FORECASTING BANK LEVERAGE:

AN ALTERNATIVE TO REGULATORY EARLY WARNING MODELS

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Abstract

Bank regulators have worked to develop statistical models predicting bank failures, but such models cannot be estimated during periods of few failures. We address this problem using an alternative approach, forecasting the leverage ratio as a continuous variable that avoids the small sample problem. The leverage ratio is a natural choice in this setting both because of its historically consistent ability to predict failures and because of regulators' primary focus on bank capitalization. Our model selection draws on both the earlier literature and more recent stress-testing studies. Out-of-sample performance shows promise as a supplement to the standard approach.

Keywords: bank leverage, forecasts, early warning
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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. Regulatory agencies, in particular, 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failures observed during normal times.[2] In many such cases, researchers and regulators are constrained to rely on outdated estimates, despite evidence that the statistical linkages vary over time (Shaffer, 2012).

The recent financial crisis has intensified regulators' need to explore improved methods for identifying banks at risk and in need of supervisory intervention. Newer studies, some prompted by the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 (Dodd-Frank), have introduced stress-testing models that attempt to improve on the earlier methods, both by exploring additional variables and by modeling a wider range of outcomes than explicit failure. These models are categorized as either top-down (using only publicly available bank-level data) or bottom-up (using detailed account and loan-level data for each bank, available only to supervisory officials). Examples include

[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.

Covas et al. (2014), Hirtle (2015), and Kapinos and Mitnik (2015).

This paper explores an 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, and bank regulation both in the U.S. and throughout the range of nations adhering to the Basel accords focuses on variations of this ratio as a primary regulatory instrument. Nevertheless, no previous study appears to have adopted our approach; the recent stress-test studies have focused on other outcomes, such as net charge-off rates and components of pre-provision net revenue (Covas et al, 2014; Hirtle et al., 2015; Kapinos and Mitnik, 2015). Out-of-sample performance during the current century suggests reasonable potential for this method to complement the standard approach, especially when applied to selected quantiles of the weakest banks.

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 within-sample regression estimate. Section 4 extends the analysis to out-of-sample forecast accuracy, Section 5 presents several robustness checks and extensions, while Section 6 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 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, as listed in Table 1 and discussed below.[5] As indicated in the table, recent top-down stress-test models have also included most of these variables as regressors. Because the event of a bank's failure or insolvency is closely linked to, or even defined

[3] Some studies such as Wheelock and Wilson (2000) 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.

[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. In the table, the signs in parentheses denote the sign of the anticipated regression coefficient predicting subsequent equity/assets, as discussed below.

by, depletion of the bank's equity capital, we should expect on theoretical grounds that variables found accurate in predicting insolvency should generally predict capitalization, and vice versa, where the sign of impact on the probability of failure has the opposite sign as the impact on equity/assets. Consistent with this reasoning, specific theoretical linkages between certain regressors and equity capital support those regressors' inclusion in a model of capitalization, as clarified below.

We then explore the potential for additional variables from the newer stress-test studies to improve the predictive performance of our model. These variables include both bank-level and macroeconomic variables, as summarized in Table 2. Our use of macroeconomic variables differs from that of the stress-test models in that we aim to characterize outcomes conditional on contemporaneous values of relevant macroeconomic measures, whereas stress-testing methods mandated by Dodd-Frank seek to characterize outcomes conditional on particular macroeconomic scenarios specified by the analyst or regulator.[6] Our approach is complementary to those stress-testing methods, in that future crises may occur under different macroeconomic conditions than in the most recent crisis or than postulated by regulators, and serves as something of a conceptual bridge between stress-testing and the Basel capital regulations.[7]

We test these variables stepwise both in-sample and out-of-sample to identify a robust subset of variables associated with subsequent leverage ratios, leading to two preferred models, which we call our Risk1 and Risk2 models; both of these models form

[6] Also, our sample is much larger than the top-down stress-testing models: Covas et al. (2014) studied 15 large bank holding companies, Kapinos and Mitnik (2015) studied 156 large banks, and Hirtle et al. (2015) studied the 200 largest bank holding companies.

[7] Moreover, because macroeconomic conditions respond to the aggregated actions of financial institutions, it is formally inconsistent to assume particular values of macroeconomic variables independently of the underlying bank-level conditions.

the focus of our subsequent analysis. Finally, because banks make strategic decisions (sometimes subject to regulatory constraints) when paying dividends, issuing new stock, or buying back their own stock – actions that directly affect subsequent capitalization levels – we estimate a model in which these variables augment our Risk1 model.[8]

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 (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. Recent top-down stress-test studies such as Kapinos and Mitnik (2015) likewise estimate dependent variables as a function of their own lag plus one or more other regressors.

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) as well as with other financial outcomes such as net charge-off rates and components of pre-provision net revenue (Covas et al, 2014; Hirtle et al., 2015; Kapinos and Mitnik, 2015). Because net income can increase retained earnings (thus boosting equity/assets, ceteris paribus) while losses reduce retained earnings (thus reducing equity/assets, ceteris paribus), we similarly expect that the return on assets is positively associated with the subsequent equity ratio.

Various measures of credit risk, such as the ratio of net chargeoffs to total loans or the ratio of nonperforming loans to total loans, have been found positively associated with

[8] We are grateful to an anonymous referee for this suggestion. We apply this extension to our Risk1 model because of its superior out-of-sample performance compared to the Risk2 model, as described below.

risk of failure (Kolari et al., 2002) and with other financial outcomes such as components of pre-provision net revenue (Covas et al, 2014; Hirtle et al., 2015; Kapinos and Mitnik, 2015). The ratio of nonperforming loans to total loans, a more forward-looking measure than net chargeoffs, has been used in Cole and Gunther (1995), Wheelock and Wilson (2000), and Cole and White (2012). Because nonperforming loans and chargeoffs require banks to replenish their allowance for loan and lease losses (ALLL) – thus reducing net earnings, retained earnings, and equity capital – we expect these ratios to be negatively related to subsequent equity ratios. As noted below, after testing variations of these measures, our preferred models use the ratio of nonperforming loans to ALLL, which proves more sensitive than the ratio of nonperforming loans to assets or to total loans.[9]

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) and with other financial outcomes such as net charge-off rates and components of pre-provision net revenue (Covas et al, 2014; Hirtle et al., 2015; Kapinos and Mitnik, 2015). Ceteris paribus, higher operating expenses (or any of its components) should reduce net income, retained earnings, and hence equity. Thus, higher operating expenses (total or by component) should be associated with lower 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.[10]

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[9] The authors are grateful to an anonymous referee for suggesting this version of the measure.

[10] Some studies have found other variables to be significant as well, such as bank size or the ratio of jumbo certificates of deposit to assets, commercial loans to assets, and insider loans to assets, but these variables

Because equity grows with net income minus dividends paid, plus any issuance of new stock, minus any stock repurchases or similar transactions, we also estimate variants of our model controlling for dividends paid on common and preferred stock (items RIAD4460 and RIAD 4470, respectively, in the regulatory Call Report), net treasury stock transactions (RIADB510), and other "sale, conversion, acquisition, or retirement of capital stock" other than treasury stock transactions (RIADB509). Our specifications that include these regressors will be labelled "strategic" in recognition of bank management's control over these actions.

