Understanding Bank Supervisors' Risk Assessments: The Influences of Market Conditions and Supervisory Standards

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The Influences of Market Conditions and Supervisory Standards*

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Abstract

A recurring criticism of U.S. bank supervisors is that their standards vary procyclicly with banking and economic conditions. Academic studies of the causes of U.S. banking crises report lapses in bank oversight caused by a pre-crisis period of greater risk tolerance by supervisors. Conversely, post-crisis periods are marked by bankers' claims of overzealous supervision and tightening of supervisory standards. The 2010 reforms of supervisory standards for bank capital adequacy and liquidity (Basel III) directly address procyclicality in supervision and its effects on credit cycles.

We revisit the question of procyclicality in bank supervisors' standards and find mixed support for the Basel III reforms. Using data on bank supervisors' safety and soundness assessments of all U.S. FDIC-insured banks between March 1985 and December 2010, as well as information on banks' financial and macroeconomic conditions, we develop a model of supervisors' risk assessments of banks—Ratings Rule Model. We use the Model to examine the relationships between changing risk assessments of banks by their supervisors, bank conditions and economic conditions. Specifically, we estimate the marginal effects of changes in explanatory variables of the Ratings Rule Model on banks' likelihood of receiving high (low) supervisory ratings. We next analyze the marginal effects and test for significant changes in effects between stressful and non-stressful periods for banking markets.

Our analysis of the Ratings Rule Model suggests that bank supervisors' risk assessments have been procyclical in some respects. We find evidence that supervisors' standards for capital adequacy under pillar II of the Basel Accord have been procyclical in the past—becoming more stringent during periods of banking market stress and less stringent during non-stressful periods. In addition, these changes in supervisory risk tolerances for equity capitalization appear to have had a greater impact on risk assessments of sound, well-managed banks than on weak, poorly managed banks. We find, however, that supervisory standards for capital adequacy did not become more stringent during the current financial crisis (2007–2010). Finally, supervisors' attitude toward other categories of risk—asset quality, earnings strength, and liquidity—appear to be somewhat countercyclical.

In addition to presenting new information on supervisory standards during the current financial crisis, we believe this is the first paper to analyze cyclicality in supervisory standards using the marginal effects of risk factors on banks' likelihood receiving high (low) supervisory ratings. Hence, we believe this is the first paper to present evidence on the treatment of different risk factors—capital adequacy, asset quality, earnings strength, liquidity and sensitivity to market risk—by supervisors across different types of banks and over banking market cycles.

1. Introduction

The global financial crisis that began in early 2007 is still ongoing in 2011.[1] While some countries' economies show signs of recovering in 2011, most are experiencing aftershocks.[2] Even though the full effects of the crisis are not yet know, bank supervisors have not hesitated in adopting regulatory reforms. In April 2009 The Group of Twenty Finance Ministers and Central Bankers (G20) committed to reform banking and supervisory practices thought to have contributed to the crisis.[3] Key G20 reforms we consider in this paper are those intended to strengthen capital adequacy and liquidity standards for banks and other financial institutions. In 2010 the Basel Committee of Bank Supervisors (BCBS) published guidelines for new capital adequacy and liquidity standards. The new standards, commonly referred to as Basel III, are scheduled for full implementation by January 2019. The delay in implementation is acknowledgement by the BCBS of the aforementioned aftershocks.

This regulatory regime change, like all others, raises questions about the motivations for and efficacy of reforms. This paper addresses two of these questions. First, are Basel III reforms of capital and liquidity standards well motivated? Second, how might bank supervisors integrate Basel III into their existing supervisory frameworks? To answer these questions we

[1] The U.S. experienced the largest number failed and assisted banks in 2010 (157) since 1990 (169). Most of these failures involved small, community banks that had taken on excessive concentrations of poorly underwritten commercial and residential real estate loans.

[2] Examples of aftershocks are the widespread legal irregularities that have arisen with recent mortgage foreclosures and hindrances to problem loan workouts in the U.S., continued uncertainty surrounding credit markets globally, and increasing concern about many countries' (e.g., Ireland, Greece, and Eastern Europe generally) ability to service sovereign debt.

[3] See Group of Twenty Central Bankers and Finance Ministers (April 2, 2009) and Financial Stability Board (April, 2010).

examine the historical relationships between banks' financial condition, local macroeconomic conditions and supervisory assessments of overall bank safety and soundness. We review the literature of banks' conditions and supervisory risk assessments in section 2. We use the relationships between banks' conditions, economic conditions and supervisory risk assessments in section 3 to develop a Ratings Rule Model that mimics U.S. bank supervisors' risk assessments of banks. More specifically, we develop a Ratings Rule Model intended to mimic supervisors' evaluations of banks' overall safety and soundness. The dependent variable of the Ratings Rule Model—composite safety and soundness (CAMELS) rating—is an ordered integer value varying between 1 (best rating) and 5 (worst rating) and, hence, the most appropriate statistical technique for explaining CAMELS ratings is ordered logistic regression. The explanatory variables in the Ratings Rule Model are financial measures of bank capital adequacy, asset quality, earning strength, liquidity and sensitivity to market risk (hereafter, CAMELS attributes), as well as measures of local macroeconomic conditions. In section 4 we use the results of estimations of the Ratings Rule Model to determine the impact of changes in the model's explanatory variables on banks' safety and soundness. Our empirical technique allows us to infer changes in marginal benefit (improvement in safety and soundness) from additional capital and liquidity during stressful and non-stressful periods for banks. In section 5 we compare and contrast the historical evidence on supervisory risk assessments with the Basel III standards and discuss options for integrating Basel III into the current U.S. bank supervisory framework. While much research has been devoted to the policy questions discussed in this paper, we believe this is the first study to quantify the separate influences of banking and macroeconomic conditions from supervisory risk tolerances on capital and liquidity requirements under pillar II.

2. Literature Review

The question of whether bank supervisors' standards change with banking and economic conditions has been frequently discussed by market participants and policymakers. There has been little rigorous research on the topic, however, due in large part to the confidential nature of supervisory ratings. In addition, all federal and state bank regulators typically only have access to the supervisory ratings they issue. The Federal Deposit Insurance Corporation (FDIC), however, has access to virtually all commercial bank and thrift examination ratings.[4]

Two recent studies—Curry, Fissel and Hanweck (2007) and Krainer and Lopez (2009)—investigate cyclicality in supervisory standards for multibank bank holding companies; specially, the examination ratings issued to the top tier holding company organization.[5] Curry, Fissel and Hanweck (2007) investigate cyclical bias in bank holding company examination ratings, where bias is defined as ratings downgrades (upgrades) persistently higher or lower than out-of-sample downgrade predictions based on models developed by the authors. Using bank holding

[4] The FDIC took over responsibilities for insuring the deposits of thrifts after the Federal Savings and Loan Insurance Corporation was closed in August 1989. As a consequence, FDIC records for thrift examination ratings are not fully populated until approximately 1991, after an examination cycle was completed.

[5] Bank holding companies are supervised by the Board of Governors of the Federal Reserve. Examination ratings for the top tier or controlling organization take into account the performance and conditions of all member banks and affiliates of the consolidated organization.

company examination ratings from 1986 to 2003, Curry, et al. find some evidence of cyclical bias; however they conclude the bias is not widespread or systematic over all economic cycles investigated. Among the positive results, Curry, et al. conclude that bank holding company examiners loosened standards between the 1990 – 1995 recovery and 1996 – 2000 expansionary periods. Conversely, Curry, et al. conclude that bank holding company examiners tightened standards between the 1996 – 2000 expansion and 2000 – 2003 recession.[6] Finally, Curry, et al. find that examination standards for bank holding companies became more stringent between 1986 and 2003.

Krainer and Lopez (2009) study bank holding company examination ratings for evidence of changing supervisory standards between 1987 and 2004. They find evidence of loosening of supervisory standards during the 1993 – 1998 economic recovery and tightening of standards during two periods of economic stress, 1989 – 1992 and 1999 – 2004. Krainer and Lopez develop a logistic model of bank holding company examination ratings and use time-variation in the model intercept as a measure of changing supervisory standards.

