Australian National University

Crawford School of Public Policy

CAMA

Centre for Applied Macroeconomic Analysis

Forecasting Bank Leverage

CAMA Working Paper 56/2012
December 2012

Gerhard Hambusch
University of Technology, Sydney
Centre for Applied Macroeconomic Analysis
Quantitative Finance Research Group

Sherrill Shaffer
University of Wyoming
Centre for Applied Macroeconomic Analysis

Abstract

Standard early warning models to predict bank failures cannot be estimated during periods of few or zero failures, precluding any updating of such models during times of good performance. Here we address this problem using an alternative approach, forecasting the simple leverage ratio (equity/assets) as a continuous variable that does not suffer from the small sample problem. Out-of-sample performance shows some promise as a supplement to the standard approach, despite measurable deterioration in prediction accuracy during the crisis years.

Keywords

Bank leverage, forecasts, early warning

JEL Classification

G21

Suggested Citation:

Hambusch, G., and Shaffer, (2012). “Forecasting Bank Leverage”, CAMA Working Paper 56/2012.

Address for correspondence:

(E) cama.admin@anu.edu.au

FORECASTING BANK LEVERAGE

Gerhard Hambusch[a,c,d,*] and Sherrill Shaffer[b,c]

[a] *Finance Discipline Group, UTS Business School, University of Technology, Sydney Broadway NSW 2007, Australia*

[b] *University of Wyoming, Department of Economics and Finance, Laramie, WY 82071, USA*

[c] *Centre for Applied Macroeconomic Analysis, Australian National University, Canberra ACT 0200, Australia*

[d] *Quantitative Finance Research Centre, University of Technology, Sydney Broadway NSW 2007, Australia*

Abstract

Standard early warning models to predict bank failures cannot be estimated during periods of few or zero failures, precluding any updating of such models during times of good performance. Here we address this problem using an alternative approach, forecasting the simple leverage ratio (equity/assets) as a continuous variable that does not suffer from the small sample problem. Out-of-sample performance shows some promise as a supplement to the standard approach, despite measurable deterioration in prediction accuracy during the crisis years.

Keywords: bank leverage, forecasts, early warning
JEL classification: G21

* Corresponding author at: University of Technology, Sydney, UTS Business School, Finance Discipline Group, PO Box 123, Broadway NSW 2007, Australia. Tel.: +61-2 9514 7749; fax: +61-2 9514 7711.
Email addresses: gerhard.hambusch@uts.edu.au (G. Hambusch), shaffer@uwyo.edu (S. Shaffer).

FORECASTING BANK LEVERAGE

1. Introduction

An extensive and long-established literature has attempted to utilize observable financial ratios to estimate the probability that a given bank will fail during a specified future period. Even regulatory agencies have developed internal models for this purpose, usually intended to be re-estimated as new financial data become available (Cole et al., 1995; Jagtiani et al., 2003).[1] While such models have generally performed well when estimated during periods of numerous bank failures, an inherent challenge to this approach is the small sample of bank failures observed during normal times.[2] In many such cases, researchers and practitioners are constrained to rely on outdated estimates, despite evidence that the statistical linkages vary over time (Shaffer, 2012).

This paper explores an alternative approach that is not subject to the small sample problem and hence can be applied during any period. Instead of estimating a logit or probit model to forecast the event of failure, as is commonly done, we estimate banks' equity/asset ratios as a continuous variable. Estrella et al. (2000) and Jagtiani et al. (2003) recommend using this ratio as a supervisory tool to identify banks in need of intervention, but no previous study appears to have adopted our approach. Out-of-sample performance during the current century suggests reasonable potential for this method to complement the standard approach.

---

[1] Some regulatory models aim at forecasting a bank's next examination rating or the probability that its current rating will be downgraded (Jagtiani et al., 2003).

[2] In the U.S., not a single bank failed during 2005-2006; see Table A1 in the Appendix. Similarly, many other countries have far fewer banks than the U.S. and often experience years with no bank failures.

Moreover, we document instability of the estimated coefficients over time as well as deterioration of predictive power over longer horizons, consistent with theoretical expectations and with prior empirical findings for failure forecasts, thereby confirming a need to re-estimate such models as new data become available. This finding reinforces the need for an approach such as ours that can always be re-estimated and is not subject to small sample problems.

The remainder of this paper is organized as follows. The next section discusses the conceptual background, related literature, and our empirical model. Section 3 characterizes our sample and reports basic results. Section 4 presents several robustness checks and extensions, while Section 5 concludes.

2. Background and Empirical Design

Statistical models to predict bank failures have a long history dating back at least to Meyer and Pifer (1970), Martin (1977), Santomero and Vinso (1977), and many others. The most common approach is to estimate a logit or probit model in which the dependent variable is a binary indicator of whether each bank failed during the chosen forecast horizon (generally one or two years) and the regressors are a vector of observable bank-specific financial ratios.[3] The study most closely related to ours is by Jagtiani et al. (2003), who estimate logit and trait recognition models to predict the probability that a bank's ratio of equity to assets would fall below 5.5 percent by the end of the following year. Unlike our

[3] Some studies estimate a time-to-failure or proportional hazard model, and a few have explored the potential for macroeconomic variables, market information, or confidential examination ratings to improve the model's performance.

approach, however, their discrete distress model exhibits a similar vulnerability to small samples as logit failure models.[4]

The starting point for our model is a vector of observable financial ratios that numerous prior studies have shown to be related to a bank's probability of subsequent failure.[5] We test these variables stepwise both in-sample and out-of-sample to identify a robust subset of variables associated with subsequent leverage ratios.

The current ratio of equity to assets has been found to be negatively associated with the probability of subsequent failure, either alone or in combination with other financial ratios (Abrams and Huang, 1987; Whalen, 1991; Cole and Gunther, 1995; Wheelock and Wilson, 2000; Estrella et al., 2000; DeYoung, 2003). We expect this variable to be positively related to the one-year-ahead equity/asset ratio because most of the remaining regressors theoretically should influence *changes* from the existing level of leverage, rather than its absolute level.

Return on assets, which is the ratio of net income to assets, has been found to be negatively associated with the risk of subsequent failure (Thomson, 1991; Cole and Gunther, 1995; Wheelock and Wilson, 2000; DeYoung, 2003). Because net income can increase retained earnings while losses reduce retained earnings, we similarly expect that the return on assets will be positively associated with the subsequent equity ratio.

---

[4] Because of this, Jagtiani et al. restricted their sample period to 1988-90 "in order to have a sufficient number of problem banks in the sample." Similarly, the Federal Reserve's SEER Risk Rank model uses probit analysis to estimate the probability that a bank would fail or become critically undercapitalized during the following two years (Cole et al., 1995; Jagtiani et al., 2003).

[5] The variables in our initial list are not the only variables previously included in early warning models, but have the distinction of a robust track record in such studies.