Our strategic model augments the regressors from our Risk1 model with dividends on common stock / assets, dividends on preferred stock / assets, change in capital stock / assets, and change in treasury stock / assets.[11] Because dividends reduce retained earnings and hence equity capital, dollar for dollar, we expect a negative coefficient on the dividend variables. We expect a positive sign on the change in capital stock because any increase in capital stock directly increases equity capital, dollar for dollar. Finally, ceteris paribus, any purchase of treasury stock under U.S. accounting rules will decrease a bank's assets dollar for dollar by reducing cash, but also reduces the bank's total equity capital by recording an offset on the right hand side of the balance sheet to reflect the purchase, thus reducing the ratio of equity / assets overall. Therefore, we expect a negative coefficient on the change in treasury stock.

Our analysis proceeds in two steps. First, we estimate regressions of the following

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did not perform well enough in our analysis to be included in our final models. We explore the effect of size separately as discussed below.

[11] The authors are grateful to an anonymous referee for suggesting these regressors. Additionally, not reported in the tables for brevity, we estimated various subsets of these variables in combination with the Risk1 regressors, and obtained virtually identical results for each variable.

form:

$$KA_{t+1} = \alpha_t + X_t \beta_t + \varepsilon_t \quad (1)$$

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). To permit the inclusion of nationwide macroeconomic variables, which exhibit no cross-section variation, we implement this step in short panel samples of two or three years to forecast equity ratios from 2002 to 2011.[12]

Next, we apply the vector of estimated coefficients from each year t (2002-2009 for two-year panels and 2003-2009 for three-year panels) to regressors from year t+1 (2001-2010 for two-year panels and 2002-2010 for three-year panels) to forecast KA as of year t+2 (2002-2011 for two-year panels and 2003-2011 for three-year panels), as shown in equation (2):

$$KA_{t+2} = \alpha_t + X_{t+1} \beta_t \quad (2)$$

This out-of-sample step represents a potential application of the model by bank supervisors or analysts using the most recent available estimates and data. We initially 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 also quantify a form of type II error in forecasting the weakest banks, as detailed in section 4 below. We

[12] Although our raw dataset has a panel structure, the research question posed here – how to use this information in one-period-ahead forecasts, as evaluated by the model's performance in holdout samples – cannot be properly addressed using the full panel, but must be approached on a primarily cross-sectional basis, especially when evaluating the stability of parameters over time. To test the performance of nationwide macroeconomic variables as used in top-down stress-test models, it is necessary to include some time-series component in our estimates, but there is a tradeoff between the time dimension versus the timeliness of the regressors. We therefore adopt the approach described in the text. Given the short time dimensions in each regression, we do not apply panel-specific estimation techniques.

subsequently explore robustness of the results in both of these steps with respect to banks in the lowest quantiles of capitalization (as being of primary supervisory concern), model specification, nonlinearity, inclusion of first differences, stability of coefficients over time, differential effects by bank size or leverage, and two types of extended lags.

3. Sample and First-Stage Results

We use year-end Call Report data for a nationwide sample of U.S. commercial banks during 1999-2011. With regard to our research question, the largest banks are in a unique position for several reasons. First, unlike community banks, they have ample market data available to supplement Call Report data. Second, the very largest banks are subject to continual supervisory scrutiny, with "examiners-in-residence" as well as ongoing offsite monitoring and additional requirements under Dodd-Frank. Third, a subset of the largest banks are subject to special "too-big-to-fail" treatment. Finally, nearly all observed bank failures have involved banks outside the largest size class. The first two reasons suggest that statistical models such as ours may be less necessary for adequate monitoring of the largest banks, while the last two suggest that statistical linkages among observable financial variables may tend to be systematically different for the largest banks compared to the rest of the industry. For these reasons, our analysis below excludes the largest 100 banks by total assets in each year.[13] If our analysis proves useful for identifying problems in banks that pose little or no systemic risk, such a model could potentially free up supervisory resources to focus more on systemically important institutions; Section 5.5 will explore this question in more detail.

[13] We are grateful to an anonymous referee for suggesting this sampling strategy. We also replicated our analysis with the inclusion of these banks, and obtained nearly identical results.

We apply additional selection criteria as summarized in Table A2 in the Appendix. Our final sample contains 65,460 bank-year observations. Table 3 reports summary statistics for the variables used in our two preferred models, while Table A3 in the Appendix reports pairwise correlation coefficients among those variables. The sample means conform to familiar industry norms for each variable, while the standard deviations indicate enough sample variation to permit a meaningful statistical test of the role of each variable. Apart from the large positive correlation between non-interest income and "other noninterest expenses," which is consistent with theory since heavy reliance on fee income normally requires a bank to invest substantial resources in the related products, the correlation coefficients are not large enough to suggest severe multicollinearity.

Tables 4 and 5 report regression estimates for the first stage of analysis, where *p*-values are based on robust (White) standard errors. The Risk1 model is estimated using rolling two-year panels to permit within-sample variation in nationwide macroeconomic variables. The row labeled 2000 in the table uses data from 1999 and 2000 to predict equity/assets for 2001, and similarly for other rows. The Risk2 model is estimated using rolling three-year panels for the same reason. The row labeled 2001 uses data from 1999-2001 to predict equity/assets for 2002, and similarly for other rows.

The fit is quite reasonable in both specifications, with adjusted R^2 values for individual years ranging from 0.77 to 0.85. The smallest values are associated with 2007-2009, during the financial crisis.[14] During the years with no bank failures, 2005-2006, the adjusted R^2 is above 0.81, suggesting some potential usefulness of the model during periods when conventional early warning models cannot be re-estimated. Our models also

[14] 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 and beyond.

continue to perform reasonably well into the crisis years, contrasting with a pattern that many statistical models are intrinsically poor at identifying turning points.

The signs and significance levels of the coefficients vary over time for most of the 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 years for the Risk2 model (two years plus the full panel for the Risk1 model), but is significantly negative in two years for the Risk2 model. It is most highly significant with the expected sign in the crisis years 2008-2009.

Nonperforming loans / ALLL is significantly negative in three years in both models, as expected, but is significantly positive in at least one year (two years in the Risk1 model). A possible explanation for the occasional positive coefficient, not tested here, is that some banks may be able to anticipate high delinquencies or chargeoffs, prompting them to increase their loan loss reserve and reduce dividend payouts in advance. This variable's mixed performance in our model suggests that capitalization may not be the primary channel through which delinquencies contribute to failure.

Total loans/assets exhibits a significantly negative coefficient in all but one year plus the full panel, as expected, in both models. Among the macroeconomic variables, the relative change in the FHFA house price index is statistically significant at the 0.01 level in six of 10 years plus the full panel in model Risk1, but with an unexpected negative coefficient in two of those years, early in the sample period. It performs similarly in model Risk2. The coefficient on the relative change in the Dow Jones U.S. Total Stock Market Index is significantly positive at the 0.01 level in five years plus the full panel in model

Risk2, but significantly negative at the 0.05 level in one year. In several individual years plus the full panel, both variables exhibit very high levels of statistical significance, with p-values rounding to 0.0000.

Specification Risk2 includes six additional bank-level variables from the top-down stress-test studies that were not reported in typical early-warning studies. The coefficient on the ratio of trading account assets to total assets exhibits a negative point estimate in all but one year, consistent with prior theoretical expectations based on the inherent risk of trading activities, is statistically significant at the 0.05 level in four of those years plus the full panel, and is marginally significant in another year. This variable is nonzero only for the larger banks in our sample.

