Contagion Effects, Macroeconomic Conditions, and the Design of Regulatory Capital Standards

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CONTAGION EFFECTS, MACROECONOMIC CONDITIONS
AND THE DESIGN OF REGULATORY CAPITAL STANDARDS

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DRAFT

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**ABSTRACT**

By extending the variable coefficient bank failure estimation procedure developed by Hiemstra et al. (1997), this paper proposes an alternative to fixed capital adequacy standards. The variable coefficient approach models the probability of bank failure conditional on bank characteristics, the state of the macro-economy, and the degree to which the banking system is experiencing a systemic event. The results suggest that the probability of bank failure increases given a rise in the unemployment rate and a significant degree of contagion in the banking system. Given that bank regulators are currently revising the risk-based capital standards, the result suggest that a "true" risk-based standard account not only for the condition of the bank, but also the macroeconomic environment the bank operates in as well as the possibility of systemic crises. Furthermore, because the model accounts for both internal and external factors, the model may be useful as an early warning system to identify banks most susceptible to failure.
INTRODUCTION

Over the last few decades, the safety and soundness of the U.S. banking system has become the focus of considerable attention. Throughout the 1970s, the capital position of many banking institutions declined significantly, thereby leading bank regulators to focus on bank capital and regulatory capital standards. In 1981, bank regulators issued explicit minimum capital standards in the form of a minimum capital to asset, or leverage, ratio. While banks increased their capital ratios in the 1980s, the number of failed banks increased to a level not seen since the Great Depression. In fact, Beim and Calomiris (2001) define the 1984 to 1991 period in the U.S. as a banking crisis, one which resulted in the failure of 1,300 banks and 1,400 savings and loan, with the cost of the savings and loan failures alone totaling $180 billion, or 3.2 percent of U.S. GDP. In part, the crisis may have occurred because, as Alfriend (1988) notes, a weakness of the leverage ratio was that it failed to incorporate risk.
More recently, regulators have taken steps to explicitly link regulatory capital standards to risk, through the development and implementation of the Basle risk-based capital standards. While banks have dramatically increased both their capital levels and ratios since the implementation of risk-based capital, the risk-based standards have not been without their critics who note that the use of rather arbitrary risk-weights may actually create an incentive for banks to increase risk (e.g., Avery and Berger, 1991, Kaufman, 1991). Furthermore, while many studies have shown that higher equity is associated with a lower future probability of bank failure (see Lane et. al., 1986, Avery and Berger, 1991), studies by Kahane (1977), Koehn and Santomero (1980), and Kim and Santomero (1988) suggest that increasingly stringent capital regulation may have the unintended effect of causing banks to increase portfolio risk.

In part, the problem may lie with using capital as the focus of regulatory attention because, as Berger et. al. (1995) note, the relationship between the equity-asset ratio and bank safety is weak, thus making capital a rather "blunt" instrument. French (1991), Jones and King (1992) and Peek and Rosengren (1996) note that capital ratios may fail to identify a severely troubled bank in a timely manner. This problem may occur because as Berger et al. (1995) note, it may be difficult to ascertain whether the failure of a bank is idiosyncratic to the particular bank or is the result of a more widespread systematic shock that could influence other banks. It should be noted that greater amounts of capital do not, in and of themselves, guarantee that banks are adequately capitalized, particularly if the
shock is related to macroeconomic or systematic shocks. Rather, from a public policy perspective, what is important is the amount of capital a bank holds relative to the risk it faces, whether the source of that risk is idiosyncratic to the bank or be from external sources. And while the current risk-based capital standards account for the perceived credit risk related to a bank's internal conditions, they do not explicitly account for the possibility of changing economic conditions or systematic shocks that could threaten numerous banks in the banking system. But recent studies by Grossman (1993) and Schoenmaker (1998) find evidence that macroeconomic conditions and contagion effects influence bank failure rates.

