STATISTICAL OPACITY IN THE U.S. BANKING INDUSTRY
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ABSTRACT: Motivated by the observation that very few banks fail in normal years, we explore the impact of that pattern on the precision of a standard statistical failure model, and discuss implications for regulation and risk management. Out-of-sample forecasting is found to be worse for a model fitted to recent data with few failures than for a model fitted to much older data with more failures. This property may mask observable drift in risk linkages until aggregate risk levels have risen high enough to trigger new failures, thus suggesting an informational basis for the puzzling recurrence of bank crises.

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1. Introduction

The persistent recurrence of banking crises around the world has been recognized as a perplexing problem, in the face of concerted regulatory efforts to prevent them and their enormous attendant costs (Rochet, 2008). Close scrutiny suggests that the underlying causes of these crises cannot in general be attributed to poorly designed regulatory policies, deposit insurance, or incompetent regulators (ibid.). While some observers have proposed political explanations of these crises (ibid.), here we propose an alternate informational explanation and present suggestive empirical evidence consistent with that hypothesis.

Within the U.S., the banking industry has long exhibited extended periods of very low failure rates interspersed with brief but more severe episodes of failures ("crises"). The primary underlying causes of failure have tended to differ from one crisis to another. Prior to 1913, banking panics in the U.S. were exacerbated by an inelastic currency. The creation of the Federal Reserve addressed this problem. In the early 1930s, during the Great Depression, more than 9,000 banks failed, driven by real-sector contraction and a sharp reduction of wealth in the capital markets. The subsequent creation of federal deposit insurance insulated depositors from potential losses due to bank failures, simultaneously removing their financial incentive to initiate bank runs. In the 1980s, the U.S. savings and loan industry suffered massive failures due to high levels of interest rate risk combined with sharp increases in market interest rates over the previous few years. In later phases

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of the crisis, moral hazard and entry into unfamiliar new product markets further contributed to some failures. Commercial banks also experienced increased failure rates in those years but, being more diversified than savings and loan associations, were less severely affected. More recently, bank failure rates have begun to rise again due to stresses in residential mortgages and related products.

This paper notes that the tiny number of bank failures during normal periods hinders any precise measurement of risk and its linkages with observable factors. We quantify the impact of this imprecision on the ability of a standard statistical failure model to identify out-of-sample failures. We further note that, to the extent those linkages may change over time (due to changes in technology, market structure, and regulation), the low failure rate hinders timely recognition of such changes, permitting occasions on which new risks may grow to the point of triggering a sudden wave of bank failures. This logic suggests an informational basis for periodic banking crises.

Other industries may not suffer from such extreme lumpiness in the pattern of failures, because elsewhere an absence of prudential regulation allows higher "normal" failure rates, permitting more ongoing updating of risk assessment and controls. In this sense, the banking industry can be deemed less financially transparent than other industries during most years (when failure rates are low), consistent with some long-held beliefs and some empirical evidence (Slovin et al., 2007).

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2 The same logic applies to both formal statistical risk models and subjective assessments of risk.

3 Indeed, this pattern appears to describe the recent buildup and collapse of the U.S. subprime mortgage market.

4 According to the 1997 Economic Report of the President, the annual U.S. business failure rate per 10,000 companies averaged 63.8 during 1955-95. (More recent values for these figures appear to be unavailable.) By contrast, just 4.9 banks per 10,000 failed each year on average during 1995-2005.
Moreover, the banking industry – like insurance and other industries in the financial sector – is intrinsically involved with risk management, making the accurate identification of risk centrally important. At the same time, the concepts of informational opacity and identifying shifting risks are qualitatively important in any industry.