Two components of relative operating expense, wages/assets and the ratio of expenses on fixed assets to total assets, are the second most highly correlated variables in our sample, with a pairwise correlation of 0.60 across the full panel – likely driven by time-series variation in the cost share of interest expenses, which declined dramatically after the onset of the crisis. The wage ratio is never individually significant in the first stage of analysis (within-sample) but is retained in our Risk2 model because it improves the out-of-sample predictive performance together with the fixed asset expense ratio. The ratio of expenses on fixed assets to total assets exhibits a significantly negative coefficient, as expected, in three years.

As noted above and in Table A3, the remaining two bank-level variables in model Risk2 are highly correlated across our full sample (rho = 0.85) but help improve both in-sample and out-of-sample accuracy. The estimated coefficient on the ratio of non-interest income to total assets is never significant at the 0.05 level, while the coefficient on the ratio of “other non-interest expenses” to total assets is significantly positive at the 0.05 level in only one year and at the 0.10 level in one other year. Both results are contrary to our initial expectations.

As might be expected, current leverage is the most consistent and statistically significant factor in both models. Its coefficient ranges between 0.83 and 0.92 for each year in each specification and is significantly less than 1 in every instance. 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 leverage. Moreover, current leverage is not an unbiased estimator of future leverage.[15] An additional observation is that its coefficient is smallest in the crisis years 2007-2009, reflecting the fact that average capitalization levels were declining over the following months.

We next summarize the regression estimates of our “strategic” model as defined above.[16] In this model, dividends on common stock exhibit a significantly negative coefficient at the 0.01 level, as anticipated, in three individual years (2005, 2006, and 2007), but also a significantly positive coefficient in 2003. Dividends on preferred stocks show a significantly negative coefficient at the 0.05 level in one year and at the 0.055 level in another year. The change in capital stock exhibits a significantly negative coefficient for three individual years and the full panel, contrary to expectations, indicating a pattern of

[15] If current leverage were the best predictor of future leverage, all of the following conditions would hold: (a) its estimated coefficient would equal 1, apart from a secular industry-wide trend in leverage; (b) the estimated intercept term would equal zero, again apart from a secular trend; (c) no other variable would exhibit significantly nonzero coefficients. If current leverage were an unbiased estimator of future leverage, the first two of these conditions would hold. Our estimates satisfy none of these conditions.

[16] These estimates are not shown in tables for brevity, but are available from the authors.

reversion to the mean. The change in treasury stock exhibits an unexpected but significant positive coefficient in 2007 and 2008. The fit is good overall, with adjusted R^2 ranging from 0.77 in 2008 to nearly 0.85 in 2002.

Before proceeding to out-of-sample forecasts, we note that the banks of primary supervisory concern in our analysis are those with the lowest equity/asset ratios. Focusing on this subset of banks requires discretion and caution, however, because of small sample sizes: only very few banks have equity/asset ratios below any low threshold (whether zero, 2 percent, or any similar figure). Accordingly, there is an inherent tradeoff between fitting the model across all banks, to benefit from a large sample size, versus focusing only on the weakest banks, a subset containing few observations.

We address this issue by the use of quantile regressions (Koenker and Bassett, 1978). Rather than selecting a fixed threshold value of equity/assets, we focus on banks with the lowest 5 percent of equity/asset values in each sample period. This approach assures similar numbers of such banks in each period, mitigating the statistical problem of too few observations in some years, while still addressing the weakest banks.[17]

In this step, we re-estimate each of our models as quantile regressions, in two ways. One version estimates quantile regressions for the lowest 5 percent of equity/assets, while the other version estimates quantile regressions for the lowest 10 percent of equity/assets. Both versions are subsequently applied in the out-of-sample step and evaluated on their ability to identify banks with the lowest 5 percent of equity/asset ratios. While the 10th quantile regression will tend to mis-identify a larger number of sound banks as weak,

[17] We are grateful to an anonymous referee for suggesting the inclusion of this focus on the lower tail of banks by capitalization. Quantile regression estimates are available from the authors but not reported in tables here for brevity.

compared to the 5^{th} quantile regression, this tradeoff is likely to be preferred by bank supervisors and practitioners, because the social costs of overlooking a bank that fails is typically higher than the cost of mistakenly devoting additional supervisory and managerial resources to a bank that turns out to be strong.

4. Out-of-sample Performance

While a reasonable fit of the model is desirable, within-sample performance falls short of demonstrating the practical usefulness of a model in forward-looking applications, and are vulnerable to the econometric problem of over-fitting (Bossaerts and Hillion, 1999; Clark, 2004). This problem is especially important when selecting and using models to inform regulatory actions and public or managerial policy (Al-Najjar and Pai, 2014). Accordingly, as reported in Table 6, we next compare the out-of-sample performance of our preferred models along with a naïve one-period-ahead benchmark using only current equity/assets to predict subsequent equity/assets.

We evaluate the out-of-sample performance using an array of measures including correlations between actual and fitted equity/assets, mean and median absolute forecast errors, the percent of banks corrected predicted to be in the bottom 5 percent of equity/assets, and four measures of type II error (banks incorrectly predicted to be in the bottom tail of equity/assets, as described in more detail below). We construct these measures by applying regression coefficients estimated in one period to a holdout sample from the following period, exactly as a regulator or practitioner would be able to apply these models. While we are aware of no formal test of statistical significance that can be applied in this exercise, it provides a heuristically useful characterization of the model's out-of-sample predictive performance among the weakest banks that comprise the locus of regulatory and managerial concern.

Two main conclusions emerge from Table 6. First, the naïve forecast performs surprisingly well in many cases, consistent with prior failure analysis by Jagtiani et al. (2003). Second, all 10th quantile regressions exhibit markedly superior accuracy in correctly predicting banks in the bottom 5 percent of equity/assets. The naïve forecast shows the best correlations, ties for the best median absolute forecast errors, and narrowly misses having the best mean absolute forecast errors. Conversely, the percentage of banks correctly predicted to be in the bottom 5 percent is nearly half again as high for each of the 10th quantile regressions compared with any other estimates, ranging as high as 77.39 percent for the strategic model and 76.24 percent for the Risk1 model.

In more detail, the correlation between actual and predicted equity/assets ranges from 0.867 to 0.898 across our preferred specifications, based on the Risk1 model. The absolute forecast errors for the Risk1 model range from 0.0085 to 0.0205 for the mean and from 0.0055 to 0.0174 for the median. These figures compare favorably with the sample mean equity/asset ratio of 0.10457 (shown in Table 3), which is 19 times the smallest median absolute forecast error.

We calculate a form of type II error as follows. First, we determine the threshold of predicted equity/assets below which the model correctly identifies all banks that subsequently exhibit actual equity/assets among the lowest x values in the sample; we set x equal to 100, 75, 50, and 25 in alternate implementations of this step. Then, for all banks with predicted equity/assets below that threshold, we report the number of banks (expressed as a percentage of the total number of banks in the lowest y percent by equity/assets) that subsequently were not among the lowest y percent of banks according to actual equity/assets. Table 6 lists the value of y selected for each value of x.[18]

The four measures of type II error show mixed comparisons across models, with the 10th quantile strategic model regressions ranging from best to fifth and the 10th quantile Risk1 regressions ranging from second to sixth. The type II error rate is 20 to 25 percent in most cases and below 20 percent in a few cases. As shown in the bottom row of Table 6, the naïve model performs worse than all but one of our models in each of these comparisons.

Of the two quantile regression levels employed, the version motivated by asymmetric supervisory costs performs better out of sample according to every measure, except for the strategic model using the 25 bank / 2 percentile criteria. That is, the 10th quantile regressions are better than the 5th quantile regressions at predicting the weakest 5 percent of banks. As shown in Table 6, all of our models show higher correlations between predicted and actual equity/assets, lower mean and median absolute forecast errors, and higher percentages of banks correctly identified as being among the lowest 5 percent of equity/assets when using the 10th quantile estimates.