Recently, Hiemstra et al. (1997) developed a variable coefficient model to estimate bank failures. While they introduced the econometrics of the variable coefficient approach in the context of estimating bank failures, the authors note that their model has logical implications for regulators setting capital adequacy requirements and propose that the variable coefficient approach should be applied as such. The purpose of this paper is to provide a variable coefficient bank failure model that recognizes that the probability of bank failure may vary because of internal bank conditions, macroeconomic conditions, or contagion effects. As such, this paper integrates studies of failure prediction models based on internal bank characteristics with studies of how macroeconomic conditions and contagion effects influence bank failures. In doing so, this study provides an innovative method for assessing risk in a regulatory capital framework, one that suggests that the revised risk-based capital standards may need to adjust
required capital to account for both internal bank conditions and the possibility of external shocks.

THE VARIABLE COEFFICIENT MODEL

In their study, Hiemstra et al. (1997) construct the relative frequencies of bank failure from cohorts of national banks beginning in 1985 and running through 1996, with each cohort being tracked for a period of five years. The rationale for using cohorts comes from Barth, Brumbaugh, and Litan (1990) who suggest that insured entities be separated into groups, or cohorts, for actuarial analysis, and from Kane and Min-Teh Yu (1995) who group financial institutions based on capital ratios. Such actuarial analysis offers a number of improvements over other research methods in studying the failure of financial institutions including an explicit recognition of the influence of time on accumulated bank losses and failure, and the possibility of more robust estimates of failure probability due to the use of peer group data.  

The Hiemstra et al. (1997) model uses a variable coefficient estimation procedure to forecast aggregate bank failures following an econometric approach pioneered by Swamy and Tavlas (1995). Swamy and Tavlas argued that the variable

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1For a discussion of this issue, see Hiemstra (2000).
coefficient approach is preferred because it is less sensitive to problems posed by measurement error, omitted variables, and specification bias. Because banking data and estimations share these problems and, in addition, the risk of bank failure varies over time (see Table 1) in relation to changing economic conditions and bank characteristics, the variable coefficient approach is well-suited to the problem of estimating bank failure risk.

Following actuarial analysis, the Hiemstra et al. (1997) model constructs 25 risk classes based on a two-way classification of banks. Banks are classified into one of 5 asset sizes and one of 5 CAMEL ratings. Cohorts are then formed for each year in the history and relative frequencies of failure are accumulated into cumulative frequencies over the next 5 years.

The dependent variable is constructed from the natural log of the ratio of the cumulative frequency of bank failures ($\lambda$) to the cumulative frequency of survival ($1 - \lambda$). This dependent variable is then written as a linear function of the age of the cohorts ($\tau$) in years, as shown in equation 1 below:

$$ Y_\tau = \log\left(\frac{\lambda_\tau}{1-\lambda_\tau}\right) = \beta_0 + \beta_\tau \tau $$

(1)
\[ \beta_{ir} = \Pi_{0ir} + \sum_{j=1}^{3} \Pi_{ijr} X_{ir} + \epsilon_r \quad (2) \]

where: \( i = 0 \) or 1

\( \tau = 1, 2, 3, 4, 5 \)

\( r = \text{Risk classes 1,2,...,25} \)

The two concomitant variables (\( X_{ir} \)) are the average county unemployment rate and the bank's capital-asset ratio. Equation 1 does not contain an error term. Instead, the error terms (\( \epsilon_r \)) appear in the variable coefficients \( \beta_{0r} \) and \( \beta_{1r} \), which vary based on the observed values of the concomitant variables given in equation 2. The logistic transformation of the dependent variable in equation 1 constrains the dependent variable to lie on the unit interval. The result takes the shape of an s-curve and can be interpreted as a probability.