Our findings complement those of Slovin et al., Morgan, and Hirtle not only by using a different methodology but also by using data from the entire U.S. banking industry rather than a small subset of the largest banks. The size distribution of U.S. banks is heavily skewed toward smaller institutions. Slovin et al. rely on a sample of 17 money center banks plus 14 regional banks. Hirtle's sample comprises the 42 largest U.S. bank holding companies while Morgan’s sample spans 220, representing only a tiny fraction of the total number of U.S. banks. Banks in the U.S. range from under $10 million to more than $1 trillion in assets, and one might suspect that banks of such very different sizes may exhibit varying levels of financial transparency. While smaller banks lack the additional information aggregation provided by market signals, the largest banks tend to be operationally complex organizations that require more information to assess adequately. An

\[ \text{5 However, Flannery et al. (2004) report contrary findings. Iannotta (2006) finds evidence that European banks are more opaque than non-banking firms after controlling for observable characteristics, and that larger banks are more opaque than smaller ones.} \]

\[ \text{6 According to the FDIC's} \textit{Quarterly Banking Profile}, \text{as of year-end 2008 nearly 40 percent of U.S. banks were smaller than $100 million in assets, while 93 percent were smaller than $1 billion in assets. In prior years, even larger percentages of banks were smaller than these respective thresholds. The largest banks, by contrast, have assets on the order of a trillion dollars each.} \]

\[ \text{7 The number of banks in the U.S. has ranged from more than 14,000 in 1986 and prior years to just over 7,000 as of year-end 2008.} \]
advantage of our approach is its ability to utilize data from all banks regardless of their size or trading status, thus encompassing a larger and more comprehensive sample and potentially yielding results that are more representative of the banking industry overall. Like Hirtle (2006), we focus on banks only, without attempting a direct comparison with nonbanking firms.

The remainder of this paper is structured as follows. Section 2 discusses the empirical model, its relation to prior literature, and the data. Section 3 reports the results, while Section 4 concludes.

2. The Empirical Model and Data

Statistical models to predict bank failures have been developed by Meyer and Pifer (1970), Martin (1977), Santomero and Vinso (1977), Kolari et al. (2002), and others. Such models have been sufficiently successful that the Federal Reserve Board in recent years has relied on a similar, internally developed model to assist in identifying emerging problems among individual banks (Cole, 1995), and recent research has indicated that even very simple models can predict bank failures or undercapitalization with considerable accuracy (Estrella et al., 2000; Jagtiani et al., 2003). Demirgüç-Kunt (1989) reviews earlier studies in this literature.

Our model follows a structure found by prior studies to be appropriate. We fit a logit model using financial data from year $t$ to predict the probability of failure in years $t+1$ through $t+2$, and then

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8 Additionally, prior studies have found that larger banks are systematically less likely to fail than smaller banks. At the very largest scales, an implicit or explicit regulatory policy of “too big to fail” contributes to this pattern. A comprehensive model to predict failures must therefore be fitted to a sample that includes banks of all sizes.

9 Demirgüç-Kunt (1989, p. 9) notes that statistical models to predict bank failure or high financial risk have been available to bank regulators since the mid-1970s.
measure the ability of the fitted model to predict failures on a separate holdout sample. The model is represented as:

\[ \text{prob}(Y_i = 1) = \Lambda(x_{1i}, x_{2i}, x_{3i}, \ldots, x_{ni}) \]  

(1)

where

\[ Y_i = 1 \text{ if bank } i \text{ fails within a specified time period, and } 0 \text{ otherwise;} \]
\[ \text{Prob}(Y_i) = \text{the probability that the event occurs;} \]
\[ X_{ji} = \text{a vector of financial variables associated with the event probability.} \]

The functional form of equation (1) is the logistic function:

\[ \Pr(y = 1) = P_i = \frac{1}{1 + e^{-w_i}} \quad i = 1, \ldots, n \]  

(2)

where \[ w_i = \alpha_0 + \alpha_{1i}X_{1i} + \alpha_{2i}X_{2i} + \ldots + \alpha_{ni}X_{ni} \] is a linear combination of the independent variables and \[ \alpha = (\alpha_1, \alpha_2, \ldots, \alpha_n) \] is a vector of coefficients to be estimated. Equations (1) and

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10 Proportional hazard or survival-time models have also been used to forecast bank failures (Whalen, 1991; Cole and Gunther, 1995; Wheelock and Wilson, 1995, 2000; DeYoung, 2003b), as have probit models (Abrams and Huang, 1987; Cole and Gunther, 1998). Kolari et al. (1996, 2002) and Jagtiani et al. (2003) estimated both logit and trait recognition models. Overall, logit models have been found to be quite accurate in such applications, have been used by the Federal Reserve in supervisory monitoring and early warning (Cole, 1995), and continue to be represented in the research literature (DeYoung, 2003a; Arena, 2008).