Indeed (not shown in the table), the percentage of banks correctly predicted to be among the weakest 5th quantile (using the 10th quantile estimates from the Risk1 model) ranges as high as 86.0 percent in 2006 and, not surprisingly, is lowest in the crisis years of 2008-2009 which represent a regime shift (56.1 percent and 69.6 percent, respectively, as a percentage of the number of banks actually in the bottom 5 percent). While this form of analysis necessarily involves a tradeoff, with a higher proportion of sound banks being mis-

[18] The authors are grateful to an anonymous referee for suggesting this direction of analysis.

classified as weak, the latter error rate is below 7 percent except in 2008, where it is below 7.6 percent. Apart from the crisis years, this model performs better during the more recent portion of the sample period than in the earlier years.

Because our Risk1 model exhibits the best out-of-sample performance overall in Table 6, we focus on that model in additional analysis. Table 7 reports statistics from the second stage of our analysis by year, in which the coefficients reported in Table 4 (relating years t and t-1 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 0.0075 to 0.0100 and from 0.0046 to 0.0066, respectively. Given that the sample mean value of equity/assets is 0.10457, 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 two lowest median absolute errors are for 2006 and 2007 leverage – one being a year of no failures and the other a year that some sources identify as the first year of the crisis, suggesting that the model performs well at both extremes of industry performance.[19] By contrast, this type of robustness is typically lacking among conventional early warning models.

We further investigate whether the Risk1 model's predictive performance is systematically different during the main years of the financial crisis, compared with other

[19] De Haan and Poghosyan (2012) test both 2007 and 2008 as starting points of the crisis, in a banking study unrelated to our research question. However, most small U.S. banks exhibited visible financial stress beginning in 2008.

sample years. To do this, we calculate both a paired t-test and a nonparametric Wilcoxon rank sum test (Mann-Whitney test) for each of our three measures of forecast accuracy – correlation, mean absolute error, and median absolute error. For 2008-2009 versus the other sample years, the correlation between actual versus predicted equity/assets is not measurably different according to either test, indicating that our model did not lose out-of-sample predictive accuracy during the crisis. For the median absolute error, the Wilcoxon test likewise indicates no significant difference, though the paired t-test indicates reduced accuracy at the 0.10 level. For the mean absolute error, the paired t-test indicates reduced accuracy at the 0.01 level but the Wilcoxon test conversely indicates improved accuracy at the 0.05 level, during 2008-2009. Alternate definitions of the crisis years give similar results, indicating no robust evidence that our model performed systematically worse during the crisis years.[20]

Table 8 compares the actual cross-sectional mean leverage ratios for each year versus the ratios predicted by the Risk1 model in our out-of-sample step. The results show a small but statistically significant bias in each year, though the sign of the bias varies across the years.

5. Robustness and Extensions

5.1. Alternate Model Specifications

Next, we explore several dimensions of robustness of the model's performance. In this step, we estimate more than 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

[20] Generally insignificant differences emerge using 2007 as an alternate starting date for the crisis. The strongest differences are found when defining 2008-2010 as crisis years, though De Haan and Poghosyan (2012) suggest 2009 as an ending date for the crisis.

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 Tables 4 and 5, we investigate whether first differences in these variables from period t–1 to t improve the in-sample and out-of-sample performance. We find no combination of first differences that improved the model's predictive power overall.

An additional step was to estimate and forecast the numerator and denominator of equity/assets separately, and then combine our estimates to forecast equity/assets ratios, to see whether additional accuracy could be obtained compared to forecasting the ratio as a single variable.[21] Because the condition of insolvency is determined by the *level* of equity/assets, and because regulatory standards likewise focus on the level of that ratio, we retain our focus on levels rather than changes in this step. In this approach, the standard error of the predicted ratio is not a simple function of the standard errors of the numerator and denominator. These results, not reported in tables, provide substantially inferior out-of-sample accuracy compared to our primary model reported in the previous section.

5.2. Model Nonlinearity

We also evaluate possible nonlinearity of the model with respect to our original regressors, by including squared terms as well as levels in various combinations and subsets. 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.

[21] The authors are grateful to an anonymous referee for suggesting this step.

5.3. *Macroeconomic Variables*

In addition to the macroeconomic variables listed in Table 3, we also test every other macroeconomic variable used in recent top-down stress-test studies, as shown in Table 2. Additionally, we test state-level values of the unemployment rate and the annual rate of gross state product growth. In each case, we estimate several versions: using one macro variable at a time, or several together, in levels or in first differences. In no case was any macro variable consistently significant across individual years or across the full panel, besides those reported in Tables 3-5.

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 other macroeconomic variables.

5.4. *Level of Capitalization*

As a complement to the quantile analysis reported above, we further explore whether the estimated coefficients or predictive power of the model would vary in a continuous fashion 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. This question is motivated by the concern of regulators and practitioners about banks with low equity ratios.

5.5. *Bank Size*

The model's performance for banks of different sizes is another 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 ($101.4 million), while an alternate threshold is the sample mean asset size ($242.2 million). A third alternate threshold is $300 million in assets, as in Cole and White (2012), where 81 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 3.7 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 from this step is summarized in Table 9. Some differences are evident across the groups, as leverage is predicted somewhat more accurately for smaller banks overall. 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 0.55 to 0.90 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 encourage its use for those institutions – especially given their large number and insubstantial systemic risk – thus freeing up supervisory resources to focus in more detail on systemically important banks.

5.6. Coefficient Stability

We next investigate 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 in our Risk1 model suggests some fluctuation over time in the statistical linkages between the 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 differs 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 10 reports the results of these Chow tests, which reject overall stability as well as stability across consecutive years. Panel A of the table indicates that the one year most unlike the others in our sample, as well as the most unlike the following year, was 2008, coinciding with the financial crisis. The most significant breakpoint in our sample was 2007, also related to the crisis. These results are generally consistent with previous findings for conventional early warning models (Shaffer, 2012), confirm the desirability of re-estimating such models as permitted by the arrival of new data as in Cole et al. (1995), and emphasize the potential usefulness of an approach such as ours that does not require pooling of data across numerous years to obtain usable sample sizes.

5.7. Intertemporal Deterioration of Predictive Power

We explore an additional aspect of intertemporal instability by estimating two further variations on our model, involving alternate lag structures. 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 between the latest financial data used and the predicted equity/assets from t+1 to t+2 and t+3. Second, we explore a within-sample aspect of intertemporal deterioration by using financial data from years t and t-1 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 11 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 Panel A, the correlation between actual and predicted out-of-sample equity/asset values, averaged over the sample years, is close to 0.90 for each lag, but is slightly lower for successively longer lags as expected. Likewise, the mean and median absolute errors are slightly but uniformly larger for longer lags. In Panel B, out-of-sample predictive accuracy also deteriorates uniformly, but more sharply, at longer lags. The mean absolute errors are 63 percent larger at t+3 than at t+1, and median absolute errors are 70 percent larger at t+3 than at t+1.

These patterns are consistent with empirical findings for failure forecasts reported by Estrella et al. (2000), Cole and White (2012), and others, and suggest a need to re-estimate this type of model frequently. This need underscores the primary advantage of our approach, since traditional early-warning failure models cannot be re-estimated during periods of very few failures, whereas our capitalization model can always be re-estimated.

