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Capital Regulation at Community Banks: Lessons from 400 Failures

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Abstract

We draw on data from the recent financial crisis and its aftermath to examine factors underlying community bank performance, failure, and regulation. In particular, we investigate the failure of some 400 community banks from 2008 to 2013, with a focus on the ability of two measures of capital, tier 1 capital to assets and tier 1 capital to risk weighted assets, to explain and forecast these failures. Both measures of capital provide useful information for explaining failures in-sample. For predicting failures out of sample, we find that both measures have similar Type I error rates for given Type II error rates, particularly when the forecast horizon is relatively short. Our results accord well with those of Estrella, Park, and Peristiani (2000) who examined an earlier failure wave, and with Haldane and Madouros (2012) who brought a different approach to examining the recent failure wave. And consistent with these previous researchers, our results lend support to keeping capital requirements for community banks simple.

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"It's fine to celebrate success but it is more important to heed the lessons of failure."[1]

1. Introduction

The 2008 financial crisis provides potentially fertile ground for financial researchers. With many corners of the financial markets under severe stress, it is unsurprising that more than 400 U.S. commercial banks failed between January 2008 and August 2013; what may in fact be surprising is that only about 5 percent of commercial banks failed, given the severe stress observed in the operating environment. These failures raise questions about what could have been done to minimize the associated costs to the FDIC, what could have been done to reduce disruptions to customers of the failed banks, what caused the failures, and what changes in regulatory practices could have helped avoid the failures.

While these questions are interrelated, the lessons of these failures that we focus on are the lessons for regulatory practices. In particular, we are most interested in the lessons for setting appropriate capital regulations. Moreover, because most of the failures were failures of community banks, we are most interested in the lessons that recent bank failures offer for capital regulation at community banks.

Capital regulation has evolved substantially in the past 30 years. Before the 1980s, capital regulation was not formulaic but instead was subjective and tailored to the particular circumstances of individual banks. In light of falling levels of capital, increasing numbers of bank failures, and macroeconomic malaise, U.S. federal bank regulators imposed explicit numerical regulatory capital requirements in 1981. These requirements were made consistent across regulators in 1985, with a 5.5 percent ratio of primary capital to adjusted total assets required (Burhouse, et al 2003).

Once an explicit formula for minimum capital requirements was laid out, the shortcomings of that formula quickly became apparent. If a formula were to supplant a judgmental approach, then many would argue that the formula would need to be more complex than a simple leverage ratio to capture the nuances previously captured by judgment. Efforts to refine the initial requirements were laid out in multiple iterations of the Basel Accords; in a recent paper, the Basel Committee on Banking Supervision itself raised the question of how much complexity might be too much (Basel Committee on Banking Supervision, 2013). Capital formulas, however, do not necessarily need to supplant the judgmental approach, but the formulas could instead supplement the judgmental approach. Whether supplanting or supplementing, the question arises of how much complexity the formula for minimum capital requirements should take on. This is the question we address in this paper.

Specifically, we look at the ratio of tier 1 capital divided by bank assets (the so-called tier 1 leverage ratio, or leverage ratio for short) and the ratio of tier 1 capital to risk-weighted assets (the so called tier 1 risk based capital ratio, or risk based ratio for short) and compare these two ratios' abilities to explain and predict bank failures. We find that both ratios provide useful information for explaining failures in-sample. For predicting failures out of sample, we find that both measures have similar Type I error rates (the percent of failing banks incorrectly flagged as non-failing) for given Type II error rates (the percent of non-failing banks incorrectly flagged as failing) at the Type II error rates we believe to be most meaningful. Moreover, even in cases where the risk based ratio outperforms the leverage ratio, we argue that any benefits of increased complexity should be weighed against the associated costs of

[1] Quote commonly attributed to Bill Gates.

additional complexity. And the costs of regulatory burden may be particularly high for community banks, as demonstrated by Feldman, Heinecke, and Schmidt (2013).

We proceed below by first reviewing some related literature. Next we describe our data and methodology. After then showing our results, we offer some conclusions.

2. Related Literature

Numerous papers have studied bank failures in general, and some have focused on bank capital in particular. We do not attempt a complete survey here, but only describe a few related studies. A study perhaps most closely similar to ours is Estrella, Park, and Peristiani (2000). Like us, they also compare the performance of the leverage ratio and the risk based ratio in terms of their ability to predict bank failure. Like us, they also find that the leverage ratio's ability to predict bank failure is similar to the risk based ratio's ability to predict failure. One of the key differences between our studies is that they are drawing on failure data from the late 1980s and early 1990s whereas we are drawing on failure data from 2006-2013, and the differing nature of these episodes raises the question of whether the relationship between capital and failure differs as well. We also supplement their analysis of capital ratios in isolation with some additional variables potentially related to bank failure.

Haldane and Madouros (2012) also has some similarity to our study. They frame the issue of the choice of complexity in capital regulation as part of the broader question of how much complexity to use in decision rules in complex environments in general. When focusing on large banks internationally, they find that the leverage ratio outperforms the risk based ratio in explaining bank failure. For U.S. banks, however, they find that when considering the two capital ratios in separate univariate models, the risk based ratio is significant but the leverage ratio is not in explaining bank failures. This result differs from ours, possibly because of differences in the definition of the timing of the failure windows.[2] With that said, their additional analysis of how much model complexity to use for predicting failures comes down on the side of using less complexity, consistent with our overall message.

Cole and White (2012) focus on the determinants of the commercial bank failures that occurred in 2009. Unlike us, they do not focus on capital ratios in particular, but instead are interested in the determinants of bank failure more generally. They do, however, include the simple ratio of total equity to total assets among their candidate variables and find that simple ratio to be highly significant in explaining bank failures one or two years in the future. Furthermore, they also find that variables proxying for the CAMELS components that were found to be significant in studies of the banking crisis of 1985-1992 such as Cole and Gunther (1995) continued to be significant in explaining more recent failures.

DeYoung and Torna (2013) also examine failures during the recent crisis, with an emphasis on the role that banks' participation in nontraditional activities has on the probability of failure. They find the influence of nontraditional activities on bank failure depends on the nature of those nontraditional activities, with nontraditional activities that are fee-based (such as insurance sales) reducing the

[2] When both ratios are entered into a single equation, Haldane and Madouros find results similar to ours, with the risk based ratio having a negative and significant sign, and the leverage ratio having a significant and positive sign.

probability of failure, and nontraditional activities that are asset-based (such as securitization) increasing the probability of failure, depending on a bank's existing financial condition.

3. Data and Methodology

We draw on financial data for commercial banks obtained from the call report over the quarters from 2004:3 – 2011:2. We then relate failures observed from 2006:4 to 2013:2 to these financial data. For most of our analysis, we limit attention to banks with under $10 billion in assets, although we do include the larger banks in one of our robustness checks.

We define failure in two ways: First, we define failure according to whether a bank is closed by or received assistance from the FDIC; second, we augment these FDIC failures with banks whose capital drops to critically undercapitalized levels. Under this second approach, we define a bank as failed according to the first date at which it either is closed by the FDIC or at which it becomes critically undercapitalized according to the regulatory capital standards as set forth in FDICIA.[3] Table 1 provides a summary of our failure data. 425 banks with under $10 billion in assets were closed over the period we examine, and an additional two banks of that size received assistance. While there is substantial overlap with closures, there were also 242 banks that became critically undercapitalized. The large number of failures provides ample data for examining the relationship between capital ratios and bank failure.

In our first approach, similar to Seamans (2013), we simply look at the median values of the leverage and risk based ratios for failed banks at various quarters before failure and compare those medians to the median values for banks that did not fail during our sample period. We also compare these failed bank medians to regulatory thresholds to provide a sense of the extent to which regulatory capital requirement tends to be most binding as a bank approaches failure.