In an earlier study, Berger, Kyle and Scalise (2001) investigate cyclicality in supervisory standards for commercial banks using commercial bank examination ratings between 1986 and 1998. Berger, et al. develop several models to test for cyclicality in standards, modeling

[6] In Curry, Fissel and Hanweck (2007), loosening of supervisory standards is associated with over prediction of rating downgrades when transitioning from weak to strong economic periods. Conversely, tightening of supervisory standards is associated with over prediction of rating upgrades when transitioning from strong to weak economic periods. Their assumption is that since the downgrade model is fitted with data from one period, out-of-sample forecasts for the next period can be used to detect changes in examiner risk weights or regression model coefficients. Curry, et al. also include time trend indicators in their rating change models as an additional test of changing standards.

supervisors' examination ratings and banks' criticized assets.[7] Their approach is fundamentally the same as that used in the more recent studies by Curry, Fissel and Hanweck (2007) and Krainer and Lopez (2009) that rely on comparisons of prediction models to outcomes and tests of model intercept changes. Berger, et al. state that they find some evidence of tightening supervisory standards during stressful market periods (1989 – 2002) and loosening of standards during expansionary economic periods (1993 – 1998) but conclude the economic significance of these changes is small. All three studies—Berger, Kyle and Scalise (2001), Curry, Fissel and Hanweck (2007) and Krainer and Lopez (2009)—acknowledge other factors could drive their results, such as correlations between model intercept terms and important missing variables. Potentially important missing variables these three papers discuss include measures of changes in banking market structure and regulation.

The empirical literature on the conditions of banks, especially their capital shortfalls, and the repercussions of bank conditions on lending and real economic activity grew dramatically following the bank "capital crunch" of the early 1990s. Bank capital shortfalls can stem from increases in loan losses, higher regulatory capital requirements and increased risk aversion at banks. Generally, studies have found that capital shortfalls reduce banks' lending and that reduced lending, in turn, reduces economic activity. Bernanke and Lown (1991), Peek and Rosengren (1995), Hancock and Wilcox (1994, 1998), and Pennacchi (2005, 2006), along with several others, document the depressing effects on U.S. banks' lending and on real economic activity that resulted from shortfalls of bank capital.

[7] For example, Berger et al. use a methodology developed by O'Keefe and Dahl (1996) in which examination ratings are forecast in a two-step selection model with corrections for potential selection bias. In O'Keefe and Dahl (1996) the likelihood of a bank being examined is modeled as a probit regression and examination ratings are modeled as an ordered logit regression that includes the inverse Mills ratio as a control of selection bias.

CAMELS ratings are broader measures of bank condition than equity capitalization, and have been the subject empirical research similar to that on bank equity capital. There have been fewer studies of the causes and effects of bank CAMELS ratings, however, primarily because CAMELS ratings are not publically available.

Cole and Guenther (1998) show that recently assigned CAMELS ratings improve (statistically significantly) forecasts of bank failures. De Young et al. (1998) conclude that CAMELS ratings help forecast yields on banks' bonds. Berger and Davies (1998) conclude that supervisors' ratings tend to reflect otherwise-private information, which subsequently came to be known and was then reflected in banks' equity share prices. Berger, Davies, and Flannery (2000) report that, in forecasting future performances of bank holding companies, supervisors' recently-assigned ratings tend to outperform forecasts that were based on capital market prices. O'Keefe et al. (2003) and O'Keefe (2010) provide evidence that supervisors' ratings of the caliber of loan underwriting standards forecast future nonperforming assets and loan charge-offs. And Bennett et al. (2008) show that the worse its CAMELS rating, the more likely a bank became troubled and failed. Taken together, these studies suggest that on-site exams and supervisors' ratings provide information about banks beyond that already captured by contemporaneous bank financial statements or by banks' bond yields and share prices.

Conversely, several studies examine the extent to which banks' future conditions, as indicated by their CAMELS ratings, could be forecast by bank financial statement data and other readily available data. Collier et al. (2003) show that banks' future conditions, and in particular CAMELS-rating downgrades, are forecastable with data from bank financial statements filed with supervisors (hereafter, Call Reports).[8] Their testing of the FDIC's Statistical CAMELS Off-site Ratings (SCOR) model indicates that the model has some ability to predict rating downgrades over a six-month horizon. Nuxoll et al. (2003) investigate whether adding measures of current, local economic conditions improve SCOR forecasts of banks' future conditions. They report mixed evidence: For some measures of bank condition and at some horizons, economic conditions contribute appreciably; for other measures and at other horizons, the contributions of economic conditions are negligible.

3. Modeling Bank Safety and Soundness Ratings

Bank supervisors rate an individual bank's overall safety and soundness according to the Uniform Financial Institutions Rating System (UFIRS). The UFIRS requires that the ratings for each bank be based on its financial performance, risk management practices, and compliance with laws and regulations. The UFIRS rates each bank's **c**apital adequacy, **a**sset quality, **m**anagement, **e**arnings, **l**iquidity, and **s**ensitivity to market risk, and therefore produce what are commonly referred to as CAMELS ratings.

To help us understand changes in banks' safety and soundness we estimate a Ratings Rule Model that approximates how individual banks' recent financial performance and local economic conditions are related to the CAMELS ratings that banks receive over the ensuing

[8] All banks covered by federal deposit insurance are required to file detailed income statement, balance and off-balance-sheet information with their primary federal bank supervisor each calendar quarter.

quarter. In subsequent sections we use these estimated relationships to learn how supervisory standards and market conditions influence ratings.

Our Ratings Rule Model accounts for CAMELS ratings with financial data banks file with their primary federal regulator each quarter (hereafter, Call Reports) and data on local economic conditions. The model is designed to approximate the CAMELS ratings that banks are likely to receive when they receive an on-site safety and soundness examination and are assigned CAMELS ratings during the 90 days that follow quarter-end financial reporting dates (financial statement "as of" dates). In the Ratings Rule Model, for example, CAMELS ratings that were assigned between January 1, 2008 and March 31, 2008 are explained by individual banks' December 31, 2007 financial data and by data on local economic conditions.

Our specification for the Ratings Rule Model is based on the FDIC's Statistical Camels Offsite Ratings (SCOR) model.[9] The Ratings Rule Model uses publicly available bank financial data as explanatory variables and does not include information on the practices and quality of bank management beyond that reflected in financial statements.[10]

Equation 1 presents the Ratings Rule Model in general form. In equation 1, $CAMELS_{j,t}$ is the CAMELS rating received by bank *j* during an on-site examination during quarter *t*; $\boldsymbol{\beta}'_t$ is a vector of regression coefficients at time *t*; and $\boldsymbol{X}_{j,t-1}$ is a vector of financial statement variables that are chosen to reflect the bank's capital adequacy, asset quality, earnings, liquidity, and sensitivity to market risk as of the end of the prior quarter, *t -1*. To control for local economic

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[9] See Collier et al. (2003) and Nuxoll et al. (2003).

[10] O'Keefe (2010) presents evidence of the role that loan underwriting standards play in banks' financial performance.

conditions, we include $\mathbf{V}_{t-1}$, a vector of the four most recent quarterly lags of a measure of local economic conditions, with associated coefficient vector, $\boldsymbol{\lambda}'_t$, and ε_t is the normally distribute error term. Details on the explanatory variables used in our estimations of equation 1 are given in the next section.

$$CAMELS_{j,t} = \alpha_t + \boldsymbol{\beta}'_t \boldsymbol{X}_{j,t-1} + \boldsymbol{\lambda}'_t \boldsymbol{V}_{j,t-1} + \varepsilon_t \quad (1)$$

Our cross-section estimation sample includes only those banks that received a CAMELS rating during the one quarter forecast horizon. The quarterly regression samples average between approximately 2,700 and 1,000 banks. Mimicking SCOR, we use the following 12 variables in our regressions to account for individual banks' CAMELS ratings: equity capital, loans delinquent 30–89 days, loans delinquent 90 days or more, nonaccrual loans, allowance for loan and lease losses, provisions for loan losses, gross charge-offs, other real estate owned (OREO), liquid assets, the sum of loans and long-term securities, volatile liabilities, and net income before taxes.[11] In the regressions, each of these variables is expressed as a percentage of each bank's gross assets.[12] Finally, all flow variables (net income before taxes, gross loan charge-offs and loan-loss provisions) are merger adjusted, annual values.