The ratio of net chargeoffs to total loans, a measure of credit risk, has been found to be positively associated with risk of failure (Kolari et al., 2002). Other studies have reported similar results for the ratio of nonperforming loans to total loans (Cole and Gunther, 1995; Wheelock and Wilson, 2000; Cole and White, 2012). Because chargeoffs require banks to replenish their allowance for loan losses, reducing net earnings and hence retained earnings, we expect these ratios to be negatively related to subsequent equity ratios.

The ratio of operating expenses to assets can be interpreted as a measure of management efficiency and has been found to be positively associated with risk of failure (Espahbodi, 1991; Fuller and Kohers, 1994; DeYoung, 2003). It should similarly be associated with lower subsequent equity ratios. The ratio of jumbo certificates of deposit to assets has been found positively associated with risk of failure (Abrams and Huang, 1987; Whalen, 1991; Cole and Gunther, 1995; DeYoung, 2003), consistent with theoretical arguments related to liquidity risk; we similarly expect it to be negatively related to subsequent equity ratios.

The ratio of total loans to assets is inversely related to liquidity but positively related to portfolio credit risk and probability of failure (Espahbodi, 1991; Thomson, 1991; Wheelock and Wilson, 2000; DeYoung, 2003) and potentially with reduced subsequent equity ratios. The ratio of commercial loans to assets has been found to be associated with a higher probability of subsequent failure (Cole and Gunther, 1995; Wheelock and Wilson, 2000) and could therefore be negatively related to subsequent equity ratios. The ratio of insider loans to assets can be regarded as a measure of managerial abuse and has been found to be positively related to the risk of failure (Thomson, 1991; Cole and Gunther, 1995); we expect that it will be negatively associated with subsequent equity ratios.

Large banks have been found less likely to fail than smaller banks (Cole and Gunther, 1995; Wheelock and Wilson, 2000; DeYoung, 2003; Arena, 2008; Cole and White, 2012). On the other hand, size could be inversely related to equity ratios because U.S. regulators generally expect smaller banks to maintain higher relative capitalization, consistent with their reduced potential for diversification.

Table 1 summarizes these variables, expected signs in our model, and supporting literature. Our analysis proceeds in two steps. First, we estimate regressions of the following form:

$$KA_{t+1} = \alpha_t + X_t \beta_t + \varepsilon_t \tag{1}$$

where KA is equity/assets, X is a vector of financial ratios as described above, ε is a stochastic error term, and t is a given year. This step establishes within-sample statistical linkages between observable characteristics and the one-year-ahead equity ratio, the forecast horizon chosen by Jagtiani et al. (2003). We implement this step in pure cross-section analysis for t ranging from 1999 to 2009, to forecast equity ratios from 2000 to 2010.

Next, we apply the vector of estimated coefficients from each year t (1999-2009) to regressors from year t+1 (2000-2010) to forecast KA as of year t+2 (2001-2011), as shown in equation (2):

$$KA_{t+2} = \alpha_t + X_{t+1} \beta_t \tag{2}$$

This out-of-sample step represents a potential application of the model by bank supervisors using the most recent available estimates and data. We evaluate the goodness of fit of this step using three standard measures: the correlation between actual and fitted values, the mean absolute error, and the median absolute error. We subsequently explore robustness of the model and results in both of these steps with respect to model specification, nonlinearity, inclusion of first differences, stability of coefficients over time, differential effects by bank size or leverage, two types of extended lags, and the ability of macroeconomic variables to improve the model's performance.

3. Sample and Basic Results

We use year-end Call Report data for a nationwide sample of U.S. banks during 1999-2011. Banks less than 10 years old were deleted due to their tendency to exhibit significantly abnormal financial behavior (DeYoung and Hasan, 1998; Shaffer, 1998). We also deleted banks with missing or nonsensical values of the variables in the model (such as negative assets, loans greater than assets, zero expenses, etc.). Table A2 in the Appendix reports a full list of our selection criteria, Table 2 reports summary statistics on our sample, and Table A3 in the Appendix reports pairwise correlation coefficients among variables in the sample. The sample means conform to familiar industry norms for each variable, while the standard deviations exhibit adequate sample variation to permit a good statistical test of the role of each variable. Correlation coefficients are never large enough to suggest a severe problem of multicollinearity, though the correlation between return on assets and net chargeoffs/total loans (–0.44) may be large enough to inflate the standard errors somewhat on those coefficients in the regressions. This negative correlation is consistent with theory, since chargeoffs reduce profitability. Similarly, correlations of 0.33-0.34 are seen between commercial loans/total assets and total loans/total assets, and between jumbo CDs/total assets and the log of total assets.

Our sample contains 66,557 bank-year observations for the full model. Table 3 reports regression estimates for the first stage of our analysis, where p-values are based on robust (White) standard errors. The fit is quite reasonable, with adjusted R-squared values for individual years ranging from 0.76 to 0.86. The lowest values are associated with 2007-2009, during the financial crisis.[6] During the years with no bank failures, 2005-2006, the adjusted R-squared is around 0.8, suggesting some potential usefulness of the model during periods when conventional early warning models cannot be re-estimated. Using financial ratios from the zero-failure year 2006 to forecast equity/asset ratios at the end of the first year of the crisis (2007), the R-squared is 0.80, contrasting with a pattern that many statistical models are poor at identifying such turning points.

The signs and significance levels of the coefficients vary over time for most of our regressors. Only the contemporaneous equity/asset ratio is highly significant with the expected sign in all years. Several other variables are significant in multiple years, while some are rarely significant. Return on assets is significantly positive, as expected, in three individual years plus the full panel, and is never significantly negative. Net chargeoffs/loans is significantly positive in four years plus the full panel, contrary to expectations, and is never significantly negative; a possible explanation, not tested here, is that high chargeoffs may be largely anticipated, in which case banks may have previously

[6] While some sources consider 2008 to be the first year of the crisis, documented stages of the crisis were already identified in 2007 (Guillén, 2009). However, only three banks failed during 2007, so the most severe financial consequences of the crisis had not yet manifested themselves among banks until 2008.

increased their loan loss reserve and reduced dividend payouts to offset the anticipated losses. The contrast between this variable's performance in our model versus prior failure models suggests that capitalization may not be the primary channel through which chargeoffs contribute to the risk of failure, a question that prior research has not explored.

Operating expenses/total assets is significantly negative, as expected, in just two individual years, and is never significantly positive. Jumbo CDs/total assets is negative, as expected, in only one year and only at the 0.07 level of significance, whereas it is positive at the 0.03 level of significance in two years and at the 0.10 level in another year. Total loans/total assets is significantly negative at a significance level better than 0.0001 in seven years plus the full panel, as expected, but is positive at the 0.05 level in one year. Commercial loans/assets is negative as expected, at the 0.09 level or better in three individual years plus the full panel, and is never significantly positive. Insider loans/assets is negative as expected at the 0.001 level in two years plus the full panel, at the 0.007 level in another year, and at the 0.03 and 0.06 level in two additional years; the point estimate of its coefficient is never positive. The log of total assets is significantly positive in four years, negative in one year, and not significant in other years.

