# Déjà Vu All Over Again: The Causes of U.S. Commercial Bank Failures *This* Time Around*

Rebel A. Cole
Kellstadt College of Commerce
DePaul University
14 E. Jackson Blvd. Suite 900
Chicago, IL USA
Rcole@depaul.edu
Phone: 312-933-0584
FAX: 888-425-4687

Lawrence J. White
Stern School of Business
New York University
44 W. 4th Street Room 7-65
New York, NY USA
Lwhite@stern.nyu.edu
Phone: 212- 998-0880
FAX: 212-995-4218

**FORTHCOMING:** ***Journal of Financial Services Research***

**Abstract:**

In this study, we analyze why commercial banks failed during the recent financial crisis. We find that traditional proxies for the CAMELS components, as well as measures of commercial real estate investments, do an excellent job in explaining the failures of banks that were closed during 2009, just as they did in the previous banking crisis of 1985 – 1992. Surprisingly, we do not find that residential mortgage-backed securities played a significant role in determining which banks failed and which banks survived. Our results offer support for the CAMELS approach to judging the safety and soundness of commercial banks, but calls into serious question the current system of regulatory risk weights and concentration limits on commercial real estate loans.

**Key words**: bank, bank failure, CAMELS, commercial real estate, FDIC, financial crisis, mortgage-backed security, risk-based capital, risk weights

**JEL codes**: G17, G21, G28

* The authors acknowledge helpful comments or discussions of Viral Acharya, Lamont Black, John Boyd, Bob DeYoung, Scott Frame, Ed Kane, Paul Kupiec, Amine Tarazi, and Haluk Unal; and participants at a Federal Reserve Board research seminar held July 8, 2010, in Washington, DC; at a Stern-NYU research seminar held Sep. 24, 2010, in New York City, NY; and at the FDIC's 10th Annual Bank Research Conference held Oct. 28-29, 2010, in Arlington, VA.

**Déjà Vu All Over Again:**
**The Causes of U.S. Commercial Banks Failures *This* Time Around**

*"It's only when the tide goes out that you learn who's been swimming naked."*[1]

## 1. Introduction

Why have U.S. commercial banks failed during the ongoing financial crisis that began in early 2008 with the failure of Bear Stearns? The seemingly obvious answer is that investments in the "toxic" residential mortgage-based securities (RMBS), primarily those that were fashioned from subprime mortgages, brought them down; but that turns out to be the wrong answer, at least for commercial banks. Certainly, toxic securities were problematic for investment banks and the largest commercial banks and their holding companies, many of which loaded up on these assets, often in the form of CDO investments, but none of these large commercial banks have technically failed.[2] Yet, the FDIC reports that it closed more than 300 smaller depository institutions during 2008 – 2010 at a cost of more than $80 billion. What were the factors that caused *these* failures? In this study, we provide the answer to this question.

There has been little analysis of recent bank failures, primarily because there were so few failures during recent years.[3] We aim to fill this gap. Using logistic regressions, we estimate an empirical model explaining the determinants of commercial bank failures that occurred during

[1] This quotation is commonly attributed to the investor Warren Buffet.
[2] Of course, in late 2008, some – perhaps many – of these large banks were insolvent on a mark-to-market basis, and, thus, could be considered to have failed economically. However, the Troubled Asset Relief Program (TARP) effectively bailed them out. An exception was the demise of Washington Mutual in September 2008; but WaMu was absorbed by an acquirer at "no cost" to the Federal Deposit Insurance Corporation (FDIC), and was not extensively invested in the toxic securities but, instead, had originated toxic mortgages that were retained in its loan portfolio. Also, Wachovia appeared headed for failure but was acquired by Wells Fargo in October 2008 at no cost to the FDIC—an acquisition that Wells Fargo would regret for years to come. Wachovia's troubles stemmed from the more than $100 billion in pay-option adjustable-rate mortgages (ARMs) that it inherited from Golden West, a thrift that it acquired during 2006.
[3] Only 31 banks failed during the eight years spanning 2000 – 2007, and only 30 banks failed during 2008. These samples are too small to conduct a meaningful analysis using cross-sectional techniques. During 2009, more than 100 banks failed, for the first time since 1992, which was the tail end of the last banking crisis.

2009, using standard proxies for the CAMELS [4] ratings as explanatory variables. An important feature of our analysis is that we estimate alternative models that predict the 2009 failures using data from successively earlier years, stretching from 2008 back to 2004. By so doing, we are able to ascertain early indicators of likely difficulties for banks, as well as late indicators.

Not surprisingly, we find that traditional proxies for the CAMELS ratings are important determinants of bank failures in 2009, just as previous research has shown for the last major banking crisis in 1985 – 1992 (see, e.g., Thomson (1992), Cole and Gunther (1995, 1998)). Banks with more capital, better asset quality, higher earnings, and more liquidity are less likely to fail. However, when we test for early indicators of failure, we find that the CAMELS proxies become successively less important, whereas portfolio variables become increasingly important. In particular, real-estate loans play a critically important role in determining which banks survive and which banks fail. Real estate construction and development loans, commercial mortgages, and multi-family mortgages are consistently associated with a *higher* likelihood of bank failure, whereas residential single-family mortgages are either neutral or associated with a *lower* likelihood of bank failure.

These results are consistent with the findings of Cole and Fenn (2008), who examine the role of real-estate loans in explaining bank failures from the 1985 – 1992 period. Our results offer support for the CAMELS approach to judging the safety and soundness of commercial banks, but call into serious question the current system of regulatory risk weights for commercial real estate loans, especially construction and development loans.

[4] CAMELS is an acronym for Capital adequacy; Asset quality; Management; Earnings; Liquidity; and Sensitivity to market risk. The Uniform Financial Rating System, informally known as the CAMEL ratings system, was introduced by U.S. regulators in November 1979 to assess the health of individual banks; in 1996, CAMEL evolved into CAMELS, with the addition of a sixth component to summarize Sensitivity to market risk. Following an onsite bank examination, bank examiners assign a score on a scale of one (best) to five (worst) for each of the six CAMELS components; they also assign a single summary measure, known as the “composite” rating.

The remainder of this study proceeds as follows: In Section 2, we provide a brief literature review. Section 3 discusses our model and our data, and introduces our explanatory variables. In Section 4, we provide our main logit regression results. Section 5 contains our robustness checks, and Section 6 offers a brief conclusion.

## 2. Literature Review

In this section, we will not try to provide a complete literature review on the causes of bank failures because recent papers by Torna (2010) and Demyanyk and Hasan (2009) contain extensive reviews; we refer interested readers to those studies for further depth.

Instead, we wish to make two points: First, there are surprisingly few papers that have econometrically explored the causes of recent bank failures.[5] We are aware only of Torna (2010), Ng and Roychowdhury (2010), and Aubuchon and Wheelock (2010).[6] Torna focuses on whether "modern banking activities and techniques"[7] are associated with commercial banks' becoming financially troubled and/or insolvent.[8] Torna empirically tests separately for what causes a healthy bank to become troubled (which is defined as being in the bottom ranks of banks when measured by Tier 1 capital [9]) and what causes a troubled bank to fail (i.e., to become

---

[5] We exclude from this category the extensive, and still growing, literature on the failures of the subprime-based residential mortgage-backed securities (RMBS). For examples of such analyses, see Gorton (2008), Acharya and Richardson (2009), Brunnermeier (2009), Coval *et al*. (2009), Mayer *et al*. (2009), Demyanyk and Van Hemert (2010), and Krishnamurthy (2010).

[6] It is striking that, in the literature reviews provided by Torna (2010) and Demyanyk and Hasan (2009), there are *no* cites to econometric efforts to explain recent bank failures (except with respect specifically to RMBS failure issues). A more recent paper (Forsyth 2010) examines the increase in risk-taking (as measured by assets that carry a 100% risk weight in the Basel I risk-weighting framework) between 2001 and 2007 by banks that are headquartered in the Pacific Northwest but does not specifically address failure issues.

[7] Torna (2010) considers the following to be "modern banking activities and techniques": brokerage; investment banking; insurance; venture capital; securitization; and derivatives trading.

[8] As do we, Torna (2010) excludes thrift institutions from the analysis.

[9] Torna (2010) cannot directly identify the banks that are on the FDIC's "troubled banks" list each quarter because the FDIC releases the total number of troubled banks, but keeps their identities confidential. As an estimate of those identities, Torna considers "troubled banks" specifically to be the number of banks at the bottom of the Tier 1 capital ranking that is equal to the number of banks that are on the FDIC's "troubled banks" list for each quarter.

insolvent and have a receivership declared by the FDIC), based on quarterly identifications of troubled banks and failures from Q4-2007 through Q3-2009. Torna employs proportional hazard and conditional logit analyses and uses quarterly FDIC Call Report data for a year prior to the quarterly identification. Torna finds that the influences on a healthy bank's becoming troubled are somewhat different from those that cause a troubled bank to fail.

For our purposes, Torna's study is different from ours in at least four important respects: First, his study focuses on the distinction between "traditional" and "modern" banking activities, but doesn't explore the finer detail among "traditional" banking activities, such as types of loans, which is a central feature of our study. Second, his study looks back for only a year to find the determinants of healthy banks' becoming troubled and troubled banks' failing, whereas we look back as far as five years prior to the failures. Third, by including only troubled banks among the candidates for failure (which is consistent with the one-year look-back period), his study is limited in its ability to consider longer and broader influences, whereas all commercial banks are included in our analysis. Fourth, a ranking based only upon capital ignores five of the six CAMELS components and likely seriously misclassifies "problem banks." For all of these reasons, we do not consider Torna's study to be a close substitute for ours.

Ng and Roychowdhury (2010) use a Cox proportional-hazard model to find that bank failures in 2008 and 2009 were positively related to additions to loan loss reserves in 2007, after controlling for other bank characteristics. However, unlike our study, Ng and Roychowdhury do not examine the influence of bank characteristics for years that were earlier than 2007 on their sample of bank failures; they do not include as failures those banks that were so financially weak that they were likely to fail after 2009; and they fail to distinguish between loans for residential

Torna's method provides only a crude approximation to these identities because this method ignores all but one of the CAMELS components that likely go into the FDIC's determination of "troubled bank" status.

real estate and for commercial real estate – a distinction that we find to be quite important. For these reasons, we believe that the Ng and Roychowdhury study is also not a close substitute for ours.

Aubuchon and Wheelock (2010) examine bank and thrift failures between January 1, 2007 and March 31, 2010. Unlike our study, however, Aubuchon and Wheelock focus mostly on the regional economic characteristics that are associated with bank failures rather than on the detailed characteristics of the banks themselves.

The second point that we wish to make in this section concerns the studies of the bank and thrift failures of the 1980s and early 1990s – e.g., Cole and Fenn (2008) for commercial banks and Cole (1993) and Cole, McKenzie, and White (1995) for thrift institutions – that show how commercial real estate investments and construction lending have often proved to be significant influences on depository institutions' failures. In our current study, we find that construction loans continue to be a harbinger of failure and that commercial real estate lending and multifamily mortgages, at least for earlier years, are significantly associated with bank failures.

