Can the Equity Markets Help Predict Bank Failures?

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July, 2004

Working Paper 2004-03

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The views expressed here are those of the authors and do not necessarily reflect those of the FDIC or its staff. The authors would like to thank Audrey Clement for extensive assistance; and Gerald Hanweck, Andrew Davenport, anonymous referees, and the participants in the 2004 Washington Area Finance Association meetings and the 2004 Western Economic Association International meetings for helpful comments.

Abstract

The paper examines the informational content of market data when these data are incorporated into traditional models that predict bank failures. To assess whether financial markets can provide timely information about firm distress, we first examine the pre-failure behavior of market variables over long periods before failure. The univariate results document distinct patterns of declining prices, negative returns, declining dividends, and rising return volatility several years before failure. Several other market-related measures, however, such as trading volume and share turnover, show no clear trend. Next we test for the contribution of market variables in relation to Call Report variables in the prediction of bank failures over the 1989–1995 period. The findings show that selected market variables like equity prices, returns, and volatility of returns add important information to the identification of failed institutions beyond the information contained in quarterly accounting data. In-sample and out-of-sample tests show that the use of market data does improve the sample forecast of bank failure.

JEL Codes: G21, G28

Keywords: Bank Failure, Market information and Off-site Surveillance Models

Introduction

Failure prediction represents a special interest in banking because of the regulated nature of the industry as well as the federal safety net provided by deposit insurance. In this regard, bank supervisors depend on "traditional" models to forecast bank failure; these models are based on financial data obtained from quarterly Reports of Income and Condition (Call Reports).[1] In recent years, at the behest of the U.S. Congress, international regulatory bodies, and the academic community, bank regulators have been exploring whether data obtained from the securities markets (debt and equity) can be used to supplement failure-prediction models. To the extent that financial markets are efficient and market price and return movements for securities can be used to anticipate events including failure, then bank regulators might apply information embedded in market prices and trading patterns to improve early-warning and off-site monitoring systems. Improved early-warning systems necessarily enhance bank supervision, thereby reducing the likelihood and cost of failures. More generally, integrating market-based information into the tools of bank supervision represents a partial response to Flannery's (1998) call for enhancing our understanding of the use of market information in prudential bank supervision.

Predicting failure is especially interesting because failure normally follows the dissemination of large amounts of negative information, often over long periods of time. Failure is also the only financial event for which the post-event stock price is known before the event. The period before failure is almost always associated with negative returns, the cessation of trading on organized exchanges, and the fall of prices to approximately zero. These regularities suggest that the period preceding failure should provide an environment conducive to the formation of trends in market-

[1] In this paper, "bank" refers to an FDIC-insured commercial bank or thrift institution.

based data.

This paper develops two themes on the relation between equity market data and bank failure.[2] The first theme examines long-term trends in market variables before failure to see if financial markets can provide timely information about firm failure. Early research by Pettway (1976, 1980) and Pettway and Sinkey (1980), and later research by Davies (1993), identified return patterns several years before bank failure. Our approach extends that previous work by exploring the longer-term pre-failure trends of a wide variety of equity market variables for actively traded institutions. This perspective provides a global view of the pre-failure price and return patterns—a view that finds several trends before bank failure.

The second theme builds on the first by testing the extent to which equity market variables improve the predictive performance of traditional "ratio"-based models of bank failure.[3] Given the breadth of our focus, the analysis uses market variable benchmarks that are not generally representative of variables commonly used in previous research. In so doing, we test the extent to which market variables can be viewed as distinct, or as providing a different perspective, from other types of financial variables identified by previous theoretical and empirical work.

The results show that univariate analysis documents distinct patterns of declining prices, negative returns, declining dividends, and rising return volatility several years before bank failure. However, no clear trend emerges for several other market measures, including trading volume and share turnover. Multivariate analysis shows that market information such as equity prices and returns improves the failure-predictive content of the traditional models, which are

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[2] The advantages of using equity market information over using data obtained from the debt markets have been articulated by Saunders (2001).

[3] Among the many papers using only financial accounting data are Sinkey (1975), Bovenzi, Marino, and McFadden (1983), Elmer and Borowski (1988), Cole and Gunther (1995, 1998), and Kolari et al. (2000). Shumway (2001) uses a limited number of market variables in a traditional ratio-based model, but otherwise focuses on the forecasting advantages of hazard models. Commercial models, such as the "KMV" model described by Crouhy,

based only on Call Report financial ratios. In-sample and out-of-sample predictions show that the use of stock market data does improve the forecast of bank failure.

The next section discusses related literature. The subsequent section presents the sample and data and is followed by a section studying long-term univariate trends of returns, risk, and other market-related variables for the period before failure for sample institutions. Then comes a section in which logistic regressions are performed to test the predictive content of market-related variables versus the content of financial data to explain bank failure. The last section concludes.

Related Literature

It is well known that equity prices of banks destined for failure appear to fall for long periods before failure, thereby generating abnormal negative returns over those periods. However, few studies have analyzed these pre-failure return patterns of failed institutions. As mentioned, Pettway (1980) and Pettway and Sinkey (1980) find patterns of negative excess returns in banks as much as three years before failure, as well as similar patterns almost a year before regulators begin the examination that initially identifies the problems preceding failure. One limitation of this work was a limited sample of only six large-bank failures. Davies (1993) found that market information can help predict bank and bank holding company insolvency (not failure) when used with accounting and supervisory data. However, the analysis suffers from the use of only a single market variable—the market-to-book capital ratio.

While not focusing on bank failures, Curry, Fissel, and Elmer (2003) found in recent work significant declines in stock prices, abnormal returns, and volatility of returns preceding regulator-assigned CAMELS ratings to the problem-bank level (3, 4, or 5) two years before the

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Galai, and Mark (2000), are also known to use market variables, but their specifications are proprietary.

rating changes. Berger and Davies (1998) use event-study methodology and find that the equity market anticipates upgrades in regulatory ratings but follows downgrades. Berger, Davies, and Flannery (2000) find that regulators acquire information sooner than bond rating agencies and the equity markets, but the regulatory assessments are less accurate in predicting the future performance of bank holding companies than either stock or bond market indicators. However, Simons and Cross (1991) found no evidence that the market was cognizant of regulator downgrades before the event for a sample of 22 large bank holding companies.

Several recent studies have incorporated market data into traditional default or bankruptcy models to determine if the information adds value in identifying troubled institutions. Krainer and Lopez (2001, 2003a, 2003b) find that equity market variables, such as stock returns and equity-based expected default frequencies, can be useful to bank regulators for assessing the financial condition of bank holding companies. Gunther, Levonian, and Moore (2001) found that a measure of financial viability based on equity market data (expected default frequency) helps predict the financial condition of bank holding companies as reflected in their regulatory ratings. Finally, Curry, Fissel, and Hanweck (2003) find that market-indicator variables such as excess returns and volatility of returns add value to models in predicting changes in bank holding company supervisory risk ratings.