Because not all variables are consistently significant, we employ stepwise selection to identify a more robust subset of explanatory variables. This process results in a final vector of four regressors: current equity/assets, loans/assets, net chargeoffs/loans, and return on assets. Table 4 reports regression estimates for this reduced model. The sample for these regressions is slightly larger than in Table 3 since we include several banks that had been omitted from estimation of the full model due to missing variables not relevant to

Table 4.[7] Adjusted R-squared values are nearly identical across the two tables, and the coefficients on each regressor are roughly similar across the models. Current equity/assets is highly significant in every year with a positive coefficient, as expected. Return on assets is significantly positive, as expected, in four individuals years plus the full panel. Net chargeoffs/loans is significantly positive in three individual years plus the full panel, and exhibits a negative point estimate in only one year.[8] Loans/assets is significantly negative in six years plus the full panel, as expected, but is significantly positive in one year (2002).

As might be expected, current leverage is the most consistent and statistically significant factor in both models. At the same time, its coefficient ranges between roughly 0.8 and 0.9 for each year in each specification and is significantly less than 1 in every instance, with robust t-statistics on the null hypothesis of a unit coefficient ranging from 3.86 to 24.12. This implies a form of convergence in the leverage ratio (in the sense of Barrow and Sala-i-Martin, 1992; and Sala-i-Martin, 1996) and, together with the significantly positive intercepts and some significant coefficients on other variables, indicates that current leverage alone is not the best available predictor of future capitalization.

While a reasonable fit of the model is desirable, any within-sample characteristics fall short of demonstrating the practical usefulness of a model in forward-looking

---

[7] We also estimated the reduced model using the same sample as in Table 3, with results nearly identical to Table 4.

[8] Although the return on assets and the net chargeoff ratio are significant in only a minority of years, their inclusion is consistent with theory and contributed to improved predictive power, both in and out of sample. One reason for the inconsistency in their significance levels is a degree of negative correlation between these two variables (–0.44, as shown in Table A3 in the Appendix).

applications. Accordingly, we next address the out-of-sample performance of our reduced model. Table 5 reports statistics from the second stage of our analysis, in which the coefficients reported in Table 4 (relating year t financial ratios to year t+1 equity/asset ratios) are applied to financial ratios from year t+1 to forecast year t+2 equity/asset ratios as explained above for equation (2). As shown in the table, the cross-sectional correlations between predicted and actual t+2 equity/ratios range from 0.87 to 0.93, while the mean and median absolute errors range from 0.0079 to 0.0105 and from 0.0047 to 0.0066, respectively. Given that the sample mean value of equity/assets is 0.1045, these errors are small enough to be useful to regulators and practitioners in monitoring the financial performance of banks and focusing on banks at future risk.

The second lowest mean absolute forecast error is for 2006 leverage, while the second and third lowest median absolute errors are for 2006 and 2007 leverage – one corresponding to a year of no failures and the other to a year that some sources would identify as the first year of the crisis, suggesting that the model performs well at both extremes of industry performance. By contrast, this type of robustness is typically lacking among conventional early warning models.

We further investigate whether the model's predictive performance is systematically different during the main years of the financial crisis, compared with other sample years. To do this, we calculate both a paired t-test and a nonparametric Wilcoxon rank sum test (Mann-Whitney test) on each of the three measures of forecast accuracy – correlation, mean absolute error, and median absolute error – reported in Table 5. Because the literature has suggested a variety of dates for the crisis, we repeat these tests for three alternative sets of dates: 2007-2009, 2007-2010, and 2008-2010, as reported in Table 6.

Both tests find significantly worse predictive accuracy in all three measures for 2008-2010 versus the other sample years, at significance levels better than 0.025 (two-tailed tests).[9] Differences were less pronounced using the other two ranges of dates. These findings suggest caution in relying excessively on the approach modeled here.

Table 7 compares the actual cross-sectional mean leverage ratios for each year versus the ratios predicted in our out-of-sample step. The results show a small but statistically significant bias that tends to alternate sign in consecutive years. It is evident from the table that this alternation is mainly driven by an alternation in actual industry mean leverage ratios, rather than by any idiosyncracies of the model.

4. Robustness and Extensions

4.1. Alternative Model Specifications

Next, we explore several dimensions of robustness of the model's performance. In this step, we estimate a total of 50 different specifications of the model, not reported in the tables for brevity. In each case, we obtain separate OLS estimates for each year as well as for the full panel. In most cases, individual regressors were statistically significant for only a few individual years, and did not result in superior out-of-sample forecasting.

Besides exploring various subsets of the initial regressors shown in Table 3, we

[9] Haan and Poghosyan (2012) test both 2007 and 2008 as starting points of the crisis, in a banking study unrelated to our research question. While they suggest 2009 as an ending date for the crisis, Table 1A in the Appendix documents that bank failures peaked in 2010 and thus it seems premature to declare the crisis as over by then. In any case, the ending point can be usefully approached as an empirical question. Our t-test indicates that the correlations differ at the 0.01 level, while the mean absolute errors differ at the 0.0004 level.

investigate whether first differences in these variables from period t–1 to t improve the in-sample and out-of-sample performance. None of these first differences improve the model's predictive power overall.

4.2. Model Nonlinearity

We also evaluate possible nonlinearity of the model with respect to our eight original regressors, by including squared terms as well as levels in various combinations and subsets. As with the first differences, the findings (not reported in the tables) indicate that the equity/assets ratio has no robustly nonlinear dependence on any of these variables. A few variables exhibit statistically significant quadratic coefficients in a few years, but none are significant in all years or consistently improve out-of-sample leverage forecasting.

4.3. Macroeconomic Variables

We evaluate macroeconomic variables in this model in several ways. Starting with two basic macroeconomic variables, the unemployment rate and the annual rate of GDP growth, we enter each variable at the national level in panel regressions incorporating all years within our sample period, in combination with the bank-level financial ratios previously found to be consistently significant. Alternatively, we enter state-level values of these variables in a series of cross-section regressions, again in combination with robust bank-level variables. In each case, we estimate several versions: using one macro variable at a time, or both together, in levels or in first differences. In no case was any macro variable consistently significant across individual years or across the full panel.

From these steps, we conclude that our preferred model remains that reported in Table 4. Its performance within sample and out of sample is not improved by alternate combinations of regressors, inclusion of first differences or nonlinear terms, or macroeconomic variables.