6. Conclusion

Motivated by a dearth of bank failures in many years, as well as by regulators' ongoing 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. 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), though the approach could be applied equally to any other observable dependent variable such as profitability, nonperforming loan ratios, liquidity, etc.

The findings indicate some 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, especially when applied to selected quantiles of the weakest banks. 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.

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. Predictive performance for the crisis years is measurably inferior to other years, indicating a vulnerability of the model to turning points or regime shifts, in common with any purely statistical approach; on the other hand, other metrics indicate that the model is somewhat more robust to turning points or extremes of industry performance than we might expect.

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 updated regardless of industry conditions.

Our findings suggest potential applicability of this approach to other countries, many of which have far fewer banks (and bank failures) than the U.S. and are therefore not amenable to standard early warning analysis of failures. Future research could usefully explore this extension, as well as exploring the predictability of other specific dimensions of banks' risk and performance.

Table A1: Failed Bank List[22]

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.

[22] 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	9,574	9,261	8,998	8,751	8,609	8,432	8,302	8,153	8,097	7,873	7,613
Missing Observations	88,625	9,022	8,743	8,528	8,293	8,159	8,010	7,887	7,755	7,627	7,424	7,177
Commercial Banks	82,893	8,431	8,167	7,938	7,752	7,630	7,499	7,387	7,263	7,146	6,960	6,720
FIPS (1-56)	82,893	8,431	8,167	7,938	7,752	7,630	7,499	7,387	7,263	7,146	6,960	6,720
Age greater 10 Years	70,011	7,403	7,064	6,822	6,610	6,464	6,282	6,131	5,973	5,850	5,732	5,680
Loans greater Zero	70,011	7,403	7,064	6,822	6,610	6,464	6,282	6,131	5,973	5,850	5,732	5,680
KA less than 50%	69,959	7,398	7,059	6,817	6,604	6,460	6,278	6,128	5,966	5,844	5,731	5,674
LA less than 90%	69,276	7,369	7,030	6,783	6,565	6,419	6,211	6,052	5,885	5,740	5,607	5,615
KA (t+1) Merge	66,560	6,937	6,716	6,546	6,386	6,204	5,993	5,817	5,653	5,515	5,417	5,376
Less largest 100 Banks per Year	65,460	6,837	6,616	6,446	6,286	6,104	5,893	5,717	5,553	5,415	5,317	5,276

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), negative loans, equity/assets greater than or equal to 50%, loans/assets greater than or equal to 90%, equity/assets not available in the following period, or less than 10 years old (due to systematically abnormal financial behavior; see DeYoung and Hasan, 1998; Shaffer, 1998).

Table A3: Data Correlation Matrix

	Current Equity/ Assets	Return on Assets	Nonperf. Loans/ Allow. L&L Losses	Total Loans/ Total Assets	Trading. Account Assets/ Assets	Non-interest Income/ Assets	Wages/ Assets	Fixed Asset Expenses/ Assets	Other Non-interest Expenses/ Assets	Other Real Estate Owned/ Assets	% Change in DJ Total US Index	% Cha in FH HP
Current Equity/ Assets	1.0000											
Return on Assets	0.1438* (0.0000)	1.0000										
Nonperf. Loans/ Allow..L&L Losses	-0.0026 (0.5086)	-0.1170* (0.0000)	1.0000									
Total Loans/ Assets	-0.2905* (0.0000)	-0.0082* (0.0360)	0.0280* (0.0000)	1.0000								
Trading. Acct. Assets/Assets	-0.0109* (0.0054)	-0.0063 (0.1070)	0.0001 (0.9749)	0.0006 (0.8787)	1.0000							
Noninterest Income/Assets	0.0534* (0.0000)	0.2329* (0.0000)	0.0684* (0.0000)	-0.0156* (0.0001)	0.0303* (0.0000)	1.0000						
Wages/Assets	0.0144* (0.0002)	-0.0629* (0.0000)	0.1043* (0.0000)	0.0477* (0.0000)	0.0133* (0.0007)	0.4659* (0.0000)	1.0000					
Fixed Asset Expenses/Assets	-0.1284* (0.0000)	-0.1674* (0.0000)	0.0597* (0.0000)	0.0898* (0.0000)	0.0106* (0.0069)	0.2910* (0.0000)	0.5998* (0.0000)	1.0000				
Other Noninterest Expenses/Assets	0.0367* (0.0000)	-0.0211* (0.0000)	0.0650* (0.0000)	0.0068 (0.0824)	0.0241* (0.0000)	0.8530* (0.0000)	0.3351* (0.0000)	0.2301* (0.0000)	1.0000			
Other Real Estate Owned/Assets	-0.0512* (0.0000)	-0.3104* (0.0000)	0.1494* (0.0000)	0.1110* (0.0000)	0.0005 (0.9039)	0.0043 (0.2698)	0.0611* (0.0000)	0.1024* (0.0000)	0.0696* (0.0000)	1.0000		
% Change in DJ Total US Index	-0.0131* (0.0008)	0.0085* (0.0304)	-0.0143* (0.0003)	-0.0270* (0.0000)	-0.006 (0.1277)	0.0027 (0.4868)	0.0049 (0.2124)	-0.0036 (0.3586)	0.0046 (0.2343)	0.0144* (0.0002)	1.0000	
% Change in FHFA HPI	-0.0491* (0.0000)	0.2344* (0.0000)	-0.1238* (0.0000)	-0.0616* (0.0000)	-0.0245* (0.0000)	0.0185* (0.0000)	0.0156* (0.0001)	0.0311* (0.0000)	-0.0206* (0.0000)	-0.2482* (0.0000)	0.1576* (0.0000)	1.00
Div. on Comm. Stock/Assets	0.0605* (0.0000)	0.2539* (0.0000)	-0.0215* (0.0000)	-0.0244* (0.0000)	-0.0047 (0.2335)	0.1697* (0.0000)	-0.0172* (0.0000)	-0.0539* (0.0000)	0.1233* (0.0000)	-0.0435* (0.0000)	-0.0065 (0.0945)	0.015 (0.00
Div. on Pref. Stock/Assets	-0.0164* (0.0000)	-0.0019 (0.6201)	-0.0009 (0.8228)	0.0072 (0.0647)	0.0008 (0.8301)	0.0033 (0.3996)	0.0067 (0.0889)	0.0063 (0.1058)	0.0004 (0.9141)	0.0008 (0.8301)	0.0044 (0.2641)	0.00 (0.41
Change in Cap. Stock/Assets	0.0380* (0.0000)	-0.1234* (0.0000)	0.0045 (0.3070)	0.0247* (0.0000)	0.001 (0.8202)	-0.0079 (0.0699)	0.0035 (0.4245)	0.0217* (0.0000)	0.0131* (0.0028)	0.0164* (0.0002)	0.0051 (0.2472)	-0.00 (0.13
Change in Treas. Stock/Assets	-0.0126* (0.0042)	-0.0048 (0.2740)	0.0008 (0.8601)	0.0054 (0.2184)	0.0005 (0.9143)	0.0016 (0.7141)	-0.0078 (0.0761)	-0.0006 (0.8831)	0.0022 (0.6191)	0.0021 (0.6302)	-0.0031 (0.4843)	0.00 (0.97

p-values in parentheses. Significance level: *0.05 or better.

