportion of failing observations declines quite rapidly with the gross revenue ratio, and failures are highly concentrated at low gross revenue ratios. The top panel may be somewhat difficult to interpret because the levels of the gross revenue ratio tend to be less familiar than the 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, the bottom panel 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 threshold. Overall, a comparison of the bottom panels of Tables 3 and 4 suggests that the gross revenue ratio classifies failures and nonfailures about as accurately as the leverage ratio. The two panels show very similar failure rates, Type I errors, and Type II errors in each percentile class.

Finally, Table 5 shows the distribution of bank failures for the tier 1 risk-weighted capital ratio. In general, the distribution of failures against tier 1 risk-weighted capital ratios is comparable to that for 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, as minimum levels, 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.[5] 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-weighted measure is not included in this article, we find that the failure rate at the 10 to 11 percent range is only 0.4 percent, suggesting that

Table 4

Distribution of Bank Failures by Gross Revenue Ratios

Cutoff Percentile	Cutoff Point	Failures 1989-93	Nonfailures 1989-93	Failure Rate for Row (Percent)	Cumulative Proportion of Nonfailures (Type II Error) (Percent)	Cumulative Proportion of Failures (Type I Error) (Percent)
			Absolute Scale			
—	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	1,755	0.7	8.3	5.7
—	70	14	3,634	0.4	16.6	3.5
—	80	13	5,431	0.2	29.0	1.4
—	90	5	5,945	0.1	42.6	0.6
—	100	1	5,431	0.0	55.1	0.5
—	110	2	4,526	0.0	65.5	0.2
—	120	0	3,499	0.0	73.5	0.2
—	Infinity	1	11,576	0.0	100.0	0.0
			Relative Scale			
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	6,179	0.3	22.9	2.4
50	94.27	11	11,057	0.1	48.3	0.6
75	120.24	3	11,065	0.0	73.6	0.2
100	Infinity	1	11,509	0.0	100.0	0.0

Sources: Federal Financial Institutions Examination Council, Consolidated Reports of Condition and Income; Board of Governors of the Federal Reserve System, National Information Center database; authors' calculations.

Notes: Noncumulative data are for the range defined by cutoffs in the current and the previous row. Cumulative data are aggregated up to the cutoff point.

the total risk-based measure may be the most binding of all the FDICIA capital adequacy ratios.

As expected, the performance of capital ratios deteriorates somewhat when we move from a one-year to a two-year horizon, that is, when we focus on failures occurring between one and two years after the capital ratio is observed. Tables 6-8 summarize the second-year failure rates and cumulative distribution of second-year failures and nonfailures for firms that survive the first year. The three capital ratios still provide a fairly clear signal, as evidenced by the sharp drop in the failure

Table 5

Distribution of Bank Failures by Risk-Weighted Capital Ratios

Cutoff Percentile	Cutoff Point	Failures 1989-93	Nonfailures 1989-93	Failure Rate for Row (Percent)	Cumulative Proportion of Nonfailures (Type II Error) (Percent)	Cumulative Proportion of Failures (Type I Error) (Percent)
			Absolute Scale			
—	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	1,251	0.6	7.5	5.9
—	10.0	10	2,217	0.4	12.6	4.3
—	11.0	5	3,061	0.2	19.6	3.5
—	12.0	8	3,492	0.2	27.6	2.2
—	Infinity	14	31,579	0.0	100.0	0.0
			Relative Scale			
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	6,183	0.2	22.9	2.7
50	14.66	10	11,058	0.1	48.3	1.1
75	19.86	2	11,066	0.0	73.6	0.8
100	Infinity	5	11,505	0.0	100.0	0.0

Sources: Federal Financial Institutions Examination Council, Consolidated Reports of Condition and Income; Board of Governors of the Federal Reserve System, National Information Center database; authors' calculations.

Notes: Noncumulative data are for the range defined by cutoffs in the current and the previous row. Cumulative data are aggregated up to the cutoff point.