In our second approach, we look at the failed banks in isolation and see what prompt corrective action capital category the failing banks would have been placed in two years before their failure based on the values of their leverage and risk based ratios. This illuminates which ratio, if either, tended to provide advanced warning of failure based on regulatory requirements.

In our final approach, we regress observed failures on capital ratios and other financial measures using logistic regression. The following equation describes the timing conventions that we use:

$$F_{i,t+j}^{t+k} = f\left(X_{i,t}\right) + \varepsilon_{i,t} \qquad (1)$$

Where

$F_{i,t+j}^{t+k}$ takes on the value of 1 if bank *i* fails between quarter t+j and t+k and 0 otherwise,

$f()$ denotes the logistic regression function,

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[3] While such critically undercapitalized banks have not actually failed, their extremely impaired capital positions make their ongoing viability highly unlikely. Taking December 31, 2010, as an example, of the 22 commercial banks that were critically undercapitalized, only 3 were still filing a call report as of December 31, 2012.

$X_{i,t}$ is a vector of financial characteristics for bank *i* at quarter t,

and

$\varepsilon_{i,t}$ is an error term reflecting the difference between realized outcomes and initial conditions.

In our basic specification, we take j=1 and k=8, so that we are capturing failures occurring over the eight quarter window following the financial data. We also consider j=1 and k=4 (failures occurring four quarters following the financial data) and j=5 and k=8 (failures occurring from between one and two years after the failure data. In this final specification, we exclude banks failing between one and four quarters after the financial data.

Depending on which specification we are considering, $X_{i,t}$ may include one or more of the variables below. While our primary objective is not to build a failure model *per se*, we do consider additional variables beyond the leverage and risk based ratios as controls; we draw heavily on the variable list used by Cole and White (2012).

LEVRAT (tier 1 leverage ratio). The ratio of tier 1 capital to bank assets. We would expect this to have a negative influence on failure, given that capital provides protection from failure.

RBC (tier 1 risk based capital ratio). The ratio of tier 1 capital to risk weighted assets. We would expect this to have a negative influence on failure, given that capital provides protection from failure.

RWA (risk weighted assets). The ratio of risk weighted assets to total assets. To the extent that risk weights are proportional to risk, we would expect higher values of this to have a positive influence on failure.

PD90 (loans past due 90 days or more and still accruing). The ratio of loans past due 90 days or more to total assets. Because this reflects weak loan quality and a potential for future losses, we would expect higher values of this to have a positive influence on failure.

NAC (loans no longer accruing interest). The ratio of loans no longer accruing interest to total assets. Because this reflects weak loan quality and a potential for future losses, we would expect higher values of this to have a positive influence on failure.

OREO (other real estate owned). The ratio of other real estate owned to total assets. Because this reflects loan decisions that turned out poorly and because these assets may have a potential for future losses, we would expect higher values of this to have a positive influence on failure.

ALLL (allowance for loan and lease losses). The ratio of allowance for loan and lease losses to noncurrent loans. Because this ratio reflects the ability to absorb losses, we would expect higher values to have a negative influence on failure.

ROA (return on assets). The ratio of net income to total assets. Because profits have the ability to augment bank capital through retained earnings, whereas losses would erode capital, we would expect higher values of this to have a negative influence on failure.

SEC (securities). The ratio of securities held for investment or sale to total assets. Because securities are generally more liquid than loans, we would expect higher values of this to have a negative influence on failure.

SIZE (total assets). The logarithm of total assets. A control variable that could reasonably be expected to have either a positive or negative influence on failure.

CASH (cash assets). The ratio of the sum of cash and balances due from depository institutions to total assets. Because this represents highly liquid assets, we would expect this to have a negative influence on failure.

MTG (mortgages). The ratio of 1-4 family mortgages held in portfolio to total assets. While this was traditionally a safe asset, the effects of the subprime mortgage crisis could result in either a positive or negative overall influence on failure.

CRE (commercial real estate loans.) The ratio of commercial real estate loans to total assets. Because this has traditionally been a risky category of lending, we would expect a positive influence on failure.

GRO (asset growth rate). The year-over-year growth in total assets. Because rapid growth may expose a bank to increased risks, we would expect a positive influence on failure.

BIGCD (large CDs). The ratio of large CDs to total assets. Because reliance on large CDs may represent exposure to "hot money", we would expect this to have a positive influence on failure.

4. Results

Table 2 shows our first univariate results, where we compare the mean values of our explanatory variables across failed and non-failed banks. Here we define a bank as failed if it was closed by or received assistance from the FDIC at any time during the two years following the reporting of financial data. Both the leverage and risk based ratios are markedly lower for banks that failed than for banks that did not. A t-test for differences in means reveals that these differences are significant at the 1 percent level for both the leverage ratio and the risk based ratio.[4]

Beyond the basic univariate results, we also consider the differences in capital ratios as failed banks approach failure. Figure 1 plots the median values of the capital ratios as the failed banks approach failure alongside historical medians, historical fifth percentiles, and supervisory thresholds. At twelve quarters prior to failure, the median failed bank leverage ratio measures close to the historical median, suggesting little difference in leverage ratios between banks failing twelve quarters later and the median for all banks. Conversely, the median risk based ratio of failed banks at twelve quarters prior to failure is visibly lower than the same measure for all banks. Both ratios remain above the historical fifth percentile of all banks, however, which brings into question whether this optical difference is practically useful,

[4] The variables beyond the capital ratios generally accord with what would be expected in comparing failed and non-failed banks. The mean value of PD90, for example, is higher for failed banks than for nonfailed banks.

given that roughly five percent of banks present at the beginning of 2008 ended up failing by the second quarter of 2013.

A more revealing comparison may be found when the timing of each ratio's breech of the historical fifth percentiles and supervisory thresholds is examined. The risk based ratio remains near, but still above, the fifth percentile of all banks until four quarters prior to failure and sinks into the bottom five percent of banks' risk based ratios one quarter sooner than the leverage ratio. As failure draws nearer, the median failed bank leverage ratio falls below the well-capitalized threshold one quarter sooner than does the median failed bank risk based ratio. Both ratios fall below the adequately-capitalized threshold into significantly-undercapitalized territory just one quarter prior to failure, providing little advance notice of severe stress in the context of supervisory minimums.

Another way to assess the two ratios' relationship to bank failure is to look at the supervisory capital category associated with each ratio at failing banks two years before failure. Under the prompt corrective action capital category system, the category to which a bank is assigned depends on both its leverage and risk based ratio.[5] Table 3 shows the prompt corrective action category that would have been assigned to the failing banks based on their leverage and risk based ratios. To be well capitalized, a bank must have a risk based ratio of 6 percent or more and a leverage ratio of 5 percent or more; as shown in the table, the vast majority of failing banks met the standard to be well capitalized under both ratios two years before they failed, and the proportions meeting the two standards were not statistically different by a chi square test. Banks that had ratios below 3 percent were significantly undercapitalized; 7 failing banks fell below this threshold on the leverage ratio, and one failing bank fell below this threshold on the risk based ratio. While these numbers are small, the proportions meeting the two standards were statistically different based on a chi square test at the 5 percent level. Overall, given that most failing banks had high enough ratios to be considered well capitalized two years before failure, neither ratio provided an effective regulatory backstop in isolation, although the leverage ratio did mark a higher proportion of failing banks as significantly undercapitalized.

To further investigate the relationship between bank failure and the capital ratios, we conduct several logistic regressions. Using the basic framework specified in (1), we first combine data for t=2008Q2 with the associated failures for j=1 and k=8. Table 4 provides the in-sample logistic regression results. For the model that includes only the leverage ratio, the leverage ratio is highly significant in explaining failures, with the expected negative sign. As a measure of in-sample fit, we consider the Goodman-Kruskal gamma "gamma", where higher values of gamma imply a closer fit between the probability of failure from the model and actual failure.[6] Gamma for this first model is positive,

[5] The prompt corrective action category also depends on a bank's total risk based capital ratio, which we do not consider here.