This paper augments the existing literature on several fronts. First, as mentioned, we focus on the long-term pre-failure trends for a wide variety of market variables that have generally not been used in previous work. This long-term analysis will shed light on the signaling and timing aspects of market data. Second, we use equity market variables along with quarterly financial data to predict bank failures, whereas most recent work focuses on predicting bank or holding company supervisory ratings. Third, we test for a wide variety of market variables with deep theoretical or empirical roots, including market returns, return volatility, return patterns, dividend policy, market valuations, and trading volume.

In summary, the several years preceding bank failure are well suited for testing the formation of market-related return patterns. This period is associated with an unusually large amount of private information regarding a fundamental change in a bank's health at the same time that published financial data are abundant. Moreover, previous research has confirmed that pre-failure return patterns in the banking industry consistent with a variety of market-related variables are potentially related to financial distress. Testing the failure-predictive content of these variables vis-à-vis that of publicly available financial data explores the ability of the variables to help predict bank failure.

Sample and Data

The sample comprises approximately 40 percent banks and 60 percent thrifts that were publicly traded and failed during the 1989–1995 period. The 1989 cutoff was chosen to avoid the many problems that existed in the banking and thrift industries before that date. In the case of thrifts, 1989 marked a watershed year with the passage of the Federal Financial Institutions Reform and Recovery Act (FIRREA), which not only provided a portion of the funds needed to resolve the thrift crisis but also contained provisions improving safety and soundness, such as higher capital requirements.[4] While the banking crisis of the 1980s was not as deep as the thrift crisis of the same era, the late 1980s nevertheless marked a sea change in bank regulation, owing to an increase in the regularity of bank examinations and other requirements.[5]

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[4] See Gupta and Misra (1999) for an overview of changes made to the banking system throughout the 1980s and early 1990s.
[5] For example, figure 12.4 in Curry et al. (1997) shows a spike in the median examination period for failed banks during the mid-1980s, followed by much lower levels beginning in approximately 1989.

Since our goal is to compare the failure-predictive content of market-related variables relative to the content of a bank's Call Report financial data, the sample excludes multibank holding companies. This restriction ensures that the Call Report financial data commonly used in failure-prediction models directly correspond to the institution that issues the stock traded in the market.[6] The restriction also reduces contamination from nonbank activities present in many holding companies as well as from "cross-subsidy" policies, whereby banks in multibank holding companies provide credit support for other members. Regrettably, the exclusion of multibank holding companies prevents inferences regarding our results from extending beyond the confines of our sample. Nevertheless, the "cost" of limited application seems more than offset by the "benefit" of fostering the cleanest possible environment for testing the failure-predictive content of market-related variables and Call Report financial data.

A bank or thrift is classified as a failure if it was either liquidated or merged with assistance by the FDIC or the RTC between January 1, 1989, and December 31, 1995.[7] All institutions in the sample have Call Report financial data and price information from the Center for Research in Securities Prices (CRSP) available for 16 quarters preceding failure. As shown on the left side of table 1, the sample size for the univariate analysis varies slightly over the 16 quarters preceding failure. The sample declines in the early years because of the lack of CRSP data, which may reflect the fact that several of these institutions were not publicly traded at the time. Also, the sample drops noticeably in quarters 1 through 3 because of the de-listing rules of

[6] This correspondence is important because the public equity of banks held by holding companies is typically issued at the holding-company level, whereas Call Report financial data are reported at the bank level. Banks are also distinguished from their holding companies in bankruptcy, for individual banks are taken over by the Federal Deposit Insurance Corporation whereas their holding companies fall under the purview of standard bankruptcy law.
[7] Bank failures after 1995 were not included in the sample because most did not meet the sample selection criteria described above. Of the two failed institutions that did qualify, stock price information from the Center for Research in Securities Prices was not available for a long-enough period for the analysis to be conducted.

the various exchanges, such as minimum capital requirements or minimum trading activity.[8] The sample of failed banks used in the multivariate analysis is slightly smaller than that used in the univariate analysis because of the lack of data for specific variables used in the regressions.[9]

Univariate Trends Preceding Bank Failure

This section analyzes the univariate trends of market-related variables of banks and thrifts destined for failure. The goal is to identify market-based variables that financial theory might view as possessing failure-predictive content, then to assess the extent to which these variables have longer-term monotonic relationships to the likelihood of default—relationships either steadily increasing or decreasing as default approaches. The analysis serves to determine whether Pettway's (1980) long-term return trends persist in a larger, more recent sample, while expanding the analysis to include new market variables.

Table 1 examines the univariate characteristics of stock prices, returns, dividends, and other market-related variables of a sample of failed banks and thrifts 16 quarters (four years) before failure. The data show stock prices declining steadily throughout the four-year period before failure. The average stock price begins at 10.64 in quarter 16, then declines to less than 1 in quarter 1. Steadily declining prices easily explain cumulative quarterly returns that are persistently negative throughout the 16-quarter sample. We calculated the cumulative quarterly compounded returns as holding-period returns by multiplying unity plus the return for each stock i on day t $(1+r_{it})$ across all trading days reported on the CRSP, less unity. The four years of negative cumulative quarterly compounded returns reported in table 1 reaffirm Pettway's (1980)

[8] In the sample, the most common reasons for de-listing were insufficient number of market makers and insufficient capital.
[9] For example, for the 4-, 8-, and 12-quarter regressions before failure, the total sample of failed banks and thrifts is 86, 85, and 63 respectively. As noted, for each set of failed institutions there is a control sample of equal

finding of negative average returns many years before bank failure. In our case, the larger sample facilitates the computation of t-statistics testing the hypotheses that the mean of the quarterly cumulative compounded returns equals zero. The t-tests show that the negative returns in 13 of the first 16 quarters preceding failure are statistically significant, suggesting a statistically recognizable pattern of negative returns for several years preceding failure.

Table 1 extends the analysis of return trends by calculating market excess or abnormal returns based on several market benchmarks. To this end, the quarterly market excess return for each stock $i=1, \ldots, j$ (MER_i) is calculated according to convention: (1)

$$MER_i = \left(\left(\prod_{t=1}^{n} (1 + r_{it})\right) - \left(\prod_{t=1}^{n} (1 + r_{mt})\right) - 1\right)$$

where r_{it} = the actual return for stock i on day $t=1, \ldots, n$ and r_{mt} = the return on a market index on day t. The three columns of excess returns shown in table 1 report the arithmetic average excess return for all stocks in each quarterly sample $\overline{MER} = (1/j)\sum_{t=1}^{j} MER_t$, where j equals the number of banks in our sample. The t-statistics below each quarterly $\overline{MER}$ test the null hypothesis that $\overline{MER} = 0$.

The $\overline{MER}$ statistics in table 1 display a consistent pattern of negative returns that are almost always significant at the 1 percent or 5 percent level in all 16 quarters preceding failure, regardless of the market index used. The CRSP equal and value-weighted return indexes resulted in very similar excess return estimates. A third effort calculated excess returns by comparing bank and thrift returns with separate value-weighted bank and thrift industry return

magnitude.

indexes.[10] This effort also resulted in excess returns that are consistently negative and significant at the 1 percent or 5 percent level. Since the behaviors of the three excess return estimates are very similar, we use the CRSP value-weighted index for the remainder of this study in the interests of transparency.