Table 6

Distribution of Bank Failures by Leverage Ratios: Two-Year Failure Horizon

Cutoff Percentile	Cutoff Point	Failures 1989-93	Nonfailures 1989-93	Failure Rate for Row (Percent)	Cumulative Proportion of Nonfailures (Type II Error) (Percent)	Cumulative Proportion of Failures (Type I Error) (Percent)
			Absolute Scale			
—	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	1,391	4.9	6.4	27.1
—	7.0	57	4,001	1.4	17.9	14.8
—	8.0	32	6,627	0.5	37.0	8.0
—	9.0	9	6,285	0.1	55.1	6.0
—	10.0	6	4,714	0.1	68.6	4.7
—	11.0	6	3,242	0.2	78.0	3.4
—	12.0	5	2,190	0.2	84.3	2.4
—	Infinity	11	5,462	0.2	100.0	0.0
			Relative Scale			
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	4,891	0.8	23.2	13.3
50	8.60	31	8,771	0.4	48.4	6.7
75	10.49	12	8,791	0.1	73.7	4.1
100	Infinity	19	9,135	0.2	100.0	0.0

Sources: Federal Financial Institutions Examination Council, Consolidated Reports of Condition and Income; Board of Governors of the Federal Reserve System, National Information Center database; authors' calculations.

Notes: Noncumulative data are for the range defined by cutoffs in the current and the previous row. Cumulative data are aggregated up to the cutoff point.

Table 7

Distribution of Bank Failures by Gross Revenue Ratios: Two-Year Failure Horizon

Cutoff Percentile	Cutoff Point	Failures 1989-93	Nonfailures 1989-93	Failure Rate for Row (Percent)	Cumulative Proportion of Nonfailures (Type II Error) (Percent)	Cumulative Proportion of Failures (Type I Error) (Percent)
			Absolute Scale			
—	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	1,183	5.1	6.6	24.1
—	70	49	2,545	1.9	13.9	13.5
—	80	25	3,998	0.6	25.4	8.2
—	90	10	4,628	0.2	38.8	6.0
—	100	5	4,429	0.1	51.5	4.9
—	110	3	3,840	0.1	62.6	4.3
—	120	3	2,988	0.1	71.2	3.7
	Infinity	17	10,023	0.2	100.0	0.0
			Relative Scale			
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	4,881	1.0	23.1	9.2
50	97.39	19	8,783	0.2	48.4	5.2
75	123.78	8	8,795	0.1	73.7	3.4
100	Infinity	16	9,138	0.2	100.0	0.0

Sources: Federal Financial Institutions Examination Council, Consolidated Reports of Condition and Income; Board of Governors of the Federal Reserve System, National Information Center database; authors' calculations.

Notes: Noncumulative data are for the range defined by cutoffs in the current and the previous row. Cumulative data are aggregated up to the cutoff point.

Table 8

Distribution of Bank Failures by Risk-Weighted Capital Ratios: Two-Year Failure Horizon

Cutoff Percentile	Cutoff Point	Failures 1989-93	Nonfailures 1989-93	Failure Rate for Row (Percent)	Cumulative Proportion of Nonfailures (Type II Error) (Percent)	Cumulative Proportion of Failures (Type I Error) (Percent)
			Absolute Scale			
—	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	1,784	2.0	11.6	14.6
—	11.0	15	2,533	0.6	18.9	11.4
—	12.0	10	2,880	0.3	27.2	9.2
—	Infinity	43	25,308	0.2	100.0	0.0
			Relative Scale			
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	4,898	0.6	23.1	10.3
50	14.66	28	8,774	0.3	48.4	4.3
75	19.73	12	8,791	0.1	73.7	1.7
100	Infinity	8	9,146	0.1	100.0	0.0

Sources: Federal Financial Institutions Examination Council, Consolidated Reports of Condition and Income; Board of Governors of the Federal Reserve System, National Information Center database; authors' calculations.

Notes: Noncumulative data are for the range defined by cutoffs in the current and the previous row. Cumulative data are aggregated up to the cutoff point.

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 perform quite similarly, although the likelihood of failure is somewhat harder to estimate than in the case of a one-year horizon.[6]

Qualitative Forecasts and the Probability of Failure

Our simple frequency distribution analysis shows that the three alternative measures of capital adequacy perform equally well in identifying failure. In this section, we employ parametric models of bank failure to examine more formally the conditional relationship between the likelihood of failure and the capital ratios. The simplest way to analyze bank failure is to use a qualitative response model. In this model, the dependent variable takes discrete outcomes (in our case, failure or nonfailure). We first estimate the likelihood of failure using a discrete logit model. Estimating the model over the entire panel may lead to biased estimates because the typical logit specification assumes that the event of failure is independent over time. To avoid the apparent time-dependency in the observations, we have estimated the logit model cross-sectionally for each year from 1989 to 1993. In addition to these cross-sectional regressions, we analyze our sample of banks using a proportional hazard model. This model of survival will enable us to better estimate the conditional likelihood of failure over time.