## 3. Model, Data, and Univariate Comparisons

### *3.1. Empirical Model.*

In our empirical model of bank failure, the dependent variable FAIL is binary (fail or survive), so that it would be inappropriate to use ordinary-least-squares regression (see Maddala 1983, pp. 15-16). Consequently, we turn to the multivariate logistic regression model, where we assume that $Failure^*_{i,\,2009}$ is an unobservable index of the probability that bank *i* fails during 2009 and is a function of bank-specific characteristics $x_t$, so that:

$$Failure^*_{i,\,2009} \;=\; \beta_t\,'\,\boldsymbol{X}_{i,\,2009\,-\,t} + \mu_{i,\,t}\,,\; t = 1, 2, \ldots, 5 \qquad (1)$$

where $\boldsymbol{X}_{i,\,2009\,-\,t}$ are a set of financial characteristics of bank $i$ as of December 31st in the calendar year that was $t$ years before 2009; $\beta_t$ is a vector of parameter estimates for the explanatory variables measures as of year $2009 - t$, $\mu_{i,\,t}$ is a random disturbance term, $i = 1, 2, \ldots, N$, where $N$ is the number of banks. Let $FAIL_{i,\,2009}$ be an observable variable that is equal to one if $Failure^*_{i,\,2009} > 0$ and zero if $Failure^*_{i,\,2009} \leq 0$. In this particular application, $FAIL_{,i,\,2009}$ is equal to one if a bank fails during 2009 and zero otherwise. Since $Failure^*_{i,\,2009}$ is equal to $\beta_t'\,\boldsymbol{X}_{i,\,2009\,-\,t} + \mu_{i,\,t}$, the probability that $FAIL_{i,\,2009} > 0$ is equal to the probability that $\beta_t'\,\boldsymbol{X}_{i,\,2009\,-\,t} > 0$, or, equivalently, the probability that $(\mu_{i,\,t} > -\,\beta_t'\,\boldsymbol{X}_{i,\,2009\,-\,t})$. Therefore, one can write the probability that $FAIL_{i,\,2009}$ is equal to one as the probability that $(\mu_{i,\,t} > -\,\beta_t'\,\boldsymbol{X}_{i,\,2009\,-\,t})$, or, equivalently, that $\text{Prob}(FAIL_{i,\,2009} = 1) = 1 - \Phi\,(-\beta_t'\,\boldsymbol{X}_{i,\,2009\,-\,t})$, where $\Phi$ is the cumulative distribution function of $\varepsilon$, here assumed to be logistic. The probability that $FAIL_{i,\,2009}$ is equal to zero is then simply $\Phi\,(-\beta_t'\,\boldsymbol{X}_{i,\,2009\,-\,t})$. The likelihood function $L$ for this model is:

$$L \;=\; \prod_{FAIL_i\,=\,0} \left[\Phi\,(-\beta_t'\,\boldsymbol{X}_{i,\,2009\,-\,t})\right] \;\prod_{FAIL_i\,=\,1} \left[1 - \Phi\,(-\beta_t'\,\boldsymbol{X}_{i,\,2009\,-\,t})\right],$$

where:

$$\Phi\,(-\beta_t'\,\boldsymbol{X}_{i,\,2009\,-\,t}) = \exp\,(-\beta_t'\,\boldsymbol{X}_{i,\,2009\,-\,t}) \,/\, [1 - \exp\,(-\beta_t'\,\boldsymbol{X}_{i,\,2009\,-\,t})]$$

$$= 1 \;/\; [1 + \exp\,(-\beta_t'\,\boldsymbol{X}_{i,\,2009\,-\,t})]$$

and

$$1 - \Phi\,(-\beta_t'\,\boldsymbol{X}_{i,\,2009\,-\,t}) = \exp(-\beta_t'\,\boldsymbol{X}_{i,\,2009\,-\,t}) \;/\; [1 + (-\beta_t'\,\boldsymbol{X}_{i,\,2009\,-\,t})]\,.$$

There were 117 commercial banks that failed during 2009; but, clearly, there are many more banks that will fail during 2010 – 2012 from the same or similar underlying causes. To ignore this latter group is to impose a form of right-hand censoring; but, of course, the identities of the banks in this latter group could not be known as of year-end 2009. Rather than ignore them, we estimate their identities as follows: We count as a "technical failure" any bank reporting that the sum of equity plus loan loss reserves was less than half of the value of its nonperforming assets or, more formally:

(Equity + Reserves – 0.5 x NPA) < 0,

where NPA equals the sum of loans past due 30-89 days and still accruing interest, loans past due 90+ days and still accruing interest, nonaccrual loans, and foreclosed real estate.[10] Our "technical failure" is equivalent to book-value insolvency when a bank is forced to write off half of the value of its bad loans. There were 148 such banks as of year-end 2009.[11] Thus, we place 265 (= 117 + 148) in the FAIL category.[12]

### *3.2. Data and Explanatory Variables*

The data that we use come from the FDIC Call Reports. Because the Call Reports for thrifts are different from those used for commercial banks, and because thrifts operate under a different charter and are usually focused in directions that are different from those of commercial banks, we use only the commercial bank data.[13]

Our explanatory variables are primarily the financial characteristics of the banks, drawn from their balance sheets and their profit-and-loss statements as of the fourth quarters of 2008

[10] In two studies of bank and thrift failures occurring during the 1980s, Thomson (1992) and Cole (1993) take a different approach to account for regulators' failure to close technically insolvent financial institutions. Thomson (1992) uses a two equation model where the first equation estimates capital-adequacy ratio and the second equation estimates closure as a function of the predicted value from the first equation. Cole (1993) uses a two-equation bivariate probit model, where the first equation estimates insolvency and then the second equation estimates closure. Regulators are also interested in the determinants of failure costs, but that is beyond the scope of our analysis here. See Schaeck (2008) for a recent study that examines issues related to estimating bank failure costs.

[11] It is worth noting that 57 of the 74 commercial banks that failed during the first half of 2010 (77%) are members of our "technical failure" group.

[12] However, in our logit regressions for 2008 and 2007, there are only 263 banks in the FAIL category because two (of the 265 FAIL) banks were de novo start-ups in 2009 and, thus, filed no financial data for 2008 or 2007.

[13] We also exclude savings banks, even though they use the same Call Report forms as commercial banks, because they too are usually focused in directions that are different from those of commercial banks. Their inclusion does not qualitatively affect our results.

and earlier years, that we believe are likely to influence the likelihood of a bank's failing. In almost all instances, the variables are expressed as a ratio with respect to the bank's total assets. The variable acronyms and full names are provided in Table 1. Our expectations for these variables' influences are as follows:

*TE (Total Equity)*: Since equity is a buffer between the value of the bank's assets and the value of its liabilities, we expect TE to have a negative influence on the likelihood of failure.

*LLR (Loan Loss Reserves)*: Since loan loss reserves represent a reduction in assets against anticipated losses on specific assets (e.g., a loan), they provide a source of strength against subsequent losses. Consequently, we expect LLR to have a negative influence on bank failures.

*ROA (Return on Assets)*: This is, effectively, net income, which we expect to have a negative influence on the likelihood of a bank's failing.

*NPA (Non-performing Assets)*: Since non-performing assets are likely to be recognized as losses in a subsequent period, we expect NPA to have a positive influence on the likelihood of a bank's failing.

*SEC (Securities Held for Investment plus Securities Held for Sale)*: Securities (e.g., bonds) have traditionally been considered to be safe, low-risk investments for banks – especially since banks are prohibited from investing in "speculative" (i.e., "junk") bonds. The subprime RMBS debacle has shown that not all bonds that are rated as "investment grade" by the major credit rating agencies will necessarily remain in that category for very long. Nevertheless, as a general matter we expect this category (which includes the RMBS) to have a negative effect on a bank's failing, especially for smaller banks that generally refrained from purchasing the subprime-based RMBS that proved so toxic.

*BD (Brokered Deposits)*: These are deposits that are raised through national brokers rather than from local customers. Although there is nothing inherently wrong with a bank's deciding to raise its funds in this way, brokered deposits have traditionally been seen as a way for a bank to gather funds and grow quickly; and rapid growth has often been synonymous with risky growth. Consequently, we expect this variable to have a positive effect on failure.

*LNSIZE (Log of Bank Total Assets)*: Smaller banks, especially younger ones, are generally more prone to failure than are larger banks. On the other hand, larger banks were more likely to have invested in the toxic RMBS. Consequently, though this variable could well be important, it is difficult to predict *a priori* the direction of the influence.

*CASHDUE (Cash & Items Due from Other Banks)*: Since this represents a liquid stock of assets, we expect it to have a negative effect on failure.

*GOODWILL (Intangible Assets)*: For banks, this largely represents the undepreciated excess over book value that a bank paid when acquiring another bank. Though it can represent legitimate franchise value, it can often represent simply the overpayment in an acquisition. We expect it to have a positive influence on a bank's failing.

*RER14 (Real Estate Residential Single-Family (1-4) Mortgages)*: Prior to the current crisis, single-family[14] residential mortgages were generally considered to be safe, worthwhile loans for banks; the failure of millions of subprime mortgages has thrown some doubt on this proposition. Because most residential mortgages are not subprime, our general expectation is that RER14 would have a negative influence on a bank's failing.

[14] Almost all U.S. housing statistics lump one-to-four residential units into the single-family category.

*REMUL (Real Estate Multifamily Mortgages)*: Lending on commercial multifamily properties has had a history of being troublesome for banks and other lenders (including Fannie Mae and Freddie Mac); consequently, we expect it to have a positive influence on failing.

*RECON (Real Estate Construction & Development Loans)*: This is a category of lending that has been extraordinarily risky for banks in the past; we expect it to have a positive influence on failure.

*RECOM (Real Estate Nonfarm Nonresidential Mortgages)*: This is a category of loans for commercial real estate, such as office buildings and retail malls, which proved especially toxic during the previous banking crisis. We expect it to be positively related to failure.

*CI (Commercial & Industrial Loans)*: This is a category of lending in which commercial banks are expected to have a comparative advantage. We expect it to have a negative influence on failure.

*CONS (Consumer Loans)*: This encompasses automobile loans, other consumer durables loans, and credit card loans, as well as personal unsecured loans. Again, this is an area where banks should have a comparative advantage. We expect a negative influence on failure.[15]

---

[15] Other financial variables that we tried, but that generally failed to yield significant results, included Trading Assets; Premises; Restructured Loans; Insider Loans; Home Equity Loans; and Mortgage-Backed Securities (classified into a number of categories).

*3.3. Univariate Comparisons*

Tables 2A – 2E provides the means and standard errors for all banks and separately for the subsamples of surviving banks and failed banks, along with *t*-tests for statistically significant differences in the means of the surviving and failing groups. Tables 2A – 2E provide descriptive statistics for 2008, 2007, 2006, 2005, and 2004, respectively, so that we can see how the differences in the two subsamples evolved over the five years prior to the 2009 failures.

In Table 2A are the univariate comparisons based upon year-end 2008 Call Report data. Not surprisingly, during this period just prior to the 2009 failures, we see that the difference in the means of virtually every variable is highly significant and with the expected sign. Among the traditional CAMELS proxies, failing banks have significantly lower capital ratios (0.076 vs. 0.124), higher ratios of NPAs (0.126 vs. 0.026), lower earnings (-0.026 vs. 0.005), and fewer liquid assets (0.045 vs. 0.062 for Cash & Due, 0.106 vs. 0.204 for Securities, and 0.172 vs. 0.043 for Brokered Deposits). Of course, this is not surprising, as regulators based their decisions to close a bank largely upon the CAMELS rating of the bank, and that rating is closely proxied by these variables (see Cole, Cornyn, and Gunther 1995).

More interesting are the loan portfolio variables, especially those that are related to real estate. Failing banks have significantly higher allocations to commercial real estate of all kinds—most notably to Construction & Development loans (0.232 vs. 0.070), but also to Nonfarm Nonresidential Mortgages (0.226 vs. 0.164) and Multifamily Mortgages (0.029 vs. 0.014). In contrast, failing banks have significantly lower allocations to Residential Single-Family Mortgages (0.104 vs. 0.143) and Consumer Loans (0.016 vs. 0.046).