An intriguing aspect of market data is that various aspects of financial theory effectively extend the list of market-related variables beyond prices and returns. For example, table 1 proceeds by examining two risk variables commonly associated with Fama and French (1993): market capitalization and the market-to-book value of equity ratio (ME/BE). Steadily declining prices cause market capitalization (price times number of shares) to follow a similar downward trend throughout the 16 quarters reported. The declining value of market equity also explains the monotonic slide of the ME/BE ratio throughout the period preceding failure. The trend in the ME/BE variable reveals the change in a consistent fashion as default approaches. Also, the dummy dividend variable shows a consistent declining path throughout the four-year period, as fewer firms pay dividends in response to declining financial fortunes or regulatory mandate.

The last risk variable shown in table 1 is return volatility. This variable is most closely associated with Merton's (1974) option model, which anticipates a rise in return volatility as an institution approaches insolvency.[11] As demonstrated, return volatility rises steadily from 2.47 in quarter 16 to 13.87 percent in quarter 1. Clearly, volatility represents an effective univariate gauge of default risk similar to the other risk variable, the ME/BE variable.

Table 2 performs a sensitivity analysis of the aggregate value-weighted excess returns

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[10] Bank and thrift industry indexes were created from approximately 2,200 institutions that could be identified on the CRSP and tied back to their specific charter. Separate value-weighted indexes were created for banks and thrifts using the CRSP utility for creating value-weighted indexes (DSXPORT). At the beginning of each year, the sample of banks or thrifts was set, then the index calculated for one year. The final index combined the yearly indexes into a continuous long-term series.

[11] French, Schwert, and Stambaugh (1987) lend empirical support to this view by documenting a positive relation

reported in table 1. The first cut breaks returns by two measures of institution size: total assets and trading volume. To the extent that larger-sized, more heavily traded firms are better known and more closely monitored by market analysts, investors, and bank regulators than smaller, less actively traded organizations, it is anticipated that the market would be more sensitive to changes in their idiosyncratic risk and financial condition. This should be reflected in market returns and trading volume as firms approach insolvency.

In both cases, the market seems to be aware of changes in financial condition across all size classes several years before insolvency, but the trends are slightly stronger for the smallest institutions. For example, returns for institutions with assets below $1 billion are negative and significant in almost all 16 quarters before failure, while almost all of the returns are statistically significant for the $1 billion to $5 billion class and slightly less significant for the over-$5 billion class. A similar pattern of return persistence in smaller firms can be seen in the three columns of excess returns split by trading volume. Apparently, local knowledge about changes in financial condition spreads quickly through the grapevine, which may account for some of these effects.

The last four columns of table 2 distinguish the excess returns of low versus high ME/BE ratios and bank versus thrift charters. In both cases, excess returns appear very similar to the aggregate excess returns shown in table 1. That is, returns are always negative, they tend to be stronger for the smaller-sized firms, they are about the same for both banks and thrifts, the highest negative values tend to be relatively close to failure, and, in most cases, the returns are statistically significant at a high level of significance. The sample line at the bottom of table 2 shows that the average number of institutions in the 16 quarters of univariate analysis was 42 banks and 48 thrifts.

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between the volatility of market returns and market excess returns (market return minus T-bill spread).

Table 3 examines the pre-failure patterns of other market variables as they relate to trading volume. Wang (1994) ties trading volume to the flow of information about a firm's financial health, suggesting that trading volume should rise as information about financial distress is released.[12] Interestingly, of the three variables, none exhibits a consistently rising trend anticipated by pre-failure behavioral theories, although some of the variables become more active immediately before failure. For example, two direct measures of trading activity, daily trading volume and the standard deviation of daily trading volume, remain largely unchanged throughout most the four years preceding failure but establish a trend with four quarters to failure. A third measure of trading activity, turnover, is calculated as the percentage of the number of shares traded in a quarter divided by the number of shares outstanding at the end of the quarter. This variable also remains largely unchanged during the two years preceding failure, with a modest downward trend over a three- to four-year period preceding failure. Thus, it appears that univariate measures of trading activity fail to follow the upward trend preceding failure anticipated by recent theories, even though this period is marked by rapidly changing private information and steadily falling stock prices.

Following Chen, Hong, and Stein (2000), we calculated another market return variable, called "skewness." It is measured as the negative of a standard measure of skewness, calculated as the third moment of daily returns divided by the standard deviation of daily returns raised to the third power. That is, the *n* daily log price differences described earlier for quarterly samples. Skewness is measured by the following equation:

$$SKEW_i = -\left(n(n-1)^{3/2} \sum_{t=1}^{n} r_{it}^3 \right) \Bigg/ \left((n-1)(n-2)\left(\sum_{t=1}^{n} r_{it}^2 \right)^{3/2} \right) \qquad (2)$$

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[12] Gallant, Rossi, and Tauchen (1992) find supportive empirical evidence that large daily price movements are

The skewness variable reported in table 3 fails to exhibit a consistent failure-related trend. For example, $SKEW_i$ moves erratically but shows some tendency to be higher in the fourth and first years before failure, but lower in the second and third years before failure. This pattern does not appear closely related to either the featureless trading volume series in table 3 or the steadily declining price and return series shown in tables 1 and 2.

In summary, the univariate analysis of the market-related variables in tables 1-3 finds a few patterns that illustrate long-term trends preceding failure. Equity price, excess returns, market-to-book equity, and return volatility variables in table 1 exhibit the most distinct trends as the banks in the sample approach failure.

The Predictive Content of Market versus Financial Variables

In the multivariate tests, we proceed by specifying a traditional bank failure-prediction model from Call Report financial data. We then alter this model by incorporating equity market variables along with the financial data. The traditional model is a bivariate discrete choice model using logistic regression to explain the fail/no-fail binary independent variable, FAIL, at 4, 8, and 12 quarters preceding failure. The one- to three-year period preceding failure is somewhat longer than the one- to two-year periods found in several earlier studies because we are especially interested in identifying market patterns before changes in financial ratios, which are already widely used for predictive purposes. In addition, analyzing this extended time before failure will test the forward-looking nature of market information to determine whether it can assist failure prediction. This approach also helps address Shumway's (2001) concern that data

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followed by high trading volume.

for extended periods preceding failure need to be included in traditional failure-prediction models.