[6] Formally, gamma is the ratio of (number of concordant pairs – number of discordant pairs) / (number of concordant pairs + number of discordant pairs), where a pair is said to be concordant if the observation that did not fail has a lower probability of failure than the observation that does fail, and a pair is said to be discordant if the observation that did not fail has a higher probability of failure than the observation that did fail. If the pair is neither concordant nor discordant, it is considered a tie and excluded from the calculation of gamma. Finally, gamma ranges from -1 to +1, with -1 indicating a strong negative association and +1 indicating a strong positive association.

indicating positive association between the model and realized failures, but at 0.38, the association is not particularly strong.

For the model including only the risk based ratio, the risk based ratio is also highly significant, with the expected sign. Moreover, gamma is also positive, and at 0.60 is somewhat higher than the value observed for the leverage ratio in model 1. We then estimate a model that includes both the leverage and risk based ratios. While both ratios are significant, only the risk based ratio has the expected negative sign, with the leverage ratio having a positive sign. Given the high correlation between these ratios, finding this odd sign is not too surprising; moreover, similar results were obtained under some of the specifications in Estrella, Park, and Peristiani (2000).

We also present analogs to the three models just discussed, but with *RWA* added as a single control variable. In the models that include the capital ratios individually, RWA is highly significant, with the expected positive sign that would be expected to the extent that the ratio of risk weighted assets to total assets serves as a proxy for overall riskiness. In the models with the capital ratios entered individually, we find that the capital ratios retain their expected signs and high degree of significance; in the model with both capital ratios, both ratios now have the expected negative sign, although only the risk based ratio is statistically significant. Perhaps most noteworthy in these specification is that the difference in gamma between models 4 and 5 is much lower than the difference in gamma between models 1 and 2; simply adding *RWA* gives the leverage ratio almost as much in-sample explanatory power (gamma=0.598) as the risk based ratio (gamma=0.614).

To further investigate this principle, models 7, 8, and 9 add a broader mix of explanatory variables to the capital ratios. After adding this mix of variables to capture other factors associated with failure, we find that both capital measures retain their expected negative sign and strong significance when entered individually (models 7 and 8). And when entered jointly (model 9), both ratios have the expected negative sign, but they are not statistically significant. Finally, we find that gamma is virtually equal for the model including the leverage ratio (gamma=0.842) and for the model including the risk based ratio (gamma=0.841). This suggests that under a supervisory approach that evaluates capital as part of a broader evaluation of the bank, it may make little difference whether a simple or more complex capital measure is employed. Finally, adding both capital ratios in model 9 does little to affect gamma, suggesting that Basel's requirement to include both the leverage and risk based ratios may be redundant.

RWA was significant in models 4, 5, and 6 but is insignificant in models 7, 8, and 9. One way to interpret this is that adding risk weighted assets to the capital ratios alone provides useful information for explaining failure, as indicated by the significance on RWA in models 4, 5, and 6. But when a broader range of variables is brought into consideration in models 7, 8, and 9 adding risk weighted assets does not add to the ability to explain failure. Thus, when considering the overall supervisory process, after examiners have evaluated the condition of the bank in general (as mimicked by the variables included in models 7, 8, and 9) adding risk weighted assets does not add information. And that overall supervisory process can add regulatory strictures such as supervisory actions that could in turn limit risk taking at risky banks. This raises the question of whether risk weighting assets adds useful information to the supervisory process.

While the in-sample results provide a measure of the capital measures' ability to explain failures, an ability to explain failures in-sample may not imply a commensurate ability to predict failures out of sample. To assess the capital measures' ability to predict failures out-of-sample, we apply the relationships estimated in Table 4 using financial data drawn from 2008Q2 to financial data drawn from 2010Q2 and see how well those relationships fit failures occurring over the subsequent two year period.

Figure 2 shows the Type I / Type II error tradeoffs associated with four of the models from Table 4. As can be seen from the chart, the curves tend to be fairly close together, but there are some notable differences. At fairly low Type II error rates, the model with the risk based ratio alone outperforms the other models to a notable degree; at a Type II error rate of 1 percent, the risk based ratio model's Type I error rate is 35.9 percent versus the leverage ratios model's Type I error rate of 45.8 percent. At higher Type II error rates, the differences between these two models diminishes; at a 10 percent Type II error rate, for example the leverage ratio model's Type I error rate is 15.0 percent while the risk based ratio model's Type I error rate is 12.4 percent.[7]

But perhaps more relevant are the error rates at the supervisory minimums for these ratios; during the time we examine, a 4 percent value for the leverage ratio was required as the minimum to be adequately capitalized. At a 4 percent value of the leverage ratio, the Type II error rate was 0.6 percent, and the Type I error rate was 55.6 percent; for comparison, the Type I error rate associated with the risk based ratio model at a Type II error rate of 0.6 percent was a similar 52.9 percent. Also, a 6 percent value of the risk based ratio was required to be well capitalized. At a 6 percent value of the risk based ratio, the type II error rate was 0.7 percent, and the Type I error rate was 52.3 percent; at a type II error rate of 0.7 percent, the leverage ratio had a similar Type I error rate of 53.6 percent.

Shorter Failure Horizon.

The results above consider an eight quarter horizon for capturing failures following the reporting of financial data, or j=1 and k=8 in the terminology of (1). Here we consider j=1 and k=4 (failures occurring four quarters following the financial data). Under this failure horizon, we estimate models analogous to those in Table 4 and report the results in Table 5. As in Table 4, both the leverage ratio and the risk based ratio are strongly statistically significant when entered individually in models 1 and 2. When both ratios are entered in model 3, both ratios are significant , and the sign on the leverage ratio is negative as would be expected in contrast with table 4. In the univariate models, the risk based ratio model has a higher gamma than the leverage ratio model, but the difference is much less than in the two year horizon. Also, when other variables are added (either *RWA* alone in models 4 and 5 or the broader list of variables in models 7 and 8), gamma for the models with the leverage ratio becomes similar to gamma for the models with the risk based ratio.

Figure 3 shows the Type I / Type II error tradeoffs associated with four of the models from Table 5. Not surprisingly, the Type I error rates for a given Type II error rate tend to be lower in Figure 3 than in Figure 2, reflecting relatively greater ease in forecasting at a shorter horizon than at a longer one. At the 1-percent Type II error rate, for example, Type I error rates across the models in Figure 3 range from 27.5 –31.4, substantially lower than the 35.9 – 50.3 range in Figure 2. Besides their lower levels, the

[7] We would also note that for Type II error rates up to around 5 percent, the models with additional variables have higher Type I error rates than the models with the capital ratios alone; loosely speaking, when the criterion for identifying possible failures is very tight, the additional variables create noise that diminishes out-of-sample accuracy.

difference in performance of the models also differs in the two figures. At a Type II error rate of 1 percent, the risk based ratio alone has a Type I error rate 9 percentage points below the leverage ratio's error rate in the two-year model but is only 4 percentage points lower in the one-year model.

One to Two Year Failure Horizon

As another variation on failure horizons, we consider failures that occurred more than one year but less than two years following the reporting of the financial data, or j=5 and k=8 in the terminology of (1). We examine such a window to examine the ability of the capital ratios to identify longer term failures alone; in the two year window initially considered, success in terms of either in-sample or out-of-sample forecasting ability may be affected by the relatively easy-to-forecast and explain near-term failures. Again, we estimate models analogous to those in Table 4, and report the results in Table 6. We find that both ratios are again statistically significant when entered individually in Models 1 and 2, and unsurprisingly, both gammas are slightly lower when the failure window excludes failures within one year. When both ratios are combined in Model 3, again we see an improvement in gamma over the univariate models and the leverage ratio sign turns positive as was observed in Table 4.