Because the focus of this paper is on the pooled relationships, the Hiemstra et al. (1997) approach is modified while employing the same data set and risk classes. Specifically, equation (2) is substituted into equation (1) and we estimate our equation with generalized least squares (GLS). The use of cohorts or “proportions” data allow the cumulative frequencies of failure of be estimated directly, thus making GLS preferable to maximum likelihood estimation. Furthermore, GLS estimation allows for the possibility of heteroskedasticity and serial correlation, and can be applied to a system (pool) of equations such as
“seemingly unrelated regression equations SURE). Thus:

\[
Y = \log \left( \frac{\lambda}{1-\lambda} \right) = \beta_0 + \sum_{i=1}^{6} \beta_{i}X + \beta_{2}\tau + \sum_{j=1}^{8} \beta_{3j}[X * \tau] + \varepsilon
\]

(3)

Where: \( \tau = 1,2,3,4,5 \)

\( \varepsilon = \) Error term where \( \varepsilon \sim N(0, \sigma^2) \)

\( \lambda = \) Cumulative frequency of resolution from equation 1

\( i = \) Number of state variables (flagged with 1)

\( j = \) Number of performance variables (flagged with 3)

Note: \( \sum_{i=1}^{8} (\beta_i = 0) \) and \( \sum_{j=1}^{6} (\beta_{3j} = 0) \) by assumption

Equation 3 has 4 parts: an intercept term \( (\beta_0) \), a measure of the independent effect of cohort age\( (\beta_2) \), explanatory variables that are not time-dependent \( (\beta_{3i}, \) hereafter referred to as state variables\), and variables that are time dependent \( (\beta_{3j}, \) hereafter referred to as performance variables\). Performance variables are explanatory variables that change over the forecast horizon and have a changing influence over failure rates with the passage of time. In this study, the performance variables are the same employed in Hiemstra et al. (1997) (unemployment and the capital-to-asset ratio). The state variables are variables
whose influence does not change over the forecast period, and includes the bank margin (a ratio of earnings to the cost of funds), and dummy variables for charter age less than 5 years (AGE = 1), assets greater than $500 million (SIZE = 1), composite CAMEL rating that is 3, 4, 5 or NA (C345NA = 1), and multi-bank holding company (BHC) status (BHC = 1). Finally, the number of commercial bank failures in the prior year (FAIL) is included, this being a proxy for the degree to which the banking system is experiencing contagion effects.

A priori, a bank's internal characteristics and condition is measured by a number of performance and state variables. Specifically, as a bank's CAMEL rating increased and its capital-asset ratio decreased, an increase in bank failure rates would be expected. Peek and Rosengren (1996) have shown that bank examiners have inside information not available to the public. Because examiners use that information in determining CAMEL ratings, a deterioration in a bank's CAMEL rating is consistent with a deterioration in a bank's financial condition and an increasing probability of failure. In addition, a decrease in the bank's capital-asset ratio suggests that for a given volume of assets and level of portfolio risk, a bank is less able to absorb unexpected losses, thereby making it more likely to become insolvent and fail. With respect to the bank margin (MARGIN), a greater margin implies greater income and lower interest rate risk exposure, thus lowering the probability of failure, ceteris paribus. A priori, the sign on charter age (AGE) would be expected to be positive, as deNovo banks are riskier and fail at a higher rate than older, more established banks. With regard
to asset size (SIZE), large banks may need fewer reserves relative to the number
of units exposed to loss than smaller banks in part, because they have a wider
array of investment opportunities and can take greater advantage of derivative
transactions, thereby further reducing risk exposures (Angbazo, 1997). Finally,
banks affiliated with a multi-bank holding company (BHC) would be expected to
have lower failure rates as holding company affiliation provides a potential source
of strength to individual banks in the form of additional capital, prestige, and
management support that may not be available to independent banks.

Besides a bank's internal conditions, the variable coefficient failure model also
accounts for exogenous factors that may influence the probability of failure.
Specifically, high unemployment rates (UE) or regional/national recessions may
increase a bank's failure rate. Thus, if the $\beta_{ij}$ corresponding to the unemployment
variable is positive and significantly different from zero, then economic conditions
increase the probability of bank failure. This is consistent with previous research
by DeBandt and Hartmann (1999) who suggest that macroeconomic shocks may
cause simultaneous problems in a number of banks. Furthermore, Whalen
(1991) documents that institutions suffering through recessions have higher
failure rates, while O'Keefe (1995) documents that unemployment rates are highly
correlated with the credit risk of a bank's portfolio, and that ultimately banks may
fail due to high credit risk.