We exclude from our samples those banks whose Call Reports reported values for the explanatory variables used in equation 1 that were far in the tails of the variables' distributions.

[11] Liquid assets include cash balances due to the bank, securities held to maturity and available for sale, securities at fair value, and federal funds and repos. Volatile liabilities include large time deposits, foreign deposits, federal funds and repos sold, tax liability accounts, and other borrowed money.

[12] Gross assets are defined as total assets gross of the allowance for loan and lease losses.

We otherwise include banks of all sizes. Because the data were not weighted by asset size, the few dozen very large, presumably multi-state banks among the thousands of banks in each cross-section estimation sample had very little effect on the estimates. Because each bank was separately examined and rated, we include banks regardless of whether they were part of multibank holding companies.

In addition to the SCOR variables, we also include recent local economic growth, as measured by the first four quarterly lags of the statewide growth rate of economic activity. We approximate that growth rate with the one-quarter growth rate of the each state's coincident Index, which are compiled by the Federal Reserve Bank of Philadelphia. We expect recent local economic growth rates to influence supervisors' judgments, and thus CAMELS ratings, in that they serve as a proxy for information that will likely soon be—but has not yet been—reflected in future Call Reports. Thus, for example, weak economic growth might be correlated with information that is either not readily quantified or not included in the Call Reports. As an illustration, local economic data for local commercial real estate vacancy rates, bankruptcy filing rates, or notices of default would not be in Call Reports but might inform supervisors' judgments. In addition, there may be some tendency for bank data revisions to be correlated with economic conditions: When the economy weakens, banks may increasingly tend to underreport problems.

4. Estimates of Bank Supervisors' Ratings Rules

In this section we present the results of our estimations of the Ratings Rule Model. In particular, we focus on the level and trend in the marginal effects of the explanatory variables of the Model and offer explanations for time variation in effects.[13]

4.1 Ordered Logit Model

The general form of the logistic function used to estimate the Ratings Rule Model is shown in equation 2, where *Z* is the linear combination of financial ratios and macroeconomic conditions thought to influence supervisors' evaluations of banks' safety in soundness shown in equation 1. The function *F(z)* is the logit cumulative density function.

$$F(z) = \frac{e^{Z}}{(1 + e^{Z})} \tag{2}$$

The nonlinear relationships between the explanatory variables and the probability of receiving a particular CAMELS rating means that the marginal effect of each explanatory variable on the probability of receiving a particular CAMELS rating is not given by the logistic regression coefficient vectors, $\boldsymbol{\beta}'_t$ and $\boldsymbol{\lambda}'_t$. The marginal effect of an explanatory variable on the probability of receiving a particular CAMELS rating is itself a nonlinear function of all explanatory variables and their estimated coefficients, as is shown by the partial derivative of *F(z)* with respect to an explanatory variable, e.g., equity capitalization, in equation 3.

[13] We cannot present estimates of the Rating Rule Model regression coefficients because this information is confidential material about the FDIC early warning system SCOR.

$$\frac{\partial F(z)}{\partial Equity} = \frac{e^Z}{(1+\ e^Z)^2}\beta_{Equity} \tag{3}$$

We estimate the marginal effects the explanatory variables in equation 1 on *F(z)* using alternative assumptions about the values of the explanatory variables as a way to disentangle the influences of banks' conditions, macroeconomic conditions and supervisory standards.

4.2 Average Marginal Effects

We begin our analysis of marginal effects by estimating the marginal effect of an explanatory variable on *F(z)* using a range of values of the variable, where the range is based on historical data between March 1985 and December 2010.[14] More specifically, we vary a particular variable's values within the observed historical range and allow all other variables to remain at observed values for each calendar quarter. This allows us to estimate the marginal effect of, for example, small changes in equity capitalization across banks as equity capitalization varies within its historical range (e.g., 1 to 46 percent), leaving all other explanatory variables at observed values. This approach to measuring the marginal effect of a variable is in a sense an experiment in which we look at the effect of small changes in that

[14] Specifically, we estimate mean values of each explanatory variable by CAMELS ratings to account for the potential variation in values by bank condition over time. Importantly, the mean estimates are for banks examined within the next quarter. This latter criterion is used to ensure ratio values are within a range observed by supervisors (examiners) when deciding on CAMELS ratings. The lower and upper values for explanatory variables we observe for "good" and "bad" banks (as indicated by CAMELS ratings) over the approximately 26 year period are used as boundaries in our marginal effect estimates. We should emphasis that our process for identify "reasonable" historical ranges for variables excludes extreme outliers, yet still accounts for cross-sectional and time series variation in variables.

variable on banks' probability of receiving a CAMELS-1 rating for various values of that variable as banks' conditions change over time. To summarize marginal effect estimates we compute the average marginal effect (hereafter, AME) for a variable on the probability of receiving a CAMELS-1 rating across banks each quarter. Changes in AME incorporate the influences of supervisory standards, banks' conditions and local economic conditions on the probability of receiving a CAMELS-1 rating.[15] Variables that have a positive (negative) effect on bank safety and soundness should have positive (negative) AME estimates. Accordingly, we interpret increases in the absolute value of AME over time for a fixed value of a variable as indication of increases in the variable's influence on banks' safety and soundness. Using this same reasoning, we interpret decreases in the absolute value of AME associated with increases in a variable's value at a point in time as indication of eventually diminishing influence on banks' safety and soundness.

We present estimates of average marginal effects using figures. When interpreting figures of the average marginal effect of a variable across values of that variable at a point in time one should keep in mind the logistic function from which average marginal effects are derived. The logistic function is a sigmoid function ("S" shaped function) and has a first derivative function that is bell shaped. As a result, a figure of the average marginal effects of a variable at a point in time will be a bell shaped curve or a segment of a bell shaped curve,

[15] We should point out that our AME measure differs somewhat from textbook measures of marginal effects. For comparison, three standard marginal effect measures are the marginal effect at the mean (MEM), marginal effect at representative values (MER) and standard average marginal effect (AME). The MEM and MER measures fix all explanatory variables at specific values, and each produces a single margin effect estimate. Conversely, standard AME measures allow all explanatory variables to be at observed values and an average effect across banks is computed.

depending on the range of values of the variable shown in the figure.[16] In interpreting our results we focus on changes in the curvature and position of average marginal effect curves for a variable over time, as well as differences in the average marginal effect curves at a point in time across explanatory variables.

4.2.1 AME of Equity Capital

Given the amount of attention bankers, their regulators and the public devote to bank capital adequacy, it would be helpful to know how capitalization has influenced bank safety and soundness over prior economic cycles. We begin our analysis by examining trends in the AME of equity during past, as well as the current, U.S. banking crises. Figures 1 through 4 show the AME of equity on the probability of being CAMELS-1 rated in the next quarter during the late 1980s, early 1990s and late 2000s U.S. banking crises. AMEs are estimated in the first quarter of each year in figures 1 through 4. In most periods, the AME of equity increases with capitalization up to a point, then gradually decreases. Figures 1 through 4 suggest that as banking market stress increases (i.e., 1987 – 1991) the AME of equity curve becomes more concave (less flat) and the peak AME occurs at capitalization rates of 15-to-25 percent, suggesting diminishing marginal benefits for "excessive" capitalization. As the banking crisis deepens (i.e., 1990 – 1993), the peak AME increases as well. Finally, as the crisis abates (i.e., 1993 – 1994) the process reverses; the AME curves flatten and the peak AME declines. Since figures 1 through 4 all show positive AMEs, there is always a benefit from increased

[16] The bell shaped curve (curve segment) is seen in figures 1 through 4 for the average marginal effect of equity capital.

capitalization, but the marginal improvement in safety and soundness typically diminishes above 15-to-25 percent capitalization.