The primary objective of the cross-sectional qualitative choice model is to evaluate how consistently these alternative capital ratios predict failure over time. In this framework, the dependent variable is the probability of failure in a given year, 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 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.[7]

Table 9 reports the results of cross-sectional logit regressions for each year between 1989 and 1993. Overall, the logit analysis shows that all three alternative capital ratios predict fairly accurately failures occurring within one year. When each capital ratio is entered separately in the regression (models 1-3), the model coefficients are, without exception, statistically significant at the 1 percent level. Looking at the concordance ratios, we observe that the logit models based solely on capital ratios can accurately predict failures.[8] The predictive performance of these capital measures is fairly robust over time. Among the three capital ratios, the leverage ratio generally achieves the highest pseudo-R^2 and concordance ratio.[9] The difference in these forecasting efficiency measures among the alternative capital ratios, however, is very small. When all three capital ratios are included together in the logit regression (model 4), the gross revenue ratio appears to have the highest significance overall. Not surprisingly, the sign and magnitude of the regression coefficients in model 4 are less stable across the different years of estimation because of the high degree of collinearity between the three capital measures. Consequently, the interpretation of the logit coefficients is quite difficult in this joint model. As Table 2 shows, however, one advantage of the gross revenue ratio is that it is relatively less correlated with the other two competing capital ratios, meaning that it has the potential to add, on average, more information in the joint regression.

Our simple frequency distribution analysis shows that the three alternative measures of capital adequacy perform equally well in identifying failure.

The relative performance of the risk-weighted ratio improves when the time horizon is extended to between one and two years (Table 10). The risk-weighted ratio outperforms the leverage ratio by small margins in terms of both the pseudo-R^2 and the concordance ratio. On the other hand, the gross revenue ratio performs about as well as the risk-weighted ratio, especially when all three ratios are included.

Based on these regression results, simple capital ratios (the leverage ratio and the gross revenue ratio) appear to predict bank failure as well as the risk-weighted capital ratio, especially over 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 the ratio, in contrast to the others, draws independent information about financial flows from both balance sheets and income statements.

Table 9

Logit Regressions

Dependent Variable: Failure in Less Than One Year

	1989			
	Model 1	Model 2	Model 3	Model 4
Intercept	-0.0878	-0.2646	-0.3497	-0.0901
	(0.5450)	(0.0591)	(0.0126)	(0.5345)
Leverage ratio	-77.8819			-74.4450
	(0.0001)			(0.0001)
Gross revenue ratio		-7.2188		0.0093
		(0.0001)		(0.9588)
Risk-weighted ratio, tier 1			-46.5865	-2.0587
			(0.0001)	(0.6595)
Pseudo-R^2	0.1190	0.1120	0.1101	0.1191
Concordant (percent)	98.0	97.7	97.0	98.1
Discordant (percent)	1.5	1.7	2.1	1.5
Tie (percent)	0.4	0.6	0.9	0.4
Failures	195			
Nonfailures	13,104			

	1990			
	Model 1	Model 2	Model 3	Model 4
Intercept	0.3984	0.2650	0.1679	0.3967
	(0.0179)	(0.1007)	(0.2992)	(0.0182)
Leverage ratio	-96.0482			-49.5560
	(0.0001)			(0.0194)
Gross revenue ratio		-10.0654		-5.0353
		(0.0001)		(0.0258)
Risk-weighted ratio, tier 1			-58.8834	0.7287
			(0.0001)	(0.7317)
Pseudo-R^2	0.1350	0.1330	0.1269	0.1359
Concordant (percent)	97.6	96.7	97.8	97.3
Discordant (percent)	1.1	1.2	1.1	1.1
Tie (percent)	1.2	2.1	1.1	1.6
Failures	161			
Nonfailures	12,742			