In Table 2E are the univariate comparisons based upon 2004 data, which should reflect the portfolio allocations that led to the shockingly high rates of NPAs and associated losses reflected in ROA and Total Equity found in Table 2A. Surprisingly, the failed banks had higher capital ratios than did the surviving banks back in 2004, although the difference is not statistically significant. Asset quality as measured by NPAs was virtually identical at 0.014. Profitability (ROA) was significantly lower for the failed banks (0.007 vs. 0.011) as was liquidity (0.036 vs. 0.049 for Cash &Due, 0.140 vs. 0.240 for Securities, and 0.065 vs. 0.019 for Brokered Deposits). However, once again, it is the loan portfolio variables that are most interesting. Even five years before failure, the group of failed banks had much higher concentrations of commercial real estate loans (0.171 vs. 0.051 for Construction and Development Loans, 0.221 vs. 0.144 for Nonfarm Nonresidential Mortgages, and 0.029 vs. 0.012 for Multifamily Mortgages) and much lower concentrations of Residential Single-Family Mortgages (0.109 vs. 0.146) and Consumer Loans (0.031 vs. 0.059).

Table 3 provides a summary of significant differences in means across the five years analyzed. As can be seen, most of the variables across the five time periods are consistently associated (positively or negatively) with failures in 2009.

One point concerning the comparisons of the results using 2008 data with those that use earlier years' data – whether the simple comparisons of means that are discussed here or the multivariate logit results that are discussed in Section 4 – should be stressed: To the extent that a category of assets from an earlier year generates losses, those losses will reduce (via write-downs) the magnitude of the assets (cet. par.) in that category in later years. Thus, if (say) investments in construction loans in 2006 lead to large losses in 2008 and the eventual failure of banks in 2009, then the failure regression that involves the 2006 data as explanatory variables will capture the positive effect of construction loans on bank failure; but the failure regression involving the 2008 data on the RHS may fail to find a significant effect from construction loans, since the write-downs may be so substantial as to make the importance of construction loans (as of 2008) appear to be relatively modest.

## 4. Results

*4.1 Logit Regression Results*

In Table 4 are the results of a set of logistic regression models that provide the main results of our study. In these models, the dependent variable is equal to one if a bank failed during 2009 or was technically insolvent (as previously defined) as of year-end 2009; and is equal to zero otherwise. The five pairs of columns present results that are based upon data (i.e., explanatory variables) from 2008, 2007, 2006, 2005, and 2004, respectively. The coefficients in the table represent the marginal effect of a change in the relevant independent variable, when all variables are evaluated at their means.

The results in the first pair of columns, which are based upon the financial data reported just prior to failure, show that the standard CAMELS proxies have the expected signs and are highly significant. Lower capital as measured by equity to assets was associated with a higher probability of failure, as was worse asset quality as measured by NPAs to assets, lower earnings as measured by ROA, and worse liquidity as measured by Cash & Due to assets, Investment Securities to assets, and Brokered Deposits to assets. These results closely follow the univariate results presented in Panel A of Table 2 and are very similar to the findings of Thomson (1992) and Cole and Gunther (1998), who analyze the determinants of U.S. bank failures during the 1980s. The loan portfolio variables indicate that failed banks had significantly higher concentrations of Construction & Development loans and significantly lower concentrations of Residential Single-Family Mortgages and Consumer Loans. Overall, this model explains more than 60 percent of the variability in the dependent variable as measured by the pseudo-R2 statistic (also known as McFadden's LRI).

As we move back in time in the subsequent pairs of columns in Table 4, our explanatory power falls off to only 20 percent for the results in the last pair of columns, which are based upon 2004 data, but we find that most of the explanatory variables that are significant for the 2008 data retain significance for the 2004 data—five years prior to the observed outcome of failure or survival. Only the capital ratio loses significance. Moreover, the prominence of the real estate loan variables rises as we go back in time, most notably the ratio of Construction & Development Loans to total assets.

In Table 5, we present a summary of the results in Table 4. As can be seen, there are six variables that are consistently significant for at least four of the five years prior to the measurement of our outcome of failure or survival. Two are standard CAMELS proxies: asset quality as measured by the ratio of Nonperforming Assets to total assets, and earnings as measured by ROA. Brokered deposits, as an indicator of rapid growth and likely a negative indicator of asset quality and of management quality, has a clear negative influence. The remaining three are real-estate loan portfolio variables that neatly summarize the underpinnings of not only this banking crisis but also the underpinnings of the previous crisis during the 1980s: High allocations to Construction & Development Loans, Nonfarm-Nonresidential Mortgages (i.e., commercial real estate), and Multifamily Mortgages are strongly associated with failure.[16]

Perhaps most notable about Table 5 are the variables that are not significant throughout the periods. Of these, the most striking is the ratio of capital (Total Equity) to assets, which loses its explanatory power when we move back more than two years prior to failure. In contrast, the

[16] A potential issue of multicollinearity should be mentioned: If the variable Nonfarm-Nonresidential Mortgages is excluded from the regressions, most of the other variables retain the signs and significance shown in Table 4, and the variable Residential Single-Family Mortgages becomes a consistently significant *negative* influence on failure.

ratio of Loan Loss Reserves to total assets is significant three and more years prior to failure but loses its significance during the two years prior to failure.

*4.2 Out-of-Sample Forecasting Accuracy*

We also are interested in whether our model can be used by bank regulators and others as a forecasting tool for identifying future bank failures. To answer this question, we follow Cole and Gunther (1998) in calculating the tradeoff between Type 1 and Type 2 errors, where a Type 1 error corresponds to misclassifying a failed bank as a survivor and a Type 2 error corresponds to misclassifying a surviving bank as a failure. This type of analysis is also known as a response-operating-characteristics ("ROC") curve. Obviously, the costs of a Type 1 error in the form of bank resolution costs are orders of magnitudes larger than the costs of a Type 2 error, which typically take the form of additional bank examination costs for the misclassified banks.[17]

To accomplish this task, we apply the coefficients of our 2008-based model (shown in Table 4) to data on all commercial banks that were operating as of Dec. 31, 2009, and that filed Q4-2009 Call Reports. Banks that were closed by the FDIC during the first three quarters of 2010 are considered failures, and all other banks are considered survivors.

The results of this analysis, which appear in Figure 1, show that our model is extremely accurate in predicting bank failures. For a Type 2 error rate of only 1%, where we misclassify 68 out of 6,793 survivors, our Type 1 error rate is only 17.8%, or 19 out of 107 failures. For a Type 2 error rate of 5% where we misclassify 340 out of 6,793 survivors,[18] our Type 1 error rate is only 3.7% or 4 out of 107 failures. From a regulator perspective, we can think of this as

[17] Of course, if a Type-2-error bank were to be put into a receivership by the FDIC, the losses to shareholders and senior managers could be larger, although still likely to be far less than the costs of Type I errors.
[18] It is likely the case that some of the "misclassified survivors" will subsequently fail, which would reduce our Type 2 error rate.

identifying for onsite examination the worst 5% of predicted probabilities of failure and successfully identifying all but four of the subsequent failures. By comparison, Cole and Gunther (1998) report that a Type 1 error rate of 9.8% is associated with a Type 2 error rate of 10%; our model is much more accurate—at a 10% Type 2 error rate, we misclassify only 3 out of 107 failures, for a Type 1 error rate of only 2.8%.

## 5. Robustness Checks and Extensions

In this section, we provide a set of robustness checks on our basic results, as well as extending them in interesting ways. First, we exclude our technical failures (i.e., we count as failures only those banks that actually failed in 2009) and re-estimate our logit models. Second, we exclude the actual failures (i.e., we count as failures only those banks that were technically insolvent at the end of 2009, including 57 banks that actually did fail during the first half of 2010) and re-estimate our logit models. Third, we rerun our logit models excluding banks with more than $10 billion in total assets. Fourth, we split our sample into large and small banks and re-estimate our logit models separately for these two groups. Fifth, we add dummy variables for the states that have had the lion's share of bank failures. Sixth, we add dummy variables that represent the primary federal regulator of the commercial bank. Seventh, we recalculate our technical failures by using a disaggregated measure of non-performing assets with varying loss ratios that are applied to the different components. And eighth, we re-estimate our logit models with the inclusion of the actual bank failures in the first half of 2010.

### *5.1. Exclusion of Technical Failures*

As was explained above, our FAIL variable includes the banks that actually failed in 2009 plus our calculation of banks that were likely to fail within the next year or two. Because the latter are estimated, for one robustness check we exclude the technically failed banks, and re-estimate our model with FAIL encompassing only the banks that actually were closed by the FDIC during 2009. As can be seen in Table 6 and the summary in Table 7, the results for this more limited sample of failed banks basically replicate our basic results in Tables 4 and 5. There are, however, some notable differences: Brokered Deposits do not show up as significant for this group; Residential Single-Family Mortgages is generally a negative influence on failure; and Nonfarm-Nonresidential Mortgages is insignificant.

### *5.2 Exclusion of Actual Failures*

In Table 8 we estimate our model with FAIL encompassing only the technically failed banks (excluding the banks that were actually closed by the FDIC in 2009), and Table 9 provides a summary. We find that the results again are basically similar to our basic results; but, again, there are some differences: Cash & Due (a liquidity measure) is less important in explaining the failures of these banks; and Consumer Loans is wholly insignificant as an influence on failure.

### *5.3. Exclusion of the Largest Banks*

It is clear that the largest banks were those that were most likely to have invested in the "toxic" RMBS securities. Perhaps these banks are atypical of the remaining thousands of smaller banks and are somehow influencing our results? As a third robustness check, we exclude the 40 banks with more than $10 billion in total assets for each earlier time period from which our alternative sets of explanatory variables are drawn. The results of this exercise, which are available upon request from the authors, basically replicate those shown in Tables 4 and 5. This indicates that our results are not driven by the oddities of these large banks.

### *5.4 Dividing the Sample into Small Banks and Large Banks.*

In addition to excluding the largest banks, we also divide our overall sample into “small” and “large” banks, using $300 million as our demarcation point. We choose $300 million in order to ensure that there are a sufficient number of failures in the “large bank” subsample for estimating the logit model. Tables 10 and 12 provide the estimation results for the large and small banks, respectively, with Tables 11 and 13 providing summaries of these respective results.

As can be seen, the basic results hold for both small and large banks, with a few notable exceptions. Specifically, ROA is a weaker negative influence on failures for large banks than for small banks; Securities plays no role in failures for large banks, whereas this variable is a significant negative influence on failures for small banks; and Nonfarm-Nonresidential Mortgages is a significant positive influence on failure for only the two years preceding the failures of large banks, whereas this variable is a significant and positive influence on failures for years two through five prior to failure but not for the year immediately preceding failure for small banks.

### *5.5 Adding State Dummy Variables*

Casual observation suggests that some states have experienced more extensive numbers of bank failures than have others. To control for this, we include as additional explanatory variables a set of indicators (i.e., dummy variables) for these “high volume” states – Arizona, California, Florida, Georgia, Illinois, Michigan, and Nevada. We find that indicators for FL, GA, IL, and NV are consistently significant positive influences on failure over all five years of data; in addition, CA also is a significant positive influence when only actual failures are included in FAIL (i.e., when technical failures are excluded from FAIL). Importantly, these additional variables add to the explanatory power of the regressions, but do not "soak up" explanatory power from our basic results of Tables 4 and 5; i.e., the basic story of the CAMELS variables and commercial real estate variables continues to hold even when the state dummy variables are included. (These results are available from the authors upon request.)

*5.6 Adding Dummy Variables for the Primary Regulator*

Commercial banks in the U.S. are prudentially regulated by one of three federal regulators: National banks are regulated by the Comptroller of the Currency (OCC); state-chartered banks that are members of the Federal Reserve System (FRS) are regulated by the Federal Reserve; and state-chartered banks that are not members of the FRS are regulated by the Federal Deposit Insurance Corporation (FDIC).[19] It is possible that the different regulatory regimes might have had different influences on the likelihoods of failures. To test this possibility, we include dummy variables for the OCC and FDIC regulatory regimes in our logit regressions. We find significant positive effects on failures for the OCC variable for the 2007 and 2008 explanatory data. Our basic results for the remaining variables from Tables 4 and 5 continue to hold. (Again, these results are available from the authors upon request)

[19] Also, all bank holding companies are regulated by the FRS, but not all banks are members of holding companies.