4.4. Level of Capitalization

Because regulators and practitioners are mainly concerned about banks with low equity ratios, we further explore whether the estimated coefficients or predictive power of the model would vary between undercapitalized banks versus better-capitalized banks. A negative answer is implied by the lack of significance of the quadratic term for current equity/assets, suggesting that the model is able use information from well-capitalized banks to augment information from the relatively few undercapitalized banks and improve the precision of its forecasts for the latter.

4.5. Bank Size

Similarly, the model's performance for banks of different sizes is a question of interest, because the majority of bank failures historically have occurred among smaller banks while concerns over systemic risk focus on potential failures or undercapitalization of the largest banks. To address this question, we re-estimate our preferred model separately for small banks and large banks, using several alternate definitions of "small" and "large." One dividing point is the sample median bank size in total assets ($103.5 million), while an alternate threshold is the sample mean asset size ($1.272 billion). A third alternate threshold is $300 million in assets, as in Cole and White (2012), where roughly 80 percent of our sample banks are smaller than this threshold. Within-sample estimates generate significantly different coefficient estimates for large banks versus smaller banks at each threshold; Chow tests yield F-statistics that exceed 9.5 for each threshold, rejecting the null hypothesis of equal coefficients at a significance level better than 0.001.

The performance of out-of-sample forecasts resulting from this step is summarized in Table 8. Some differences are evident across the groups, with leverage being predicted somewhat more accurately for smaller banks. This comparison is not solely a consequence of sample size, as is apparent in Panel B with equal numbers of large and small banks. The correlation coefficient between actual and predicted leverage ratios ranges from 0.88 to nearly 0.94 for the smaller banks, and from 0.73 to 0.91 for the larger banks. These results suggest that, while the model may be able to offer some help in identifying troubled large banks as an additional tool to supplement other approaches, its comparatively better performance for smaller banks may permit a relatively greater reliance on this approach for these numerous institutions that pose no systemic risk, potentially freeing up resources to focus on systemically important banks.

4.6. Coefficient Stability

Finally, we attempt to characterize the stability of model coefficients over time, a question of considerable importance in view of the banking industry's historical fluctuation between strong performance and crisis. Our sample period is capable of addressing this question, spanning as it does two recessions, the recent crisis, and a pair of consecutive years with zero failures. As a preliminary observation, the pattern of coefficient estimates shown in Table 4 suggests some fluctuation over time in the statistical linkages between our regressors and equity/asset ratios. To explore and quantify this impression more precisely, we perform two types of Chow tests: one to test whether each year's vector of estimated coefficients differed significantly from that of the full panel (overall stability) and another to test for significant differences between the coefficients estimated for year t and those estimated for year t+1 (consecutive-year stability).

Table 9 reports the results of these Chow tests, which reject overall stability as well as stability across most consecutive years.[10] Panel B of the table indicates that the single most significant break point in our sample coincides with the onset of the financial crisis in 2007. These results are generally consistent with previous findings for conventional early warning models (Shaffer, 2012) and confirm the desirability of re-estimating such models as permitted by the arrival of new data.

4.7. Intertemporal Deterioration of Predictive Power

We explore this interpretation further by estimating two additional variations on our model, involving variable lags. First, we explore the intertemporal deterioration of predictive power by applying our existing in-sample coefficients to out-of-sample holdout periods in the more distant future, increasing the lag from t+1 to t+2 and t+3. Second, we explore a within-sample aspect of intertemporal deterioration by using financial data from year t to predict equity/assets in years t+j for j ranging from 1 to 3. In both cases, theoretical considerations and prior empirical studies predicting bank failure suggest that longer lags should be associated with poorer predictive performance.

Table 10 summarizes the results of these extensions. For ease of comparison, the results of our original t+1 lag are reported in the top row of each panel. In the first step, the correlation between actual and predicted out-of-sample equity/asset values, averaged over the sample years, is around 0.9 for each lag, but is slightly lower for longer lags as

[10] The only exception is the two years with zero failures (2005 and 2006), which exhibit statistically indistinguishable coefficients.

expected. Likewise, the mean and median absolute errors tend to increase with longer lags. This pattern implies a need to re-estimate this type of model frequently. This need underscores the primary advantage of our approach, since failure models cannot be re-estimated during periods of very few failures, whereas our capitalization model can always be re-estimated.

In the second instance, out-of-sample predictive accuracy also tends to deteriorate with longer lags. This pattern is consistent with empirical findings for failure forecasts reported by Estrella et al. (2000), Cole and White (2012), and others. The deterioration at longer lags is more dramatic than in the top panel, with mean absolute errors and median absolute errors both more than 60 percent larger at t+3 than at t+1.

5. Conclusion

Motivated by a dearth of bank failures in many years, as well as by continued interest in early warning models predicting banks' financial distress, this study has explored the ability of observable financial ratios to predict future leverage ratios as a continuous variable. The findings indicate reasonable potential for this approach as a useful complement to conventional models forecasting banks' failure. Our model exhibits reasonable ability to forecast leverage ratios out of sample, as required for practical implementation by regulators or practitioners. The forecasting performance is robust to variations in the included regressors, functional form, lags, and macroeconomic conditions. At the same time, our preferred model is quite parsimonious in its data requirements. However, predictive performance during the crisis years was measurably inferior to other years, indicating a limitation of the model.

Two aspects of the estimates indicate a need to re-estimate such models frequently, using the most recent available data. First, the estimated coefficients vary significantly from year to year. Second, the model's forecasting performance deteriorates over longer forecast horizons. Both of these patterns are consistent with several previous studies predicting bank failure. This finding supports extant regulatory practice and further underscores the need for our approach, which – unlike failure models – can always be implemented regardless of industry conditions.

Large banks exhibit significantly different linkages between leverage and other observable financial ratios than smaller banks. Out-of-sample forecasts are less accurate for larger banks than for smaller banks, but there is no apparent association between forecast accuracy and leverage. Our selection of equity/assets as the dependent variable is supported by prior studies such as Estrella et al. (2000) and Jagtiani et al. (2003). Future extensions of our approach could explore the potential to predict other important indicators of financial health such as the return on assets, loan chargeoff rate, or measures of liquidity.

Table A1: Failed Bank List[11]

Year	Number of Failed Banks
2000[a]	2
2001	4
2002	11
2003	3
2004	4
2005	0
2006	0
2007	3
2008	25
2009	140
2010	157
2011	92

[a] Refers to the period from 1 October 2000 to 31 December 2000 only.

[11] Source: Federal Deposit Insurance Corporation (2012). The complete list of failed banks since October 1, 2000 can be accessed at http://www.fdic.gov/bank/individual/failed/banklist.html.