Table 1: Initial Explanatory Variables from Early Warning Studies

(also used in recent stress test models where shown in italics)

Explanatory Variable	**Illustrative References**
Current Equity/Total Assets (+)[a]	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); *Covas et al. (2014), Hirtle et al. (2015)*[b]
Nonperforming Loans / Total Loans (–)	Cole and Gunther, 1995; Wheelock and Wilson, 2000; Cole and White, 2012; *Covas et al. (2014, net chargeoffs by loan type), Hirtle et al. (2015, net chargeoffs by loan type)*[b]
Total Loans/Total Assets (–)	Espahbodi (1991), Thomson (1991), Wheelock and Wilson (2000), DeYoung (2003); *Kapinos and Mitnik (2015)*
Log of Total Assets (–)	Cole and Gunther (1995), Wheelock and Wilson (2000), DeYoung (2003), Arena (2008), Cole and White (2012); *Hirtle et al. (2015)*
Dividends on Common Stock/Total Assets(–)	n/a[c]
Dividends on Preferred Stock/Total Assets (–)	n/a[c]
Change in Capital Stock/Total Assets(+)	n/a[c]
Change in Treasury Stock/Total Assets (–)	n/a[c]

[a] Anticipated sign of regression coefficient in parentheses, as discussed in the text.

[b] Hirtle et al. (2015) use this variable alternately as a lagged regressor or as a dependent variable.

[c] We thankfully acknowledge an anonymous referee's suggestion for these explanatory variables.

Table 2: Additional Explanatory Variables Used in Top-Down Stress-Testing Studies

Variable	**References**
Macroeconomic Variables:	
10-year Treasury yield	Covas et al. (2014); Kapinos and Mitnik (2014; spread); Hirtle et al. (2015)
3-month Treasury yield	Covas et al. (2014); Kapinos and Mitnik (2014; spread); Hirtle et al. (2015)
Civilian unemployment rate	Covas et al. (2014); Kapinos and Mitnik (2014; change); Hirtle et al. (2015)
Real GDP (growth)	Covas et al. (2014); Kapinos and Mitnik (2014); Hirtle et al. (2015)
CoreLogic or Federal Housing Finance Agency (FHFA) house price index	Covas et al. (2014); Kapinos and Mitnik (2014; growth); Hirtle et al. (2015)
BBB bond index yield (10-year)	Covas et al. (2014); Kapinos and Mitnik (2014); Hirtle et al. (2015)
Dow Jones Total U.S. Stock Market Index (DJI)	Kapinos and Mitnik (2014; "DJIA Growth"); Hirtle et al. (2015)
Chicago Board Options Exchange Volatility Index (VIX)	Covas et al. (2014); Kapinos and Mitnik (2014)
NCREIF Commercial Real Estate Index	Covas et al. (2014); Kapinos and Mitnik (2014; "CREPI growth"); Hirtle et al. (2015)
CPI inflation	Kapinos and Mitnik (2014)
Bank Variables:	
Asset growth	Kapinos and Mitnik (2014)
Loan growth	Kapinos and Mitnik (2014)
Consumer / loans (or assets) <or credit card + other>	Covas et al. (2014); Kapinos and Mitnik (2014); Hirtle et al. (2015)
Commercial (or residential) real estate / loans (or assets)	Covas et al. (2014); Kapinos and Mitnik (2014); Hirtle et al. (2015)
Deposits/assets	Kapinos and Mitnik (2014)
Other real estate owned / assets	Kapinos and Mitnik (2014)
Nonperforming loans / loans (or assets)	Kapinos and Mitnik (2014)
Trading account assets / total assets	Kapinos and Mitnik (2014); Covas et al. (2014); (Hirtle uses a similar measure)
Securities / assets (various measures)	Kapinos and Mitnik (2014)
Securitization (by type) / assets	Kapinos and Mitnik (2014)
Net interest income / assets	Covas et al. (2014); Hirtle (as LHV and lagged RHV)
Trading income / assets	Covas et al. (2014); Hirtle (as LHV and lagged RHV)
Noninterest income / assets	Covas et al. (2014)
Various measures of risk-weighted assets	Kapinos and Mitnik (2014); Hirtle et al. (2015; risk-weighted assets / total assets)
Liquidity = (cash + interest-bearing balances + securities + fed funds sold)/assets	Hirtle et al. (2015)

Table 3: Summary Statistics for Variables Used in our Final Models

Variable	**Mean**	**Standard Deviation**
Current Equity/Assets	0.10457	0.03436
Return on Assets	0.01010	0.00942
Nonperforming Loans/Allowances for Loan and Lease Losses	0.85852	2.14410
Loans/Assets	0.62249	0.14868
Trading Account Assets/Total Assets	0.00015	0.00341
Noninterest Income/Assets	0.00849	0.01750
Wages/Assets	0.01652	0.00645
Fixed Asset Expenses/Assets	0.00412	0.00211
Other Noninterest Expenses/Assets	0.01000	0.01314
Other Real Estate Owned/Assets	0.00208	0.00535
Percent Change in Dow Jones US Total Stock Market Index	0.02318	0.20130
Percent Change in Federal Housing Finance Agency (FHFA) House Price Index (HPI), by state	0.04055	0.05043
Dividends on Common Stock/Assets[a]	0.00664	0.01940
Dividends on Preferred Stock/Assets[a]	0.00001	0.00017
Change in Capital Stock/Assets[a]	0.00039	0.00538
Change in Treasury Stock/Assets[a]	-0.00001	0.00068

[a] Regressors for the "strategic" model are available from 2001.

Table 4: Regression Results, Equation (1), Risk1 Model

Year	Current Equity / Assets	Return on Assets	Nonperf. Loans / ALLL	Loans / Assets	% Change of FHFA HPI	Intercept	Number of Obs.	Adjusted R^2
1999-2009	0.8922* (0.0000)	0.0462** (0.0144)	-0.0001*** (0.0903)	-0.0093* (0.0000)	0.0180* (0.0000)	0.0165* (0.0000)	65,460	0.8156
2000	0.8970* (0.0000)	0.0154 (0.8111)	-0.0002* (0.0000)	-0.0177* (0.0000)	-0.0068 (0.1983)	0.0232* (0.0000)	13,453	0.8497
2001	0.8970* (0.0000)	0.1115*** (0.0597)	0.0001 (0.6511)	-0.0119* (0.0000)	-0.0156* (0.0004)	0.0189* (0.0000)	13,062	0.8590
2002	0.8997* (0.0000)	-0.0272 (0.6398)	0.0002 (0.1783)	-0.0045* (0.0015)	-0.0180* (0.0003)	0.0155* (0.0000)	12,732	0.8439
2003	0.9099* (0.0000)	-0.0908*** (0.0680)	0.0004** (0.0146)	0.0014 (0.2289)	0.0025 (0.6782)	0.0093* (0.0000)	12,390	0.8156
2004	0.9163* (0.0000)	-0.0522 (0.1953)	0.0006* (0.0003)	-0.0027** (0.0234)	0.0133* (0.0055)	0.0099* (0.0000)	11,997	0.8085
2005	0.9127* (0.0000)	0.0153 (0.7100)	0.0002 (0.2782)	-0.0075* (0.0000)	0.0213* (0.0000)	0.0130* (0.0000)	11,610	0.8172
2006	0.9179* (0.0000)	0.0508 (0.3174)	-0.0001 (0.6709)	-0.0107* (0.0000)	0.0166* (0.0001)	0.0163* (0.0000)	11,270	0.8118
2007	0.8797* (0.0000)	0.0821 (0.1729)	-0.0006* (0.0007)	-0.0118* (0.0000)	0.0413* (0.0000)	0.0185* (0.0000)	10,968	0.7811
2008	0.8298* (0.0000)	0.1317* (0.0004)	-0.0013* (0.0000)	-0.0140* (0.0000)	0.0054 (0.1917)	0.0252* (0.0000)	10,732	0.7739
2009	0.8555* (0.0000)	0.1128* (0.0000)	-0.0001 (0.3577)	-0.0069* (0.0000)	0.0200* (0.0000)	0.0185* (0.0000)	10,593	0.7866

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. Number of observations shown for each year equals the sum of sample banks in that year plus those in the prior year, as explained in the text. ALLL is the allowance for loan and lease losses. FHFA HPI is the Federal Housing Finance Agency House Price Index, by state.