*5.7 Disaggregating Non-Performing Assets*

In our basic results, we describe a technical failure as a bank that did not fail during 2009 but that had at year-end 2009:

(Equity + Reserves – 0.5*NPA) < 0.

Since there are a number of components to NPA, as an additional robustness check we explore the possibility of applying different "haircuts" (i.e., percentage estimates of loss) to the different components. Specifically, we apply a haircut of 20% to loans that were past due 30-89 days and still accruing interest (PD3089), a haircut of 50% to loans that were past due 90+ days and still accruing interest (PD90+), and a haircut of 100% (i.e., a total writeoff) to nonaccrual loans (NonAccrual) and to other real estate owned (OREO). These haircuts correspond to the write-downs required for the classified-asset categories of "substandard," "doubtful," and "loss" that are used by U.S. bank examiners. We then redefined technical failures as:

Equity + Reserves – 0.2*PD3089 – 0.5*PD90+ – 1.0*(NonAccrual + OREO) < 0.

At the end of 2009, there were 347 banks that satisfied this modified definition of technical failure.[20] When we include these modified technical failures in our measure of FAIL and re-estimate our basic logit regressions, our basic results continue to hold. (Again, these results are available from the authors on request)

*5.8 Including the Failed Banks from the First Half of 2010*

There were 74 commercial banks that failed during the first half of 2010. When we include these banks in FAIL and re-estimate our logit regressions, our basic results continue to

[20] Of the 74 banks that failed in the first half of 2010, 68 (92%) were in this modified group of 347 technical failures.

hold. This is not surprising, as 57 of these 74 were members of our technically insolvent failures. (Again, these results are available from the authors on request)

*5.9 Miscellaneous Additional Robustness Tests*

In addition to the robustness checks described above, we tested a number of additional modifications to our explanatory variables, but failed to find significant results. These included: home equity loans; annual percentage growth of assets; a dummy variable for RECOM > 300% of equity; a dummy variable for RECON > 100% of equity; squared terms for RECOM, RECON, and REMUL; advances from the Federal Home Loan Bank System as a percentage of assets; and separate categories of charge-offs corresponding to consumer, C&I, and various categories of real estate loans.[21]

## 6. Conclusion

In this paper we address the question, "what have been the financial characteristics of commercial banks in earlier years that led to their failure or expected failure in 2009?" Using logit analysis on alternative explanatory data sets drawn from 2008, 2007, etc., back to 2004, we find that traditional proxies for the CAMELS ratings are important determinants of bank failures in 2009, just as they were during the last banking crisis, which spanned 1985 – 1992.

Our results suggest that the number of bank failures will continue at elevated levels for several years, just as they did during the 1980s crisis. We also find that real-estate loans play an especially important role in determining which banks survive and which banks fail. Banks with higher loan allocations to construction-and-development loans, commercial mortgages, and

[21] We are grateful to seminar participants at the Federal Reserve Board for many of these suggestions and to Scott Frame for the suggestion regarding FHLB advances.

multi-family mortgages are especially likely to fail, whereas higher loan allocations to residential single-family mortgages are either neutral or help banks to survive. These results point to the importance of separating residential from commercial real estate when examining bank loan portfolios. Surprisingly, investments in mortgage-backed securities appear to have little or no impact on the likelihood of failure. In fact, banks with higher allocations to investment securities of all kinds are significantly less likely to fail.

These results are important for at least two reasons: First, they offer strong support for the CAMELS approach to judging the safety and soundness of commercial banks. In particular, proxies for capital adequacy, asset quality, earnings and liquidity prove to be powerful predictors of bank failure during 2009-2010, just as they did during the 1984-1992 period. Second, they indicate that most banks in the current crisis are failing in ways that are quite recognizable to anyone who has studied the hundreds of bank failures that occurred during the 1984-1992 period; hence, the phrase "déjà vu all over again." Banks that invest heavily in commercial real estate loans, including construction and development loans, non-residential mortgages, and multifamily mortgages, are taking levels of risk that are simply not captured by existing capital requirements, just as they were back in the 1980s. The implementation of arbitrary asset risk weights following the last banking crisis has done little to change this fact. When commercial real estate values plummeted, as they did both in the late 1980s and in the 2007-2010 period, losses on these risky investments simply overwhelmed the capital that was available to absorb losses at banks with large exposures to these types of loans. The parallels of the causes of the two crises, taking place twice within twenty years, makes it highly implausible to argue that the recent commercial real estate bust was a "black swan" that could not have rationally been anticipated.

From a policy perspective, these outcomes argue for higher risk weights on these high-risk assets, as well as for tighter limits on loan concentrations in such assets. Had either of these reforms been in place, then the FDIC most likely would not have been forced to close more than 300 banks during 2008 – 2010 at an estimated cost of more than $80 billion, yet still face hundreds of additional bank failures and tens of billions of dollars in additional losses during 2011 and beyond.

Plus ça change, plus c'est la même chose…

## References


Acharya, Viral, and Matthew Richardson, eds. 2009. *Restoring Financial Stability: How to Repair a Failed System*. New York: Wiley.

Aubuchon, Craig P. and David C. Wheelock. 2010. The geographic distribution and characteristics of U.S. bank failures, 2007-2010: Do bank failures still reflect local economic conditions? *Federal Reserve Bank of St. Louis Review*, 395-416.

Brunnermeier, Markus K. 2009. Deciphering the liquidity and credit crunch 2007–2008. *Journal of Economic Perspectives* 23, 77–100.

Cole, Rebel A. 1993. When are thrift institutions closed? An agency-theoretic model. *Journal of Financial Services Research* 7, 283-307.

Cole, Rebel A., Barbara G. Cornyn and Jeffery W. Gunther. 1995. FIMS: A new monitoring system for banking organizations. *Federal Reserve Bulletin* 81, January. Board of Governors of the Federal Reserve System, Washington, DC. 1-15.

Cole, Rebel A. and Jeffery W. Gunther. 1995. Separating the likelihood and timing of bank failure. *Journal of Banking & Finance* 19, 1073-1089.

Cole, Rebel A. and Jeffery W. Gunther. 1998. Predicting bank failures: A comparison of on- and off-site monitoring systems. *Journal of Financial Services Research* 13, 103-117.

Cole, Rebel A. and George W. Fenn. 2008. The role of commercial real estate investments in the banking crisis of 1985-92. Paper presented at the Annual Meetings of the American Real Estate and Urban Economics Association held in January 1995 in Washington, DC. Available at: http://ssrn.com/abstract=1293473.

Cole, Rebel A., Joseph A. McKenzie, and Lawrence J. White. 1995. Deregulation gone awry: Moral hazard in the savings and loan industry. In *Bank Failures: Causes, Consequences and Cures*, edited by Michael S. Lawler and John H. Wood, Kluwer Academic Publishers: Norwell, MA. Available at: http://ssrn.com/abstract=1293468.

Coval, Joshua, Jakub Jurek, and Erik Stafford. 2009. The economics of structured finance. *Journal of Economic Perspectives* 23, 3–25.

Demyanyk, Yuliya and Otto Van Hemert. 2011. Understanding the subprime mortgage crisis. *Review of Financial Studies* 24, 1848-1880.

Demyanyk, Yuliya and Iftekhar Hasan. 2009. Financial crises and bank failures: A review of prediction methods. *Omega* 28, 315-324.

Forsyth, Grant D. 2010. Trough to peak: A note on risk-taking in the Pacific Northwest's banking sector, 2001 to 2007. Working paper, Eastern Washington University.

Gorton, Gary B. 2008. The panic of 2007. NBER Working Paper 14358. Available at: http://www.nber.org/papers/w14358.

Krishnamurthy, Arvind. 2010. How debt markets have malfunctioned in the crisis. *Journal of Economic Perspectives* 24, 3-28.

Maddala, G. S. 1983. *Limited-Dependent and Qualitative Variables in Economics*. New York: Cambridge University Press.

Mayer, Christopher, Karen Pence, and Shane M. Sherlund. 2009. The Rise in Mortgage Defaults. *Journal of Economic Perspectives* 23, 27–50.

Ng, Jeffrey and Sugata Roychowdhury. 2010. Loan loss reserves, regulatory capital, and bank Failures: evidence from the 2008-2009 economic crisis. Available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1646928

Schaeck, Klaus. 2008. Bank liability structure, FDIC loss, and time to failure: A quantile regression approach. *Journal of Financial Services Research* 33, 163-179.

Thomson, James B. 1992. Modeling the bank regulator's closure option: A two-step logit regression approach. *Journal of Financial Services Research* 6, 5-23.

Torna, Gokhan. 2010. Understanding Commercial Bank Failures in the Modern Banking Era. Available at: http://www.fma.org/NY/Papers/ModernBanking-GTORNA.pdf

**Table 1:**
**Variable Acronyms and Explanations**

All variables (except LNSIZE) are expressed as a decimal fraction of total assets.

| | |
|---|---|
| TE | Total Equity |
| LLR | Loan Loss Reserves |
| ROA | Return on Assets (Net Income) |
| NPA | Non-performing Assets = sum of (PD3089, PD90+, NonAccrual, OREO): |

| | |
|---|---|
| PD3089 | Loans Past Due 30-89 Days but Still Accruing Interest |
| PD90+ | Loans Past Due 90+ Days but Still Accruing Interest |
| NonAccrual | Nonaccrual Loans |
| OREO | Other Real Estate Owned |

| | |
|---|---|
| SEC | Securities Held for Investment plus Securities Available for Sale |
| BD | Brokered Deposits |
| LNSIZE | Log of Bank Total Assets |
| CASHDUE | Cash & Due |
| GOODWILL | Intangible Assets: Goodwill |
| RER14 | Real Estate Residential Single-Family (1–4) Family Mortgages |
| REMUL | Real Estate Multifamily Mortgages |
| RECON | Real Estate Construction & Development Loans |
| RECOM | Real Estate Nonfarm Nonresidential Mortgages |
| CI | Commercial & Industrial Loans |
| CONS | Consumer Loans |