11 Demirgüç-Kunt (1989) notes a conceptual distinction between financial insolvency and the regulatory decision to close a failed bank, but also notes that empirical studies that have tried to incorporate this distinction typically use similar vectors of financial regressors. A change in federal law in 1991 removed most of the regulatory discretion that previously permitted this distinction.
(2) can be combined to form equation (3), where $P_i$ is the probability that bank $i$ fails within the specified time period:

$$\ln \left[ \frac{P_i}{1-P_i} \right] = \alpha_{0i} + \alpha_{1i} X_{1i} + \alpha_{2i} X_{2i} + \ldots + \alpha_{ni} X_{ni}. \quad (3)$$

Our model uses a vector of explanatory variables that have been found consistently and significantly associated with probabilities of subsequent failure in the empirical banking literature. Financial data are from the Federal Reserve’s web site; failure data are from the FDIC’s web site. Our regressors include the following, as summarized in Table 1: log(assets), equity / assets, loans / assets, jumbo CDs / assets, nonperforming loans / assets, net income / assets, and expenses / assets. Previous studies have found that larger banks fail less often than smaller banks, so we expect a negative coefficient on the log of assets. The other variables are financial ratios associated with various standard dimensions of risk and performance monitored by bank regulators, as reflected in the examiners’ CAMELS acronym (capital adequacy, asset quality, management, earnings, liquidity, and sensitivity to market risk) and shown in the table. The subjective management dimension is not directly linked to any specific financial ratio, although the expense / asset ratio could arguably be interpreted as reflecting a combination of management effectiveness and possible expense-preference behavior by management (Edwards, 1977). Our variables also fail to address sensitivity to market risk, consistent with most published empirical studies of bank failure.

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Equity provides both a financial cushion to absorb losses and a financial incentive for owners to avoid excessive risk-taking in banking operations, implying a negative coefficient as in prior empirical studies. Loans / assets is positively associated with credit risk and negatively associated with liquidity, implying a positive coefficient as found in prior studies. Jumbo CDs / assets is a measure of volatile liability dependence, inversely associated with liquidity and implying a positive coefficient as in prior studies. Nonperforming loans / assets is a direct measure of credit risk, implying a positive coefficient as in prior studies. Net income / assets, or return on assets, is a positive measure of earnings capacity and ability to build financial equity through retained earnings. Accordingly, it should exhibit a negative coefficient, as found in prior studies. Finally, expenses / assets negatively affects earnings and might indicate some combination of ineffective management and managerial agency problems, suggesting a positive coefficient as found in prior empirical studies.

Table 2 reports summary statistics on these variables for two periods, distinguished in each case according to banks that failed during the subsequent two years versus banks that did not. Paired t-tests, also reported in the table, indicate that all of these variables except assets differ significantly between failed banks and nonfailed banks in the earlier period, while nearly all differ significantly between failed banks and nonfailed banks in the later period. Where significant, the signs of the differences are all consistent with the anticipated regression coefficients discussed above. These univariate distinctions provide a preliminary indication that the multivariate logit model will exhibit significant ability to distinguish failed banks from nonfailed banks on the basis of these variables.