The gap in gamma between the leverage ratio and risk based ratio is greatly reduced when the RWA variable is added in Models 4, 5, and 6. The leverage and risk based ratios hold their negative signs when RWA is added to the univariate models (Models 4 and 5). When the additional variable set is added in Models 7, 8, and 9, the observed gammas across the models are nearly equal.

Figure 4 shows the out of sample performance under this alternative failure window. Performance is generally poorer than in figures 2 and 3, reflecting the greater difficulty of forecasting failures more than a year away. At low Type II error rates, the difference in performance between the leverage ratio and the risk based ratio is small, with Type I error rates of 78.4 and 77.1 respectively at a Type II error rate of 1 percent. As was the case for the other failure windows, when additional variables are considered, the performance of the model with the leverage ratio is very similar to the performance of the model with the risk based ratio.

Alternative Failure Definition

We have focused on analyzing failures defined as the actual closure of a bank by the FDIC. But beyond outright closure, a bank whose capital position deteriorates to critically undercapitalized under FDICIA's prompt corrective action capital guidelines is generally required to be closed under those capital guidelines.[8] Because one or more quarters may elapse between the time a bank becomes critically undercapitalized and the time at which the FDIC closes the bank, becoming critically undercapitalized may be a more timely indicator of the time at which the bank fails in an economic sense, even if it continues operating (generally under various regulatory strictures) for some time. With that background, we adjusted our definition of failure to be the earliest quarter at which a bank either becomes critically undercapitalized or is closed by the FDIC.

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[8] Banks with tangible equity capital to total assets less than or equal to 2 percent are critically undercapitalized under the guidelines. A bank that becomes critically undercapitalized is required to be put into receivership or conservatorship shortly after becoming critically undercapitalized unless the FDIC and other relevant regulators agree that another action would better serve the intentions of prompt corrective action (Spong, 2000).

Under this alternative definition of failure, we estimated models analogous to those in Table 4, and we continue to find a strong in-sample relationship between failure and both the leverage ratio and the risk based ratio. As shown in Table 7, both capital ratios are strongly significant when entered in univariate form. When RWA is added, both ratios continue to be statistically significant with the expected sign in models 4 and 5, and as was the case in Table 4, the difference in gamma between the model with the leverage ratio and the model with the risk based ratio is greatly diminished after adding RWA. Finally, we would note that RWA becomes insignificant after the additional variables are added in models 7, 8, and 9, consistent with the idea that risk weighting assets provides little supplemental information after the supervisory process has reviewed the condition of the bank in general.

All-Bank Results

We also estimated a model that included all banks, not just those with assets under $10 billion. We do not show a table of results here, but the results were generally similar to those obtained when the sample was limited to the smaller banks. Given that we are estimating an unweighted model, and smaller banks make up the vast majority of banks by number, it is not surprising that our results are little changed when the larger banks are added to the sample.

5. Conclusion

We have found that a simple capital ratio can be about as effective as a more complex one in predicting bank failures during and after the recent financial crisis. Such a result is consistent with the findings of Estrella, Park, and Peristiani (2000) who studied an earlier wave of failures in the late 1980s and early 1990s. The similarity of our findings is perhaps not surprising, given that Cole and White (2012) found that the factors predicting the early wave of failures in the recent financial crisis were similar to the factors predicting failures in the earlier period as well.

Also unsurprising is that capital has a strong negative relationship with bank failure. An ample supply of capital provides a cushion that absorbs losses and protects against failure. Moreover, an ample supply of capital heightens bank managers' incentives to avoid losses in the first place. These simple benefits are, to a first order approximation, similar for either the leverage ratio or the risk based ratio.

What is more surprising is the ongoing call for ever more complex formulas for assessing capital. Our results suggest that a simple ratio in conjunction with regulatory judgment could go a long way toward promoting safety and soundness. And even if a more complex capital regime may offer some benefits for larger institutions, one is left wondering whether the associated costs are justifiable for community banking organizations.

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Table 1. Failures During 2006:Q1 – 2013:Q2*

	Banks with assets $10B or less			Banks with assets over $10B		
Quarter	FDIC Closures	FDIC Assistances	Became Critically Undercapitalized	FDIC Closures	FDIC Assistances	Became Critically Undercapitalized
2006:01	0	0	0	0	0	0
2006:02	0	0	0	0	0	0
2006:03	0	0	0	0	0	0
2006:04	1	0	0	0	0	0
2007:01	0	0	0	0	0	0
2007:02	0	0	0	0	0	0
2007:03	1	0	0	0	0	0
2007:04	1	0	1	0	0	0
2008:01	2	0	1	0	0	0
2008:02	5	0	1	0	0	0
2008:03	9	2	2	0	2	0
2008:04	16	0	3	0	6	0
2009:01	19	0	15	0	0	0
2009:02	40	0	15	1	0	0
2009:03	35	0	16	1	0	0
2009:04	29	0	26	0	0	0
2010:01	49	0	19	1	0	0
2010:02	36	0	19	0	0	0
2010:03	28	0	16	0	0	0
2010:04	27	0	15	0	0	0
2011:01	19	0	19	0	0	0
2011:02	23	0	15	0	0	0
2011:03	22	0	11	0	0	0
2011:04	10	0	9	0	0	0
2012:01	10	0	9	0	0	0
2012:02	14	0	8	0	0	0
2012:03	9	0	7	0	0	0
2012:04	4	0	7	0	0	0
2013:01	9	0	5	0	0	0
2013:02	7	0	3	0	0	0
Total	425	2	242	3	8	0

*For banks where FDIC closure and becoming critically undercapitalized occur in the same quarter, those banks are recorded as FDIC closures only.

Table 2: Means and Standard Deviations for Failed and Non-Failed Banks

	Banks with Under $10 Billion in Assets			
	Failed		Non-Failed	
Variable	Mean	Standard Deviation	Mean	Standard Deviation
LEVRAT**	7.19	3.38	11.26	6.54
RBC**	8.92	4.13	16.99	12.37
RWA**	0.80	0.11	0.71	0.15
PD90**	0.35	0.61	0.17	0.35
NAC**	5.47	3.90	0.97	1.53
OREO**	2.19	2.32	0.40	0.87
ALLL**	4.79	27.63	23.42	61.52
ROA**	-1.87	2.69	0.63	1.49
SEC**	0.11	0.09	0.21	0.15
SIZE**	12.52	1.16	11.85	1.21
CASH	0.06	0.06	0.06	0.06
MTG**	0.14	0.10	0.17	0.12
CRE**	0.46	0.16	0.24	0.17
GRO**	6.35	24.16	9.77	21.21
BIGCD**	0.22	0.11	0.16	0.08
Observations	3,179		158,783	

	All Banks			
	Failed		Non-Failed	
Variable	Mean	Standard Deviation	Mean	Standard Deviation
LEVRAT**	7.22	3.40	11.23	6.52
RBC**	9.02	4.20	16.94	12.34
RWA**	0.80	0.11	0.71	0.15
PD90**	0.35	0.60	0.17	0.36
NAC**	5.36	3.93	0.97	1.52
OREO**	2.14	2.32	0.40	0.87
ALLL**	4.69	27.27	23.26	61.32
ROA**	-1.80	2.70	0.63	1.49
SEC**	0.11	0.09	0.21	0.15
SIZE**	12.67	1.46	11.91	1.34
CASH	0.06	0.06	0.06	0.06
MTG**	0.14	0.11	0.17	0.12
CRE**	0.45	0.16	0.24	0.17
GRO**	6.91	25.10	9.81	21.28
BIGCD**	0.22	0.11	0.16	0.08
Observations	3,266		160,541	

**Difference between means of failed and non-failed banks significant at 1 percent; *difference between means of failed and non-failed banks significant at 5 percent

Note: Here we define a bank as failed if it was closed by or received assistance from the FDIC at any time during the two years following the reporting of financial data. Financial data drawn from 2006Q1 – 2011Q2.