Figure 4 shows estimates of the AME of equity for the current banking crisis (2007 – 2010). Interestingly, the AME curves for 2007 and 2008 are nearly flat but become sharply concave in 2009 and 2010. While the peak AME for the most recent crisis is similar to that for the early 1990s banking crisis, the pre-crisis AME curves are much flatter. This latter result is likely due to the fact that the late 1980s banking crisis in the southwestern region of the U.S. was well underway in 1987, hence the importance of equity capitalization in 1987 (figure 1) reflects a much more stressful period than 2007 and 2008 (figure 4).[17]

Figure 5 presents quarterly estimates of the AME of equity from March 1985 to December 2010. To capture the influence of different equity capitalization rates on AMEs, we use capitalization rates of 1, 4, 8, 15 and 20 percent. Figure 5 indicates increases in AMEs with capitalization rates through at least 15 percent and often up to 20 percent, consistent with the results shown in figures 1 through 4. In addition, differences in AMEs between capitalization rates are much greater during stressful periods than when economic conditions are not stressful. A closer look at the AME of equity trends by capitalization rates indicates the AMEs at 20 percent capitalization exceed those at 15 percent capitalization between March 1985 and December 1992, the period corresponding to the 1980s and early 1990s U.S. banking crises. In the post-1990s crisis period (March 1993 to June 2008), however, the differences in AMEs between 20 and 15 percent capitalization rates are often negative and near zero. After June

[17] The number of failed and assisted FDIC-insured banks indicate the differences in market stress for these years; the year (number of failures) are 1987 (203), 2007 (3) and 2008 (30).

2008, the AME of equity at 20 percent capitalization substantially exceeds that at 15 percent capitalization.

The trends in the AME of equity across time and capitalization rates are much as we expected. There are clear indications of increased marginal benefit from higher capitalization during periods of banking market stress but there are also indications that the marginal benefit diminishes at high capitalization rates (15-to-25 percent). Finally, trends in the AME of equity are consistent with the procyclical nature of banks' capital requirements.

4.3 Crisis versus Non-crisis Period Interaction Effects

Figures 1 through 5 suggest that equity capital has greater influence on bank safety and soundness ratings during periods of severe banking market stress than during non-stressful periods. In this section we test the statistical significance of such procyclical effects by estimating interaction effects between continuous financial variables of the CAMELS attributes and a discrete, binary variable indicating the presence or absence of a bank market crisis.

Equation 4 presents the Ratings Rule Model with the aforementioned interaction term in general form. For simplicity, equation 4 does not include time subscripts. In equation 4, $X_{1,j}$ represents one of the continuous variables measuring the CAMELS attributes, such as equity capital, and $X_{2,j}$ is a dummy variable set equal to one if equation 4 is estimated using financial data from a period of severe banking market stress and is zero otherwise. Finally, the vector $\boldsymbol{X}_j$

includes all remaining financial variables for the Ratings Rule Model and $\boldsymbol{V_j}$ is the vector of state economic conditions.

$$CAMELS_j = \alpha + \beta_1 X_{1,j} + \beta_2 X_{2,j} + \beta_{12} X_{1,j} X_{2,j} + \boldsymbol{\beta}' \boldsymbol{X}_j + \boldsymbol{\lambda}' \boldsymbol{V}_j + \varepsilon \qquad (4)$$

As is the case for the marginal effects of each individual explanatory variable, the marginal effect of the interaction term, $X_{1,j} X_{2,j}$, is a nonlinear function of all explanatory variables in equation 4. The marginal effect of interaction between two continuous explanatory variables is equal to the cross partial derivative of the cumulative density function with respect to both variables. When one of the interaction variables is discrete, however, the cross partial derivative may not be used to obtain the marginal effect. Rather, as Norton, Wang and Ai (2004) show, the marginal effect of the interaction term is equal to the discrete change in the marginal effect of the continuous interaction variable, as the discrete variable varies from zero to one. Equation 5 shows this interaction term marginal effect in general form.

$$\frac{\Delta\left(\frac{\partial \mathrm{F(z)}}{\partial X_1}\right)}{\Delta X_2} = \frac{\Delta \mathrm{F}'(\mathrm{z})(\beta_1 + \beta_{12} X_2)}{\Delta X_2} \qquad (5)$$

Evaluating equation 5 at both values for X_2 (1 and 0, respectively) and taking the difference gives the complete marginal effect of the interaction term, $X_1 X_2$, as shown in equation 6.

$$\frac{\Delta\left(\frac{\partial \mathrm{F(z)}}{\partial X_1}\right)}{\Delta X_2} = [(\beta_1 + \beta_{12})\mathrm{F}'(\beta_1 X_1 + \beta_{12} X_1 + \beta_2 + \boldsymbol{\beta}'\boldsymbol{X} + \boldsymbol{\lambda}'\boldsymbol{V})] - [(\beta_1)\mathrm{F}'(\beta_1 X_1 + \boldsymbol{\beta}'\boldsymbol{X} + \boldsymbol{\lambda}'\boldsymbol{V})] \qquad (6)$$

Equation 6 makes clear that the marginal effect of the interaction term can be statistically and economically significant even if the estimated coefficient on the interaction term, β_{12}, is statistically insignificant.

4.4 Estimates of Crisis versus Non-crisis Period Interaction Effects

To estimate interaction effects between the bank financial variables and crisis period time dummy variables we use a problem bank prediction model (Problem Bank Model, hereafter). We define problem banks as those banks that receive CAMELS ratings of 3 or worse in the succeeding quarter. Conversely, non-problem banks are defined as banks that receive CAMELS ratings of 1 or 2 in the succeeding quarter. Since the dependent variable is a binary variable indicating problem bank status (problem bank = 1, non-problem bank = 0) we estimate the Problem Bank Model using binary logistic regression. Aside from the introduction of the interaction term, all explanatory variables of the Ratings Rule Model as retained in the Problem Bank Model. We use this approach because estimation and interpretation of interaction effects are greatly simplified in a binary problem bank prediction model compared to a multinomial CAMELS rating prediction model.

Tables 1 through 8 present estimates of average marginal effects of interaction terms (hereafter, interaction effects) on the probability of becoming a problem bank for the key financial variables that represent the CAMELS financial attributes and table 9 summarizes our overall findings. As discussed previously, each bank-date observation in the estimation sample will have a separate interaction effect (see equation 6). To summarize our results, we group estimates of interaction effects into five categories, based on banks' estimated probability of being a problem bank: 1.) 0%-to-20%, 2.) 20%-to-40%, 3.) 40%-to-60%, 4.) 60%-to-80% and 5.) 80%-to-100%.[18]

To estimate crisis period interaction effects we estimate the Problem Bank Model using panels of data where each panel combines data from one crisis period year-end and one non-crisis period year-end. We define banking crisis periods as the years 1988-to-1992, and 2007-to-2011 (current).[19] We form several pre- and post-1980s crisis period data panels, as well as data panels for the current crisis. As shown in table 1, our data panels use data during and after the late 1980s and early 1990s banking crisis, and years leading up to the most recent crisis.

Table 1 shows estimates of mean interaction effects and Z scores for each bank grouping and data panel. The interaction effects indicate the change in the probability of becoming a problem bank in the ensuing quarter due to the interaction term. As such, a negative (positive) interaction effect means the probability of becoming a problem bank is reduced (increased) by the interaction term. Table 1 shows that the mean interaction effects for equity capital and the crisis period dummy are negative and generally statistically significant for the late 1980s and early 1990s crisis periods, but are not statistically significant for the

[18] These groupings are based on the statistical software used to estimate interaction effects, the Stata inteff application.

[19] Crisis periods are periods with high numbers of bank failures, as well as high numbers of problem banks.

current financial crisis.[20] These results are consistent with figures 1 through 7, indicating that equity capital played a procyclical role in bank safety and soundness during the late 1980s and early 1990s banking crises. Interestingly, we do not find a statistically significant procyclical role for equity capital during the current financial crisis (2007 – 2010). This latter result may be due to the wide-spread government support programs that were available to many troubled banks during this most recent crisis, such as government capital infusions, government guarantees of bank subordinated debt, liquidity facilities provided by the Federal Reserve and dramatic increases in deposit insurance coverage. Countering the government support explanation, however, is the fact that 338 community banks have failed since 2007 and the number of banks with CAMELS ratings of 3 or worse reached approximately 1,500. These obvious signs of banking market stress suggest supervisors did not assume government support program would "save" all banks from failure. An analysis of the effect of these and other government support programs on bank examination ratings is beyond the scope of this paper, however.