Table A2: Number of Observations Retained After Sequential Application of Each Selection Criterion

Sample Selection Criteria	1999-2009	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Call report	93,663	9,261	8,998	8,751	8,609	8,432	8,302	8,153	8,097	7,873	7,613	9,261
Missing observations	88,991	8,778	8,540	8,325	8,198	8,040	7,921	7,791	7,665	7,456	7,214	8,778
Commercial banks	83,255	8,202	7,976	7,784	7,666	7,526	7,416	7,295	7,180	6,988	6,753	8,202
FIPS (1-56)	83,069	8,184	7,958	7,767	7,649	7,510	7,400	7,278	7,163	6,972	6,737	8,184
Age greater 10 years	70,104	7,071	6,828	6,619	6,474	6,289	6,137	5,982	5,859	5,742	5,693	7,071
Loans greater zero	70,104	7,071	6,828	6,619	6,474	6,289	6,137	5,982	5,859	5,742	5,693	7,071
KA less than 50%	70,015	7,064	6,822	6,609	6,464	6,282	6,132	5,972	5,849	5,735	5,682	7,064
LA less than 90%	69,331	7,035	6,788	6,570	6,422	6,215	6,056	5,891	5,745	5,611	5,623	7,035
NCHL less than 100%	69,329	7,035	6,788	6,570	6,422	6,215	6,056	5,890	5,745	5,611	5,623	7,035
OEA between 0% and 30%	69,266	7,026	6,781	6,564	6,419	6,210	6,050	5,885	5,738	5,605	5,622	7,026
KA (t+1) merge	66,557	6,714	6,545	6,385	6,205	5,992	5,817	5,652	5,514	5,416	5,381	6,714

Banks were deleted during each period within which any of the following criteria were met: Non-commercial bank charter, headquartered in territories or possessions outside of actual U.S. states and the District of Columbia (i.e. Federal Information Processing Standard state code greater than 56), less than 10 years old, negative loans, equity/assets greater than or equal to 50%, loans/assets greater than or equal to 90%, net chargeoffs/loans greater or equal 100%, operating expenses/assets between 0% and 30%, equity/assets not available in the following period.

Table A3: Data Correlation Matrix

	Current Equity/ Total Assets	Return on Assets	Net Chargeoffs/ Total Loans	Operating Expenses/ Total Assets	Jumbo CDs/ Total Assets	Total Loans/ Total Assets	Commercial Loans/ Total Assets	Insider Loans/ Total Assets	Log of Total Assets
Current Equity/ Total Assets	1.0000								
Return on Assets	0.1274	1.0000							
Net Chargeoffs/ Total Loans	0.0114	–0.4389	1.0000						
Operating Expenses/ Total Assets	–0.1482	–0.1888	0.2041	1.0000					
Jumbo CDs/Total Assets	–0.1529	0.0805	–0.0536	–0.1083	1.0000				
Total Loans/Total Assets	–0.2849	–0.0035	–0.0349	0.1550	0.0283	1.0000			
Commercial Loans/Total Assets	–0.1360	–0.0121	0.0206	0.0885	0.2169	0.3446	1.0000		
Insider Loans/Total Assets	–0.0408	–0.0108	–0.0432	0.0041	0.0646	0.1357	0.1379	1.0000	
Log of Total Assets	–0.1967	0.0285	0.0507	–0.0778	0.3335	0.2053	0.1651	–0.0281	1.0000

Table 1: Explanatory Variables

Explanatory Variable	**Illustrative References**
Current Equity/Total Assets (+)[a]	Abrams and Huang (1987), Whalen (1991), Cole and Gunther (1995), Wheelock and Wilson (2000), Estrella et al. (2000), DeYoung (2003)
Return on Assets (+)	Thomson (1991), Cole and Gunther (1995), Wheelock and Wilson (2000), DeYoung (2003)
Net Chargeoffs/Total Loans (–)	Kolari et al. (2002), Cole and Gunther (1995), Wheelock and Wilson (2000), Cole and White (2012)
Operating Expenses/Total Assets (–)	Espahbodi (1991), Fuller and Kohers (1994), DeYoung (2003)[b]
Jumbo Certificates of Deposits/Total Assets (–)	Abrams and Huang (1987), Whalen (1991), Cole and Gunther (1995), DeYoung (2003)[c]
Total Loans/Total Assets (–)	Espahbodi (1991), Thomson (1991), Wheelock and Wilson (2000), DeYoung (2003)
Commercial Loans/Total Assets (–)	Cole and Gunther (1995), Wheelock and Wilson (2000) (both used loans as denominator)
Insider Loans/Total Assets (–)	Thomson (1991), Cole and Gunther (1995)
Log of Total Assets (–)	Cole and Gunther (1995), Wheelock and Wilson (2000), DeYoung (2003), Arena (2008), Cole and White (2012)

[a] Anticipated sign of regression coefficient in parentheses

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

[c] Similarly, Kolari et al. (1996) included the ratio of time deposits more than $100,000 / total time deposits.

Table 2: Summary Statistics

Variable	Mean	Standard Deviation
Current Equity/Assets	0.10448	0.03448
Return on Assets	0.01008	0.00932
Net Chargeoffs/Loans	0.00454	0.00938
Operating Expenses/Assets	0.05326	0.01419
Jumbo CDs/Assets	0.27303	0.11523
Loans/Assets	0.62224	0.14919
Commercial Loans/Assets	0.09522	0.06696
Insider Loans/Assets	0.01242	0.01410
Log of Assets	11.70047	1.34551