After the early 1990s, economic growth, enhanced capital requirements, regulatory "prompt corrective action" as mandated by the FDIC Improvement Act of 1991, and other changes combined
to reduce the number of bank failures to very low levels similar to those observed between 1950 and 1980. Indeed, no banks failed anywhere in the U.S. during 2005-06. These considerations have prompted other recent studies of banking failure (e.g., Estrella et al., 2000; Kolari et al., 2002) to select nearly identical sample periods. However, as a major goal of this study is to compare the ability of standard statistical models to predict bank failures when estimated on contrasting numbers of failures, we select two different sample periods separated by a decade and sharply distinguished by rates of failure.

Our initial sample uses financial data as of year-end 1989 and failures in 1990-91, with a holdout sample of failures in 1992-93 predicted by year-end 1991 financial data. We selected this time period to ensure an ample number of bank failures (see Figure 1), as well as to achieve some overlap with the sample periods of Morgan (2002), Hirtle (2006), and prior studies of bank failure, to facilitate comparison of our findings with theirs.

Our later sample is fitted to financial data from 1999 and failure data from the following two years. This late model is then applied to out-of-sample failures during 2002-03 based on financial data from 2001. This choice of period, in conjunction with the earlier period, satisfies several useful criteria. First, both failure periods span a mild recession (1990-91 and 2001) and are thus comparable in regard to cyclical macroeconomic conditions. Second, separating the two periods by a decade affords ample time for structural changes to occur in the true model’s coefficients, driven in

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13 Other major federal legislative changes during the 1990s included the Riegle-Neal Interstate Banking Act in 1994 and the Financial Modernization Act (Gramm-Leach-Bliley) in 1999. These changes arguably improved banks’ ability to diversify their operations in terms of location and product lines, but may have allowed offsetting increases in overall risk-taking, thus having potentially ambiguous effects on the incidence of bank failure.
part by specific known changes in regulation, technology, and market structure. Third, far fewer banks failed during 2000-01 than in 1990-91, permitting a clear comparison of the predictive power of models fitted to few versus many failures. Few, if any, alternate time periods would satisfy these criteria.\(^{14}\)

As a further test, we also assess the ability of the early model’s estimated coefficients to predict bank failures during 2002-03. Conventional wisdom would suggest that the various regulatory, technological, and competitive changes during the 1990s would render the 1989 coefficients very poor at relating 2001 financial data to failures during 2002-03, but – as we shall see – this is an empirical question.

Our sample is drawn from the nationwide population of FDIC-insured depository institutions in the U.S. We removed banks less than 10 years old because such banks have been found to exhibit systematically atypical financial behavior (DeYoung and Hasan, 1998; Shaffer, 1998). Some recent failure studies have begun to incorporate this refinement (Jagtiani et al., 2003) while others have explored predictors of de novo bank failure as a separate issue (DeYoung, 2003a, b). We also removed banks that were voluntarily acquired during the two years following the relevant financial data.\(^{15}\)

\(^{14}\) Numerous bank failures also occurred in the early 1930s and the latter half of the 1980s, but detailed financial data are unavailable for banks in the 1930s while the latter half of the 1980s did not match 2001 in cyclical macroeconomic performance. The number of bank failures began to rise again by the end of 2008 but, as of this writing, not by enough to permit a direct comparison with 1990-91.

\(^{15}\) Some unknown fraction of voluntarily acquired banks would otherwise have failed (see Thomson, 1991), and misclassifying them as surviving would bias the estimated coefficients. Most studies have ignored this problem; Wheelock and Wilson (1995) treat voluntarily acquired banks as censored. An alternate approach, using financial ratios to distinguish healthy acquired
Finally, we removed banks with missing data or highly implausible values of key ratios, suggesting data reporting errors, retaining banks that satisfied the following criteria: 

\[-1 \leq \frac{\text{equity}}{\text{assets}} \leq 0.5, \quad 0 \leq \frac{\text{loans}}{\text{assets}} \leq 1, \quad \frac{\text{jumbo CDs}}{\text{assets}} \leq 0.8, \quad -0.25 \leq \frac{\text{net income}}{\text{assets}} \leq 0.25, \quad \text{and} \quad 0 < \frac{\text{expenses}}{\text{assets}} \leq 0.3.\]