Source: FFIEC, FDIC, authors' calculations.

Table 3: Number of Failing Banks in Prompt Corrective Action Category by Leverage and Risk Based Ratio Requirements Two Years before Failure

Prompt Corrective Action Category	Based on Leverage Ratio	Based on Risk Based Ratio
Well Capitalized	401	408
Adequately Capitalized	12	10
Undercapitalized	5	6
Significantly Undercapitalized	7	1

Note: Represents the 425 banks that were either closed by or received assistance from the FDIC between 2006Q1-2013Q2 and that had reported financial data two years before failure.

Table 4: Logistic Regression Results: 8 Quarter Failure Window, FDIC Closures and Assistances Only, Banks under $10 Billion in Assets Only, Estimated Using 2008Q2 Financials and 2008Q3 – 2010Q2 Failures

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Intercept	-1.0779**	0.7390*	0.1430	-5.5996**	-2.2095**	-0.7450**	-6.7014**	-4.5502**	-6.3382**
	(0.3128)	(0.3601)	(0.3604)	(0.4937)	(0.6946)	(1.9024)	(1.4761)	(1.6206)	(2.1736)
LEVRAT	-0.2417**		0.2328**	-0.3471**		-0.1526	-0.2142**		-0.1810
	(0.0340)		(0.0440)	(0.0423)		(0.1790)	(0.0380)		(0.1511)
RBC		-0.3432**	-0.4777**		-0.2850**	-0.4092**		-0.1725**	-0.0273
		(0.0329)	(0.0451)		(0.0339)	(0.1526)		(0.0309)	(0.1208)
RWA				6.9032**	2.8210**	1.0384	0.9246	-1.7437	0.4938
				(0.5960)	(0.5831)	(2.2035)	(1.2208)	(1.2283)	(2.2471)
PD90							0.7305**	0.7280**	0.7299**
							(0.1521)	(0.1521)	(0.1521)
NAC							0.3356**	0.3329**	0.3352**
							(0.0449)	(0.0448)	(0.0449)
OREO							0.3166**	0.3139**	0.3160**
							(0.0917)	(0.0916)	(0.0917)
ALLL							-0.0013	-0.0013	-0.0013
							(0.0032)	(0.0031)	(0.0032)
ROA							-0.2757**	-0.2692**	-0.2747**
							(0.0489)	(0.0486)	(0.0490)
SEC							-0.6719*	-0.6737	-0.6686
							(1.3064)	(1.3261)	(1.3116)
SIZE							0.2356**	0.2407**	0.2358**
							(0.0759)	(0.0759)	(0.0760)
CASH							-8.0635*	-8.2082*	-8.1002*
							(3.5427)	(3.5701)	(3.5537)
MTG							-2.7586**	-2.8496**	-2.7823**
							(1.0492)	(1.0583)	(1.0557)
CRE							3.2279**	3.2110**	3.2252**
							(0.6689)	(0.6684)	(0.6690)
GRO							0.0093**	0.0090**	0.0092**
							(0.0029)	(0.0029)	(0.0029)
BIGCD							1.6511	1.6572	1.6508
							(0.8640)	(0.8634)	(0.8641)
Fails	235	235	235	235	235	235	235	235	235
Nonfails	7,292	7,292	7,292	7,292	7,292	7,292	7,292	7,292	7,292
Gamma	0.379	0.602	0.623	0.598	0.614	0.621	0.842	0.841	0.843
AIC	2,009.0	1,865.2	1,843.7	1,849.8	1,844.1	1,845.5	1,364.1	1,365.2	1,366.1

**significant at 1 percent; *significant at 5 percent. Standard errors in parentheses.

Table 5: Logistic Regression Results: 4 Quarter Failure Window, FDIC Closures and Assistances Only, Banks under $10 Billion in Assets Only, Estimated Using 2008Q2 Financials and 2008Q3 – 2009Q2 Failures and 2009Q2 Financials and 2009Q3 – 2010Q2 Failures

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Intercept	4.1759**	4.8278*	5.0614**	-0.6620	6.7497**	4.0780*	-4.7988**	-0.5657	-5.3969**
	(0.3221)	(0.3483)	(0.3529)	(0.5805)	(0.7196)	(1.5942)	(1.4828)	(1.7113)	(1.5807)
LEVRAT	-1.0212**		-0.2879**	-1.1174**		-0.4281	-0.6263**		-0.7040**
	(0.0451)		(0.0440)	(0.0485)		(0.2355)	(0.0575)		(0.0944)
RBC		-0.8583**	-0.6486**		-0.8681**	-0.5378**		-0.4642**	0.0595
		(0.0381)	(0.0664)		(0.0382)	(0.1839)		(0.0442)	(0.0558)
RWA				7.2855**	-2.2012**	1.2565	2.8397*	-3.0031*	3.6154*
				(0.7376)	(0.7253)	(1.8984)	(1.2094)	(1.4050)	(1.4077)
PD90							0.4473**	0.4389**	0.4479**
							(0.1439)	(0.1431)	(0.1439)
NAC							0.2533**	0.2542**	0.2531**
							(0.0328)	(0.0326)	(0.0328)
OREO							0.1677**	0.1702**	0.1679**
							(0.0587)	(0.0582)	(0.0587)
ALLL							0.0050	0.0052	0.0046
							(0.0052)	(0.0052)	(0.0053)
ROA							-0.2335**	-0.2357**	-0.2341**
							(0.0368)	(0.0365)	(0.0368)
SEC							0.0269	0.4030	-0.0270
							(1.3486)	(1.4494)	(1.3041)
SIZE							0.1660*	0.1718*	0.1650*
							(0.0789)	(0.0788)	(0.0787)
CASH							-5.2388*	-4.8388*	-5.2922*
							(2.1593)	(2.1970)	(2.1426)
MTG							-3.5576**	-3.4926**	-3.5184**
							(1.1329)	(1.1485)	(1.1281)
CRE							2.1571**	2.0799**	2.1883**
							(0.7753)	(0.7718)	(0.7765)
GRO							0.0053	0.0050	0.0053
							(0.0040)	(0.0039)	(0.0039)
BIGCD							1.8363	1.8092	1.8379
							(0.9449)	(0.9397)	(0.9448)
Fails	235	235	235	235	235	235	235	235	235
Nonfails	14,566	14,566	14,566	14,566	14,566	14,566	14,566	14,566	14,566
Gamma	0.772	0.843	0.839	0.834	0.842	0.839	0.931	0.929	0.930
AIC	1,710.9	1,588.2	1,577.3	1,585.5	1,579.9	1,578.9	1,203.3	1,214.2	1,204.7

**significant at 1 percent; *significant at 5 percent. Standard errors in parentheses.

Table 6: Logistic Regression Results: 4 Quarter Failure Window Starting 4 Quarters After Financial Data Reported, FDIC Closures and Assistances Only, Banks under $10 Billion in Assets Only, Estimated Using 2007Q2 Financials and 2008Q3 – 2009Q2 Failures and 2008Q2 Financials and 2009Q3 – 2010Q2 Failures