As previously noted, the sample of failed banks for the logistic regression differs slightly from that used in the univariate analysis because of data constraints. The sample for the logistic regression contains 86 publicly traded institutions that failed during the 1989 to 1995 period and for which complete Call Report and CRSP data were available 4 quarters preceding failure. For the 8 and 12 quarters before failure regressions, the sample contains 85 and 63 failed banks, respectively. For each period, the failed institutions are matched at 4, 8, and 12 quarters before failure to a similar number of nonfailed institutions containing similar total assets and complete Call Report and CRSP data for the same periods as the failed banks. The control sample of banks consisted of either unit banks or one-bank holding companies, and all were publicly traded institutions. They were matched on the basis of asset size, and the most actively traded nonfailed banks were ultimately selected for the sample. The control sample was required to have CAMELS ratings of 1 or 2 for two years before the date of failure of the matched bank and for one year afterward. This requirement ensures the continuity of a healthy control sample. The market variables for each quarter are matched with Call Report financial data from the preceding quarter in an effort to synchronize the public release of the Call Report data with the movement of the market variables.[13]

The variable definitions and statistics are presented in Table 4. The first independent variable, INSBIF, controls for charter type by assigning a value of unity to institutions that are insured by the Bank Insurance Fund (BIF), and a value of zero to

[13] Typically, Call Report financial data are not available to the public for 65 days after the end of the quarter. Thus, as mentioned, market data for a quarter are matched with Call Report data from the previous quarter to account for this reporting lag.

institutions insured by the Savings Association Insurance Fund. This variable is specified because FIRREA provided funds in 1989 to deal with a backlog of troubled thrifts. The INSBIF mean value equals 0.37, signifying that BIF-insured banks represent 37 percent of our sample of failed banks, whereas thrifts represent 63 percent. This variable is used to separate these institutions and to account for the relatively high failure rates that thrifts and later banks experienced in the post-FIRREA period. The coefficient for the "charter" dummy has no expected value in the failure prediction models for this paper because neither banks nor thrifts will tend to have higher failure probabilities, given similar financial ratios and asset sizes. Moreover, the role of the charter dummy is ambiguous in models with market data because market efficiency suggests that market assessments of the likelihood of failure should not be systematically biased by charter or other industry indexes.

A traditional failure-prediction model is specified with financial ratios from the Call Reports (table 4).[14] The first variable, the book equity-to-assets ratio, EQ_AS, is a standard capital ratio expected to vary inversely with failure. An asset-quality variable, NC_RES, measures credit risk as the difference between noncurrent (delinquent) assets and loss reserves, divided by total assets, and is expected to be positively related to the likelihood of failure. Loan provisions to total assets, PROV_AS, could be positively or negatively correlated with the likelihood of failure, depending on the period examined. For example, for the year before bank failure, a negative relationship could result because banks in serious financial straits may be unable to set aside earnings (most such banks are experiencing losses). Conversely, two or three

[14] Several size variables were also tried, but none appeared to have a material effect on the reported results. The limited effect of size can be seen in subsequent specifications that include the market value of equity. To avoid

years before failure, banks may be provisioning for possible loan losses in an effort to replenish reserves and restore capital in order to remain solvent and satisfy regulatory scrutiny. In this instance, loan provisioning may be positively related to the likelihood of failure. A common return-on-assets variable, ROA, is expected to have a negative coefficient. A securities-to-assets ratio, SC_AS, is a liquidity variable with an expected negative sign. A second measure of liquidity, volatile liabilities divided by assets, VOL_AS, has an expected positive sign because of an association between funding problems and higher levels of volatile liabilities.

The first group of independent market variables consists of widely used, or "core," market variables. Obvious starting points are the excess market price, EXPRC, and excess return, EXRET, variables as defined in table 4. The DIV variable measures dividend policy before failure, with a dummy variable that equals unity for periods when dividends are paid, and zero otherwise.[15] As mentioned, typically dividends are postponed during times of distress, often with the encouragement of regulators.[16] We expect all three core variables to be negatively related to failure.

The second set of market variables measures risk with the use of the Fama and French standard market model, which contains the natural logarithm of market capitalization (LN_ME) and market equity divided by book equity (ME_BE). These two variables are expected to have negative signs. The option theoretic variable, the standard deviation of returns (SDRET) as cited by Merton (1974), is also included as an additional risk measure. Since risk rises as failure

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conflicting size effects, we elected to omit a size variable from our traditional Call Report model.

[15] We define DIV as a market-related variable because the dividend amounts that the banks distributed were obtained with the other market data from CRSP. However, data on bank dividends paid on capital stock are available from the Call Report.

[16] Bank regulators generally insist on the postponement of dividend payments when institutions enter a "problem-bank" stage, which is typically at a CAMELS rating of 4 or 5, although it can occur earlier.

approaches, the coefficient for the SDRET variable are expected to be positively related to failure.

The remaining market variables are selected to test for other patterns or trends before failure. Two trading activity variables from table 3, trading volume and turnover, are very similar measures of the same effect, so we use only the turnover measure (TURN) in our published tests, and report here that the choice has not affected the results. A related measure, the standard deviation of volume (SDVOL), is used alongside TURN because the volatility of trading volume is one step removed from direct measures of trading activity. The signs of the two trading activity variables, TURN and SDVOL, are predicted to be positive.

In summary, the logistic regressions are organized as follows: (3)

$$\Phi_i = \alpha + \beta_1(Charter_{i,t-k}) + \sum_{j=2}^{7}\beta_j(Call\ \mathrm{Re}\ portVariables_{i,t-k-1}) + \sum_{j=8}^{10}\beta_j(CoremarketVariables_{i,t-k}) + \sum_{j=11}^{13}\beta_j(RiskVariables_{i,t-k}) + \sum_{j=14}^{15}\beta_j(OtherMarketVariables_{i,t-k}) + \varepsilon_{it}$$

where Φ_i represents the failed and nonfailed groups; t= quarter of failure; k= 4, 8, and 12 quarters before failure; β_1 controls for charter type; $\beta_2, \ldots \beta_7$ are a vector of variables for the traditional failure prediction model, based on Call Report financial variables; $\beta_8 \ldots . \beta_{10}$ are a vector of variables that measure the impact of core market variables; $\beta_{11} \ldots \beta_{13}$ are the coefficients that control for risk effects; and $\beta_{14} \ldots \beta_{15}$ take account of other market variables. We report here that correlation between the independent variables did not appear to be a problem.[17]

[17] The correlation coefficients fell at acceptable levels except for SC_AS and VL_AS which fell between –0.81 and –0.83, and PROV_AS and ROA which ranged from 0.77 to 0.78 depending on the sample. However, since eliminating these variables had no meaningful effect on the reported results, both variables are included in the reported regressions.

The regression results are shown in table 5. Specifications 1 through 6 initialize two failure-prediction models, one focused on Call Report financial data and the other on market-related variables, with controls in both for charter type. In specification 1, the performance of the Call Report financial ratios is generally consistent with expectations, as five Call Report coefficients are significant at the 10 percent or higher level, and all but the PROV_AS variable have their anticipated signs. The unanticipated negative and significant sign for the PROV_AS variable could be explained by the inability of a bank, which fails within a year, to provision for loan losses because in all likelihood, the bank is reporting earnings losses during this period. In specification 2, the coefficients for all three core market variables are statistically significant at the 1 percent level. However, the explanatory power of specification 2 is less than that of the Call Report model as measured by pseudo-R^2 ($\overline{R}^2$) and the Akaike Information Criterion (AIC), so the core market model has less explanatory power than the traditional financial ratios.[18]

Specifications 3 through 5 incorporate the risk and other market variables into the core market variable regression of specification 2. The comparison begins in specification 3, where the risk variables are added to the core market model of specification 2. In this case, only the risk variable, SDRET, becomes significant. The explanatory power of the regression shows a marginal improvement from specification 2. However, comparison of specifications 2 and 3, through a likelihood ratio test (LRT) using a chi-square statistic, finds that the risk variables significantly improve the performance of the core market variable model at the 5 percent level.