Table 5: Regression Results, Equation (1), Risk2 Model

Year	Current Equity / Assets	Return on Assets	Nonperf. Loans / ALLL	Loans / Assets	Trading. Account Assets / Assets	Non-interest Income / Assets	Wages/ Assets	Fixed Asset Expenses/ Assets	Other Non-interest Expenses/ Assets	Other Real Estate Owned/ Assets	% Chang in DJ Tota US Index
1999-2009	0.8913* (0.0000)	0.0318*** (0.0755)	-0.0001 (0.1389)	-0.0088* (0.0000)	-0.0503** (0.0350)	0.0005 (0.9841)	0.0058 (0.8445)	-0.1623*** (0.0734)	0.0077 (0.8018)	-0.0695* (0.0000)	0.0026* (0.0000)
2001	0.9005* (0.0000)	-0.0464 (0.3175)	-0.0002* (0.0002)	-0.0149* (0.0000)	-0.1061*** (0.0925)	0.0882*** (0.0974)	-0.0035 (0.9471)	-0.1475 (0.4818)	-0.0804 (0.1788)	0.0265 (0.5496)	0.0049* (0.0000)
2002	0.8994* (0.0000)	-0.0312 (0.3766)	0.0002 (0.2528)	-0.0059* (0.0000)	-0.0211 (0.6281)	0.0969 (0.1249)	-0.0050 (0.9203)	-0.3562* (0.0019)	-0.0841 (0.1387)	0.0883** (0.0298)	0.0180* (0.0000)
2003	0.9035* (0.0000)	-0.0688** (0.0273)	0.0002*** (0.0649)	-0.0029* (0.0077)	-0.0100 (0.7884)	0.0322 (0.5754)	-0.0016 (0.9782)	-0.2655** (0.0289)	0.0044 (0.8998)	0.0975** (0.0116)	0.0006 (0.2580)
2004	0.9114* (0.0000)	-0.0683** (0.0392)	0.0005* (0.0013)	-0.0007 (0.5225)	0.0117 (0.7316)	-0.0142 (0.7868)	0.0391 (0.5441)	-0.2019 (0.1082)	-0.0094 (0.8024)	0.1326* (0.0003)	0.0023* (0.0000)
2005	0.9122* (0.0000)	-0.0010 (0.9769)	0.0002*** (0.0733)	-0.0056* (0.0000)	-0.0340** (0.0291)	-0.0403 (0.2576)	0.0256 (0.5568)	-0.1134 (0.2681)	0.0292 (0.4258)	0.1031* (0.0066)	-0.0023** (0.0339)
2006	0.9168* (0.0000)	0.0315 (0.3921)	0.0001 (0.4150)	-0.0080* (0.0000)	-0.0643* (0.0002)	-0.0392 (0.2786)	0.0292 (0.5577)	-0.1248 (0.1895)	0.0652 (0.2719)	0.0154 (0.6909)	-0.0006 (0.8574)
2007	0.8855* (0.0000)	0.0855** (0.0466)	-0.0004* (0.0021)	-0.0121* (0.0000)	-0.0732* (0.0090)	-0.0759*** (0.0825)	0.0271 (0.6125)	-0.1322 (0.2280)	0.1072*** (0.0938)	-0.1110* (0.0025)	0.0260* (0.0000)
2008	0.8603* (0.0000)	0.1240* (0.0017)	-0.0008* (0.0000)	-0.0118* (0.0000)	-0.0514** (0.0186)	-0.0596 (0.1755)	-0.0234 (0.6997)	-0.0956 (0.4045)	0.1310** (0.0437)	-0.1768* (0.0000)	-0.0006 (0.4556)
2009	0.8430* (0.0000)	0.0912* (0.0035)	-0.0001 (0.3678)	-0.0096* (0.0000)	-0.0286 (0.1901)	-0.0499 (0.1973)	0.0413 (0.4591)	-0.4556* (0.0021)	0.0210 (0.6206)	-0.1031* (0.0000)	0.0018* (0.0002)

Dependent variable: one-year-ahead equity/assets ratio. *p*-values in parentheses, based on robust (White) standard *0.01, **0.05, and ***0.10. Number of observations shown for each year equals the sum of sample banks in that ye years year, as explained in the text.

Table 6: Out-of-Sample Forecast Accuracy for Equity/Assets

Model[a]	**Regression Type[b]**	**Average of 2001-2011 Correlations between Actual and Fitted Equity/Assets**	**Average of 2001-2011 Mean Absolute Forecast Errors**	**Average of 2001-2011 Median Absolute Forecast Errors**	**Average Percent of Banks Correctly Predicted to be in Bottom 5%**	**Type II error (100 banks vs bottom 5%)[c]**	**Type II error (75 banks vs bottom 4%)[c]**	**Type II error (50 banks vs bottom 3%)[c]**	**Type II error (25 banks vs bottom 2%)[c]**
Risk1	OLS	**0.8980[d]**	**0.0085**	**0.0055**	54.98%	20.00%	**20.12%**	**20.88%**	**20.00%**
Risk1	0.05	0.8670	0.0205	0.0174	54.87%	20.03%	22.78%	22.98%	22.45%
Risk1	0.10	0.8851	0.0151	0.0124	**76.24%**	**18.67%**	20.91%	21.12%	**21.66%**
Risk2	OLS	**0.8955**	0.0098	0.0070	56.06%	**19.08%**	**19.43%**	**20.98%**	22.66%
Risk2	0.05	0.8515	0.0220	0.0188	53.03%	24.32%	26.12%	29.11%	27.59%
Risk2	0.10	0.8772	0.0161	0.0133	**75.48%**	20.73%	23.56%	24.46%	22.46%
Strategic	OLS	0.8926	**0.0087**	**0.0056**	56.89%	19.52%	**18.46%**	**21.03%**	**19.21%**
Strategic	0.05	0.8546	0.0209	0.0177	55.86%	20.02%	22.05%	23.95%	22.58%
Strategic	0.10	0.8752	0.0156	0.0128	**77.39%**	**18.58%**	20.54%	22.83%	22.25%
Naïve	OLS	**0.9021**	**0.0086**	**0.0055**	54.21%	20.28%	24.51%	25.55%	24.10%

[a] See Tables 4-5 for regressors in Risk1 and Risk2 models. Regressors in the "Strategic" model are Equity/Assets, Return on Assets, Nonperforming Loans/Allowances for Loan and Lease Losses, Loans/Assets, Percent Change in Federal Housing Finance Agency's House Price Index (by state), Dividends on Common Stock/Assets, Dividends on Preferred Stock/Assets, Change in Capital Stock/Assets, and Change in Treasury Stock/Assets; this is essentially our Risk1 model augmented by four dynamic dividend and capital stock measures. The sole regressor in the "Naïve" model is current Equity/Assets.

[b] Regression Types: OLS (Ordinary Least Squares Regression), 0.05 (5^{th} Quantile Regression), 0.10 (10^{th} Quantile Regression). All samples exclude the 100 largest banks by assets each year.