Table 2 presents estimates of interaction effects for loan loss reserves and crisis period dummy variables. As was the case for equity capital, we find in general a negative and statistically significant interaction effect for loan loss reserves for the late 1980s and early 1990s crises, but do not find statistically significant interaction effects for the current crisis. The reason for the lack of significant interaction effects for loan loss allowances for the current financial crisis could also be due to the widespread government support programs for troubled banks.

[20] Robustness tests of data panels using the 2008 and 2010 crisis year yielded similar results to those using 2009.

Like equity capital, bank earnings play an important role in supporting bank safety and soundness. We had expected that earnings strength would become even more important to bank safety and soundness during banking crises, potentially reducing the likelihood of becoming a problem bank more so than during non-crisis periods. That is, we expected negative interaction effects for net income and crisis period dummy variables; but table 3 shows this is not the case. Rather, table 3 shows that the interaction effect for net income during the late 1980s and early 1990s varies from negative to positive as banks' probability of becoming a problem bank increases. We interpret this latter result to mean that net income plays a procyclical role for bank safety and soundness for banks that are in generally sound condition but plays a counter-cyclical role for banks that are in generally weak condition.

Table 4 presents estimates of average interaction effects for liquid assets and crisis period dummy variables. As expected, we find evidence of procyclical effects during the late 1980s but no statistically significant interaction effects for the late 1990s and current financial crisis. The lack of significant interaction effects for recent years suggests the Basel III reforms to supervisory liquidity standards are well motivated.

Table 5 shows estimates of average interaction effects for volatile liabilities and crisis period dummy variables vary from positive to negative during the late 1980s and early 1990s crises. We do not find a pattern in these results and find interaction effects are generally insignificant for most of that period. Interaction effects for volatile liabilities are, in some instances, significant and positive for the current crisis, however, suggesting a weak procyclical effect during the current crisis.

Tables 6, 7 and 8 present estimates of average interaction effects for three measures of credit quality—nonaccrual loans, gross loan charge-offs, and loan loss provisions—and crisis period dummy variables. We find the interaction effect for nonaccrual loans (table 6) varies from positive to negative as banks' condition weakens for the late 1980s and early 1990s and is in some instances negative for the current crisis. For gross loan charge-offs and loan-loss provisions (tables 7 and 8) we find consistently negative interaction effects. The results for these credit quality measures are counter-intuitive. We expect instead that all three credit quality measures would have positive, procyclical effects. As is the case for net income, the counter-cyclical effects for the credit quality measures suggest that bank examiners place more emphasis on credit quality during non-crisis periods than during crisis periods. This may be due to their expectation that all banks will experience deterioration of credit quality during periods of widespread economic stress, but that only poorly managed banks run into similar problems during periods of strong economic growth.

For brevity, we do not present results for the remaining Problem Bank Model explanatory variables—past due loans, other real estate owned and loans and long-term securities. Table 9 summarizes our findings for all explanatory variables, however

4.5 Marginal Effect at Representative Values

In this section we look more closely at the reasons for changing marginal effects. As shown in equation 3, the marginal effect of a variable on the probability of receiving a CAMELS-1 rating depends on the coefficient vectors, $\boldsymbol{\beta}'_t$ and $\boldsymbol{\lambda}'_t$, and the vectors for financial and macroeconomic explanatory variables, $\boldsymbol{X}_{t\text{-}1}$ and $\boldsymbol{V}_{t\text{-}k}$, respectively. By holding the financial and macroeconomic variable vectors constant, we can measure changes in marginal effects caused solely by changes in supervisors' risk-weights ($\boldsymbol{\beta}'_t$ and $\boldsymbol{\lambda}'_t$) for the explanatory variables. The marginal effect measured at fixed values for all explanatory variables is commonly known as the marginal effect at representative values (hereafter, MER).

We select representative values for regressors as of specific points in time and specific types of banks. To estimate MERs for well-run, sound banks during stressful and non-stressful periods we use the mean values of all financial and macroeconomic explanatory variables for CAMELS-1 rated banks for year-ends 1990 and 2006, respectively.[21] To control for management quality, we also require banks to have a management component rating of 1. Similarly, to estimate MERs for weak, poorly-managed banks we estimate MERs using mean variable values for CAMELS-3 rated banks with management ratings of 3 as of year ends 1990 and 2006.

Figure 6 shows trends in MERs for CAMELS-1 rated banks' representative values for equity capital. Figure 6 shows a high degree of consistency in MERs based on crisis (December 1990) and non-crisis (December 2006) periods' representative values. While there is significant variation in the mean values for the CAMELS-1 rated banks' covariates between year-ends 1990 and 2006, figure 6 shows the trends in equity MERs are nearly identical for crisis and non-crisis period representative values. These MER trends indicate that the majority of the time

[21] Between 1985 and 1992 there were 1,373 FDIC-insured failed and assisted banks; approximately 171 failures per year. By 1990, the banking crisis in the southwestern portion of the U.S. was ending while a similarly severe crisis was beginning in the northeast. This turbulent period was followed by a remarkably calm period for banks, with only 43 banks failing between 1998 and 2007. No banks failed between 2004:Q3 and 2006:Q4.

variation in marginal effects of equity capital for CAMELS-1 rated banks is due to changes in the coefficient vectors, $\boldsymbol{\beta}'_t$ and $\boldsymbol{\lambda}'_t$, or more intuitively, due to changes in supervisors' risk tolerances. In addition, the consistency in equity MERs between CAMELS-1 rated banks' representative values for crisis and non-crisis periods suggests a high degree in consistency over time in supervisors' risk assessments within CAMELS rating groups.

Figure 7 shows the results of a similar analysis of equity MERs for CAMELS-3 rated banks with management component ratings of 3. As was the case for CAMELS-1 rated banks, we find strong consistency in CAMELS-3 rated banks' MERs between representative values for crisis and non-crisis periods. A significant difference in the trend in MERs between CAMELS-3 and CAMELS-1 rated banks is that CAMELS-3 rated banks' MERs are low (near zero) and do not appear to vary systematically over time. This result is due to the differences in representative values of covariates between CAMELS-1 and CAMELS-3 rated banks. We expect the marginal effect of a variable to eventually diminish and approach zero as the variable increases given the bell-shaped marginal effect function. In terms of the vector of financial explanatory variables, $\boldsymbol{X}_{t-1}$, it appears that the representative values of delinquent and nonaccrual loans, repossessed real estate, loan charge-offs, loan-loss provisions and loan-loss reserves for CAMELS-3 rated banks place our estimates of MERs in this near-zero marginal effect portion of the marginal effect curve.

Additional analysis (not presented here) indicates similarity in MERs for CAMELS-1 and CAMELS-2 rated banks, as well as similarity in MERs for CAMELS-3, 4 and 5 rated banks. Thus it appears that changes in examiner risk tolerances toward equity capital between 1985 and 2010 have influenced risk assessments of generally sound, well-managed banks to a much greater degree than risk assessments of weak, poorly managed banks.

5. Conclusion: Reconciling Results with Basel III

The marginal effect estimates for the Ratings Rule Model and Problem Bank Model indicate that equity capital has had a greater impact on bank condition and/or received greater supervisory emphasis during past periods of banking market stress than have other performance measures, such as net income. We do not, however, find statistically significant procyclicality in equity standards for the current financial crisis. We expect this latter result is attributable, in part, to the widespread government support programs for banks during the current financial crisis but do not test this hypothesis. Overall, we believe the equity capital results support the conclusion of the G20 and BCBS that Basel II capital standards (pillars 1 and 2) are procyclical. The measures the procyclicality of capital standards that we present are estimates of time variation in marginal effects and support the widely accepted notion of the procyclicality of supervisory standards found by previous studies that use summary measures of supervisory standards.[22] We add to this literature by showing that changing supervisory risk tolerance for capital adequacy has had the greatest influence on the safety and soundness ratings of generally sound, well-managed banks and almost no influence on the safety and soundness ratings of weak, poorly-managed banks.