Specification 4 combines the core market model with the other market-related variables to find that the addition of these variables slightly improves the core model from specification 2. Three of the core market variables have statistically significant coefficients. In contrast, only

[18] The lower the value for the AIC variable, the better the fit of the model.

one of the other market variables is statistically significant (TURN). An LRT statistic significant at the 1 percent level confirms the importance of adding the other market variables to the core model in specification 2, while the $\overline{R}^2$ shows a slightly improved explanatory power of specification 4.

Specification 5 combines the performance of all the market variables into a single model. The results show that four of the eight market variables are significant at the 1 percent to 10 percent level. In this case, the LRT test finds that the regression represents again a slight improvement over the core market model in specification 2, with a fit that is statistically significant at the 1 percent level. This is supported by a higher a $\overline{R}^2$ and a lower AIC value.

Specification 6 incorporates the benchmark Call Report model in specification 1 and combines the best-performing market variables from specification 5. In this case, an LRT finds that the regression represents a significant improvement over the initial Call Report model as shown in specification 1. The combined model in specification 6 exhibits a lower AIC value and higher $\overline{R}^2$ relative to specification 1 and is statistically significant at the 5 percent level, demonstrating that selected market variables do add value to the basic Call Report model—despite the surprising observation that only two of the Call Report variables are statistically significant, and none of the market variables. However, the market variables do have the correct signs and contribute significantly to the model, as revealed by the LRT test. In summary, the market variables do provide some explanatory power to accounting data in the identification of bank failures.

Table 6 contains in- and out-of sample tests for the regressions in table 4, where the critical probability is set at 50 percent because of the use of a matched sample of failed and nonfailed institutions. The bootstrap procedure as suggested by Efron and Tibshirani (1998) and

Freedman and Peters (1984) is used to estimate the in-sample and out-of-sample classification accuracy for each of the six logistic regressions performed in the table. With the bootstrap technique, 120 separate iterations were performed, with each iteration composed of a unique sample of failed and nonfailed banks and thrifts. The results in table 6 represent averages of those iterations.

The in-sample tests show that market data incrementally improve the identification of failed and nonfailed institutions as we pass from Call Report data in equation 1 to the combined model in specification 6. The correctly identified failed institutions increase from an already high 97 percent to 99 percent—or (in terms of the number of institutions) from 53 to about 55, or a modest 3 percent increase. The correct identification of banks that survived also increases slightly.

The out-of-sample tests show larger but insignificant increases in the correct classifications of failed and nonfailed institutions when equity market data are added to the Call Report model. In percentage terms, the predictive accuracy of the Call Report model in specification 1 (94 percent) is higher than the accuracy of the models that incorporated market data (specifications 2 through 5) but is below the combined model in specification 6 (95 percent); in terms of the average number of banks correctly identified, this increases from 29.13 to 29.46 banks for specifications 1 and 6, respectively. While the change is not large, it should be noted that the average resolution cost to the FDIC of the failed banks in this study was $220.3 million. Thus, even if the model identified only one additional failed bank by incorporating market data, it would be worth it. In addition, as with the in-sample test, the correct prediction of surviving banks also increased slightly.

Table 7 repeats the primary regressions of table 5 (specifications 1, 2, 5, 6) and finds similar results, but for 8 and 12 quarters preceding failure. Specifications 1 and 5 in table 7 show the Call Report variables generally robust with respect to explaining failure two and three years preceding the event. In these regressions most of the Call Report variables perform as expected, and many are significant at high levels. Specifications 2 and 3 in the 8-quarter model and 6 and 7 in the 12-quarter model find that the market variables by themselves contribute less to the identification of failed institutions than does the benchmark accounting model. However, the LRT test finds that the addition of the market variables to the Call Report variables is statistically significant at the 1 percent level in both specification 4 and 8. As was the case in table 5, the addition of market variables significantly improves the performance of the traditional bank failure model.

Conclusions

This paper explores the notion that market-related variables may be used to augment financial ratios for the purpose of predicting bank failures over the 1989–1995 period. Univariate analysis documents distinct patterns of declining prices, negative returns, rising return volatility, declining dividends and falling market-to-book equity ratios for several years before failure. However, no clear trend emerges for several other market measures, such as trading volume and return skewness.

Multivariate tests examine and support the ability of market-related variables to improve the failure-predictive content of more traditional models, which are based on Call Report financial ratios. The inclusion of equity market variables such as stock price, return, and volatility of returns significantly improves the ability of the model to identify institutions that failed over the 1989–1995 period for up to three years before the failed event. The in-sample and out-of-sample classifications show that the simultaneous use of equity market data and Call Report variables does generally yield larger numbers of failed and nonfailed banks being correctly predicted. The empirical results of this paper support the use of forward-looking equity market variables to complement the Call Report financial variables to produce a more accurate failure-prediction model. In this regard, relatively simple measures of market activity, such as price, excess return, and volatility of returns, appear to capture the primary failure-predictive content of observable market activity.

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Table 1
Stock Return Characteristics 16 Quarters Prior to Bank Failure

The stock price, excess return, and other variables reported on the 16 quarter-to-failure lines are calculated as simple averages from the individual sample values. The stock price and market capital (stock price times shares outstanding) variables are averaged over all trading days in each quarter. All excess returns are calculated as the difference between the cumulative quarterly return of each stock and the cumulative quarterly return of the index. The "Dividend Paid in Qtr. Dummy" variable equals unity if an institution pays a dividend in the current quarter, and 0 otherwise. ME/BE is the market-to-book equity ratio, calculated as the market value of equity divided by the Call Report value of the equity, where both are measured as of end-of-quarter values. T-statistics are shown in parenthesis below the quarterly average return percentages. A single, double or triple "*" indicates significance at the 10%, 5% and 1% percent levels respectively