In addition, the number of commercial bank failures in the prior year measures
the degree of contagion in the banking system. Here FAIL measures the intertemporal correlation in bank failures (Schoenmaker 1999, DeBandt and Hartmann 1999), given the internal bank conditions and the macroeconomic conditions of the economy. Controlling for other factors, if no contagion effect exists and bank failures are independent of each other, then the parameter estimate on FAIL should equal zero. But DeBandt and Hartmann (1999) argue that reckless lending and bad loans might build up in the banking system over time, thus ultimately leading to a systemic event, while Schoenmaker (1999) and Grossman (1993) find evidence of contagion effects.

While equation 3 is similar to equations 1 and 2, this study differs from the previous research in two major respects. First, by focusing on the pooled estimates, we assume that failures are subject to a single data-generating process, where Hiemstra et al. (1997) allows the data-generating process to vary across risk classes. Second, in analyzing the probability of bank failures, this study integrates previous research which suggests that bank failure can be predicted by internal variables reflecting the banks condition, with studies suggesting that external factors, such as the unemployment rate and contagion effects, influence bank failure probabilities. If the probability of bank failure increases as macroeconomic conditions deteriorate or the degree of contagion in the banking system increases, then a "true" risk-based capital standard may need to account for such fluctuations in risk.
The coefficients estimated for equation 3 are presented in Appendix Table 2. For estimates of the probability of bank failure over a five-year time horizon, the signs of the variables agree with our expectations and the existing research. The coefficients on CAMEL ratings and charter age are positive and significant suggesting that banks with CAMEL ratings of 3, 4, 5 or not available, as well as banks with charters less than five years old both experience significantly higher failure probabilities. In contrast, banks affiliated with a multi-bank holding company and banks with greater than $0.5 billion in assets show markedly lower failure rates. This is not surprising as banks that are part of a multi-bank holding company may have their capital or risk managed at the holding company level, while larger banks have greater access to financial markets. Finally, the parameter on bank margin is negative and significant suggesting that banks with greater margins have lower failure rates.

Of particular interest in this study are the variables for the capital-asset ratio, county unemployment rates, and the contagion effect. The negative sign on the capital-asset ratio suggests that increases in the ratio reduce the probability of failure. This result is consistent with previous research and suggests that to the degree regulators can raise bank capital ratios, without an offsetting increase in risk, the probability of bank failure will decrease. To the extent that banks can
raise their capital levels relative to assets, bank supervisors can presumably
manipulate bank risk exposure through capital rules and onsite oversight (chart
1). For the unemployment rate, the parameter estimate is positive and significant,
and consistent with previous research, suggests that increases in unemployment
increase the probability of bank failure. Finally, the coefficient on the number of
commercial banks failing the in prior year is positive. This suggests that bank
failures are not independent and that the impact of a contagion effect can be
estimated. Consistent with Schoenmaker (1999), this result suggests that
controlling for internal bank characteristics and macroeconomic conditions, bank
failures are related and a contagion effect needs to be accounted for in
understanding the probability of bank failure over a given time horizon.

Estimates of the equations are used to construct forecasts of the probability of
bank failure conditional on the values of the independent variables. In the
comments that follow, the focus is on 5-year forecasts for large banks (assets
exceed $0.5 billion) that are part of a multi-bank holding company and have a
bank margin of 0.7. See Appendix Table 3 for the simulations discussed.

**CAMEL Ratings**

First, an analysis of the results shows how CAMEL ratings impact the probability
of bank failure. Specifically, assuming a large bank with a 5 percent capital-asset
ratio facing a 6 percent unemployment rate and a minimum number of bank failures in the previous year, a CAMEL 1 or 2 bank is found to have a five year failure probability of 0.3 percent, while a CAMEL 3, 4, or 5 bank has a corresponding failure probability of 2.95 percent. Not surprisingly, the failure probabilities of the CAMEL 1 or 2 and CAMEL 3, 4, or 5 banks are similar, and approaching zero, for banks with very high capital-asset ratios. However, for a given unemployment rate and bank failures in the previous period, as capital-asset ratios fall, the probability of failure at the CAMEL 3, 4, or 5 institutions increases much more rapidly than the failure probability of CAMEL 1 and 2 banks. In that sense, the results are consistent with Peek and Rosengren (1996) who show that CAMEL ratings provide valuable information, above and beyond capital-asset ratios, that can be used in assessing the health of financial institutions.