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Intercept	-3.0724**	-1.6186*	-2.0572**	-6.9579	-5.2694**	-8.1621**	-7.6594**	-7.1558**	-8.9149**
	(0.2387)	(0.2784)	(0.2704)	(0.4327)	(0.5344)	(0.5425)	(1.3124)	(1.4050)	(1.3716)
LEVRAT	-0.1027**		0.1810**	-0.2040**		-0.3207**	-0.1084**		-0.2115**
	(0.0235)		(0.0323)	(0.0315)		(0.0459)	(0.0290)		(0.0460)
RBC		-0.1923**	-0.2986**		-0.1345**	0.0873**		-0.0656**	0.0800**
		(0.0232)	(0.0326)		(0.0223)	(0.0215)		(0.0219)	(0.0239)
RWA				6.1426**	3.6580**	7.6973**	0.4552	-0.8241	2.0387
				(0.5247)	(0.4835)	(0.6940)	(1.0407)	(1.0176)	(1.1822)
PD90							0.7428**	0.7451**	0.7447**
							(0.1428)	(0.1424)	(0.1430)
NAC							0.2486**	0.2458**	0.2503**
							(0.0474)	(0.0472)	(0.0474)
OREO							0.3685**	0.3704**	0.3708**
							(0.0979)	(0.0977)	(0.0980)
ALLL							-0.0040*	-0.0042*	-0.0042*
							(0.0019)	(0.0019)	(0.0019)
ROA							-0.1566**	-0.1499**	-0.1598**
							(0.0540)	(0.0533)	(0.0541)
SEC							-1.0743	-1.1860	-0.9555
							(1.1813)	(1.1749)	(1.1409)
SIZE							0.2220**	0.2470**	0.2142**
							(0.0709)	(0.0703)	(0.0705)
CASH							-12.4932**	-12.5076**	-12.2169**
							(4.1406)	(4.1147)	(4.0619)
MTG							-2.6767**	-2.6390**	-2.4754*
							(0.9896)	(0.9853)	(0.9866)
CRE							4.3067**	4.2857**	4.3514**
							(0.6102)	(0.6089)	(0.6098)
GRO							0.0110**	0.0105**	0.0111**
							(0.0025)	(0.0025)	(0.0025)
BIGCD							1.6859*	1.7014*	1.7197*
							(0.7457)	(0.7447)	(0.7450)
Fails	235	235	235	235	235	235	235	235	235
Nonfails	14,880	14,880	14,880	14,880	14,880	14,880	14,880	14,880	14,880
Gamma	0.263	0.535	0.595	0.590	0.599	0.585	0.804	0.803	0.805
AIC	2,394.0	2,293.4	2,263.3	2,218.8	2,235.3	2,214.8	1,817.4	1,824.5	1,814.8

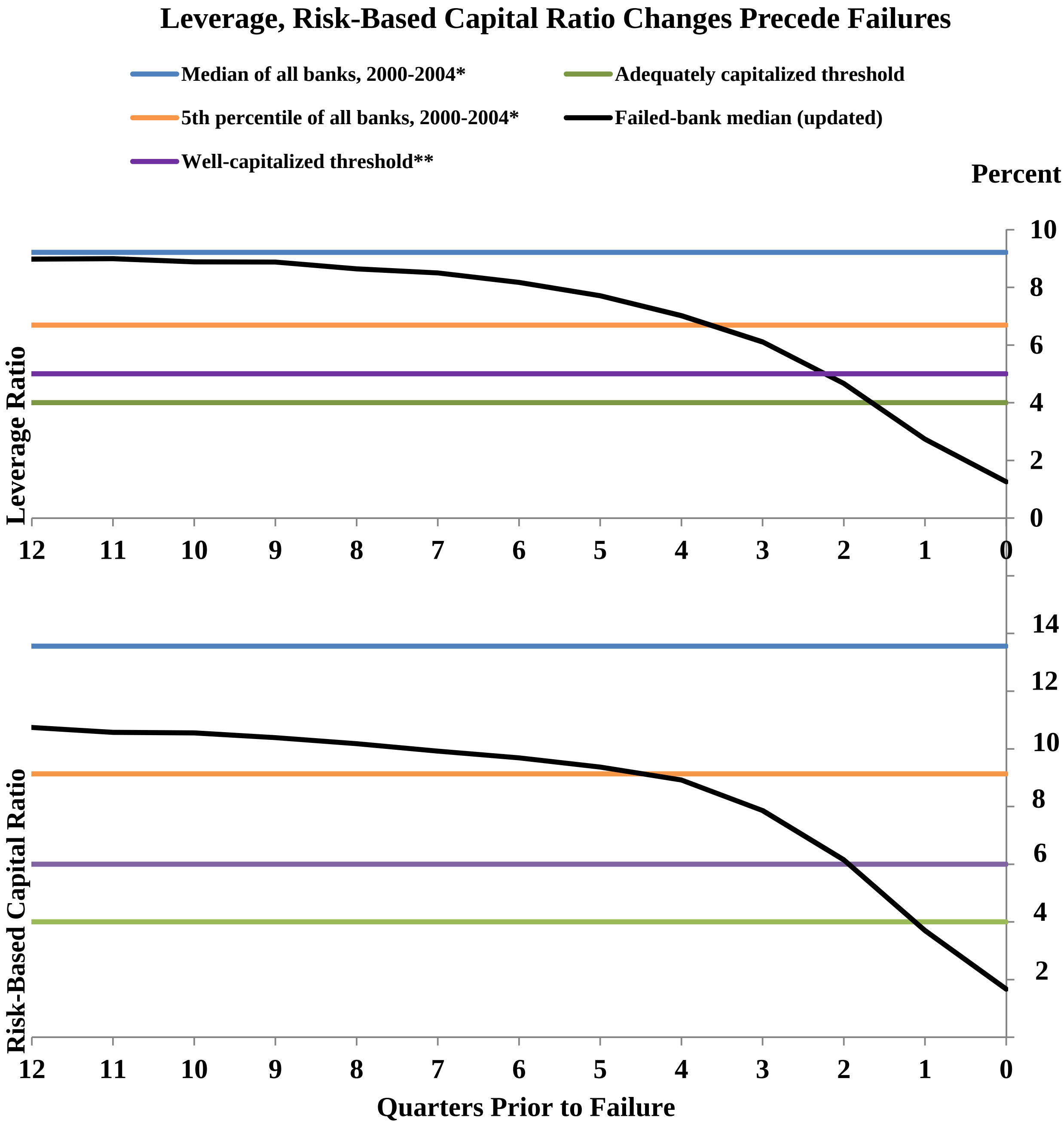
**significant at 1 percent; *significant at 5 percent. Standard errors in parentheses.

Table 7: Logistic Regression Results: 8 Quarter Failure Window, FDIC Closures and Assistances and Critical Undercapitalizations, Banks under $10 Billion in Assets Only, Estimated Using 2008Q2 Financials and 2008Q3 – 2010Q2 Failures

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Intercept	-1.5862**	-0.2449	-0.7722**	-5.9048**	-3.6417**	-6.2423**	-7.0397**	-5.8821**	-7.9779**
	(0.2651)	(0.2888)	(0.2827)	(0.4558)	(0.5938)	(1.0923)	(1.3547)	(1.4589)	(1.4719)
LEVRAT	-0.1719**		0.2124**	-0.2382**		-0.2721**	-0.1421**		-0.2148**
	(0.0277)		(0.0364)	(0.0329)		(0.1050)	(0.0292)		(0.0512)
RBC		-0.2415**	-0.3653**		-0.1815**	0.0263		-0.0996**	0.0575
		(0.0251)	(0.0360)		(0.0250)	(0.0769)		(0.0226)	(0.0319)
RWA				6.2454**	3.3346**	6.6698**	0.3728	-1.4864	1.5459
				(0.5363)	(0.5316)	(1.3637)	(1.1005)	(1.1017)	(1.3276)
PD90							0.8038**	0.8052**	0.8052**
							(0.1427)	(0.1422)	(0.1428)
NAC							0.3019**	0.2990**	0.3038**
							(0.0424)	(0.0423)	(0.0424)
OREO							0.3543**	0.3546**	0.3565**
							(0.0859)	(0.0856)	(0.0860)
ALLL							0.0031	0.0027	0.0029
							(0.0026)	(0.0026)	(0.0026)
ROA							-0.3140**	-0.3067**	-0.3167**
							(0.0460)	(0.0455)	(0.0461)
SEC							-1.0863	-1.2062	-0.9696
							(1.2043)	(1.2147)	(1.1823)
SIZE							0.2539**	0.2727**	0.2485**
							(0.0718)	(0.0715)	(0.0716)
CASH							-7.1672*	-7.3095*	-7.1155*
							(3.1706)	(3.1724)	(3.1334)
MTG							-1.9904*	-2.0325*	-1.8430
							(0.9436)	(0.9466)	(0.9442)
CRE							3.2870**	3.2664**	3.3035**
							(0.6279)	(0.6266)	(0.6282)
GRO							0.0064*	0.0060*	0.0064*
							(0.0028)	(0.0028)	(0.0028)
BIGCD							1.7499*	1.7738*	1.7602*
							(0.8149)	(0.8135)	(0.8142)
Fails	266	266	266	266	266	266	266	266	266
Nonfails	7,259	7,259	7,259	7,259	7,259	7,259	7,259	7,259	7,259
Gamma	0.359	0.580	0.601	0.573	0.583	0.571	0.822	0.821	0.824
AIC	2,238.6	2,119.1	2,093.0	2,077.7	2,082.1	2,079.6	1,537.4	1,544.0	1,537.6