Qtrs. To Failure	Sample	Stock Price ($)	Cum. Qtrly. Return (%)	CRSP Eq. Wt. Excess Return (%)	CRSP Va. Wt. Excess Return (%)	Industry Va. Wt. Excess Return (%)	Dividend Paid in Qtr. Dummy	Market Capital ($000s)	ME/BE	St. Dev. Daily Return (%)
16	75	10.64	0.00	-7.80	-8.02	-5.03	0.40	28,323	0.86	2.47
			(0.00)	(4.04) ***	(4.06) ***	(2.57) **				
15	81	10.42	-2.38	-8.30	-8.05	-7.40	0.36	30,136	0.81	2.66
			(1.00)	(3.68) ***	(3.61) ***	(3.33) ***				
14	85	9.77	-9.26	-11.21	-11.20	-10.31	0.38	25,995	0.79	2.89
			(4.41) ***	(6.45) ***	(6.10) ***	(5.61) ***				
13	89	9.44	-2.95	-8.34	-6.93	-7.62	0.34	25,485	0.78	2.82
			(1.23)	(4.16) ***	(3.15) ***	(3.58) ***				
12	90	8.28	-4.48	-9.91	-7.43	-9.40	0.36	24,153	0.70	3.20
			(1.73) *	(4.76) ***	(3.26) ***	(4.50) ***				
11	92	8.06	-3.60	-14.133	-11.25	-10.23	0.36	21,874	0.64	3.32
			(1.76) *	(7.42) ***	(5.73) ***	(5.41) ***				
10	94	6.61	-9.92	-13.225	-12.63	-12.77	0.31	19,831	0.61	3.84
			(3.65) ***	(5.22) ***	(4.87) ***	(4.99) ***				
9	97	6.08	-11.39	-16.173	-13.14	-11.60	0.31	15,303	0.57	4.00
			(3.99) ***	(6.83) ***	(5.22) ***	(4.98) ***				
8	97	5.04	-15.28	-20.298	-18.30	-16.16	0.28	13,560	0.54	4.30
			(4.85) ***	(7.42) ***	(6.41) ***	(5.66) ***				
7	97	4.09	-10.00	-15.244	-14.17	-14.29	0.22	12,585	0.53	4.45
			(2.35) **	(4.01) ***	(3.52) ***	(3.69) ***				
6	99	3.61	-19.64	-21.16	-21.40	-18.49	0.18	10,456	0.44	5.01
			(8.07) ***	(9.06) ***	(8.89) ***	(7.76) ***				
5	99	2.68	-23.48	-23.614	-23.34	-21.76	0.15	8,221	0.42	7.47
			(4.95) ***	(5.78) ***	(5.31) ***	(5.17) ***				
4	99	1.81	-31.25	-35.251	-30.69	-29.31	0.09	6,919	0.33	8.25
			(6.53) ***	(8.27) ***	(6.66) ***	(6.62) ***				
3	95	1.40	-28.57	-36.745	-30.56	-31.40	0.03	5,318	0.25	9.52
			(5.21) ***	(7.23) ***	(5.59) ***	(5.94) ***				
2	86	0.97	-33.33	-36.243	-35.41	-37.30	0.02	3,818	0.24	12.06
			(5.63) ***	(6.48) ***	(5.97) ***	(6.49) ***				
1	75	0.77	-39.13	-47.782	-40.55	-42.49	0.00	2,584	0.19	13.87
			(4.24) ***	(5.58) ***	(4.44) ***	(4.78) ***				

Table 2
Breakout of Value Weighted Excess Returns 16 Quarters Prior to Bank Failure (%)

The stock price, excess return, and other reported variables are calculated as simple averages from the individual sample values. All returns are expressed as percentages, and calculated as the difference between the cumulative quarterly return of each stock and cumulative quarterly return of the value weighted CRSP index. Asset size is determined by total assets, as reported on the Call Reports. Trading volume is the average of all daily trading volumes reported throughout the quarter on the CRSP tapes. ME/BE is the market-to-book equity ratio, calculated as the market value of equity divided by the Call Report book value of equity, where both are measured as end-of-quarter values. Institutions are classified as banks (thrifts) if they are insured by the bank insurance fund (savings asociation insurance fund). T-statistics are shown in parentiesis below the quarterly average return percentages. A single, double or triple "*" indiciates significance at the 10%, 5% and 1 % levels respectively.

Qtrs. To Failure	Assets <= $1b	Assets $1 - 5b	Assets > $5b	Daily Trading Volume <= 10,000	Daily Trading Volume 10-30,000	Daily Trading Volume > 30,000	ME/BE <= 1.0	ME/BE > 1.0	Banks	Thrifts
16	-7.53 ***	-9.49 **	-3.67	-8.61 ***	-6.18	-3.67	-8.54 ***	-3.82	-6.38 ***	-8.96 ***
	(3.11)	(2.08)	(1.50)	(3.60)	(1.43)	(0.66)	(3.21)	(1.31)	(2.83)	(2.78)
15	-8.04 ***	-8.38 *	-7.57 **	-8.93 ***	-3.60	-7.57	-8.37 ***	-7.36 *	-7.57 **	-8.89 ***
	(2.66)	(1.93)	(1.98)	(3.51)	(0.78)	(1.04)	(3.37)	(1.71)	(2.34)	(2.87)
14	-9.23 ***	-14.94 ***	-5.62	-9.51 ***	-14.94 ***	-8.07	-11.99 ***	-9.54 **	-8.98 ***	-13.06 ***
	(4.21)	(3.80)	(1.08)	(4.05)	(4.93)	(1.54)	(5.97)	(2.47)	(3.86)	(4.65)
13	-7.84 ***	-5.47	-3.12	-7.84 ***	-5.91	-3.12	-7.29 **	-6.72 ***	-7.70 ***	-5.69
	(3.05)	(1.12)	(0.48)	(2.86)	(1.25)	(0.51)	(2.44)	(3.02)	(3.21)	(1.60)
12	-5.89 **	-12.27 **	-14.76 **	-5.89 **	-14.77 ***	-12.77 **	-7.48 **	-6.40 **	-7.56 **	-7.34 **
	(2.55)	(2.09)	(2.14)	(2.13)	(3.80)	(2.15)	(2.55)	(2.07)	(2.23)	(2.38)
11	-12.03 ***	-9.35 **	-10.59 ***	-12.27 ***	-13.50 ***	-2.49	-13.82 ***	-5.19 *	-14.59 ***	-8.82 ***
	(4.69)	(2.16)	(3.41)	(5.13)	(4.90)	(0.40)	(5.90)	(1.66)	(5.54)	(3.24)
10	-10.82 ***	-14.70 **	-18.85 ***	-12.63 ***	-5.16	-23.64 ***	-14.20 ***	-7.73 *	-14.17 ***	-12.27 ***
	(4.59)	(2.03)	(2.81)	(3.79)	(1.06)	(3.84)	(4.53)	(1.81)	(4.44)	(3.16)
9	-13.59 ***	-10.79	-23.52 ***	-12.79 ***	-15.13 ***	-11.69	-13.38 ***	-12.86 ***	-13.19 ***	-13.14 ***
	(5.41)	(1.57)	(2.74)	(4.64)	(4.62)	(1.22)	(4.57)	(2.84)	(3.30)	(4.06)
8	-15.59 ***	-20.51 ***	-20.85 ***	-17.38 ***	-46.19	-26.43 ***	-20.25 ***	-6.48	-24.47 ***	-13.01 ***
	(4.74)	(2.93)	(2.79)	(4.88)	(0.06)	(5.09)	(6.34)	(1.06)	(6.31)	(3.31)
7	-15.63 ***	-14.17	-11.57	-16.26 ***	-10.07	5.23	-15.63 ***	-8.68 *	-14.37 **	-14.17 ***
	(6.25)	(1.06)	(0.91)	(4.09)	(0.66)	(0.48)	(3.40)	(1.75)	(2.31)	(2.67)
6	-18.27 ***	-26.60 ***	-25.53 ***	-14.94 ***	-34.22 ***	-31.89 ***	-25.11 ***	-8.58 *	-28.92 ***	-15.83 ***
	(5.84)	(5.20)	(5.72)	(5.02)	(5.65)	(9.87)	(9.59)	(1.86)	(9.23)	(4.67)
5	-19.64 ***	-33.44 ***	-26.52 ***	-18.34 ***	-33.52 ***	-26.33 ***	-23.43 ***	-8.45	-23.58 ***	-20.70 ***
	(3.03)	(5.92)	(3.50)	(3.05)	(5.70)	(3.87)	(4.98)	(0.88)	(5.05)	(2.92)
4	-30.69 ***	-31.27 ***	-28.92 **	-27.76 ***	-45.26 ***	-38.89 **	-34.51 ***	-22.41 ***	-33.91 ***	-28.41 ***
	(5.56)	(3.12)	(2.34)	(5.40)	(5.52)	(2.05)	(6.75)	(3.17)	(6.01)	(4.03)
3	-34.58 ***	-31.33 **	-20.11 *	-30.48 ***	-39.53 ***	-17.60	-35.74 ***	-24.26	-28.15 ***	-40.85 ***
	(6.65)	(2.12)	(1.68)	(4.58)	(3.21)	(1.11)	(6.18)	(1.40)	(4.06)	(4.89)
2	-31.87 ***	-39.63 ***	-26.56 **	-29.79 ***	-50.66 ***	-38.89 ***	-34.54 ***	-46.11 ***	-39.63 ***	-33.66 ***
	(3.44)	(7.60)	(1.98)	(3.41)	(8.26)	(3.01)	(5.25)	(4.74)	(4.16)	(4.62)
1	-36.56 ***	-53.66 ***	-42.33	-39.20 ***	-52.09 **	-55.72 **	-44.66 ***	-33.01 **	-43.85 ***	-39.20 ***
	(2.75)	(4.47)	(1.40)	(3.89)	(2.22)	(2.12)	(4.23)	(2.04)	(2.99)	(3.50)
Avg. Sample	56.00	25.06	9.38	57.81	17.88	14.75	72.25	18.19	42.06	48.38