Table 3: Regression Results, Equation (1), Full Model

Year	Current Equity/ Assets	Return on Assets	Net Chargeoffs/ Loans	Operating Expenses/ Assets	Jumbo CDs/ Assets	Loans/ Assets	Commercial Loans/ Assets	Insider Loans/ Assets	Log of Assets	Intercept	Number of Obs.	Adjusted R^2
1999-2009	0.8901* (0.0000)	0.0938* (0.0000)	0.0560* (0.0029)	0.0087 (0.4644)	0.0008 (0.3056)	–0.0094* (0.0000)	–0.0019*** (0.0871)	–0.0236* (0.0000)	0.0000 (0.6647)	0.0162* (0.0000)	66,557	0.8124
1999	0.9141* (0.0000)	–0.0604 (0.3540)	0.0347 (0.3609)	0.0435 (0.3819)	0.0029 (0.2753)	–0.0210* (0.0000)	–0.0082** (0.0112)	–0.0127 (0.3320)	–0.0001 (0.7254)	0.0235* (0.0000)	6,936	0.8570
2000	0.9122* (0.0000)	0.2263* (0.0003)	0.0942 (0.1714)	0.1270 (0.1015)	0.0007 (0.7761)	–0.0129* (0.0000)	–0.0027 (0.4330)	–0.0270** (0.0269)	0.0009* (0.0000)	–0.0045 (0.4746)	6,714	0.8482
2001	0.9005* (0.0000)	–0.0291 (0.6006)	–0.0063 (0.9405)	0.0198 (0.5985)	–0.0022 (0.2566)	–0.0119* (0.0000)	–0.0032 (0.3446)	–0.0064 (0.5509)	–0.0001 (0.7312)	0.0211* (0.0001)	6,545	0.8661
2002	0.9173* (0.0000)	–0.0192 (0.7440)	0.1275** (0.0130)	0.0352 (0.5565)	0.0039*** (0.0905)	0.0048** (0.0404)	–0.0027 (0.4169)	–0.0324* (0.0062)	0.0002 (0.4068)	0.0005 (0.9297)	6,385	0.8337
2003	0.9186* (0.0000)	–0.0534 (0.3511)	0.1159** (0.0311)	–0.0105 (0.7521)	–0.0044*** (0.0679)	0.0007 (0.6718)	–0.0017 (0.6030)	–0.0432* (0.0005)	0.0008* (0.0050)	0.0026 (0.5005)	6,205	0.7950
2004	0.9128* (0.0000)	0.0105 (0.8449)	0.1510* (0.0056)	–0.0714** (0.0152)	–0.0001 (0.9703)	–0.0006 (0.7724)	–0.0074*** (0.0779)	–0.0264*** (0.0559)	–0.0002 (0.5696)	0.0143* (0.0016)	5,992	0.8136
2005	0.9058* (0.0000)	0.0674 (0.2747)	0.0925 (0.1923)	–0.0517 (0.1258)	0.0054** (0.0255)	–0.0088* (0.0000)	–0.0066*** (0.0567)	–0.0096 (0.4794)	–0.0001 (0.5748)	0.0194* (0.0000)	5,817	0.8200
2006	0.9284* (0.0000)	–0.0272 (0.6513)	0.0871 (0.1240)	–0.0141 (0.8025)	0.0058** (0.0215)	–0.0098* (0.0000)	–0.0057 (0.1255)	–0.0160 (0.3282)	0.0003 (0.2118)	0.0128* (0.0049)	5,652	0.7982
2007	0.8091* (0.0000)	0.1647** (0.0185)	0.1352** (0.0326)	–0.1586* (0.0006)	–0.0018 (0.5342)	–0.0103* (0.0000)	0.0002 (0.9631)	–0.0171 (0.3034)	–0.0014* (0.0000)	0.0491* (0.0000)	5,514	0.7681
2008	0.8406* (0.0000)	0.2304* (0.0000)	0.0734 (0.1589)	0.0067 (0.8580)	0.0013 (0.6589)	–0.0175* (0.0000)	0.0023 (0.6281)	–0.0165 (0.3446)	0.0010* (0.0003)	0.0123* (0.0067)	5,416	0.7769
2009	0.8799* (0.0000)	0.0325 (0.5152)	–0.0276 (0.5521)	–0.0669 (0.2191)	0.0033 (0.1617)	0.0009 (0.6520)	0.0031 (0.4855)	–0.0533* (0.0003)	0.0004*** (0.0900)	0.0091*** (0.0834)	5,381	0.7949

Dependent variable: one-year-ahead equity/assets ratio. p-values in parentheses, based on robust (White) standard errors. Significance levels are *0.01, **0.05, and ***0.10.

Table 4: Regression Results, Equation (1), Final Model

Year	Current Equity/ Assets	Return on Assets	Net Chargeoffs/ Loans	Loans/ Assets	Intercept	Number of Obs.	Adjusted R^2
1999-2009	0.8881* (0.0000)	0.0870* (0.0001)	0.0530** (0.0195)	–0.0099* (0.0000)	0.0173* (0.0000)	66,607	0.8123
1999	0.9021* (0.0000)	–0.0911 (0.2179)	0.0311 (0.4276)	–0.0220* (0.0000)	0.0273* (0.0000)	6,943	0.8492
2000	0.8947* (0.0000)	0.2780* (0.0008)	0.1866* (0.0072)	–0.0112* (0.0000)	0.0139* (0.0000)	6,720	0.8459
2001	0.9033* (0.0000)	0.0641 (0.4526)	0.1038 (0.3193)	–0.0121* (0.0000)	0.0191* (0.0000)	6,551	0.8665
2002	0.9074* (0.0000)	–0.1140 (0.2513)	0.0738 (0.3218)	0.0038*** (0.0509)	0.0078* (0.0034)	6,390	0.8320
2003	0.9157* (0.0000)	–0.0023 (0.9622)	0.1309** (0.0100)	0.0002 (0.8770)	0.0092* (0.0000)	6,207	0.7954
2004	0.9180* (0.0000)	–0.0379 (0.5921)	0.0297 (0.7455)	–0.0034*** (0.0736)	0.0105* (0.0000)	5,997	0.8149
2005	0.9031* (0.0000)	0.0624 (0.3040)	0.0358 (0.6384)	–0.0108* (0.0000)	0.0185* (0.0000)	5,821	0.8207
2006	0.9276* (0.0000)	0.0145 (0.8263)	0.1139*** (0.0782)	–0.0102* (0.0000)	0.0164* (0.0000)	5,657	0.8004
2007	0.8214* (0.0000)	0.1590** (0.0253)	0.0170 (0.8074)	–0.0158* (0.0000)	0.0250* (0.0000)	5,519	0.7647
2008	0.8304* (0.0000)	0.2026* (0.0000)	0.0592 (0.2692)	–0.0160* (0.0000)	0.0248* (0.0000)	5,420	0.7752
2009	0.8764* (0.0000)	0.0673*** (0.0971)	–0.0147 (0.7696)	0.0003 (0.8727)	0.0120* (0.0000)	5,382	0.7931

Dependent variable: one-year-ahead equity/assets ratio. p-values in parentheses, based on robust (White) standard errors. Significance levels are *0.01, **0.05, and ***0.10.

Table 5: Out-of-sample Forecast Accuracy for Equity/Assets

Year	Correlation between Actual vs. Predicted Equity/Assets	Mean Absolute Error between Actual vs. Predicted Equity/Assets	Median Absolute Error between Actual vs. Predicted Equity/Assets
2001	0.91580	0.00823	0.00555
2002	0.92956	0.00787	0.00531
2003	0.90950	0.00860	0.00578
2004	0.89143	0.00791	0.00469
2005	0.90248	0.00827	0.00544
2006	0.90532	0.00791	0.00470
2007	0.89453	0.00817	0.00475
2008	0.87337	0.01054	0.00627
2009	0.88039	0.00998	0.00655
2010	0.88633	0.00914	0.00588
2011	0.91734	0.00882	0.00615
AVG	**0.90055**	**0.00868**	**0.00555**

Table 6: Difference of Means Tests for Forecast Accuracy Measures, Crisis vs. Non-crisis Years

Panel A: T-test

Crisis period	Correlation between Actual vs. Predicted Equity/Assets	Mean Absolute Error between Actual vs. Predicted Equity/Assets	Median Absolute Error between Actual vs. Predicted Equity/Assets
2007-2009	2.6889** (0.0248)	–2.5158** (0.0330)	–0.9493 (0.3673)
2007-2010	3.7715* (0.0044)	–2.9387** (0.0168)	–1.2307 (0.2496)
2008-2010	3.6206* (0.0056)	–5.4705* (0.0004)	–2.7404** (0.0228)

Panel B: Wilcoxon rank sum test (Mann-Whitney test)

Crisis period	Correlation between Actual vs. Predicted Equity/Assets	Mean Absolute Error between Actual vs. Predicted Equity/Assets	Median Absolute Error between Actual vs. Predicted Equity/Assets
2007-2009	–2.041** (0.0412)	1.432 (0.1521)	1.225 (0.2207)
2007-2010	–2.547** (0.0140)	1.894*** (0.0582)	1.512 (0.1306)
2008-2010	–2.449** (0.0143)	2.455** (0.0141)	2.245** (0.0247)

Significance levels are *0.01, **0.05, and ***0.10.