These criteria removed fewer than 2 percent of the banks (none of which failed during the relevant years), leaving a sample of 12,930 banks in 1989 (of which 247 failed in 1990-91) and 8,913 banks in 1999 (of which six failed in 2000-01).16

3. Results and Interpretation

Table 3 reports logit regression coefficients on the early model and the late model, along with two goodness-of-fit indicators. In the early model, nearly all of the coefficients are highly significant with the anticipated signs. In the later model, only the jumbo CD ratio is significant at conventional levels, but the point estimates again have the expected signs for all coefficients. Consistent with regulatory and other changes noted above, a chi-square test confirms that the vector of estimated coefficients is significantly different between the earlier and later models. However, the imprecision of the later estimates is so severe that a Wald test, reported in the table, finds no significant differences in the individual coefficients across time except for the equity / assets ratio. These results are robust to a correction, not reported in the tables, for possibly unequal residual variation across the two time periods (Allison, 1999).

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16 King and Zeng (2001) suggest a method of stratified sampling for logit regressions with rare events, but acknowledge that using the full population is always preferable when available. We therefore base our sample on the full population, thereby also maintaining comparability to prior bank failure studies and regulatory models.
The key step in our analysis is to compare the out-of-sample forecast accuracy of the two models. Several methods of such comparison have been proposed in the literature. Because a logit model simply predicts a probability of failure for each bank, a researcher, analyst, or regulator must select which threshold probability to interpret as a prediction of failure. Although a commonly selected threshold is 0.5, this value is arbitrary and generally not optimal. Instead, an appropriate choice of threshold may depend on the relative cost of each type of error and on the proportion of failed banks in the sample, which tends to vary from year to year (Greene, 2003, page 685; King and Zeng, 2001).

We present the comparison in Figure 2, a graph of Type I error versus Type II error as in Cole (1995), Kolari et al. (2002), Jagtiani et al. (2003), and others. We define a Type I error as a nonfailed bank that the model predicted to fail, and a Type II error as a failed bank that the model predicted to survive. Zero Type I error can always be achieved by predicting that no banks fail (yielding 100 percent Type II error), while zero Type II error can always be achieved by predicting that all banks fail (yielding 100 percent Type I error). A perfect model would have zero error of either type, generating a graph that coincides with the axes. The farther the graph is from the axes, the worse is the predictive power of the underlying model.

A graph of this sort, relating the two types of errors for alternate thresholds, depicts the full range of tradeoffs and allows each reader to select her preferred threshold (which is implicit in the graph). Such a graph also provides a convenient way of visualizing the relative performance of alternate models. If the graph of one model is uniformly closer to the origin than that of another, the former model is more accurate at all thresholds. If two graphs cross, the preferred model would
depend on the preferred threshold. This method of comparison is easy to understand, but lacks a formal test of statistical significance of the differences between models.

As shown in Figure 2, the early model is substantially more accurate than the later model in forecasting near-term holdout samples (two years after the estimation period), at all thresholds. That is, the early model exhibits lower type 2 error at any level of type 1 error, and vice versa, compared to the later model. Given the paucity of bank failures during 2000-01, this result is not qualitatively surprising, but the magnitude of the difference is nevertheless striking.

The real surprise in Figure 2 is that bank failures in 2002-2003 are much more accurately predicted by 2001 financial data using the coefficients estimated using the 1989 data rather than those estimated using the 1999 data. Apparently, the severe imprecision of the 1999 estimates more than offsets the impact of any structural shifts since 1989 in terms of predictive accuracy. This is the key empirical finding, lending support not only to the idea that sparse failures hinder accurate estimates of risk, but also to an informational basis for periodic banking crises in that shifts in linkages between risk and observable factors cannot be reliably identified with sparse failures.

Also in Figure 2, we can compare the accuracy of the 1989 coefficients in forecasting failures during 1992-93 versus the accuracy of the 1989 coefficients in forecasting failures in 2002-03. Unsurprisingly, the near-term holdout sample is more accurately predicted than the much later one, consistent with the significant difference between the 1989 and 1999 coefficients, and reflecting some depreciation over time of the information contained in the 1989 estimates.