## Table 2A:
## Descriptive Statistics for 2008 Data

Descriptive statistics for the variables that are used to explain bank failures. Statistics are presented for all banks and separately for surviving banks and failed banks. A t-test for significant differences in the means of the surviving banks and failed banks appears in the last column. FAIL takes on a value of one if a bank failed during 2009 or was technically insolvent at the end of 2009, and a value of zero otherwise. Explanatory variables are defined in Table 1. There are 263 failures and 6,883 survivors when we use year-end 2008 data; 263 failures and 7,092 survivors when we use year-end 2007 data; 258 failures and 7,138 survivors when we use year-end 2006 data; 245 failures and 7,276 survivors when we use year-end 2005 data; and 232 failures and 7,397 survivors when we use year-end 2004 data. The 263 failures include 117 banks that were closed by the FDIC during 2009 and 148 banks that were technically insolvent at the end of 2009 (minus 2 denovo banks that began operations in 2009). Technical insolvency is defined as (TE + LLR) < (0.5 x NPA). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

| | **All** | | **Survivors** | | **Failures** | | | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **S.E.** | **Mean** | **S.E.** | **Mean** | **S.E.** | **Difference** | **t-Difference** |
| **TE** | 0.123 | 0.001 | 0.124 | 0.001 | 0.076 | 0.002 | 0.048 | 22.67 *** |
| **LLR** | 0.010 | 0.000 | 0.009 | 0.000 | 0.020 | 0.001 | -0.011 | -12.71 *** |
| **ROA** | 0.004 | 0.000 | 0.005 | 0.000 | -0.026 | 0.002 | 0.031 | 14.98 *** |
| **NPA** | 0.030 | 0.000 | 0.026 | 0.000 | 0.126 | 0.005 | -0.099 | -20.41 *** |
| **SEC** | 0.200 | 0.002 | 0.204 | 0.002 | 0.106 | 0.005 | 0.097 | 18.41 *** |
| **BD** | 0.048 | 0.001 | 0.043 | 0.001 | 0.172 | 0.010 | -0.129 | -13.44 *** |
| **LNSIZE** | 11.925 | 0.016 | 11.899 | 0.017 | 12.593 | 0.074 | -0.694 | -9.14 *** |
| **CASHDUE** | 0.062 | 0.001 | 0.062 | 0.001 | 0.045 | 0.003 | 0.018 | 5.74 *** |
| **GOODWILL** | 0.005 | 0.000 | 0.006 | 0.000 | 0.003 | 0.001 | 0.003 | 3.84 *** |
| **RER14** | 0.142 | 0.001 | 0.143 | 0.001 | 0.104 | 0.005 | 0.039 | 6.93 *** |
| **REMUL** | 0.015 | 0.000 | 0.014 | 0.000 | 0.029 | 0.003 | -0.015 | -5.43 *** |
| **RECON** | 0.076 | 0.001 | 0.070 | 0.001 | 0.232 | 0.008 | -0.162 | -21.09 *** |
| **RECOM** | 0.166 | 0.001 | 0.164 | 0.001 | 0.226 | 0.007 | -0.062 | -9.28 *** |
| **CI** | 0.100 | 0.001 | 0.100 | 0.001 | 0.092 | 0.004 | 0.008 | 1.77 * |
| **CONS** | 0.045 | 0.001 | 0.046 | 0.001 | 0.016 | 0.001 | 0.030 | 18.75 *** |
| **Obs** | 7,146 | | 6,883 | | 263 | | | |

## Table 2B:
## Descriptive Statistics for 2007 Data

Descriptive statistics for the variables that are used to explain bank failures. Statistics are presented for all banks and separately for surviving banks and failed banks. A t-test for significant differences in the means of the surviving banks and failed banks appears in the last column. FAIL takes on a value of one if a bank failed during 2009 or was technically insolvent at the end of 2009, and a value of zero otherwise. Explanatory variables are defined in Table 1. There are 263 failures and 6,883 survivors when we use year-end 2008 data; 263 failures and 7,092 survivors when we use year-end 2007 data; 258 failures and 7,138 survivors when we use year-end 2006 data; 245 failures and 7,276 survivors when we use year-end 2005 data; and 232 failures and 7,397 survivors when we use year-end 2004 data. The 263 failures include 117 banks that were closed by the FDIC during 2009 and 148 banks that were technically insolvent at the end of 2009 (minus 2 denovo banks that began operations in 2009). Technical insolvency is defined as (TE + LLR) < (0.5 x NPA). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

| | **All Banks** | | **Survivors** | | **Failures** | | | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **S.E.** | **Mean** | **S.E.** | **Mean** | **S.E.** | **Difference** | **t-Difference** |
| **TE** | 0.132 | 0.001 | 0.133 | 0.001 | 0.105 | 0.003 | 0.028 | 9.68 *** |
| **LLR** | 0.0086 | 0.000 | 0.0085 | 0.000 | 0.0116 | 0.000 | -0.003 | -8.12 *** |
| **ROA** | 0.0097 | 0.000 | 0.0099 | 0.000 | 0.0043 | 0.001 | 0.006 | 6.49 *** |
| **NPA** | 0.019 | 0.000 | 0.018 | 0.000 | 0.047 | 0.003 | -0.029 | -11.18 *** |
| **SEC** | 0.204 | 0.002 | 0.207 | 0.002 | 0.112 | 0.005 | 0.095 | 16.41 *** |
| **BD** | 0.034 | 0.001 | 0.030 | 0.001 | 0.127 | 0.008 | -0.097 | -11.54 *** |
| **LNSIZE** | 11.848 | 0.016 | 11.823 | 0.016 | 12.533 | 0.075 | -0.710 | -9.23 *** |
| **CASHDUE** | 0.048 | 0.001 | 0.049 | 0.001 | 0.027 | 0.002 | 0.021 | 10.81 *** |
| **GOODWILI** | 0.006 | 0.000 | 0.006 | 0.000 | 0.006 | 0.001 | 0.000 | -0.13 |
| **RER14** | 0.136 | 0.001 | 0.138 | 0.001 | 0.093 | 0.005 | 0.045 | 8.47 *** |
| **REMUL** | 0.013 | 0.000 | 0.012 | 0.000 | 0.027 | 0.003 | -0.015 | -5.57 *** |
| **RECON** | 0.085 | 0.001 | 0.077 | 0.001 | 0.280 | 0.010 | -0.203 | -20.86 *** |
| **RECOM** | 0.154 | 0.001 | 0.152 | 0.001 | 0.217 | 0.007 | -0.065 | -9.76 *** |
| **CI** | 0.102 | 0.001 | 0.102 | 0.001 | 0.097 | 0.005 | 0.005 | 1.08 |
| **CONS** | 0.048 | 0.001 | 0.049 | 0.001 | 0.018 | 0.001 | 0.031 | 19.18 *** |
| Obs. | 7,355 | | 7,092 | | 263 | | | |

## Table 2C:
## Descriptive Statistics for 2006 Data

Descriptive statistics for the variables that are used to explain bank failures. Statistics are presented for all banks and separately for surviving banks and failed banks. A t-test for significant differences in the means of the surviving banks and failed banks appears in the last column. FAIL takes on a value of one if a bank failed during 2009 or was technically insolvent at the end of 2009, and a value of zero otherwise. Explanatory variables are defined in Table 1. There are 263 failures and 6,883 survivors when we use year-end 2008 data; 263 failures and 7,092 survivors when we use year-end 2007 data; 258 failures and 7,138 survivors when we use year-end 2006 data; 245 failures and 7,276 survivors when we use year-end 2005 data; and 232 failures and 7,397 survivors when we use year-end 2004 data. The 263 failures include 117 banks that were closed by the FDIC during 2009 and 148 banks that were technically insolvent at the end of 2009 (minus 2 denovo banks that began operations in 2009). Technical insolvency is defined as (TE + LLR) < (0.5 x NPA). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

| | **All Banks** | | **Survivors** | | **Failures** | | | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **S.E.** | **Mean** | **S.E.** | **Mean** | **S.E.** | **Difference** | **t-Difference** |
| **TE** | 0.122 | 0.001 | 0.122 | 0.001 | 0.123 | 0.006 | 0.000 | -0.04 |
| **LLR** | 0.009 | 0.000 | 0.0086 | 0.000 | 0.0093 | 0.000 | -0.001 | -3.69 *** |
| **ROA** | 0.010 | 0.000 | 0.0101 | 0.000 | 0.0074 | 0.001 | 0.003 | 2.89 *** |
| **NPA** | 0.014 | 0.000 | 0.014 | 0.000 | 0.018 | 0.001 | -0.004 | -2.77 *** |
| **SEC** | 0.210 | 0.002 | 0.213 | 0.002 | 0.117 | 0.006 | 0.096 | 15.86 *** |
| **BD** | 0.033 | 0.001 | 0.031 | 0.001 | 0.108 | 0.008 | -0.077 | -9.71 *** |
| **LNSIZE** | 11.823 | 0.016 | 11.803 | 0.016 | 12.379 | 0.080 | -0.576 | -7.06 *** |
| **CASHDUE** | 0.046 | 0.001 | 0.046 | 0.001 | 0.034 | 0.003 | 0.012 | 4.23 *** |
| **GOODWILL** | 0.005 | 0.000 | 0.005 | 0.000 | 0.005 | 0.001 | 0.000 | 0.25 |
| **RER14** | 0.139 | 0.001 | 0.141 | 0.001 | 0.091 | 0.005 | 0.050 | 9.17 *** |
| **REMUL** | 0.012 | 0.000 | 0.012 | 0.000 | 0.027 | 0.003 | -0.015 | -5.24 *** |
| **RECON** | 0.080 | 0.001 | 0.073 | 0.001 | 0.255 | 0.010 | -0.182 | -18.20 *** |
| **RECOM** | 0.152 | 0.001 | 0.150 | 0.001 | 0.213 | 0.007 | -0.063 | -8.98 *** |
| **CI** | 0.100 | 0.001 | 0.100 | 0.001 | 0.098 | 0.005 | 0.002 | 0.50 |
| **CONS** | 0.051 | 0.001 | 0.052 | 0.001 | 0.020 | 0.002 | 0.032 | 16.01 *** |
| **Obs.** | 7,396 | | 7,138 | | 258 | | | |

**Table 2D:**
**Descriptive Statistics for 2005 Data**

Descriptive statistics for the variables that are used to explain bank failures. Statistics are presented for all banks and separately for surviving banks and failed banks. A t-test for significant differences in the means of the surviving banks and failed banks appears in the last column. FAIL takes on a value of one if a bank failed during 2009 or was technically insolvent at the end of 2009, and a value of zero otherwise. Explanatory variables are defined in Table 1. There are 263 failures and 6,883 survivors when we use year-end 2008 data; 263 failures and 7,092 survivors when we use year-end 2007 data; 258 failures and 7,138 survivors when we use year-end 2006 data; 245 failures and 7,276 survivors when we use year-end 2005 data; and 232 failures and 7,397 survivors when we use year-end 2004 data. The 263 failures include 117 banks that were closed by the FDIC during 2009 and 148 banks that were technically insolvent at the end of 2009 (minus 2 denovo banks that began operations in 2009). Technical insolvency is defined as (TE + LLR) < (0.5 x NPA). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

| | **All Banks** | | **Survivors** | | **Failures** | | | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **S.E.** | **Mean** | **S.E.** | **Mean** | **S.E.** | **Difference** | **t-Difference** |
| **TE** | 0.117 | 0.001 | 0.117 | 0.001 | 0.120 | 0.006 | -0.003 | -0.44 |
| **LLR** | 0.009 | 0.000 | 0.009 | 0.000 | 0.009 | 0.000 | 0.000 | -1.86 * |
| **ROA** | 0.010 | 0.000 | 0.011 | 0.000 | 0.008 | 0.001 | 0.003 | 2.72 *** |
| **NPA** | 0.013 | 0.000 | 0.013 | 0.000 | 0.013 | 0.001 | 0.000 | 0.24 |
| **SEC** | 0.223 | 0.002 | 0.227 | 0.002 | 0.129 | 0.006 | 0.098 | 14.55 *** |
| **BD** | 0.034 | 0.008 | 0.033 | 0.008 | 0.086 | 0.007 | -0.053 | -4.90 *** |
| **LNSIZE** | 11.767 | 0.016 | 11.751 | 0.016 | 12.244 | 0.082 | -0.493 | -5.91 *** |
| **CASHDUE** | 0.048 | 0.001 | 0.049 | 0.001 | 0.035 | 0.002 | 0.014 | 6.75 *** |
| **GOODWILL** | 0.005 | 0.000 | 0.005 | 0.000 | 0.003 | 0.001 | 0.002 | 2.09 ** |
| **RER14** | 0.142 | 0.001 | 0.143 | 0.001 | 0.102 | 0.006 | 0.041 | 6.81 *** |
| **REMUL** | 0.012 | 0.000 | 0.012 | 0.000 | 0.029 | 0.004 | -0.017 | -4.70 *** |
| **RECON** | 0.068 | 0.001 | 0.063 | 0.001 | 0.211 | 0.010 | -0.147 | -15.38 *** |
| **RECOM** | 0.150 | 0.001 | 0.147 | 0.001 | 0.221 | 0.007 | -0.073 | -9.68 *** |
| **CI** | 0.100 | 0.001 | 0.100 | 0.001 | 0.100 | 0.005 | 0.000 | -0.04 |
| **CONS** | 0.054 | 0.001 | 0.055 | 0.001 | 0.023 | 0.002 | 0.032 | 13.96 *** |
| **Obs.** | 7,521 | | 7,256 | | 245 | | | |