Table 3
Other Market Variable Trends 16 Quarters Prior to Bank Failure

The stock price, excess return, and other variables reported on the 16 quarter-to-failure lines are calculated as simple averages from the individual sample values. The daily trading volume and standard deviation of trading volume are the simple mean and standard deviation statistics calculated across the daily trading activity of each quarter. Turnover is the number of times each share is traded in a quarter. Skewness is calculated from equation 2 in the text.

Qtrs. To Failure	Sample	Daily Trading Volume	St. Dev. Daily Trading Volume	Turnover	Return Skewness
16	75	6,386	10,899	0.13	0.30
15	81	5,636	11,105	0.13	0.30
14	85	6,657	9,307	0.15	0.29
13	89	6,241	8,020	0.12	0.39
12	90	4,630	7,338	0.12	0.24
11	92	5,589	7,790	0.13	0.16
10	94	5,239	7,994	0.13	0.19
9	97	4,595	7,544	0.11	0.18
8	97	5,787	8,261	0.12	0.22
7	97	5,076	7,493	0.10	0.31
6	99	4,227	8,317	0.10	0.28
5	99	3,967	7,339	0.09	0.23
4	99	4,537	8,028	0.09	0.34
3	95	5,212	10,264	0.09	0.28
2	86	6,844	12,222	0.12	0.46
1	75	6,959	12,495	0.10	0.50

Table 4

Variable Definitions, Means, and Standard Deviations[1]

		Failed Sample		Control Sample	
		Mean	Standard Deviation	Mean	Standard Deviation
Dependent Variable					
FAIL	Dummy variable equal to 1 if the institutionn failed, and 0 otherwise.				
Charter					
INSBIF	Dummy variable equal to 1 if the institution is associated with the the Bank Insurance Fund, and 0 if it is associated with the Savings Association Insurance Fund.	0.372	0.486	0.919	0.275
Call Report Variables					
EQAP	Book value of equity divided by total assets (%).	2.540	2.676	11.601	13.864
NC_RES	Non-Current (delinquent) assets, less loan-loss reserves, divided by total assets (%).	4.497	4.039	0.271	0.859
ROA	Year-to-date annualized earnings, divided by total assets (%).	-2.701	3.682	0.984	0.737
SC_AS	Securities divided by total assets (%).	17.911	14.207	27.110	16.071
PROV_AS	Year-to-date annualized Loan-loss Provisions, divided by total assets (%).	1.954	2.609	0.333	0.446
VL_AS	Volatile liabilities divided by total assets (%).	25.524	12.018	16.990	10.731
Core Market Variables					
EXPRC	Market excess price, calculated as the natural logarithm of the average quarterly stock price and the Wilshire 500 stock index.	-7.410	1.044	-5.142	1.042
EXRET	Market excess return, calculated as the difference between the cumulative quarterly return of each stock and the cumulative quarterly return of the CRSP value weighted index.	-0.229	0.479	-0.003	0.188
DIV	Dummy variable equal to 1 if a dividend is paid during the quarter, and 0 otherwise.	0.093	0.292	0.860	0.349
Risk Variables					
LN_ME	Natural logarithm of market capitalization.	8.633	1.272	11.136	1.300
ME_BE	Market capitalization divided by book equity.	0.762	3.102	1.395	1.119
SDRET	Standard deviation of daily returns during the quarter.	0.105	0.071	0.027	0.016
Other Market Variables					
SDVOL	Standard deviation of trading volume (rescaled by 1,000,000).	0.019	0.027	0.012	0.044
TURN	Number of shares traded in a quarter divided by the number of shares outstanding at the end of the quarter (%).	14.806	15.026	8.170	15.726

[1]Data are for 4 quarters prior to failure.

Table 5
Logit Regression Results: 4 Quarters Before Failure

This table performs logit regression analysis on a sample of 86 banks and thrifts and an equal number of institutions in the control sample. All independent variables are defined in Table 4. T-statistics are shown in parentheses below their corresponding coefficients. A single, double, or triple "*" indicates significance at the 10%,5% and 1% levels respectively.

Independent Variable	Anticipated Sign	Specification 1		2		3		4		5		6	
Intercept	+	0.52		-9.69		-1.05		-11.51		-10.85		-9.43	
		(0.43)		(3.03)	***	(0.17)		(2.91)	***	(1.22)		(1.14)	
Charter													
INSBIF		-5.62		-2.86		-3.44		-3.76		-3.94		-4.88	
		(2.83)	***	(3.68)	***	(3.55)	***	(3.73)	***	(3.62)	***	(1.82)	*
Call Report Variables													
EQ_AS(1)	-	N/A										N/A	
NC_RES	+	1.63										1.69	
		(2.98)	***									(1.75)	**
ROA	-	-2.98										-1.54	
		(2.71)	***									(0.96)	
SC_AS	-	-0.14										-0.14	
		(2.64)	***									(1.64)	
PROV_AS	+	-2.06										-0.45	
		(1.70)	*									(0.24)	
VL_AS	+	0.21										0.29	
		(2.49)	**									(1.87)	*
Core Market Variables													
EXPRC	-			-1.98		-0.78		-2.33		-1.57		-1.11	
				(3.99)	***	(1.53)		(3.69)	***	(1.98)	*	(1.24)	
EXRET	-			-2.69		-3.96		-2.92		-3.80		-2.57	
				(3.17)	***	(2.61)	***	(3.00)	***	(2.47)	**	(0.96)	
DIV	-			-2.26		-2.78		-2.73		-3.02		-2.77	
				(2.97)	***	(2.93)	***	(2.72)	***	(2.69)	***	(1.44)	
Risk Variables													
LN_ME	-					-0.30				0.26			
						(0.74)				(0.49)			
ME_BE	-					0.15				0.20			
						(0.44)				(0.50)			
SDRET (1)	+					48.21				37.74		N/A	
						(2.79)	***			(1.90)	*		
Other Market Variables													
SDVOL	+							-23.41		-25.15			
								(1.45)		(1.18)			
TURN	+							0.06		0.05			
								(2.42)	**	(1.62)			
Pseudo R^2		0.70		0.65		0.66		0.67		0.67		0.71	
Akaike Information Criterion (AIC)		39.99		65.48		60.52		58.50		59.59		35.58	
χ^2 (relative to specification 1)		N/A		N/A		N/A		N/A		N/A		10.42	**
degrees of freedom												3	
χ^2 (relative to specification 2)		N/A		N/A		10.96	**	10.98	***	15.90	***	39.90	***
degrees of freedom						3		2		5		5	