	1991			
	Model 1	Model 2	Model 3	Model 4
Intercept	-0.3688	-0.2871	-0.4797	-0.2754
	(0.0260)	(0.0781)	(0.0034)	(0.0939)
Leverage ratio	-74.3724			-0.4529
	(0.0001)			(0.9353)
Gross revenue ratio		-8.2146		-8.0113
		(0.0001)		(0.0001)
Risk-weighted ratio, tier 1			-46.6516	-0.9220
			(0.0001)	(0.7826)
Pseudo-R^2	0.0790	0.0756	0.0648	0.0757
Concordant (percent)	97.5	97.5	97.4	97.5
Discordant (percent)	1.5	1.3	1.5	1.3
Tie (percent)	1.0	1.1	1.1	1.1
Failures	122			
Nonfailures	12,266			

	1992			
	Model 1	Model 2	Model 3	Model 4
Intercept	0.5121	0.4550	0.2586	0.5875
	(0.0166)	(0.0242)	(0.2099)	(0.0057)
Leverage ratio	-87.2859			-7.2337
	(0.0001)			(0.3267)
Gross revenue ratio		-8.8321		-7.9533
		(0.0001)		(0.0001)
Risk-weighted ratio, tier 1			-52.4554	-1.8505
			(0.0001)	(0.5221)
Pseudo-R^2	0.0832	0.0770	0.0665	0.0781
Concordant (percent)	96.0	92.7	91.9	92.8
Discordant (percent)	2.4	3.2	4.0	3.1
Tie (percent)	1.6	4.1	4.1	4.1
Failures	114			
Nonfailures	11,827			

	1993			
	Model 1	Model 2	Model 3	Model 4
Intercept	-2.4270	0.0234	-2.3277	0.0534
	(0.0001)	(0.9416)	(0.0001)	(0.8761)
Leverage ratio	-40.6257			2.4996
	(0.0001)			(0.3609)
Gross revenue ratio		-7.9371		-7.8714
		(0.0001)		(0.0001)
Risk-weighted ratio, tier 1			-25.8946	-2.0740
			(0.0001)	(0.2988)
Pseudo-R^2	0.0192	0.0290	0.0157	0.0293
Concordant (percent)	91.4	92.9	93.8	92.9
Discordant (percent)	4.8	2.2	3.4	2.2
Tie (percent)	3.8	5.0	2.8	5.0
Failures	42			
Nonfailures	11,431			

Sources: Federal Financial Institutions Examination Council, Consolidated Reports of Condition and Income; Board of Governors of the Federal Reserve System, National Information Center database; authors' calculations.

Notes: Numbers in parentheses are p-values. Pseudo-R^2 is defined in endnote 9. See also Estrella (1998).

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

Thus far, we have focused on the capacity of the capital measures to predict failure over shorter time horizons. One would expect that the efficacy of these regulatory capital ratios might deteriorate if we evaluate their forecasting ability beyond the one- or two-year horizon. Peek and Rosengren (1997) point out that most banks that failed during the New England banking crisis of 1989-93 were well capitalized two years before failure. Similarly, Jones and King (1995) argue that between 1984 and 1989 most troubled banks would not have been classified as undercapitalized under the FDICIA rules. Those studies suggest that prompt corrective action rules mandated by FDICIA would have been ineffective in dealing with banking problems during those periods.

Table 10

Logit Regressions

Dependent Variable: Failure between One and Two Years

	1990			
	Model 1	Model 2	Model 3	Model 4
Intercept	-0.1870 (0.2954)	-0.4087 (0.0177)	-0.5030 (0.0034)	-0.2442 (0.1774)
Leverage ratio	-62.1593 (0.0001)			-22.2474 (0.0437)
Gross revenue ratio		-5.7019 (0.0001)		-0.6953 (0.4567)
Risk-weighted ratio, tier 1			-36.5074 (0.0001)	-19.7745 (0.0001)
Pseudo-R^2	0.0437	0.0425	0.0449	0.0466
Concordant (percent)	86.7	87.1	88.8	88.8
Discordant (percent)	10.4	10.0	8.6	8.8
Tie (percent)	2.9	2.8	2.6	2.4
Failures	167			
Nonfailures	12,550			