**significant at 1 percent; *significant at 5 percent. Standard errors in parentheses.

Figure 1: Capital Ratios Preceding Failure



***The median and 5th percentile values are constants calculated using the five-year period preceding the analysis window and include all commercial banks from 2000:Q1 through 2004:Q4. Failed bank medians include banks that failed between 2008:Q1 and 2013:Q2.**

****To be considered well capitalized, banks must have a tier 1 leverage ratio of 5 percent or more, a tier 1 risk-based capital ratio of 6 percent or more and a total risk-based capital ratio of 10 percent or more.**

SOURCES: Federal Deposit Insurance Corp.; Report of Condition and Income from the Federal Financial Institutions Examination Council.

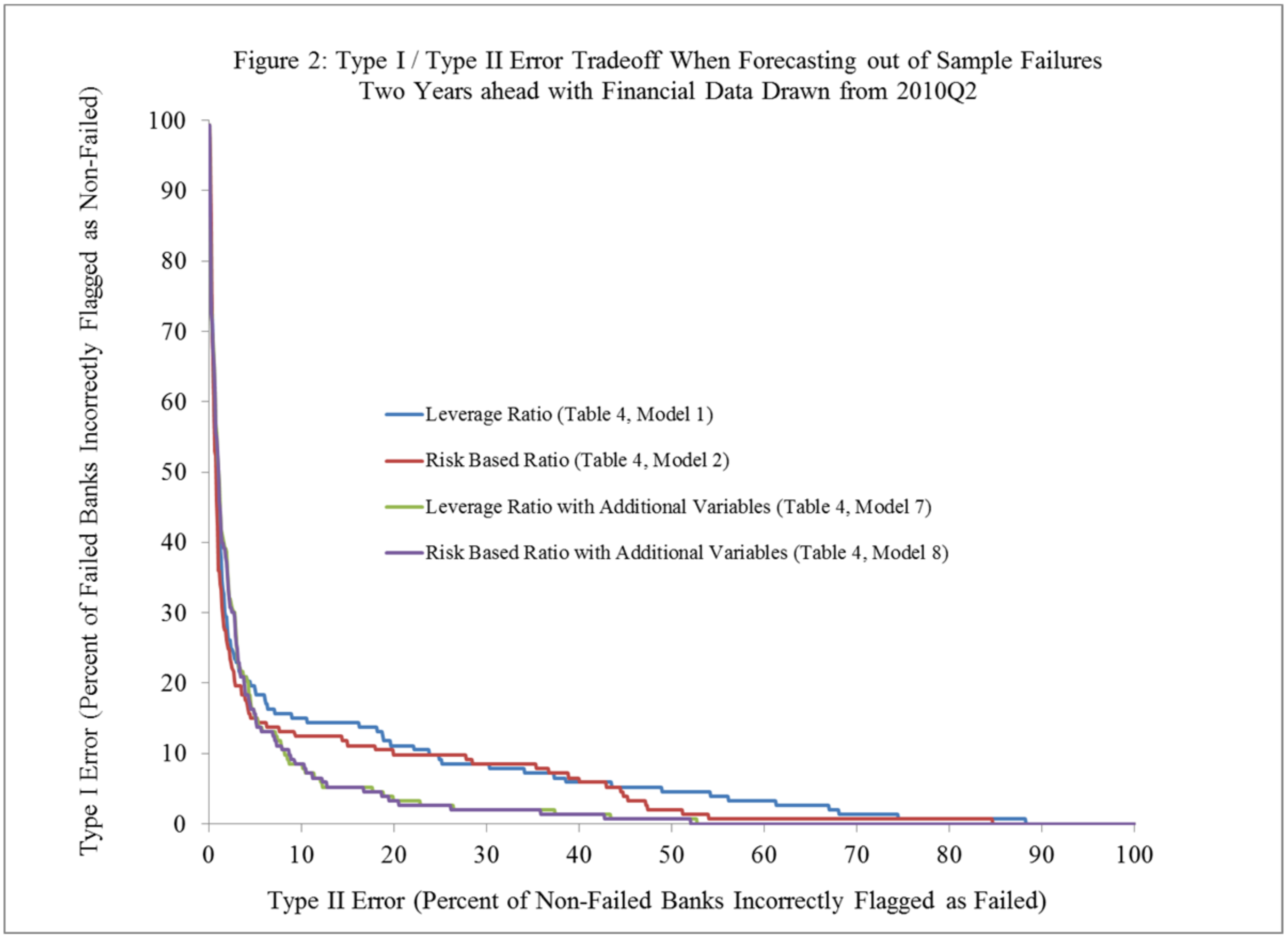


Figure 2: Type I / Type II Error Tradeoff When Forecasting out of Sample Failures
Two Years ahead with Financial Data Drawn from 2010Q2
Type I Error (Percent of Failed Banks Incorrectly Flagged as Non-Failed)
100
90
80
70
60
50
40
30
20
10
0
Leverage Ratio (Table 4, Model 1)
Risk Based Ratio (Table 4, Model 2)
Leverage Ratio with Additional Variables (Table 4, Model 7)
Risk Based Ratio with Additional Variables (Table 4, Model 8)
0
10
20
30
40
50
60
70
80
90
100
Type II Error (Percent of Non-Failed Banks Incorrectly Flagged as Failed)