Second, for a large bank rated CAMEL 1 or 2, holding the unemployment rate and failures in the previous period constant, the probability of bank failure shows little change for changes in the bank's capital-asset ratio. For example, with a 10 percent capital-asset ratio the estimated probability of failure over the next five years is 0.07 percent. As the capital-asset ratio declines, the probability of failure over the five-year horizon rises in small increments. Similar results are reported for banks with CAMEL ratings of 3, 4, 5 or NA, with the probability of failure equaling 2.95 percent with a 5 percent capital-asset ratio. Together these results reinforce the argument that capital is a blunt instrument; holding other factors...
constant, significant increases in a bank's capital-asset ratio reduce, but only to a small extent, the probability of bank failure.

**Macroeconomic Conditions**

In contrast, the results show some significant changes for bank failure probabilities under changing macroeconomic conditions. Specifically, the probability of failure estimates suggest that, holding a bank's CAMEL rating, capital-asset ratio, and bank failures in the previous period constant, changes in the unemployment rate lead to varying probabilities of failure over the five year time horizon. Specifically, for a large CAMEL 1 or 2 rated bank, assuming a 5 percent capital-asset ratio and a minimum number of failures in the previous period, an unemployment rate of 4 percent over the next five years corresponds to a 0.08 percent probability of failure over the same time interval. For an unemployment rate of 6 percent the probability of failure rises to 0.31 percent, while a 10 percent unemployment rate corresponds to a 4.35 percent failure rate. A similar result is reported for large, CAMEL 3, 4, 5, or not available banks. Here the failure probability over the 5-year time horizon ranges from 0.79 percent, when unemployment equals 4 percent, to 30.60 percent if the unemployment rate is 10 percent. Taken together these results suggest that conditional on a given capital-asset ratio and minimum number of bank failures in the banking system, the probability of a bank failing over a five-year period varies widely as the unemployment rate changes.
Contagion Effects

Finally, the results and corresponding charts show the effects of contagion in the banking system on the probability of failure. For a large, CAMEL 1 or 2 rated bank with a 5 percent capital-asset ratio and assuming a 6 percent unemployment rate, the probability of bank failure changes markedly depending on the number of failures in the banking system. If bank failures are at a minimum (5), such as existed in the U.S. throughout the mid-1990s, then the probability of failure is only 0.31 percent. But if the number of failures rises to 117, as averaged in the U.S. during the 1984 to 1986 period, then the probability of failure rises to 1.28 percent. But if the number of failures rises to 229, as was averaged during the 1987 - 89 peak in bank failures, then the probability of failures rise to 5.23 percent. These numbers suggest that even for healthy banks, periods of significantly high contagion leads to significant increases in the probability of failure. For large, CAMEL 3, 4, 5, or not rated banks, the result is similar, but more drastic. For these banks, a period of little contagion (5 failures) yields a 5-year probability of failure of 2.95 percent, while periods of greater contagion, with failures of 116 and 229 banks, yield failure rates of 11.19 and 34.88 percent, respectively. Thus, consistent with Schoenmaker (1998), these results suggest that contagion effects do exist and significantly raise the probability of additional bank failures.
In addition, the interactions between capital-asset ratios and bank failures in the previous year provide some interesting results. Specifically, assuming a period of significant contagion, similar to the peak of U.S. bank failures during the period, 1987-1989, higher capital ratios insulate banks against failure in the sense that they significantly reduce the probability of failure. For example, a large CAMEL 1 or 2 rated with a capital-asset ratio of 4 percent had a 6.97 percent probability of failure over the next five years. This capital-asset ratio is roughly equivalent to the minimum Tier 1 leverage ratio required for U.S. banks under the prompt corrective action provisions of the FDICIA. If the capital-asset ratio is increased to 5 percent, a ratio roughly consistent with the minimum standard for being well capitalized under FDICIA, then the failure probability falls to 5.23 percent, a reduction of almost 25 percent. Finally, for banks with a 10 percent capital-asset ratio, the probability of failure falls to 1.19 percent, despite the presence of significant contagion in the banking system. These results are consistent with Kitamura and Kobayakawa (1999) in suggesting that one way to avoid the risk of contagion effects is for regulators to implement higher capital standards.