	1991			
	Model 1	Model 2	Model 3	Model 4
Intercept	-0.9504 (0.0001)	-0.6484 (0.0010)	-0.9654 (0.0001)	-0.6917 (0.0007)
Leverage ratio	-50.6460 (0.0001)			18.8294 (0.0001)
Gross revenue ratio		-5.9608 -0.0001		-4.6201 (0.0001)
Risk-weighted ratio, tier 1			-31.9536 (0.0001)	-19.3007 (0.0002)
Pseudo-R^2	0.0191	0.0278	0.0252	0.0299
Concordant (percent)	86.1	87.2	89.7	88.4
Discordant (percent)	10.9	9.6	8.1	8.4
Tie (percent)	3.0	3.2	2.2	3.2
Failures	125			
Nonfailures	12,205			

	1992			
	Model 1	Model 2	Model 3	Model 4
Intercept	-0.6818 (0.0016)	-0.8511 (0.0001)	-0.5561 (0.0079)	-0.6623 (0.0027)
Leverage ratio	-56.1702 (0.0001)			19.9661 (0.0805)
Gross revenue ratio		-5.5291 (0.0001)		-0.4750 (0.5797)
Risk-weighted ratio, tier 1			-37.8934 (0.0001)	-47.2949 (0.0001)
Pseudo-R^2	0.0236	0.0242	0.0302	0.0305
Concordant (percent)	88.1	87.4	89.4	88.4
Discordant (percent)	9.3	9.7	8.2	8.5
Tie (percent)	2.6	2.9	2.4	3.1
Failures	119			
Nonfailures	11,702			

	1993			
	Model 1	Model 2	Model 3	Model 4
Intercept	-2.4512 (0.0001)	-1.7406 (0.0001)	-2.1743 (0.0001)	-1.6986 (0.0001)
Leverage ratio	-41.4685 (0.0001)			13.1137 (0.0419)
Gross revenue ratio		-5.2671 (0.0001)		-4.3610 (0.0001)
Risk-weighted ratio, tier 1			-28.6207 (0.0001)	-14.0894 (0.0741)
Pseudo-R^2	0.0048	0.0091	0.0072	0.0097
Concordant (percent)	79.0	85.0	83.2	85.5
Discordant (percent)	11.6	8.1	9.4	7.8
Tie (percent)	9.4	6.9	7.4	6.7
Failures	43			
Nonfailures	11,292			

Sources: Federal Financial Institutions Examination Council, Consolidated Reports of Condition and Income; Board of Governors of the Federal Reserve System, National Information Center database; authors' calculations.

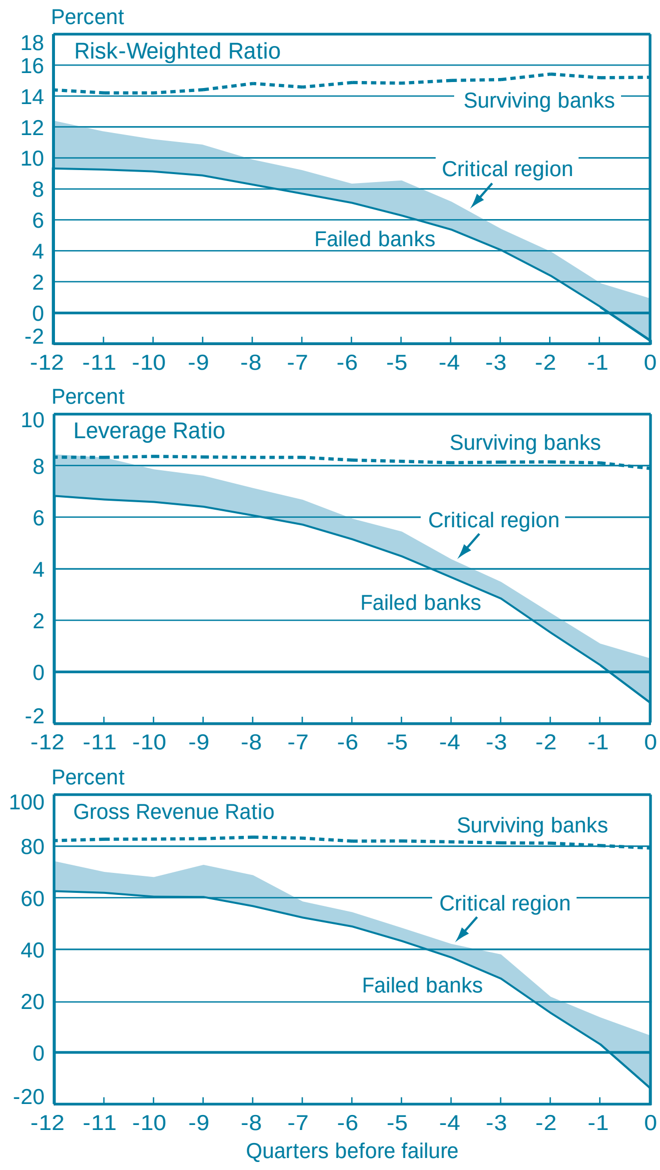
Notes: Numbers in parentheses are p-values. Pseudo-R^2 is defined in endnote 9. See also Estrella (1998).