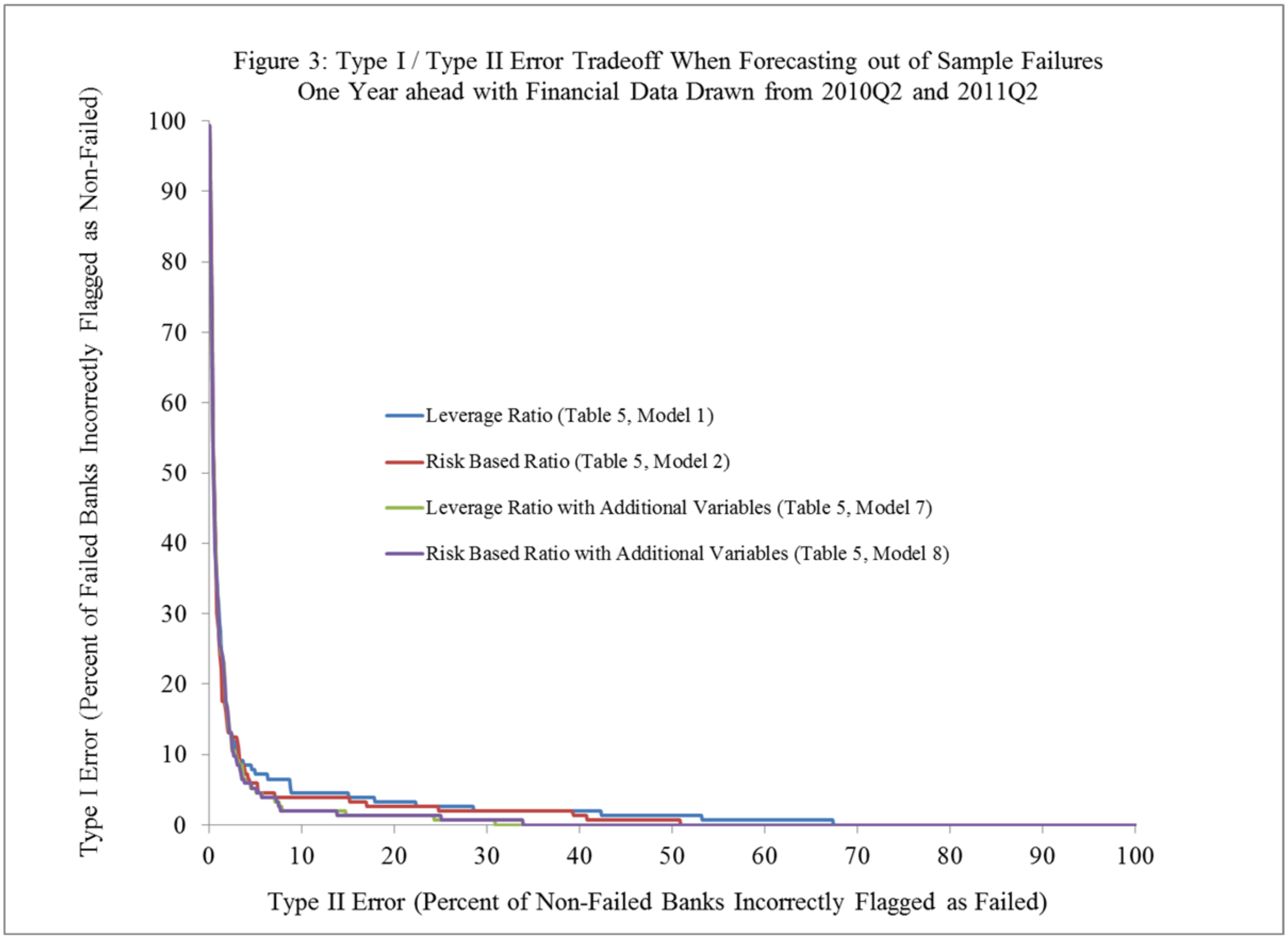


Figure 3: Type I / Type II Error Tradeoff When Forecasting out of Sample Failures One Year ahead with Financial Data Drawn from 2010Q2 and 2011Q2
Type I Error (Percent of Failed Banks Incorrectly Flagged as Non-Failed)
Leverage Ratio (Table 5, Model 1)
Risk Based Ratio (Table 5, Model 2)
Leverage Ratio with Additional Variables (Table 5, Model 7)
Risk Based Ratio with Additional Variables (Table 5, Model 8)
Type II Error (Percent of Non-Failed Banks Incorrectly Flagged as Failed)
0
10
20
30
40
50
60
70
80
90
100

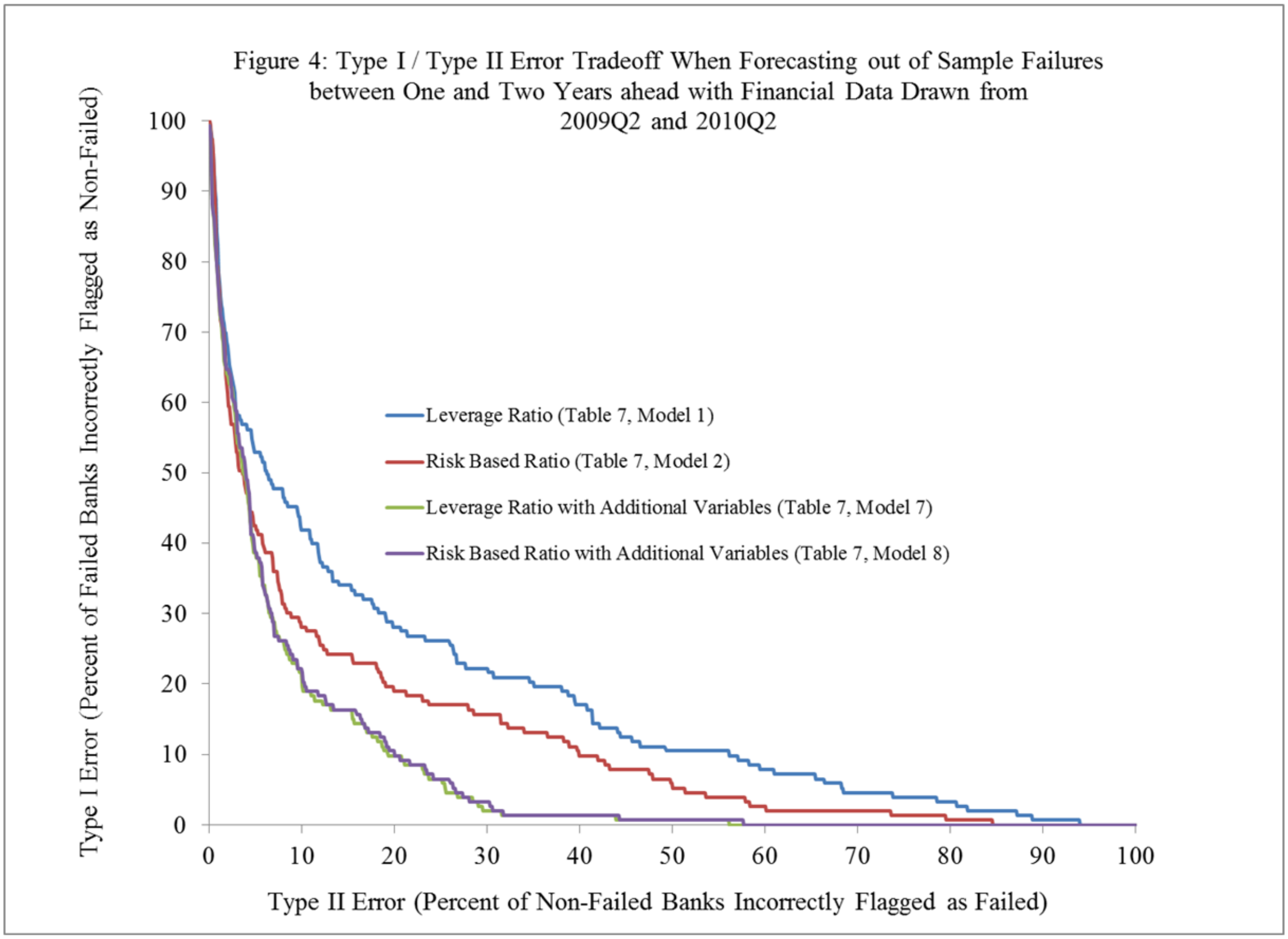


Figure 4: Type I / Type II Error Tradeoff When Forecasting out of Sample Failures between One and Two Years ahead with Financial Data Drawn from 2009Q2 and 2010Q2
Type I Error (Percent of Failed Banks Incorrectly Flagged as Non-Failed)
100
90
80
70
60
50
40
30
20
10
0
Leverage Ratio (Table 7, Model 1)
Risk Based Ratio (Table 7, Model 2)
Leverage Ratio with Additional Variables (Table 7, Model 7)
Risk Based Ratio with Additional Variables (Table 7, Model 8)
0
10
20
30
40
50
60
70
80
90
100
Type II Error (Percent of Non-Failed Banks Incorrectly Flagged as Failed)