4. Summary and Conclusion
This paper has explored the notion that low failure rates during normal times render the banking industry informationally opaque with respect to the linkages between observable factors and the risk of failure.\textsuperscript{17} Consistent with this hypothesis, we found that regression coefficients estimated during a period of higher failure rates more accurately predicted out-of-sample failures more than a decade later, compared to regression coefficients estimated much closer to the holdout sample period but with very few failures. This result is striking, given the extensive regulatory and other changes that occurred during the intervening decade, which might be expected to cause the earlier coefficients to become less valid for the later sample.

A general implication of these results is that sparse failures can impede both regulatory supervision and effective market discipline of banks due to the resulting informational opacity (Flannery and Thakor, 2006). Another, more specific, implication is that regulators and other users of explicit statistical models of bank failure may be better advised to re-estimate their models only in years of high failure rates, rather than every feasible quarter as in Cole (1995). A more general implication is that it may be difficult or impossible to quantify precise changes in the linkages between observable factors and bank risk until aggregate risk levels have risen high enough to trigger a wave of new failures. This latter property suggests an informational basis for the pessimistic notion that periodic banking crises may be an unavoidable price of having very low failure rates during normal times.

The high cost of banking crises makes it important to identify policy implications of these findings, but the most obvious policy lessons would seem to lie in the area of recognizing

\textsuperscript{17} Note that this is a somewhat different notion of opacity than that studied by Morgan (2002), Hirtle (2006), and others.
unwelcome tradeoffs. On the one hand, effective prudential regulation will normally result in very low failure rates, which benefit not only bankers but also the broader economy. On the other hand, those low failure rates make it harder to identify new risks in a timely fashion while they can still be easily controlled. A logical corollary would seem to be that allowing somewhat higher failure rates in non-crisis years might make it possible to recognize emerging risks more precisely at an earlier stage, thus permitting more timely responses that could mitigate the frequency and severity of banking crises. An open question is whether smoothing the rate of bank failures over time in this fashion could potentially reduce the total number or costs of such failures. An additional tradeoff is that the lower informational transparency due to sparse failures may help mitigate the likelihood of inefficient bank runs, as suggested by Chen and Hasan (2006).

Another possible tradeoff underlying the observed patterns is that major regulatory changes, while beneficially incorporating the most recent findings from research and experience, may themselves contribute to shifts in the linkages between observable factors and bank risk, and thus – given the apparent difficulty of quantifying those shifts during periods of few failures – contribute in the medium term to banking crises. To the extent this is true, one possible response might be to consider reserving major regulatory changes for periods of crisis, when banks are already failing and the linkages can therefore be readily quantified. A further advantage of this strategy could be to combine such revisions with any crisis-specific regulatory response. This idea may be viewed as a regulatory analogue to the strategy of “opportunistic disinflation” sometimes considered in monetary policy (Aksoy et al., 2006). The additional
tradeoff here, of course, is that some types of regulatory changes might either entail transition costs or pose new moral hazard, both of which could be more problematic during crisis periods.

Subsequent work on this topic could extend the analysis across countries, not only to see whether the same pattern holds outside the U.S. but also to test whether the deterioration over time of information contained in statistical failure models is weaker in countries where ordinary failure rates have been higher. A related test would be whether banking crises have differed in frequency or severity as an inverse function of the failure rates in non-crisis years. Similarly, a comparison of these properties across industries could provide additional insight into the important question of whether banking exhibits systematically greater informational opacity than other industries, a question that remains unresolved in light of the contrasting findings of Slovin et al. (1992) and Morgan (2002) versus Flannery et al. (2004).