IMPLICATIONS FOR REGULATORY CAPITAL STANDARDS

One of the primary purposes of capital is to serve as a buffer against unexpected shocks or losses to equity. But as Berger et. al. (1995) have noted, capital is a
blunt instrument, one to which Peek and Rosengren (1996) suggest replacing with CAMEL downgrades as an impetus for intervention by bank regulators. The results in this study explain, in part, Berger et. al.’s conclusion; capital is a blunt instrument as can be seen by the fact that estimated failure probabilities can vary widely for banks depending on conditions. Historically, bank regulators have set regulatory capital standards, whether a leverage ratio or a risk-based capital ratio, as a fixed percentage that remains static over time. The results of this study suggest that if regulators set minimum capital adequacy standards as a fixed percentage of assets, or some variant thereof, then the probability of bank failure will vary not only as a bank’s financial condition changes, but also as macroeconomic and systemic conditions change.

Given the results of this research, one possibility for supervisory policy is that bank regulators set capital standards for banks in terms of a risk measure, such as a threshold probability of failure over five years, and not a fixed minimum capital requirement or other quantitative restrictions not explicitly linked to a bank’s probability of failure. Under such a system, bank’s required capital-asset ratios would vary depending upon not only the bank’s internal characteristics including CAMEL ratings and current capital-asset ratio, but also the macroeconomic conditions the bank faces, and the likelihood of contagion effects in the banking system. As such, the measure developed herein does not render capital adequacy standards or prompt corrective action irrelevant. Rather, this approach extends these regulatory mechanisms by making them conditional upon
additional financial and economic information, and incorporating that information into a regulatory framework.

While feasible in theory, such a suggestion may not be practical for a number of reasons. First, this research presupposes that bank regulators choose capital regulations so as to reduce the probability of bank failure. In reality, bank regulators may set capital standards so as to achieve any number of purposes including using capital as a buffer to absorb unexpected losses. Capital regulations for purposes such as these may or may not be consistent with setting a capital regulation to achieve a certain minimum level of bank failure.

Second, Baer and McElravey (1993) note that raising capital from external sources is very costly for banks with deteriorating capital positions. Furthermore, in studying the impact of the risk-based capital standards, Jacques and Nigro (1997) argue that poorly capitalized banks were unlikely to meet the new risk-based standards by raising capital because capital is costly to raise externally and because many poorly capitalized institutions were already experiencing a negative return on assets (ROA). Under these conditions, the regulatory scheme suggested by this paper would place the greatest burden for raising capital on those banks least likely to do so, poor CAMEL rated banks with low capital-asset ratios faced with difficult macroeconomic conditions or systemic problems in the banking sector. As a result, banks may instead practice regulatory avoidance by seeking and developing loopholes to circumvent regulatory capital requirements.
(Kane, 1977).

Third, the regulatory scheme may not be practical because of legal considerations, such as the codification of fixed capital ratios in bank regulations or standards. Finally, the regulatory scheme may not be practical because regulators may fear that setting capital levels to account for macroeconomic conditions or possible systemic problems may require excessive levels of capital, thereby impairing a bank's return on equity and competitive advantage (Hanweck and Shull, 1996).

Rather, the value of this model may lie in being used as an early warning system, given that the ability of regulators to provide effective early intervention is predicated on their ability to both identify and influence bank behavior in a timely manner. The advantage of this model is that it allows regulators to understand how the probability of failure changes as internal bank conditions, macroeconomic conditions, and the degree of contagion in the banking system change.