[22] See Berger, Kyle and Scalise (2001), Curry, Fissel and Hanweck (2007) and Krainer and Lopez (2009).

Basel III mandates for strengthening capital requirements call for higher minimum capital ratios, improvements in the quality of capital (contingent capital requirements) and discretionary use of countercyclical capital buffers by supervisors. These mandates suggest a reversal in supervisors' risk-weightings for equity between stressful and non-stressful economic periods. As our results make clear, risk assessment is contextual. If Basel III mandates for countercyclical capital requirements increase supervisory emphasis on equity during non-stressful economic periods, how should supervisors weight other risks? That is, if supervisors become more alarmed by low equity capitalization during non-crisis periods, will they counterbalance this with decreased emphasis on earnings and asset quality? Or will supervisors maintain the same risk weightings for the CAMELS attributes and effectively discount a large portion of bank equity as, e.g., a regulatory tax for deposit insurance.

A comparison of crisis and non-crisis period marginal effects for the CAMELS attributes shows quantitatively how supervisors might adopt Basel III mandates for equity and liquidity. There appears to be ample flexibility in supervisors' risk assessments to permit increased emphasis on equity and liquidity during non-stressful periods. Estimation of marginal effects for Ratings Rules in the future will show how supervisors implemented Basel III mandates.

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Figure 1.

Average Marginal Effect of Equity: 1987 - 1990

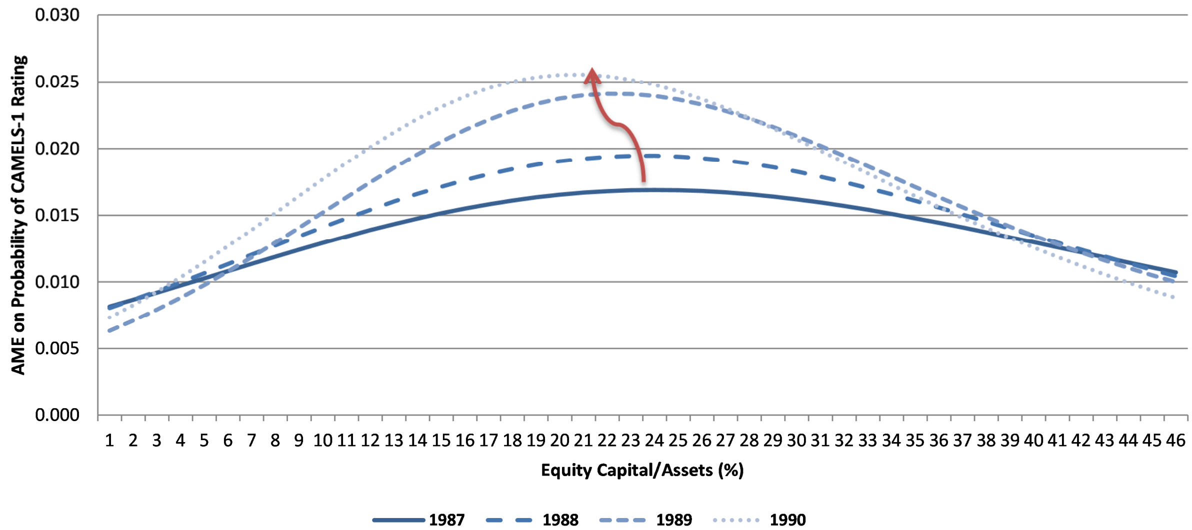

Figure 2.

Average Marginal Effect of Equity: 1990 - 1993

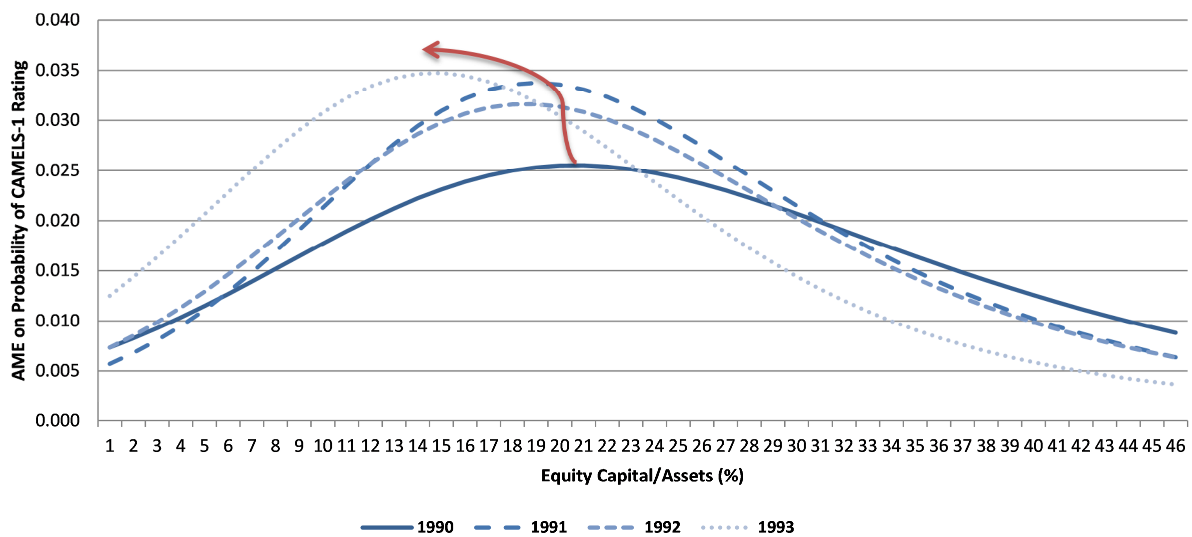

Figure 3.

Average Marginal Effect of Equity: 1993 - 1994

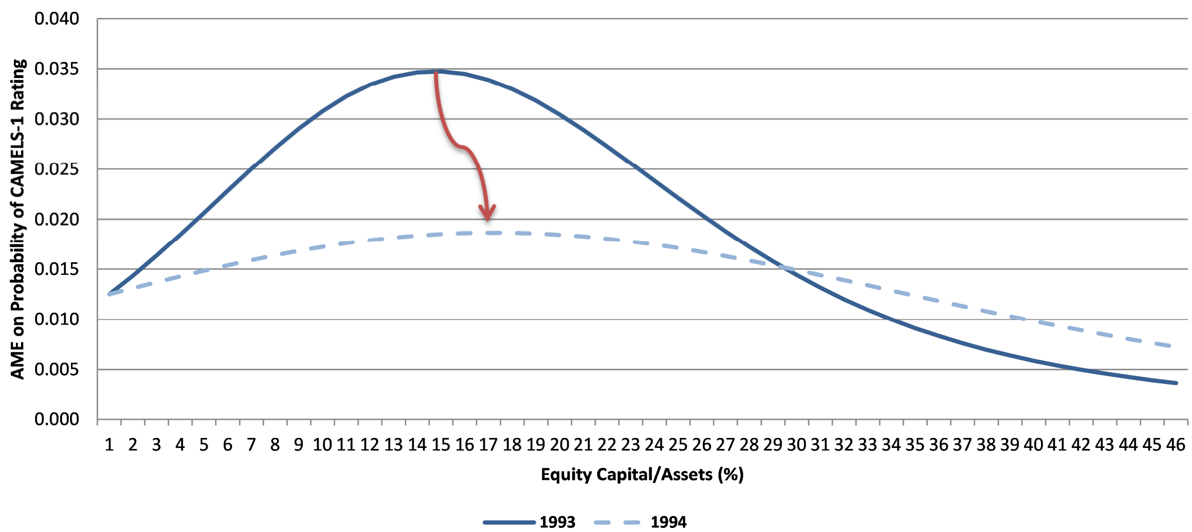

Figure 4.