**Table 2E:**
**Descriptive Statistics for 2004 Data**

Descriptive statistics for the variables that are used to explain bank failures. Statistics are presented for all banks and separately for surviving banks and failed banks. A t-test for significant differences in the means of the surviving banks and failed banks appears in the last column. FAIL takes on a value of one if a bank failed during 2009 or was technically insolvent at the end of 2009, and a value of zero otherwise. Explanatory variables are defined in Table 1. There are 263 failures and 6,883 survivors when we use year-end 2008 data; 263 failures and 7,092 survivors when we use year-end 2007 data; 258 failures and 7,138 survivors when we use year-end 2006 data; 245 failures and 7,276 survivors when we use year-end 2005 data; and 232 failures and 7,397 survivors when we use year-end 2004 data. The 263 failures include 117 banks that were closed by the FDIC during 2009 and 148 banks that were technically insolvent at the end of 2009 (minus 2 denovo banks that began operations in 2009). Technical insolvency is defined as (TE + LLR) < (0.5 x NPA). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

| | All Banks | | Survivors | | Failures | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **S.E.** | **Mean** | **S.E.** | **Mean** | **S.E.** | **Difference** | **t-Difference** | |
| **TE** | 0.114 | 0.001 | 0.114 | 0.001 | 0.118 | 0.007 | -0.004 | -0.51 | |
| **LLR** | 0.009 | 0.000 | 0.009 | 0.000 | 0.009 | 0.000 | 0.000 | -1.26 | |
| **ROA** | 0.010 | 0.000 | 0.011 | 0.000 | 0.007 | 0.001 | 0.003 | 3.15 | *** |
| **NPA** | 0.014 | 0.000 | 0.014 | 0.000 | 0.014 | 0.001 | 0.000 | 0.17 | |
| **SEC** | 0.237 | 0.002 | 0.240 | 0.002 | 0.140 | 0.007 | 0.099 | 14.34 | *** |
| **BD** | 0.021 | 0.001 | 0.019 | 0.001 | 0.065 | 0.007 | -0.045 | -6.54 | *** |
| **LNSIZE** | 11.707 | 0.015 | 11.696 | 0.015 | 12.079 | 0.083 | -0.383 | -4.54 | *** |
| **CASHDUE** | 0.049 | 0.001 | 0.049 | 0.001 | 0.036 | 0.002 | 0.013 | 5.51 | *** |
| **GOODWILL** | 0.004 | 0.000 | 0.004 | 0.000 | 0.003 | 0.001 | 0.001 | 1.86 | * |
| **RER14** | 0.145 | 0.001 | 0.146 | 0.001 | 0.109 | 0.006 | 0.037 | 5.75 | *** |
| **REMUL** | 0.012 | 0.000 | 0.012 | 0.000 | 0.029 | 0.004 | -0.017 | -4.63 | *** |
| **RECON** | 0.056 | 0.001 | 0.052 | 0.001 | 0.171 | 0.009 | -0.118 | -13.60 | *** |
| **RECOM** | 0.147 | 0.001 | 0.144 | 0.001 | 0.221 | 0.008 | -0.077 | -9.71 | *** |
| **CI** | 0.100 | 0.001 | 0.099 | 0.001 | 0.109 | 0.006 | -0.009 | -1.64 | |
| **CONS** | 0.058 | 0.001 | 0.059 | 0.001 | 0.031 | 0.003 | 0.028 | 8.57 | *** |
| **Obs.** | 7,629 | | 7,397 | | 232 | | | | |

**Table 3:**
**Summary of Univariate Comparisons of Failed and Surviving Banks from Table 2**

The results of t-tests on the differences in the means of the explanatory variables for earlier years with respect to the 2009 Failure and Survivor sub-samples shown in Table 2; +,- indicate significant differences at the 10% level of significance or stronger. + indicates that the mean for surviving banks is greater than the mean for failing banks, and - indicates that the mean for surviving banks is less than the mean for failing banks.

| Variable | 2008 | 2007 | 2006 | 2005 | 2004 |
|---|---|---|---|---|---|
| TE | + | + | | | |
| LLR | - | - | - | - | |
| ROA | + | + | + | + | + |
| NPA | - | - | - | | |
| SEC | + | + | + | + | + |
| BD | - | - | - | - | - |
| LNSIZE | - | - | - | - | - |
| CASHDUE | + | + | + | + | + |
| GOODWILL | + | | | + | + |
| RER14 | + | + | + | + | + |
| REMUL | - | - | - | - | - |
| RECON | - | - | - | - | - |
| RECOM | - | - | - | - | - |
| CI | + | | | | |
| CONS | + | + | + | + | + |

**Table 4:**
**Logistic Regression Results: All Banks**

Results from estimating a logistic regression model to explain bank failures, where the dependent variable FAIL takes on a value of one if a bank failed during 2009 or was technically insolvent at the end of 2009, and a value of zero otherwise. Explanatory variables are defined in Table 1. There are 263 failures and 6,883 survivors when we use year-end 2008 data; 263 failures and 7,092 survivors when we use year-end 2007 data; 258 failures and 7,138 survivors when we use year-end 2006 data; 245 failures and 7,276 survivors when we use year-end 2005 data; and 232 failures and 7,397 survivors when we use year-end 2004 data. The 263 failures include 117 banks that were closed by the FDIC during 2009 and 148 banks that were technically insolvent at the end of 2009 (minus 2 denovo banks that began operations in 2009). Technical insolvency is defined as (TE + LLR) < (0.5 x NPA). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

| | 2008 | | 2007 | | 2006 | | 2005 | | 2004 | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Marginal Effect** | **t-stat** | **Marginal Effect** | **t-stat** | **Marginal Effect** | **t-stat** | **Marginal Effect** | **t-stat** | **Marginal Effect** | **t-stat** |
| **TE** | -1.08 | -11.33 *** | -0.25 | -3.86 *** | 0.00 | 0.02 | 0.00 | -0.10 | 0.05 | 2.08 ** |
| **LLR** | -0.21 | -0.90 | -0.65 | -1.34 | -1.95 | -3.10 *** | -2.04 | -3.14 *** | -1.69 | -2.70 *** |
| **ROA** | -0.22 | -3.42 *** | -0.36 | -2.66 *** | -0.46 | -3.91 *** | -0.57 | -3.48 *** | -0.26 | -2.29 ** |
| **NPA** | 0.50 | 12.43 *** | 0.50 | 7.17 *** | 0.65 | 6.35 *** | 0.54 | 4.34 *** | 0.39 | 3.09 *** |
| **SEC** | -0.08 | -3.22 *** | 0.02 | 0.54 | -0.02 | -0.73 | -0.05 | -1.92 * | -0.05 | -2.08 ** |
| **BD** | 0.06 | 4.83 *** | 0.07 | 4.53 *** | 0.06 | 3.69 *** | 0.00 | 1.00 | 0.07 | 4.05 *** |
| **LNSIZE** | 0.00 | -0.52 | 0.00 | 0.61 | 0.00 | 2.23 ** | 0.00 | 1.99 ** | 0.00 | 1.40 |
| **CASHDUE** | -0.10 | -2.47 ** | -0.02 | -0.21 | 0.00 | -0.09 | -0.21 | -2.73 *** | -0.10 | -1.67 * |
| **GOODWILL** | 0.91 | 5.90 *** | 0.21 | 1.67 * | -0.16 | -1.41 | -0.38 | -2.24 ** | -0.31 | -1.96 * |
| **RER14** | -0.09 | -3.65 *** | -0.02 | -0.64 | -0.05 | -1.59 | -0.04 | -1.45 | -0.03 | -1.26 |
| **REMUL** | 0.04 | 1.17 | 0.16 | 3.74 *** | 0.17 | 3.80 *** | 0.15 | 3.92 *** | 0.17 | 4.10 *** |
| **RECON** | 0.10 | 5.00 *** | 0.23 | 9.30 *** | 0.24 | 10.90 *** | 0.23 | 10.63 *** | 0.22 | 10.46 *** |
| **RECOM** | -0.01 | -0.49 | 0.08 | 3.01 *** | 0.07 | 2.86 *** | 0.06 | 2.64 *** | 0.05 | 2.43 ** |
| **CI** | -0.07 | -2.31 ** | 0.01 | 0.17 | 0.00 | 0.00 | 0.00 | -0.03 | 0.01 | 0.36 |
| **CONS** | -0.08 | -1.26 | -0.16 | -1.75 * | -0.19 | -2.19 ** | -0.18 | -2.35 ** | -0.07 | -1.40 |
| | | | | | | | | | | |
| **Pseudo-R2** | 0.621 | | 0.349 | | 0.281 | | 0.236 | | 0.206 | |
| **Failures** | 263 | | 263 | | 258 | | 245 | | 232 | |
| **Obs.** | 7,146 | | 7,355 | | 7,396 | | 7,521 | | 7,628 | |

**Table 5:**
**Summary of Significant Results from Table 4**
**Logistic Regression Results: All Banks**

+,- indicate significant (at the 10% level or stronger) positive or negative regression coefficients from the logistic regressions in Table 4. + indicates a positive relation with the probability of failure, and - indicates a negative relation with the probability of failure.

| Variable | 2008 | 2007 | 2006 | 2005 | 2004 |
|---|---|---|---|---|---|
| TE | - | - | | | + |
| LLR | | | - | - | - |
| ROA | - | - | - | - | - |
| NPA | + | + | + | + | + |
| SEC | - | | | - | - |
| BD | + | + | + | | + |
| LNSIZE | | | + | + | |
| CASHDUE | - | | | - | - |
| GOODWILL | + | + | | - | - |
| RER14 | - | | | | |
| REMUL | | + | + | + | + |
| RECON | + | + | + | + | + |
| RECOM | | + | + | + | + |
| CI | - | | | | |
| CONS | | - | - | - | |

**Figure 1:**
**Out-of-Sample Forecasting Accuracy**

This chart shows the trade-off between Type 1 and Type 2 errors for the first three quarters of 2010, where a Type 1 error corresponds to misclassifying a failed bank as a survivor and a Type 2 error corresponds to misclassifying a surviving bank as a failure. The chart is based upon the estimated probability of failure based upon the logistic-regression coefficients that were obtained by explaining 2009 failures based upon Q4-2008 data, as shown in Table 4. In turn these coefficients are applied to Q4-2009 data, so as to predict failures and survivors. As such, they represent one-year-ahead forecasts of the probability of failure.