Finally, one might argue that the binary fail / survive variable is a narrow measure of risk, albeit the one most relevant to regulatory and systemic costs. It would be interesting, therefore, to see whether a similar pattern of informational depreciation might hold for alternate measures of risk and, in particular, whether continuous measures of risk may permit more timely updating in response to new sources of risk or evolution of linkages between observable factors and risk. In that regard, a few measures of risk (such as the Z-score, equity/asset ratio, or loan chargeoff ratio) could be calculated for all banks using available accounting data, while market-based measures of risk such as equity beta or volatility would necessarily restrict the sample to the largest subset of banks. A complication here is that some such variables, including the equity/asset ratio and nonperforming loan ratio, are commonly used as regressors in statistical
failure models and are thus interpreted as observable factors rather than outcomes. These various issues suggest that the ideas identified here may open fruitful new areas of research.
Table 1: Explanatory Variables

<table>
<thead>
<tr>
<th>CAMELS Factors</th>
<th>Bank-Specific Financial Indicators</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Management</td>
<td>Expenses/Total Assets</td>
<td>Whalen (1991), DeYoung (2003a, b)</td>
</tr>
</tbody>
</table>

"Similarly, Abrams and Huang (1987) included the ratio of allowance for possible loan loss / total loans, Whalen (1991) included a variable defined as the difference between primary capital / average total assets and nonperforming loans / average total assets, Kolari et al. (2002) included the ratio of net loan charge-offs / total assets, and Arena (2008) included the ratio of loan-loss provisions / total loans.

"Similarly, Cole and Gunther (1995) included three components of expenses as a fraction of average net assets.

"Similarly, Kolari et al. (1996) included the ratio of time deposits more than $100,000 / total time deposits."
Table 2: Descriptive Statistics

Variable means, medians, standard deviations, and a difference of means statistic

<table>
<thead>
<tr>
<th></th>
<th>Nonfailed</th>
<th>Failed</th>
<th>Difference of Means</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
<td>Std Dev</td>
</tr>
<tr>
<td><strong>1989 Sample</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Assets (000's)</td>
<td>255623</td>
<td>45952</td>
<td>3</td>
</tr>
<tr>
<td>Equity Ratio</td>
<td>0.0895</td>
<td>0.0818</td>
<td>0.0378</td>
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<tr>
<td>Loan Ratio</td>
<td>0.5338</td>
<td>0.5447</td>
<td>0.1512</td>
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<tr>
<td>Jumbo CDs Ratio</td>
<td>0.1044</td>
<td>0.0880</td>
<td>0.0768</td>
</tr>
<tr>
<td>Nonperf Loans Ratio</td>
<td>0.0109</td>
<td>0.0069</td>
<td>0.0135</td>
</tr>
<tr>
<td>Net Income Ratio</td>
<td>0.0073</td>
<td>0.0093</td>
<td>0.0105</td>
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<tr>
<td>Expenses Ratio</td>
<td>0.0848</td>
<td>0.0835</td>
<td>0.0127</td>
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<tr>
<td>Log Total Assets</td>
<td>10.897</td>
<td>10.735</td>
<td>1.2818</td>
</tr>
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<td></td>
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<td>4</td>
<td>1.2818</td>
</tr>
<tr>
<td><strong>1999 Sample</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Assets (000's)</td>
<td>659256</td>
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<td>2</td>
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<tr>
<td>Equity Ratio</td>
<td>0.1030</td>
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<tr>
<td>Loan Ratio</td>
<td>0.6136</td>
<td>0.6290</td>
<td>0.1431</td>
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<tr>
<td>Jumbo CDs Ratio</td>
<td>0.1135</td>
<td>0.0991</td>
<td>0.0701</td>
</tr>
<tr>
<td>Nonperf Loans Ratio</td>
<td>0.0053</td>
<td>0.0029</td>
<td>0.0076</td>
</tr>
<tr>
<td>Net Income Ratio</td>
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<td>0.0104</td>
<td>0.0094</td>
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<tr>
<td>Expenses Ratio</td>
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<td>0.0604</td>
<td>0.0113</td>
</tr>
<tr>
<td>Log Total Assets</td>
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<td>11.284</td>
<td>1.3009</td>
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<tr>
<td></td>
<td>1</td>
<td>5</td>
<td>1.3009</td>
</tr>
</tbody>
</table>