Table 7: Mean Leverage, Actual versus Predicted (Out of Sample)

Year	Mean Actual Equity/Assets	Mean Predicted Equity/Assets	t-test of Equal Means between Actual vs. Predicted Equity/Assets
2001	0.10255	0.10526	–15.73140*
2002	0.10541	0.10255	17.97450*
2003	0.10468	0.10800	–18.76570*
2004	0.10569	0.10412	7.92030*
2005	0.10513	0.10652	–7.07370*
2006	0.10713	0.10424	14.74060*
2007	0.10948	0.10892	2.53180**
2008	0.10629	0.11162	–22.40540*
2009	0.10450	0.10340	5.04000*
2010	0.10455	0.10338	5.69380*
2011	0.10847	0.10450	22.00350*
AVG	**0.10581**	**0.10568**	**–**

Significance levels are *0.01 and **0.02.

Table 8: Out-of-sample Forecast Accuracy for Equity/Assets (Large Banks versus Small Banks)

Panel A: Large versus Small Banks (Threshold = Sample Mean = $1.272bn Total Assets)

	Large Banks (3,194 Observations)			Small Banks (63,413 Observations)		
Year	**Correlation between Actual vs. Predicted Equity/Assets**	**Mean Absolute Error between Actual vs. Predicted Equity/Assets**	**Median Absolute Error between Actual vs. Predicted Equity/Assets**	**Correlation between Actual vs. Predicted Equity/Assets**	**Mean Absolute Error between Actual vs. Predicted Equity/Assets**	**Median Absolute Error between Actual vs. Predicted Equity/Assets**
2001	0.87418	0.01046	0.00606	0.91838	0.00816	0.00557
2002	0.82950	0.01046	0.00579	0.93401	0.00788	0.00533
2003	0.83796	0.01124	0.00698	0.91097	0.00855	0.00577
2004	0.83878	0.01160	0.00546	0.89656	0.00775	0.00469
2005	0.87604	0.01339	0.00874	0.90477	0.00808	0.00542
2006	0.88916	0.00976	0.00520	0.90570	0.00784	0.00471
2007	0.85669	0.01257	0.00691	0.89858	0.00794	0.00472
2008	0.73388	0.02019	0.01335	0.88283	0.01004	0.00604
2009	0.82440	0.01691	0.01199	0.88366	0.00962	0.00638
2010	0.77406	0.01429	0.00887	0.89670	0.00886	0.00581
2011	0.86061	0.01153	0.00732	0.91968	0.00871	0.00611
AVG	**0.83593**	**0.01295**	**0.00788**	**0.90471**	**0.00849**	**0.00550**

Panel B: Large versus Small Banks (Threshold = Sample Median = $103.5mTotal Assets)

	Large Banks (33,303 Observations)			Small Banks (33,303 Observations)		
Year	**Correlation between Actual vs. Predicted Equity/Assets**	**Mean Absolute Error between Actual vs. Predicted Equity/Assets**	**Median Absolute Error between Actual vs. Predicted Equity/Assets**	**Correlation between Actual vs. Predicted Equity/Assets**	**Mean Absolute Error between Actual vs. Predicted Equity/Assets**	**Median Absolute Error between Actual vs. Predicted Equity/Assets**
2001	0.87820	0.00791	0.00510	0.93486	0.00847	0.00601
2002	0.90926	0.00741	0.00485	0.93876	0.00830	0.00572
2003	0.86798	0.00843	0.00542	0.93122	0.00878	0.00625
2004	0.86411	0.00774	0.00463	0.90256	0.00818	0.00490
2005	0.89410	0.00791	0.00531	0.90144	0.00864	0.00569
2006	0.90089	0.00727	0.00435	0.90439	0.00860	0.00517
2007	0.87960	0.00790	0.00460	0.89968	0.00862	0.00513
2008	0.82028	0.01075	0.00629	0.90611	0.01034	0.00644
2009	0.85499	0.01054	0.00711	0.88506	0.01000	0.00640
2010	0.86950	0.00904	0.00582	0.89661	0.00938	0.00610
2011	0.91262	0.00858	0.00598	0.91851	0.00912	0.00620
AVG	**0.87741**	**0.00850**	**0.00541**	**0.91084**	**0.00895**	**0.00582**

Panel C: Large versus Small Banks (Threshold = $300m Total Assets)

	Large Banks (13,254 Observations)			Small Banks (53,353 Observations)		
Year	**Correlation between Actual vs. Predicted Equity/Assets**	**Mean Absolute Error between Actual vs. Predicted Equity/Assets**	**Median Absolute Error between Actual vs. Predicted Equity/Assets**	**Correlation between Actual vs. Predicted Equity/Assets**	**Mean Absolute Error between Actual vs. Predicted Equity/Assets**	**Median Absolute Error between Actual vs. Predicted Equity/Assets**
2001	0.84772	0.00943	0.00548	0.93031	0.00805	0.00558
2002	0.87342	0.00823	0.00492	0.93835	0.00795	0.00543
2003	0.83966	0.00937	0.00563	0.91934	0.00858	0.00594
2004	0.82834	0.00847	0.00433	0.90327	0.00785	0.00490
2005	0.86745	0.00898	0.00574	0.90650	0.00813	0.00537
2006	0.89997	0.00728	0.00427	0.90492	0.00810	0.00483
2007	0.87188	0.00861	0.00510	0.89879	0.00809	0.00476
2008	0.74974	0.01299	0.00756	0.89766	0.00978	0.00596
2009	0.80226	0.01304	0.00875	0.89240	0.00923	0.00616
2010	0.83369	0.01025	0.00640	0.90005	0.00876	0.00577
2011	0.88909	0.00884	0.00596	0.92434	0.00878	0.00618
AVG	**0.84575**	**0.00959**	**0.00583**	**0.91054**	**0.00848**	**0.00553**