Despite the evidence that the performance of capital ratios is not very good at more distant horizons, our analysis suggests that these measures are actually able to disseminate useful signals long before the event of failure. For one, we find that failing banks begin to show signs of weakness (that is, become undercapitalized) two to three years before they are closed by supervisors. The chart 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 measures for a control sample of nonfailed banks. The control group consists of randomly chosen banks located in the same state and having an asset size similar to that of the banks in the failed group.

As the chart shows, the median capital ratios for the group of failed banks are consistently lower than the median ratios for 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 for 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 the same at the 1 percent level. For the most part, the median capital ratio for the control group of nonfailed banks is outside the shaded critical region, suggesting that all three capital ratios are fairly good predictors of failure even as far back as two to three years.

Another simple but interesting way to test the long-run effectiveness of the capital ratios in predicting failure is hazard analysis. Although the hazard specification is closely related to binary models such as logit or probit models, it offers a better way to analyze the apparent time-dependency in the conditional probability of failure. More specifically, the dependent variable in hazard analysis is the probability that an institution will fail given that it has not failed until that point of time.[10] Thus, in contrast to the cross-sectional logit model that examines failure over shorter horizons, the proportional hazard specification analyzes the conditional likelihood farther into the future. To simplify our analysis, Table 11 examines two scenarios of survival. The top panel of the table evaluates the efficacy of capital ratios in forecasting the probability of failure from the first quarter of 1988. In this case, the implied dependent variable is the duration of time from the first quarter of 1988 until the bank fails or until the fourth quarter of 1993 for nonfailing banks (so-called censored observations). The explanatory variables in the hazard models (models 1-4) consist of the competing capital adequacy ratios as of the first quarter of 1988. Thus, in contrast to the yearly logit regression, which estimates the effectiveness of capital ratios in forecasting failure within one year or between one and two years, the hazard regressions evaluate the early warning capacity of the capital measures from the first quarter of 1988. To account for the economic downturn in 1990, the bottom panel of Table 11 also estimates the probability of bank failure from the first quarter of 1990.

Capital Ratios before Failure



Sources: Federal Financial Institutions Examination Council, Consolidated Reports of Condition and Income; Board of Governors of the Federal Reserve System, National Information Center database; authors' calculations.

Notes: The shaded area represents a 1 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.

Table 11

Cross-Sectional Proportional Hazard Analysis

Capital as of 1988:1

	Model 1	Model 2	Model 3	Model 4
Leverage ratio	-22.7113			7.3990
	(0.0001)			(0.0207)
Gross revenue ratio		-1.8274		0.0263
		(0.0001)		(0.7664)
Risk-weighted ratio, tier 1			-13.3307	-18.5383
			(0.0001)	(0.0001)
Pseudo-R^2	0.0320	0.0240	0.0470	0.0620
Model χ^2	280.789	213.624	418.078	549.112
Failures	475			
Nonfailures (censored)	8,189			

Capital as of 1990:1

	Model 1	Model 2	Model 3	Model 4
Leverage ratio	-10.3256			21.5610
	(0.0001)			(0.0001)
Gross revenue ratio		-1.3772		-1.7109
		(0.0001)		(0.0001)
Risk-weighted ratio, tier 1			-10.4816	-17.7188
			(0.0001)	(0.0001)
Pseudo-R^2	0.0310	0.0430	0.0550	0.0740
Model χ^2	269.647	382.794	487.820	660.746
Failures	326			
Nonfailures (censored)	8,348			

Sources: Federal Financial Institutions Examination Council, Consolidated Reports of Condition and Income; Board of Governors of the Federal Reserve System, National Information Center database; authors' calculations.

Notes: Numbers in parentheses are p-values. Pseudo-R^2 is defined in endnote 9. See also Estrella (1998).