**CONCLUSIONS**

In revising capital adequacy standards, regulators might consider the approach presented herein. Using the variable coefficient model developed by Hiemstra et al. (1997), this study has developed a model for estimating the probability of bank
failure that incorporates not only internal bank characteristics, but also macroeconomic conditions and the degree of contagion in the banking system in estimating the probability of failure. The results suggest that for large banks, capital-asset ratios, the unemployment rate, and the degree of contagion in the banking system are important factors in the probability of bank failure over a given time horizon. This result is especially true for large banks with low CAMEL ratings. Given these results, the use of capital standards where required capital is a fixed percentage of assets may be of limited value as failure rates for well-capitalized banks can vary widely depending on macroeconomic conditions and contagion. As such, this approach offers an innovative design for assessing the capital adequacy in financial institutions.
BIBLIOGRAPHY


Table 1: Commercial Bank Failures, 1984-98

<table>
<thead>
<tr>
<th>Year</th>
<th>National</th>
<th>State</th>
<th>Total</th>
<th>National</th>
<th>State</th>
<th>Total</th>
<th>National</th>
<th>State</th>
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<tbody>
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<td>1984</td>
<td>4,924</td>
<td>9,924</td>
<td>14,848</td>
<td>18</td>
<td>63</td>
<td>81</td>
<td>0.366%</td>
<td>0.635%</td>
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<td>1985</td>
<td>4,995</td>
<td>9,909</td>
<td>14,904</td>
<td>30</td>
<td>90</td>
<td>120</td>
<td>0.601%</td>
<td>0.908%</td>
<td>0.805%</td>
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<td>1986</td>
<td>4,929</td>
<td>9,882</td>
<td>14,811</td>
<td>49</td>
<td>99</td>
<td>148</td>
<td>0.994%</td>
<td>1.002%</td>
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<tr>
<td>1987</td>
<td>4,698</td>
<td>9,684</td>
<td>14,382</td>
<td>68</td>
<td>131</td>
<td>199</td>
<td>1.447%</td>
<td>1.353%</td>
<td>1.384%</td>
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<tr>
<td>1988</td>
<td>4,481</td>
<td>9,399</td>
<td>13,880</td>
<td>122</td>
<td>160</td>
<td>282</td>
<td>2.723%</td>
<td>1.702%</td>
<td>2.032%</td>
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<tr>
<td>1989</td>
<td>4,317</td>
<td>9,163</td>
<td>13,480</td>
<td>111</td>
<td>96</td>
<td>207</td>
<td>2.571%</td>
<td>1.048%</td>
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<tr>
<td>1990</td>
<td>4,115</td>
<td>8,955</td>
<td>12,070</td>
<td>96</td>
<td>71</td>
<td>167</td>
<td>2.333%</td>
<td>0.793%</td>
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<td>1991</td>
<td>3,877</td>
<td>8,720</td>
<td>12,597</td>
<td>44</td>
<td>81</td>
<td>125</td>
<td>1.135%</td>
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<td>1992</td>
<td>3,676</td>
<td>8,533</td>
<td>12,209</td>
<td>34</td>
<td>88</td>
<td>122</td>
<td>0.925%</td>
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<td>1993</td>
<td>3,388</td>
<td>8,328</td>
<td>11,716</td>
<td>23</td>
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<td>0.679%</td>
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<td>3,140</td>
<td>8,055</td>
<td>11,195</td>
<td>3</td>
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<td>0.096%</td>
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<td>1995</td>
<td>2,925</td>
<td>7,794</td>
<td>10,719</td>
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<td>5</td>
<td>6</td>
<td>0.034%</td>
<td>0.064%</td>
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<td>10,299</td>
<td>2</td>
<td>3</td>
<td>5</td>
<td>0.071%</td>
<td>0.040%</td>
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<td>7,210</td>
<td>9,898</td>
<td>0</td>
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<td>1</td>
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<td>0.014%</td>
<td>0.010%</td>
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<td>1998</td>
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Chart 1: Relative Frequency of Failure by Capital-to-asset Ratio, 1984-98