[c] Applying a threshold that identifies a fixed number of banks (100, 75, 50, or 25) in the bottom tail (5%, 4%, 3%, 2%, or 1%), the Type II error represents the number of banks that were incorrectly predicted to be in the bottom tail, as discussed in the text. The table shows the average across all sample years of incorrect predictions in percent of bottom tail banks.

[d] Boldface entries denote any of the three best outcomes for each measure of accuracy.

Table 7: Out-of-sample Forecast Accuracy by Year Based on Risk1 Model

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
2002	0.92909	0.00750	0.00500
2003	0.90809	0.00817	0.00540
2004	0.89467	0.00785	0.00487
2005	0.90367	0.00802	0.00530
2006	0.90523	0.00773	0.00460
2007	0.89545	0.00801	0.00474
2008	0.87560	0.00996	0.00588
2009	0.88266	0.00988	0.00663
2010	0.86844	0.00937	0.00618
2011	0.91726	0.00891	0.00629
AVG	**0.89802**	**0.00854**	**0.00549**

Table 8: Mean Leverage, Actual versus Predicted (Out of Sample), Risk1 Model

Year	Mean Actual Equity/Assets	Mean Predicted Equity/Assets	t-test of Equal Means between Actual vs. Predicted Equity/Assets
2002	0.10546	0.10407	8.8124*
2003	0.10482	0.10666	-10.3192*
2004	0.10561	0.10585	-1.2305
2005	0.10502	0.10572	-3.5930*
2006	0.10702	0.10488	10.9956*
2007	0.10925	0.10699	10.4850*
2008	0.10615	0.11021	-17.4241*
2009	0.10424	0.10261	7.4604*
2010	0.10429	0.10182	11.0672*
2011	0.10818	0.10382	23.9376*
ALL	**0.10592**	**0.10530**	**10.7519***

Significance levels is *0.01.

Table 9: Out-of-Sample Forecast Accuracy for Equity/Assets (Large Banks versus Small Banks), Risk1 Model

Panel A: Large versus Small Banks (Threshold = Sample Mean = $242.2m Total Assets)

Large Banks (15,232 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
2002	0.87374	0.00721	0.00422
2003	0.82962	0.00864	0.00511
2004	0.82831	0.00780	0.00467
2005	0.87603	0.00764	0.00515
2006	0.90222	0.00650	0.00401
2007	0.85611	0.00777	0.00447
2008	0.73180	0.01117	0.00616
2009	0.80133	0.01307	0.00959
2010	0.54888	0.01142	0.00714
2011	0.89757	0.00877	0.00592
AVG	**0.81456**	**0.00900**	**0.00564**

Small Banks (50,228 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
2002	0.93728	0.00758	0.00513
2003	0.92287	0.00805	0.00543
2004	0.90381	0.00788	0.00496
2005	0.90532	0.00816	0.00532
2006	0.90276	0.00817	0.00488
2007	0.90132	0.00814	0.00494
2008	0.89853	0.00958	0.00593
2009	0.89514	0.00910	0.00603
2010	0.90091	0.00885	0.00588
2011	0.92271	0.00892	0.00640
AVG	**0.90907**	**0.00844**	**0.00549**

Panel B: Large versus Small Banks (Threshold = Sample Median = $101.4m Total Assets)

Large Banks (32,730 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
2002	0.90658	0.00711	0.00450
2003	0.86289	0.00813	0.00518
2004	0.87388	0.00749	0.00476
2005	0.90044	0.00747	0.00508
2006	0.90118	0.00690	0.00422
2007	0.87990	0.00755	0.00446
2008	0.81493	0.00979	0.00562
2009	0.86406	0.01051	0.00741
2010	0.79028	0.00958	0.00626
2011	0.90725	0.00854	0.00598
AVG	**0.87014**	**0.00831**	**0.00535**

Small Banks (32,730 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
2002	0.93813	0.00785	0.00540
2003	0.93083	0.00820	0.00557
2004	0.90141	0.00822	0.00504
2005	0.90049	0.00858	0.00559
2006	0.90236	0.00864	0.00517
2007	0.89953	0.00861	0.00521
2008	0.90673	0.01029	0.00649
2009	0.88352	0.01013	0.00634
2010	0.89653	0.00932	0.00602
2011	0.92467	0.00928	0.00641
AVG	**0.90842**	**0.00891**	**0.00573**

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

Large Banks (12,114 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
2002	0.85695	0.00727	0.00427
2003	0.83093	0.00893	0.00522
2004	0.82510	0.00815	0.00473
2005	0.87042	0.00789	0.00527
2006	0.89761	0.00664	0.00412
2007	0.86509	0.00772	0.00460
2008	0.72914	0.01149	0.00614
2009	0.80951	0.01330	0.01009
2010	0.83838	0.01117	0.00739
2011	0.88142	0.00903	0.00614
AVG	**0.84045**	**0.00916**	**0.00580**

Small Banks (53,346 Observations)

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
0.93708	0.00755	0.00510
0.92116	0.00802	0.00540
0.90291	0.00782	0.00492
0.90607	0.00809	0.00529
0.90423	0.00802	0.00481
0.89833	0.00811	0.00484
0.89546	0.00958	0.00588
0.89286	0.00914	0.00611
0.88922	0.00892	0.00588
0.92355	0.00889	0.00628
0.90709	**0.00842**	**0.00545**

Table 10: Chow Tests for Stability of Coefficients over Time, Risk1 Model

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*
2000	25.135 (6, 65,448)	5.66×10^{-30}	8.237 (6, 26,503)	6.25×10^{-9}
2001	16.732 (6, 65,448)	2.15×10^{-19}	14.204 (6, 25,782)	3.16×10^{-16}
2002	21.288 (6, 65,448)	4.09×10^{-25}	11.912 (6, 25,110)	2.13×10^{-13}
2003	51.740 (6, 65,448)	6.76×10^{-64}	3.205 (6, 24,375)	3.80×10^{-3}
2004	31.140 (6, 65,448)	1.35×10^{-37}	5.957 (6, 23,595)	3.12×10^{-6}
2005	6.357 (6, 65,448)	1.05×10^{-6}	16.170 (6, 22,868)	1.15×10^{-18}
2006	39.027 (6, 65,448)	1.21×10^{-47}	17.546 (6, 22,226)	2.22×10^{-20}
2007	14.410 (6, 65,448)	1.68×10^{-16}	18.769 (6, 21,688)	6.61×10^{-22}
2008	100.447 (6, 65,448)	2.39×10^{-126}	27.991 (6, 21,313)	1.67×10^{-33}
2009	23.752 (6, 65,448)	3.18×10^{-28}	–	–

Panel B: Test of Single Breakpoint at Year t

Break Year:	*F-statistic (Degrees of Freedom)*	*p-value*
2002	47.780 (6, 65,448)	7.91×10^{-59}
2003	25.491 (6, 65,448)	2.00×10^{-30}
2004	25.411 (6, 65,448)	2.53×10^{-30}
2005	38.765 (6, 65,448)	2.62×10^{-47}
2006	32.766 (6, 65,448)	1.15×10^{-39}
2007	65.684 (6, 65,448)	9.22×10^{-82}

Table 11: Effect of Longer Lags on Predictive Performance, Risk1 Model

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	0.89802	0.00854	0.00549
2	0.89742	0.00870	0.00563
3	0.89724	0.00873	0.00569

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	0.89802	0.00854	0.00549
2	0.80266	0.01194	0.00783
3	0.75147	0.01394	0.00932

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