Average Marginal Effect of Equity: 2007 - 2010

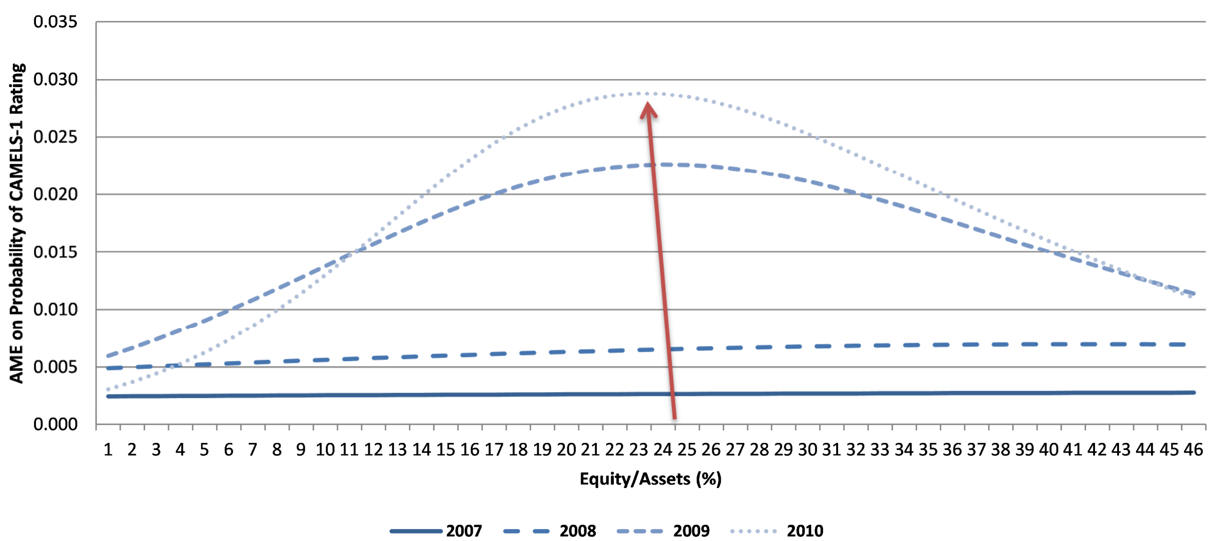

Figure 5.

Average Marginal Effect of Equity: 1985:Q1 - 2010:Q4

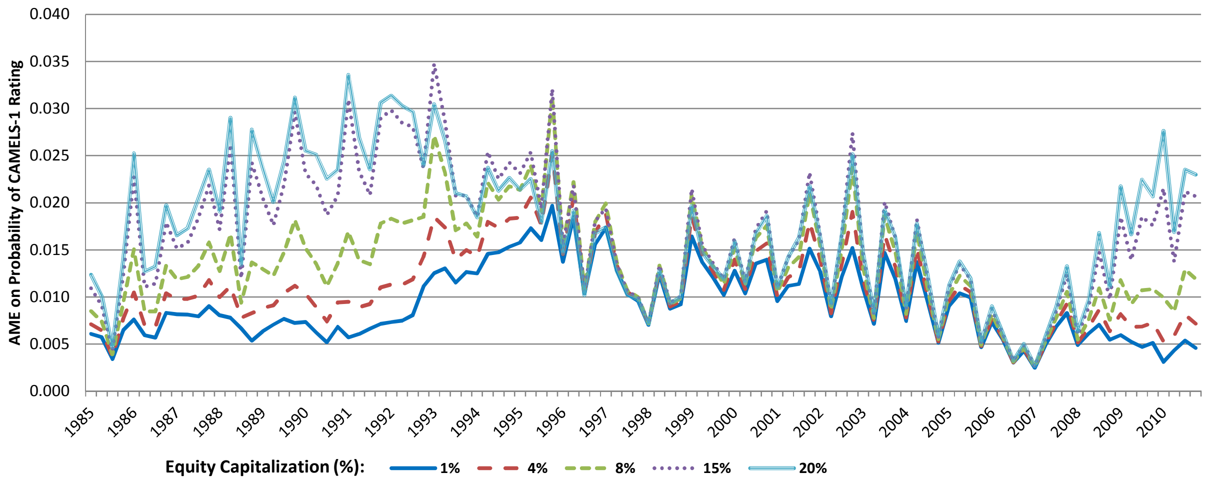

Figure 6.

Marginal Effect of Equity on Probability of a CAMELS 1 Rating (Fixed Covariates at CAMELS 1, M-Rating 1 Banks Means as of Date)

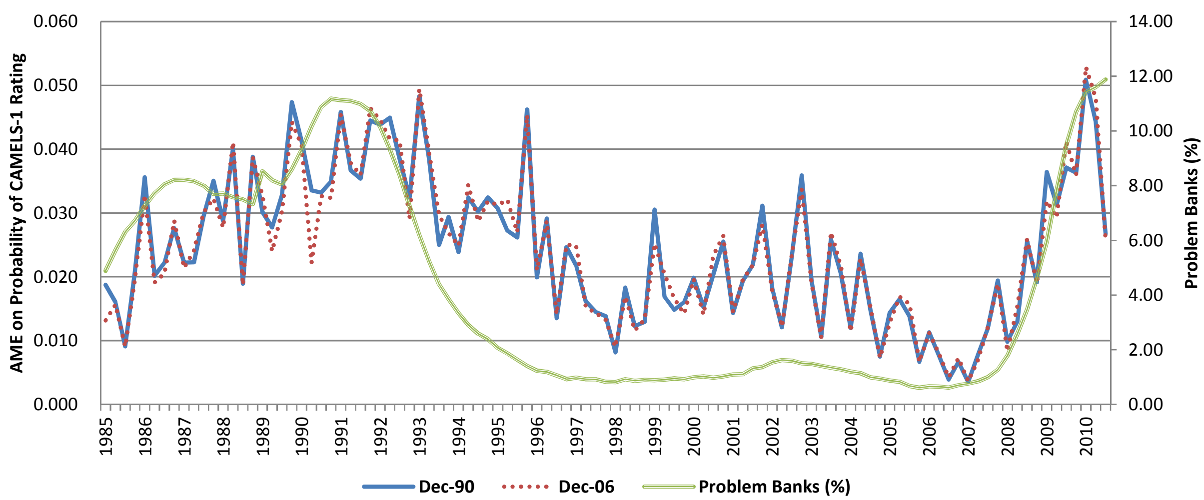

Figure 7.

Marginal Effect of Equity at Representative Values
(Fixed Covariates at CAMELS 3, M-Rating 3 Banks Means as of Date)

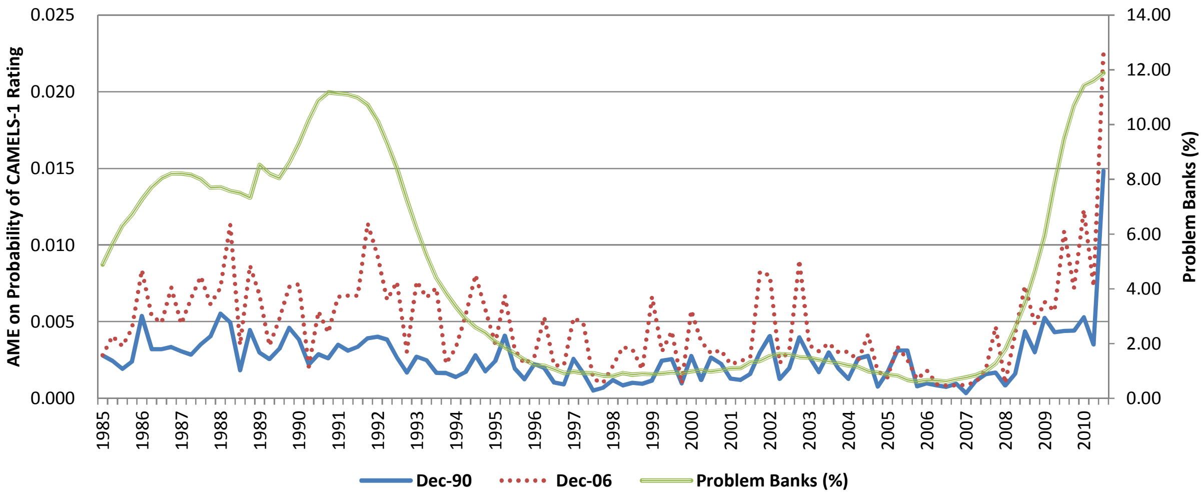

Table 1.
Interaction of Equity and Crisis Period Dummy
Average Marginal Effect (Z score) on Probability of Being a Problem Bank*
(AME in Percentage Points)