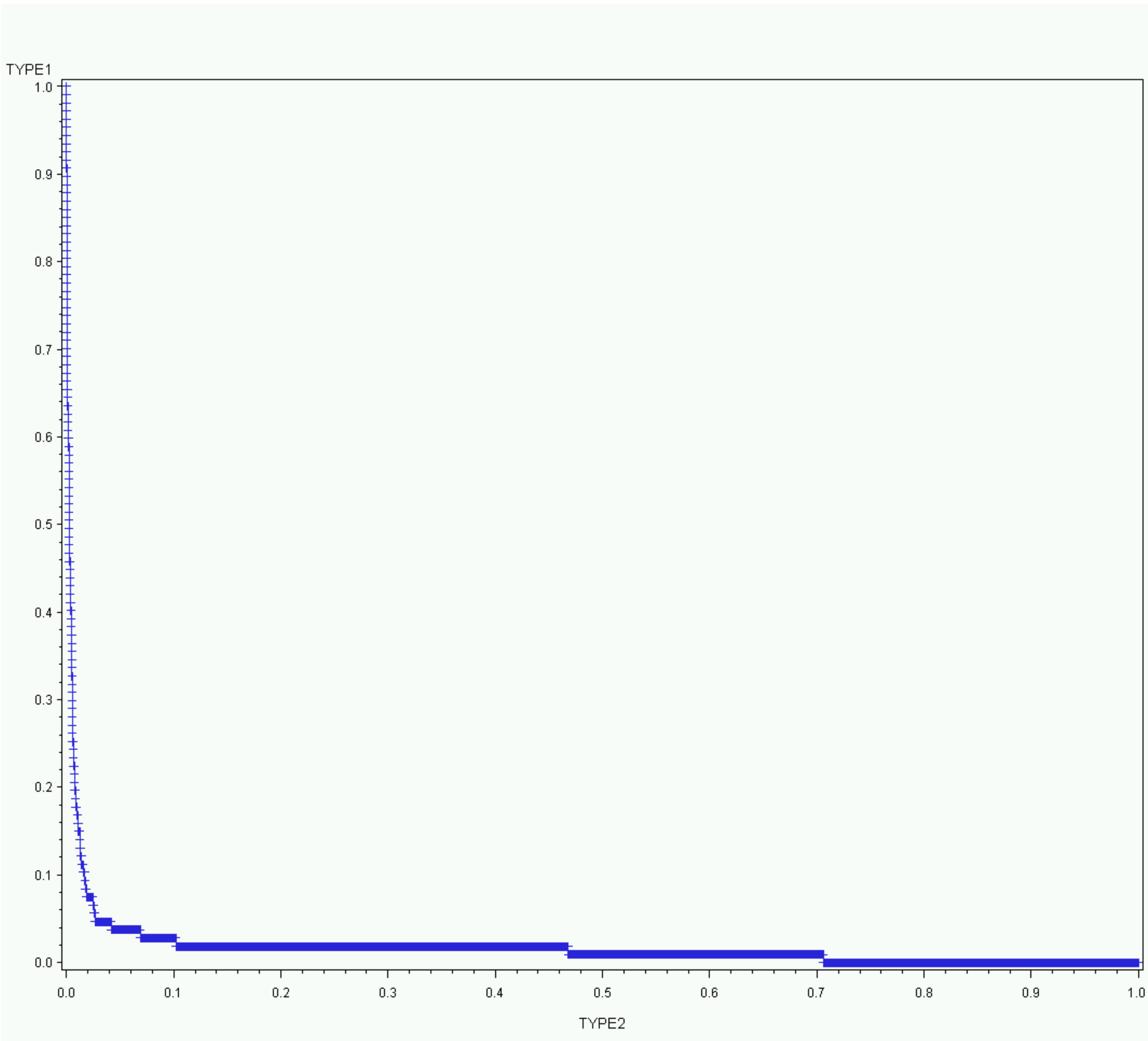

**Table 6:**
**Logistic Regression Results: FDIC Closed Banks Only**

Results from estimating a logistic regression model to explain bank failures, where the dependent variable FAIL takes on a value of one if a bank failed (i.e., was closed by the FDIC) during 2009, and a value of zero otherwise. Explanatory variables are defined in Table 1. There are 117 failures and 6,883 survivors when we use year-end 2008 data; 117 failures and 7,092 survivors when we use year-end 2007 data; 114 failures and 7,138 survivors when we use year-end 2006 data; 111 failures and 7,276 survivors when we use year-end 2005 data; and 106 failures and 7,396 survivors when we use year-end 2004 data. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

| | 2008 | | 2007 | | 2006 | | 2005 | | 2004 | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Marginal Effect** | **t-stat** | **Marginal Effect** | **t-stat** | **Marginal Effect** | **t-stat** | **Marginal Effect** | **t-stat** | **Marginal Effect** | **t-stat** |
| **TE** | -0.62 | -9.54 *** | -0.16 | -2.94 *** | -0.01 | -0.55 | -0.04 | -1.43 | 0.03 | 1.70 * |
| **LLR** | 0.03 | 0.22 | -0.45 | -1.30 | -1.03 | -2.26 ** | -1.03 | -2.17 ** | -1.34 | -2.80 *** |
| **ROA** | -0.12 | -3.62 *** | -0.07 | -0.75 | -0.18 | -2.44 ** | -0.40 | -3.18 *** | -0.09 | -1.42 |
| **NPA** | 0.17 | 7.21 *** | 0.27 | 5.83 *** | 0.35 | 5.14 *** | 0.20 | 1.91 * | 0.26 | 3.00 *** |
| **SEC** | -0.04 | -2.59 *** | 0.01 | 0.38 | 0.00 | -0.28 | -0.01 | -0.47 | -0.02 | -1.17 |
| **BD** | 0.01 | 1.37 | 0.02 | 1.28 | 0.01 | 0.71 | 0.00 | 0.56 | 0.02 | 1.57 |
| **LNSIZE** | 0.00 | 0.01 | 0.00 | 0.98 | 0.00 | 2.15 ** | 0.00 | 1.49 | 0.00 | 1.27 |
| **CASHDUE** | -0.05 | -2.25 ** | -0.20 | -2.31 ** | -0.26 | -2.85 *** | -0.21 | -2.99 *** | -0.20 | -2.87 *** |
| **GOODWILL** | 0.60 | 6.63 *** | 0.19 | 2.36 ** | 0.01 | 0.11 | -0.03 | -0.39 | -0.09 | -1.04 |
| **RER14** | -0.06 | -4.19 *** | -0.05 | -2.14 ** | -0.04 | -1.95 * | -0.03 | -1.41 | -0.03 | -1.82 * |
| **REMUL** | 0.03 | 1.59 | 0.07 | 2.68 *** | 0.06 | 2.16 ** | 0.08 | 3.14 *** | 0.10 | 4.19 *** |
| **RECON** | 0.04 | 2.96 *** | 0.08 | 5.07 *** | 0.09 | 6.33 *** | 0.10 | 7.09 *** | 0.10 | 7.73 *** |
| **RECOM** | -0.01 | -0.74 | 0.01 | 0.90 | 0.02 | 1.12 | 0.02 | 1.13 | 0.01 | 0.77 |
| **CI** | -0.04 | -2.19 ** | -0.01 | -0.64 | -0.02 | -0.88 | -0.02 | -0.87 | -0.01 | -0.46 |
| **CONS** | -0.03 | -0.71 | -0.19 | -2.35 ** | -0.26 | -3.14 *** | -0.19 | -2.67 *** | -0.06 | -1.43 |
| **Pseudo-R2** | 0.690 | | 0.321 | | 0.255 | | 0.227 | | 0.205 | |
| **Failures** | 117 | | 117 | | 114 | | 111 | | 106 | |
| **Survivors** | 6,883 | | 7,092 | | 7,138 | | 7,276 | | 7,396 | |
| **Obs.** | 7,000 | | 7,209 | | 7,252 | | 7,387 | | 7,502 | |

**Table 7**
**Summary of Significant Results from Table 6**
**Logistic Regression Results: FDIC Closed Banks Only**

+,- indicate significant (at the 10% level or stronger) positive or negative regression coefficients from the logistic regressions in Table 6. + indicates a positive relation with the probability of failure, and - indicates a negative relation with the probability of failure.

| Variable | 2008 | 2007 | 2006 | 2005 | 2004 |
|---|---|---|---|---|---|
| TE | - | - | | | + |
| LLR | | | - | - | - |
| ROA | - | | - | - | |
| NPA | + | + | + | + | + |
| SEC | - | | | | |
| BD | | | | | |
| LNSIZE | | | + | | |
| CASHDUE | - | - | - | - | - |
| GOODWILL | + | + | | | |
| RER14 | - | - | - | | - |
| REMUL | | + | + | + | + |
| RECON | + | + | + | + | + |
| RECOM | | | | | |
| CI | - | | | | |
| CONS | | - | - | - | |

**Table 8:**
**Logistic Regression Results: Technically Insolvent Banks Only**

Results from estimating a logistic regression model to explain bank failures, where the dependent variable FAIL takes on a value of one if a bank was technically insolvent at the end of 2009, and a value of zero otherwise. (Banks that were closed by the FDIC during 2009 are excluded.) Explanatory variables are defined in Table 1. There are 147 failures and 6,882 survivors when we use year-end 2008 data; 146 failures and 7,092 survivors when we use year-end 2007 data; 144 failures and 7,138 survivors when we use year-end 2006 data; 134 failures and 7,276 survivors when we use year-end 2005 data; and 125 failures and 7,396 survivors when we use year-end 2004 data. Technical insolvency is defined as (TE + LLR) < (0.5 x NPA). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

| | **2008** | | **2007** | | **2006** | | **2005** | | **2004** | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Marginal Effect** | **t-stat** | **Marginal Effect** | **t-stat** | **Marginal Effect** | **t-stat** | **Marginal Effect** | **t-stat** | **Marginal Effect** | **t-stat** |
| **TE** | -0.65 | -7.97 *** | -0.12 | -2.59 *** | -0.01 | -0.32 | 0.02 | 0.96 | 0.01 | 0.52 |
| **LLR** | -0.45 | -2.08 ** | -0.38 | -0.90 | -0.84 | -1.78 * | -1.14 | -2.39 ** | -0.50 | -1.18 |
| **ROA** | -0.11 | -1.64 | -0.24 | -2.34 ** | -0.30 | -2.79 *** | -0.22 | -1.90 * | -0.17 | -2.13 ** |
| **NPA** | 0.40 | 11.26 *** | 0.19 | 3.46 *** | 0.30 | 3.82 *** | 0.35 | 4.10 *** | 0.15 | 1.57 |
| **SEC** | -0.07 | -2.81 *** | 0.00 | -0.07 | -0.03 | -1.17 | -0.05 | -2.62 *** | -0.04 | -2.04 ** |
| **BD** | 0.05 | 5.00 *** | 0.04 | 3.55 *** | 0.04 | 3.10 *** | 0.00 | 0.78 | 0.05 | 3.62 *** |
| **LNSIZE** | 0.00 | -0.48 | 0.00 | -0.02 | 0.00 | 1.16 | 0.00 | 1.61 | 0.00 | 0.76 |
| **CASHDUE** | -0.09 | -2.25 ** | 0.06 | 1.26 | 0.05 | 1.64 | -0.06 | -1.18 | 0.00 | -0.06 |
| **GOODWILL** | 0.49 | 3.13 *** | -0.03 | -0.27 | -0.29 | -1.91 * | -0.60 | -2.52 ** | -0.30 | -1.76 * |
| **RER14** | -0.04 | -2.01 ** | 0.04 | 1.30 | -0.01 | -0.41 | -0.02 | -0.78 | 0.00 | -0.20 |
| **REMUL** | 0.01 | 0.23 | 0.10 | 2.60 *** | 0.10 | 2.69 *** | 0.07 | 2.20 ** | 0.05 | 1.15 |
| **RECON** | 0.08 | 4.55 *** | 0.17 | 7.71 *** | 0.15 | 8.59 *** | 0.13 | 8.20 *** | 0.12 | 7.51 *** |
| **RECOM** | 0.00 | -0.09 | 0.08 | 3.51 *** | 0.05 | 2.87 *** | 0.04 | 2.47 ** | 0.04 | 2.56 ** |
| **CI** | -0.04 | -1.43 | 0.03 | 1.06 | 0.02 | 0.93 | 0.01 | 0.63 | 0.02 | 0.99 |
| **CONS** | -0.06 | -0.96 | -0.01 | -0.19 | -0.02 | -0.34 | -0.04 | -0.88 | -0.02 | -0.66 |
| **Pseudo R2** | 0.621 | | 0.314 | | 0.269 | | 0.220 | | 0.186 | |
| **Failures** | 147 | | 146 | | 144 | | 134 | | 126 | |
| **Survivors** | 6,882 | | 7,092 | | 7,138 | | 7,276 | | 7,396 | |
| **Obs.** | 7,029 | | 7,238 | | 7,282 | | 7,410 | | 7,522 | |