Descriptive statistics for bank failures and nonfailures. Failure is defined as those banks which fail in the subsequent 2 years. Log Total Assets is the natural logarithm of bank total assets. Equity Ratio is the bank equity-to-asset ratio. Jumbo CDs Ratio is the ratio of jumbo certificates of deposit to bank total assets. Nonperf Loans Ratio is the ratio of non-performing loans to bank total assets. Net Income Ratio is the ratio of bank net income to bank total assets. Expense Ratio is the ratio of bank total expense to bank total assets. Difference of means is significant at the ***0.01, **0.05, or *0.10 level.
Table 3: Estimated Logit Coefficients for Bank Failure

<table>
<thead>
<tr>
<th></th>
<th>1989 Sample</th>
<th>1999 Sample</th>
<th>Wald Test for Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>coefficient (p-value)</td>
<td>coefficient (p-value)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-3.950 (0.0003)</td>
<td>-1.983 (0.7519)</td>
<td>0.10</td>
</tr>
<tr>
<td>Log Total Assets</td>
<td>-0.235 (0.0008)</td>
<td>-0.719 (0.1769)</td>
<td>0.81</td>
</tr>
<tr>
<td>Equity Ratio</td>
<td>-53.398 (&lt;0.0001)</td>
<td>-13.870 (0.2474)</td>
<td>9.75*</td>
</tr>
<tr>
<td>Loan Ratio</td>
<td>3.399 (&lt;0.0001)</td>
<td>1.397 (0.6816)</td>
<td>0.33</td>
</tr>
<tr>
<td>Jumbo CDs Ratio</td>
<td>4.442 (&lt;0.0001)</td>
<td>8.783 (0.0224)</td>
<td>1.20</td>
</tr>
<tr>
<td>Nonperf Loans Ratio</td>
<td>18.772 (&lt;0.0001)</td>
<td>27.820 (0.1121)</td>
<td>0.26</td>
</tr>
<tr>
<td>Net Income Ratio</td>
<td>-8.464 (0.0969)</td>
<td>-25.459 (0.3251)</td>
<td>0.42</td>
</tr>
<tr>
<td>Expenses Ratio</td>
<td>27.951 (&lt;0.0001)</td>
<td>21.869 (0.4764)</td>
<td>0.04</td>
</tr>
<tr>
<td>Sample Size</td>
<td>12930</td>
<td>8913</td>
<td></td>
</tr>
<tr>
<td>R-square (Cox &amp; Snell, 1989, pp. 208f.)</td>
<td>0.0873</td>
<td>0.0030</td>
<td></td>
</tr>
<tr>
<td>Nagelkerke (1991) R-Square</td>
<td>0.5387</td>
<td>0.2689</td>
<td></td>
</tr>
</tbody>
</table>

Logit regressions for the probability that a bank fails within the subsequent 2 years. The dependent variable is equal to 1 if the bank fails within the subsequent 2 year period and 0 otherwise. The 1989 sample regression estimates bank failure in 1990 and 1991. The 1999 sample regression estimates bank failure in 2000 and 2001. Log Total Assets is the natural logarithm of bank total assets. Equity Ratio is the bank equity-to-asset ratio. Jumbo CDs Ratio is the ratio of jumbo certificates of deposit to bank total assets. Nonperf Loans Ratio is the ratio of non-performing loans to bank total assets. Net Income Ratio is the ratio of bank net income to bank total assets. Expense Ratio is the ratio of bank total expense to bank total assets. *significant at the 0.01 level.
Figure 1: Commercial Bank Failures  
(excludes savings banks)  

Source: www.fdic.gov.
Figure 2: Type I vs. Type II Error in Predicting Out-of-Sample Failures
Based on 1989 vs. 1999 Fitted Model, and Failures in 1992-93 vs. 2002-03
References