NOTE: (1) EQ_AS and SDRET cause frequent complete separations between failed and nonfailed banks in specified regressions and are labelled as 'N/A'.

Table 6
Failure Prediction Accuracy and Error Analysis: 4 Quarters Before Failure

This table shows the prediction accuracy of the 6 bootstrapped regressions that mimic the regressions performed in Table 5. The bootstrap procedure (Efron and Tibshirani, 1998; Freedman and Peters, 1984) is used to estimate the in-sample and out-of-sample classification accuracy of the 6 logistic regressions performed in Table 5. With this bootstrap technique, 120 separate repetitions were performed where each repetition was composed of a unique sample of failed and non-failed banks. The top half of this table shows the predictive accuracy of these regresions applied to a sample of 110 (55 failed and 55 non-failed) institutions. The botton half of the table shows the accuracy of the regressions applied to a sample of 62 banks and thrifts (31 failed and 31 non-failed) held in the out-of-sample group. The critical probability used to determine failure is 50 percent.

Equation Specification	Correctly Predict Failure (%)	N	Predict Survival, But Fails (Type 1 Error) (%)	N	Correctly Predict Survival (%)	N	Predict Failure, But Survives (Type 2 Error) (%)	N
In-Sample Classification								
1	96.95	53.33	3.05	1.68	97.83	53.81	2.17	1.19
2	95.12	52.32	4.88	2.68	95.80	52.69	4.20	2.31
3	95.42	52.48	4.58	2.52	96.08	52.84	3.92	2.16
4	97.05	53.38	2.96	1.63	97.12	53.42	2.88	1.58
5	97.12	53.42	2.88	1.58	96.91	53.30	3.09	1.70
6	99.61	54.78	0.39	0.22	99.41	54.68	0.59	0.33
Out-of-Sample Classification								
1	93.98	29.13	6.02	1.87	96.52	29.92	3.48	1.08
2	92.55	28.69	7.45	2.31	95.11	29.48	4.89	1.52
3	89.73	27.82	10.27	3.18	94.57	29.32	5.43	1.68
4	92.66	28.72	7.34	2.28	95.22	29.52	4.78	1.48
5	88.81	27.53	11.19	3.47	94.32	29.24	5.68	1.76
6	95.03	29.46	4.97	1.54	97.04	30.08	2.96	0.92

Table 7
Logit Regression Results: 8 and 12 Quarters Before Failure

This table extends the logit regressions performed in Table 7, using a sample of 85 failed banks and thrifts and and equal number of institutions in a control sample for 8 quarters before failure and a sample of 63 failed banks and thrifts and an equal number of non-failed instituions for 12 quarters before failure. T-statistics are shown in parentheses below their corresponding regression coefficents. A single, double or triple "*" indicates significance at the 10%, 5%, and 1% levels, respectively.

Independent Variable	Anticipated Sign	Specification: 8 quarters before Failure				Specification: 12 quarters before Failure			
		1	2	3	4	5	6	7	8
Intercept	+	4.78	-9.76	1.84	-26.48	4.50	-5.51	14.50	28.46
		(2.89) ***	(3.71) ***	(0.31)	(1.15)	(2.38) **	(1.99) **	(2.35) **	(3.30) ***
Charter									
INSBIF		-2.9596	-2.7291	-2.7706	-4.7696	-4.8552	-1.95521	-2.268	-5.8108
		(3.07) ***	(4.71) ***	(4.19) ***	(2.62) ***	(3.69) ***	(3.02) ***	(2.64) ***	(2.75) ***
Call Report Variables									
EQAP	-	-0.13			-0.28	-0.08			-0.03
		(1.14)			(1.81) *	(2.31) **			(0.55)
NC_RES	+	0.32			-0.06	0.95			1.98
		(1.05)			(0.19)	(2.24) **			(2.33) **
ROA	-	-2.78			-0.50	-0.31			1.04
		(2.82) ***			(0.43)	(0.74)			(1.56)
SC_AS	-	-0.10			-0.23	-0.14			-0.29
		(2.90) ***			(2.43) **	(3.62) ***			(2.81) ***
PROV_AS	+	0.11			0.34	1.68			3.41
		(0.09)			(0.23)	(1.27)			(1.63)
VL_AS	+	0.09			0.20	0.08			0.25
		(1.64)			(2.09) **	(2.45) **			(2.80) ***
Core Market Variables									
EXPRC	-		-2.09	-1.19	-5.93		-1.39	0.13	
			(4.57) ***	(2.07) **	(2.03) **		(2.96) ***	(0.24)	
EXRET	-		-1.25	-1.13			-3.00	-3.26	1.92
			(1.03)	(0.88)			(1.87) *	(1.66) *	(0.41)
DIV	-		-1.03	-0.84			-1.39	-1.23	-2.26
			(1.92) *	(1.34)			(2.61) ***	(2.05) **	(1.60)
Risk Variables									
LN_ME	-			-0.75	-0.31			-1.15	-2.41
				(1.78) *	(0.27)			(2.86) ***	(3.10) ***
ME_BE	-			-0.93				-0.63	
				(1.45)				(0.84)	
SDRET	+			26.21				35.37	
				(1.33)				(1.43)	
Other Market Variables									
SDVOL (1)	+			N/A				N/A	
TURN	+			0.05	0.08			0.0141	
				(2.62) ***	(2.59) ***			(0.87)	
$\overline{R}^2$		0.64	0.54	0.58	0.70	0.58	0.42	0.49	0.66
Akaike Information Criterion(AIC)		72.33	110.10	99.75	45.37	75.43	112.01	101.20	52.46
χ^2 (relative to specification 1)		N/A	N/A	N/A	32.96 ***	N/A	N/A	N/A	28.97 ***
degrees of freedom					3				3
χ^2 (relative to specification 2)		N/A	N/A	18.34 ***	76.73 ***	N/A	N/A	18.82	71.55 ***
degrees of freedom				4	8			4	7

NOTE: (1) STDVOL perfectly separates failed and nonfailed banks in particular regressions, and are labelled as 'N/A'.