It is clear from the estimated hazard that capital ratios continue to be fairly good predictors of failure even over longer time horizons. When each capital ratio is entered individually in the hazard regression (models 1-3), we find that all three capital ratios are again statistically significant at the 1 percent level. As the pseudo-R^2 statistics indicate, the explanatory power of these capital measures is lower than that obtained with a one-year horizon (Table 9). This finding is not surprising, because the controls are now asked to forecast the likelihood of failure over a longer duration, sometimes as long as six years.

The risk-based measure shows a relatively high pseudo-R^2 in the hazard models separately estimating the effect of each capital ratio and also shows high statistical significance in the models including all three capital ratios. The good performance of the risk-based capital ratio is more pronounced in the analysis using a longer time horizon (top panel). The statistical significance of the gross revenue ratio is comparable to that of the risk-weighted ratio in model 4 of the bottom panel, using a shorter time horizon. This finding is consistent with the result of the logit analysis, which shows that the relative performance of the risk-weighted ratio improves over a longer time horizon.

The risk-weighted ratio takes into account the riskiness of assets, and the gross revenue ratio reflects the asset risk to the extent that riskier assets have higher expected returns. The results in a longer time horizon are more consistent with these expectations. Risk weighting is an attempt to reflect heterogeneous return variances across assets. In a short time horizon, however, differences in return variances across assets may not be significant. For example, the probability that default occurs within a month may be very low even for a risky loan that is highly likely to default within three years. Thus, a possible explanation for the improved performance of the risk-weighted capital ratio over a longer time horizon is that the realization of differences in asset return variances takes time. This possibility also implies that in a short time horizon, risk weighting can overstate differences in asset return variances and hence reduce the accuracy of the risk-weighted ratio as a measure of capital adequacy.

Conclusion

This article compares the effectiveness of different types of capital ratios in predicting bank failure. An important result of our study is that simple ratios—specifically the leverage ratio and the ratio of capital to gross revenue—predict bank failure about as well as the more complex risk-weighted ratio over one- or two-year time horizons. This finding suggests that bank regulators may find a useful role for the simple ratios in the design of regulatory capital frameworks, particularly as indicators of the need for prompt supervisory action. Risk-weighted ratios, in contrast, tend to perform better over longer horizons.

Our intention, however, is not to argue against the use of more sophisticated measures of capital adequacy in regulation. On the contrary, we suggest that simple capital ratios may not be well suited for the determination of optimum levels of bank capital. However, we show that simple capital ratios contain useful information and are virtually costless to compute. Thus, it may be possible to derive substantial benefits from the use of simple ratios—for instance, as supplementary or backstop requirements—even when more sophisticated measures are available for use in formulating the primary requirements.

Endnotes

1. If banks prefer riskier assets (moral hazard), they might choose riskier borrowers within the highest risk-weight category. This effect, however, is unlikely to be large enough to offset the primary effect of reducing assets in the highest risk-weight category.

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

3. 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 article, we base our illustrations on Table 3, which is based on the leverage ratio. Tangible equity ratios produce similar results.

4. Equality of Type I and Type II errors is an interesting illustrative benchmark, but regulators can clearly choose different levels of this trade-off to suit their goals and preferences.

5. Tier 2 includes loan-loss reserves and a number of convertible and subordinated debt instruments. Banks are allowed to use loan-loss reserves up to a maximum of 1.25 percent of risk-weighted assets.

6. 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 when p is closer to ½ and n is smaller, both of which apply in the case of second-year rates as compared with one-year rates.

7. Early warning models use various balance-sheet and income-statement variables to predict bank failure (see, for example, Cole, Cornyn, and Gunther [1995], Cole and Gunther [1995], and 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.

8. 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 for nonfailure ($m \times [n-m]$ 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 failure and nonfailure.

9. The pseudo-R^2 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.

10. Because bank failure is a terminal event, the probability of bank failure at time τ given that it has not failed until that point in time or hazard rate is $h(\tau, x) = f(\tau, x)/(1-F(\tau, x))$, where $F(\tau, x)$ is the cumulative probability of failure up to time τ. The proportional hazard specification assumes that the hazard function is separable, that is, $h(\tau, x) = h_0(\tau)\exp[x\beta]$, where x is a vector of explanatory variables and $h_0(\tau)$ is the baseline hazard function.

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