**Table 9:**
**Summary of Significant Results from Table 8**
**Logistic Regression Results: Technically Insolvent Banks Only**

+,- indicate significant (at the 10% level or stronger) positive or negative regression coefficients from the logistic regressions in Table 8. + indicates a positive relation with the probability of failure, and - indicates a negative relation with the probability of failure.

| Variable | 2008 | 2007 | 2006 | 2005 | 2004 |
|---|---|---|---|---|---|
| TE | - | - | | | + |
| LLR | - | | - | - | |
| ROA | | - | - | - | - |
| NPA | + | + | + | + | + |
| SEC | - | | | - | - |
| BD | + | + | + | | + |
| LNSIZE | | | | | |
| CASHDUE | - | | | | |
| GOODWILL | + | + | | | |
| RER14 | - | | | | |
| REMUL | | + | + | + | + |
| RECON | + | + | + | + | + |
| RECOM | | + | + | + | + |
| CI | | | | | |
| CONS | | | | | |

**Table 10:**

**Logistic Regression Results: Banks with More than $300 Million in Total Assets**

Results from estimating a logistic regression model to explain bank failures, where the dependent variable FAIL takes on a value of one if a bank failed during 2009 or was technically insolvent at the end of 2009, and a value of zero otherwise. Explanatory variables are defined in Table 1. There are 114 failures and 1,652 survivors when we use year-end 2008 data; 116 failures and 1,624 survivors when we use year-end 2007 data; 111 failures and 1,584 survivors when we use year-end 2006 data; 88 failures and 1,513 survivors when we use year-end 2005 data; and 66 failures and 1,422 survivors when we use year-end 2004 data. Technical insolvency is defined as (TE + LLR) < (0.5 x NPA). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

| | 2008 | | 2007 | | 2006 | | 2005 | | 2004 | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Marginal Effect** | **t-stat** | **Marginal Effect** | **t-stat** | **Marginal Effect** | **t-stat** | **Marginal Effect** | **t-stat** | **Marginal Effect** | **t-stat** |
| **TE** | -2.29 | -7.72 *** | -0.69 | -2.04 ** | -0.37 | -1.30 | 0.16 | 0.72 | 0.00 | 0.03 |
| **LLR** | -0.41 | -0.69 | -2.63 | -1.76 * | -3.06 | -1.29 | -2.11 | -1.07 | -2.94 | -1.71 * |
| **ROA** | -0.32 | -2.23 ** | 0.59 | 1.27 | -1.09 | -2.74 *** | -2.92 | -3.55 *** | -0.30 | -0.48 |
| **NPA** | 0.89 | 7.76 *** | 0.94 | 3.98 *** | 1.02 | 2.53 ** | 1.18 | 2.35 ** | 1.33 | 3.27 *** |
| **SEC** | -0.05 | -0.63 | 0.13 | 1.44 | 0.08 | 0.91 | -0.01 | -0.11 | -0.03 | -0.56 |
| **BD** | 0.07 | 2.52 ** | 0.13 | 3.02 *** | 0.10 | 2.31 ** | 0.04 | 1.06 | 0.00 | 0.03 |
| **LNSIZE** | 0.00 | 0.42 | 0.01 | 1.27 | 0.01 | 0.89 | 0.01 | 1.69 * | 0.01 | 1.86 * |
| **CASHDUE** | 0.03 | 0.27 | -0.11 | -0.38 | 0.13 | 0.66 | -0.60 | -2.00 ** | -0.57 | -1.85 * |
| **GOODWILL** | 2.15 | 5.36 *** | 0.48 | 1.10 | -0.26 | -0.56 | -1.59 | -2.59 *** | -1.06 | -1.92 * |
| **RER14** | 0.04 | 0.52 | 0.03 | 0.30 | -0.08 | -0.73 | -0.18 | -1.87 * | -0.18 | -2.26 ** |
| **REMUL** | 0.13 | 1.56 | 0.28 | 2.47 ** | 0.27 | 2.42 ** | 0.17 | 1.90 * | 0.15 | 1.90 * |
| **RECON** | 0.31 | 4.10 *** | 0.47 | 5.46 *** | 0.49 | 5.61 *** | 0.39 | 5.68 *** | 0.34 | 5.55 *** |
| **RECOM** | 0.13 | 1.85 * | 0.16 | 1.81 * | 0.14 | 1.51 | 0.06 | 0.91 | 0.02 | 0.35 |
| **CI** | 0.03 | 0.37 | -0.09 | -0.76 | -0.13 | -1.06 | -0.24 | -2.13 ** | -0.26 | -2.41 ** |
| **CONS** | -0.05 | -0.26 | -0.37 | -1.27 | -0.47 | -1.58 | -0.40 | -1.75 * | -0.08 | -0.82 |
| **Pseudo-R2** | 0.684 | | 0.315 | | 0.291 | | 0.316 | | 0.293 | |
| **Failures** | 114 | | 116 | | 111 | | 88 | | 66 | |
| **Survivors** | 1,652 | | 1,624 | | 1,584 | | 1,513 | | 1,422 | |
| **Obs.** | 1,766 | | 1,740 | | 1,695 | | 1,601 | | 1,488 | |

**Table 11:**
**Summary of Significant Results from Table 10**
**Logistic Regression Results: Banks with More than $300 Million in Total Assets**

+,- indicate significant (at the 10% level or stronger) positive or negative regression coefficients from the logistic regressions in Table 10. + indicates a positive relation with the probability of failure, and - indicates a negative relation with the probability of failure.

| Variable | 2008 | 2007 | 2006 | 2005 | 2004 |
|---|---|---|---|---|---|
| TE | - | - | | | |
| LLR | | - | | | - |
| ROA | - | | - | - | |
| NPA | + | + | + | + | + |
| SEC | | | | | |
| BD | + | + | + | | |
| LNSIZE | | | | | + |
| CASHDUE | | | | - | - |
| GOODWILL | + | | | - | - |
| RER14 | | | | | - |
| REMUL | | + | + | + | |
| RECON | + | + | + | + | + |
| RECOM | + | + | | | |
| CI | | | | - | - |
| CONS | | | | - | |

**Table 12:**
**Logistic Regression Results: Banks with Less than $300 Million in Total Assets**

Results from estimating a logistic regression model to explain bank failures, where the dependent variable FAIL takes on a value of one if a bank failed during 2009 or was technically insolvent at the end of 2009, and a value of zero otherwise. Explanatory variables are defined in Table 1. There are 149 failures and 5,231 survivors when we use year-end 2008 data; 147 failures and 5,468 survivors when we use year-end 2007 data; 147 failures and 5,554 survivors when we use year-end 2006 data; 157 failures and 5,763 survivors when we use year-end 2005 data; and 166 failures and 5,974 survivors when we use year-end 2004 data. Technical insolvency is defined as (TE + LLR) < (0.5 x NPA). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

| | 2008 | | | 2007 | | | 2006 | | | 2005 | | | 2004 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Marginal Effect** | **t-stat** | | **Marginal Effect** | **t-stat** | | **Marginal Effect** | **t-stat** | | **Marginal Effect** | **t-stat** | | **Marginal Effect** | **t-stat** | |
| **TE** | -0.724 | -7.851 | *** | -0.22 | -4.02 | *** | 0 | 0.11 | | 0.01 | 0.35 | | 0.05 | 1.97 | ** |
| **LLR** | -0.220 | -0.945 | | -0.24 | -0.52 | | -1.4 | -2.43 | ** | -1.65 | -2.56 | ** | -1.63 | -2.39 | ** |
| **ROA** | -0.256 | -3.102 | *** | -0.53 | -3.35 | *** | -0.34 | -2.63 | *** | -0.37 | -2.32 | ** | -0.24 | -2.21 | ** |
| **NPA** | 0.376 | 9.297 | *** | 0.34 | 5.49 | *** | 0.48 | 5.36 | *** | 0.39 | 3.35 | *** | 0.21 | 1.61 | |
| **SEC** | -0.065 | -2.670 | *** | -0.02 | -0.72 | | -0.05 | -1.99 | ** | -0.07 | -2.63 | *** | -0.06 | -2.45 | ** |
| **BD** | 0.047 | 3.480 | *** | 0.05 | 2.86 | *** | 0.05 | 3.07 | *** | 0.00 | 0.78 | | 0.09 | 4.56 | *** |
| **LNSIZE** | 0.001 | 0.468 | | 0.00 | -0.36 | | 0 | 0.05 | | 0.00 | 0.51 | | 0.00 | 0.84 | |
| **CASHDUE** | -0.095 | -2.262 | ** | 0.00 | -0.07 | | -0.02 | -0.51 | | -0.13 | -1.97 | ** | -0.06 | -1.19 | |
| **GOODWILL** | 0.584 | 3.471 | *** | 0.27 | 2.46 | ** | 0.04 | 0.41 | | -0.09 | -0.61 | | -0.07 | -0.49 | |
| **RER14** | -0.094 | -3.982 | *** | -0.03 | -0.95 | | -0.04 | -1.35 | | -0.01 | -0.54 | | -0.01 | -0.43 | |
| **REMUL** | 0.070 | 1.556 | | 0.12 | 2.66 | *** | 0.14 | 2.67 | *** | 0.12 | 2.45 | ** | 0.14 | 2.57 | ** |
| **RECON** | 0.060 | 2.977 | *** | 0.17 | 7.45 | *** | 0.17 | 8.47 | *** | 0.18 | 8.40 | *** | 0.18 | 8.30 | *** |
| **RECOM** | -0.017 | -0.967 | | 0.06 | 2.45 | ** | 0.05 | 2.54 | ** | 0.06 | 2.51 | ** | 0.05 | 2.13 | ** |
| **CI** | -0.055 | -2.030 | ** | 0.02 | 0.71 | | 0.03 | 0.99 | | 0.03 | 1.14 | | 0.04 | 1.47 | |
| **CONS** | -0.051 | -0.903 | | -0.07 | -0.93 | | -0.07 | -1.02 | | -0.12 | -1.51 | | -0.07 | -1.25 | |
| **Pseudo-R2** | 0.595 | | | 0.369 | | | 0.268 | | | 0.213 | | | 0.198 | | |
| **Failures** | 149 | | | 147 | | | 147 | | | 157 | | | 166 | | |
| **Survivors** | 5,231 | | | 5,468 | | | 5,554 | | | 5,763 | | | 5,974 | | |
| **Obs.** | 5,380 | | | 5,615 | | | 5,701 | | | 5,920 | | | 6,140 | | |

**Table 13:**
**Summary of Significant Results from Table 12**
**Logistic Regression Results: Banks with Less than $300 Million in Total Assets**

+, - indicate significant (at the 10% level or stronger) positive or negative regression coefficients from the logistic regressions in Table 12. + indicates a positive relation with the probability of failure, and - indicates a negative relation with the probability of failure.

| Variable | 2008 | 2007 | 2006 | 2005 | 2004 |
|---|---|---|---|---|---|
| TE | - | - | | | + |
| LLR | | | - | - | - |
| ROA | - | - | - | - | - |
| NPA | + | + | + | + | |
| SEC | - | | - | - | - |
| BD | + | + | + | | + |
| LNSIZE | | | | | |
| CASHDUE | - | | | - | |
| GOODWILL | + | + | | | |
| RER14 | | | | | - |
| REMUL | | + | + | + | + |
| RECON | + | + | + | + | + |
| RECOM | | + | + | + | + |
| CI | - | | | - | - |
| CONS | | | | | |