Table 9: Chow Tests for Stability of Coefficients over Time

Panel A: Individual Years

	Year t versus Full Panel		**Year t versus Year t+1**	
Year	*F-statistic (degrees of freedom)*	*p-value*	*F-statistic (degrees of freedom)*	*p-value*
1999	66.811 (5, 66,597)	7.14×10^{-70}	66.009 (5, 13,653)	2.37×10^{-68}
2000	21.600 (5, 66,597)	1.13×10^{-21}	38.915 (5, 13,261)	8.16×10^{-40}
2001	28.811 (5, 66,597)	2.65×10^{-29}	64.006 (5, 12,931)	3.33×10^{-66}
2002	45.087 (5, 66,597)	1.22×10^{-46}	11.317 (5, 12,587)	6.52×10^{-11}
2003	21.142 (5, 66,597)	3.43×10^{-21}	7.271 (5, 12,194)	8.25×10^{-07}
2004	17.620 (5, 66,597)	1.73×10^{-17}	25.935 (5, 11,808)	3.91×10^{-26}
2005	20.077 (5, 66,597)	4.55×10^{-20}	3.186 (5, 11,468)	7.07×10^{-03}
2006	45.063 (5, 66,597)	1.30×10^{-46}	79.658 (5, 11,166)	2.11×10^{-82}
2007	70.957 (5, 66,597)	2.59×10^{-74}	3.317 (5, 10,929)	5.38×10^{-03}
2008	52.818 (5, 66,597)	6.72×10^{-55}	23.106 (5, 10,792)	3.71×10^{-23}
2009	23.100 (5, 66,597)	2.95×10^{-23}	–	–

Panel B: Test of Single Break Point at Year t

Break Year:	*F-statistic (degrees of freedom)*	*p-value*
2002	60.567 (5, 66,597)	3.45×10^{-63}
2003	29.318 (5, 66,597)	7.68×10^{-30}
2004	43.223 (5, 66,597)	1.20×10^{-44}
2005	50.047 (5, 66,597)	6.15×10^{-52}
2006	66.106 (5, 66,597)	4.06×10^{-69}
2007	144.905 (5, 66,597)	1.70×10^{-153}

Table 10: Effect of Longer Lags on Predictive Performance

Panel A: Lag Between Base Year and Holdout Year

Lag in Years	Average correlation between actual and predicted equity/assets	Mean absolute error between actual and predicted equity/assets, averaged across sample years	Median absolute error between actual and predicted equity/assets, averaged across sample years
1	0.90055	0.00868	0.00555
2	0.89988	0.00869	0.00556
3	0.89961	0.00892	0.00582

Panel B: Lag Between Financial Data and Predicted Equity/Assets

Lag in Years	Average correlation between actual and predicted equity/assets	Mean absolute error between actual and predicted equity/assets, averaged across sample years	Median absolute error between actual and predicted equity/assets, averaged across sample years
1	0.90055	0.00868	0.00555
2	0.80628	0.01190	0.00773
3	0.75401	0.01400	0.00931

References

Arena, M., 2008. Bank failures and bank fundamentals: A comparative analysis of Latin America and East Asia during the nineties using bank-level data. Journal of Banking and Finance 32, 299-310.

Abrams, B.A., Huang, C.J., 1987. Predicting bank failures: The role of structure in affecting recent failure experiences in the USA. Applied Economics 19, 1291-1302.

Barro, R.J., Sala-i-Martin, X., 1992. Convergence. Journal of Political Economy 100, 223–251.

Cole, R.A., Cornyn, B., Gunther, J., 1995. FIMS: A new monitoring system for banking institutions. Federal Reserve Bulletin 81, 1-15.

Cole, R.A., Gunther, J., 1995. Separating the likelihood and timing of bank failure. Journal of Banking and Finance 19, 1073-1089.

Cole, R.A., White, L.J., 2012. Déjà vu all over again: The causes of U.S. commercial bank failures this time around. Journal of Financial Services Research 42, 5-29.

De Haan, J., Poghosyan, T., 2012. Size and earnings volatility of US bank holding companies. Journal of Banking and Finance 36, 3008-3016.

DeYoung, R., 2003. De novo bank exit. Journal of Money, Credit, and Banking 35, 711-728.

DeYoung, R., Hasan, I., 1998. The performance of de novo commercial banks: A profit efficiency approach. Journal of Banking and Finance 22, 565-87.

Espahbodi, P., 1991. Identification of problem banks and binary choice models. Journal of Banking and Finance 15, 53-71.

Estrella, A., Park, S., Peristiani, S., 2000. Capital ratios as predictors of bank failure. Federal Reserve Bank of New York Economic Policy Review 6, 33-52.

Federal Deposit Insurance Corporation, 2012. Failed Bank List. <http://www.fdic.gov/bank/individual/failed/banklist.html> (accessed 10/28/12).

Fuller, P., Kohers, T., 1994. Developing a decision rule to predict failure: The case of savings and loan associations. Journal of Economics and Finance 18, 43-54.

Guillén, M., 2009. The global economic & financial crisis: A timeline. The Lauder Institute, University of Pennsylvania. http://www-management.wharton.upenn.edu/guillen/2009_docs/crisis_financiera_formato_nuevo.pdf> (accessed 10/28/12).

Jagtiani, J., Kolari, J., Lemieux, C., Shin, H., 2003. Early warning models for bank supervision: Simpler could be better. Federal Reserve Bank of Chicago Economic Perspectives 27, 49-60.

Kolari, J., Glennon, D., Shin, H., Caputo, M., 2002. Predicting large US commercial bank failures. Journal of Economics and Business 54, 361-387.

Martin, D., 1977. Early warning of bank failure: A logit regression approach. Journal of Banking and Finance 1, 249-276.

Meyer, P.A., Pifer, H.W., 1970. Prediction of bank failures. Journal of Finance 25, 853-868.

Sala-i-Martin, X., 1996. The classical approach to convergence analysis. Economic Journal 106, 1019–1036.

Santomero, A., Vinso, J., 1977. Estimating the probability of failure for firms in the banking system. Journal of Banking and Finance 1, 185-206.

Shaffer, S., 1998. The winner's curse in banking. Journal of Financial Intermediation 7, 359-392.

Shaffer, S., 2012. Bank failure risk: Different now? Economics Letters 116, 613-616.

Thomson, J.B., 1991. Predicting bank failures in the 1980s. Federal Reserve Bank of Cleveland Economic Review 27, 9-20.

Whalen, G., 1991. A proportional hazards model of bank failure: An examination of its usefulness as an early warning tool. Federal Reserve Bank of Cleveland Economic Review 27, 21-31.

Wheelock, D.C., Wilson, P.W., 2000. Why do banks disappear? The determinants of U.S. bank failures and acquisitions. Review of Economics and Statistics 82, 127-138.