Year-ends	Probability of Problem Bank = 1 Range				
	0 - .2	**.2 - .4**	**.4 - .6**	**.6 - .8**	**.8 – 1**
1988 & 1997	-0.02 (-4.89)***	-0.05 (-6.60)***	-0.06 (-6.46)**	-0.04 (-4.11)***	-0.00 (-0.19)
1989 & 1997	-0.01 (-5.03)***	-0.05 (-6.71)***	-0.05 (-6.51)***	-0.04 (-4.01)***	-0.00 (-0.09)
1990 & 1997	-0.01 (-4.54)***	-0.04 (-5.56)***	-0.04 (-4.77)***	-0.03 (-2.90)***	-0.00 (0.30)
1991 & 1997	-0.01 (-4.46) ***	-0.04 (-5.34)***	-0.04 (-4.74)***	-0.03 (-3.04)***	-0.00 (0.03)
1992 & 1997	-0.01 (-3.45)***	-0.02 (-3.23)***	-0.02 (-2.49)**	-0.01 (-1.40)	-0.00 (0.41)
1988 & 1998	-0.01 (-4.15) ***	-0.04 (-5.38) ***	-0.05 (-4.79) ***	-0.03 (-2.94) ***	-0.0 (0.44)
1988 & 1999	-0.01 (-4.35) ***	-0.04 (-5.61) ***	-0.05 (-5.15) ***	-0.03 (-3.07) ***	-0.00 (0.52)
1988 & 2000	-0.00 (-1.96)**	-0.01 (-0.78)	0.00 (0.34)	0.02 (1.64)	0.00 (1.87)*
1988 & 2001	-0.01 (-3.37) ***	-0.03 (-3.48) ***	-0.02 (-2.11)	-0.01 (-0.46)	0.00 (1.71)*
2002 & 2009	0.00 (0.93)	0.01 (0.93)	0.01 (0.55)	0.00 (0.07)	-0.00 (-0.47)
2003 & 2009	-0.00 (-0.18)	-0.00 (-0.28)	-0.00 (-0.28)	-0.00 (-0.21)	-0.00 (-0.07)
2004 & 2009	-0.00 (-0.62)	-0.01 (-0.95)	-0.01 (-0.96)	-0.01 (-0.76)	-0.00 (-0.27)
2005 & 2009	-0.01 (-2.47)***	-0.04 (-4.12)***	-0.04 (-4.41)***	-0.03 (-3.65)***	-0.01 (-1.85)*
2006 & 2009	-0.00 (-0.22)	-0.01 (-0.80)	-0.01 (-1.18)	-0.01 (-1.16)	-0.00 (-0.77)

*Mean values of interaction effects and Z score for banks in each problem bank probability range.
Note: ***, **, * denote significance levels of 1%, 5% and 10%, respectively.[23]

[23] The critical values of the Z score for 1%, 5% and 10% significance levels are 2.58, 1.96 and 1.64, respectively.

Table 2.
Interaction of Loan Loss Reserve and Crisis Period Dummy
Average Marginal Effect (Z score) on Probability of Being a Problem Bank*
(AME in Percentage Points)

Year-ends	Probability of Problem Bank = 1 Range				
	0 - .2	**.2 - .4**	**.4 - .6**	**.6 - .8**	**.8 – 1**
1988 & 1997	0.01 (1.14)	-0.00 (0.06)	-0.05 (-0.92)	-0.10 (-1.91)*	-0.03 (-2.03)**
1989 & 1997	-0.00 (0.08)	-0.04 (-0.96)	-0.09 (-1.85)*	-0.13 (-2.76)***	-0.04 (-2.28)**
1990 & 1997	0.04 (3.26)***	0.09 (2.68)***	0.07 (1.33)	-0.00 (-0.06)	-0.02 (-1.62)
1991 & 1997	0.01 (1.57)	0.02 (0.59)	-0.02 (-0.39)	-0.07 (-1.37)	-0.03 (-1.96)**
1992 & 1997	-0.00 (0.15)	-0.03 (-0.75)	-0.07 (-1.38)	-0.10 (-2.03)**	-0.03 (-2.03)**
1988 & 1998	-0.00 (0.11)	-0.04 (-0.80)	-0.09 (-1.52)	-0.11 (-2.26)**	-0.02 (-1.96)*
1988 & 1999	-0.01 (-0.06)	-0.06 (-1.34)	-0.13 (-2.43)**	-0.17 (-3.38)***	-0.04 (-2.22)**
1988 & 2000	-0.01 (-0.29)	-0.05 (-1.17)	-0.11 (-1.92)*	-0.13 (-2.51)**	-0.03 (-1.92)*
1988 & 2001	-0.00 (0.28)	-0.04 (-0.84)	-0.10 (-1.78)*	-0.14 (-2.68)***	-0.03 (-2.04)**
2002 & 2009	-0.03 (-1.39)	-0.08 (-1.46)	-0.07 (-1.14)	-0.03 (-0.55)	0.00 (0.53)
2003 & 2009	-0.01 (-0.57)	-0.05 (-0.86)	-0.07 (-1.03)	-0.05 (-0.87)	-0.01 (-0.13)
2004 & 2009	-0.00 (-0.07)	-0.02 (-0.29)	-0.03 (-0.49)	-0.03 (-0.53)	-0.01 (-0.22)
2005 & 2009	0.02 (1.08)	0.07 (1.14)	0.06 (0.87)	0.03 (0.40)	-0.00 (-0.45)
2006 & 2009	-0.02 (-1.02)	-0.09 (-1.39)	-0.10 (-1.45)	-0.06 (-0.89)	-0.00 (0.19)

*Mean values of interaction effects and Z score for banks in each problem bank probability range.
Note: ***, **, * denote significance levels of 1%, 5% and 10%, respectively.[24]

[24] The critical values of the Z score for 1%, 5% and 10% significance levels are 2.58, 1.96 and 1.64, respectively.

Table 3.
Interaction of Net Income and Crisis Period Dummy
Average Marginal Effect (Z score) on Probability of Being a Problem Bank*
(AME in Percentage Points)

Year-ends	Probability of Problem Bank = 1 Range				
	0 - .2	**.2 - .4**	**.4 - .6**	**.6 - .8**	**.8 – 1**
1988 & 1997	-0.02 (-3.51)***	-0.04 (-1.81)*	0.01 (0.25)	0.08 (2.75)***	0.03 (2.15)**
1989 & 1997	-0.03 (-3.72)***	-0.04 (-2.12)**	0.01 (0.12)	0.07 (2.68)***	0.03 (2.35)**
1990 & 1997	-0.03 (-3.95)***	-0.06 (-2.92)***	-0.02 (-0.48)	0.06 (2.07)**	0.03 (2.49)**
1991 & 1997	-0.02 (-3.36)***	-0.03 (-1.81)*	0.02 (0.51)	0.08 (2.85)***	0.03 (2.38)**
1992 & 1997	-0.03 (-3.76)***	-0.08 (-3.24)***	-0.05 (-1.39)	0.02 (0.87)	0.03 (2.31)**
1988 & 1998	-0.01 (-2.33)**	0.01 (0.15)	0.07 (2.00)**	0.11 (3.75)***	0.02 (1.17)
1988 & 1999	-0.02 (-2.97)***	-0.02 (-1.29)	0.02 (0.65)	0.07 (3.04)***	0.02 (2.04)**
1988 & 2000	-0.02 (-2.25)**	-0.03 (-1.20)	0.01 (0.26)	0.04 (1.91)*	0.01 (1.68)*
1988 & 2001	-0.02 (-2.60)***	-0.02 (-0.91)	0.04 (1.15)	0.09 (3.52)***	0.03 (1.76)*
2002 & 2009	0.03 (1.41)	0.11 (3.17)***	0.10 (2.93)***	0.04 (1.15)	-0.01 (-1.49)
2003 & 2009	0.01 (0.50)	0.07 (2.02)**	0.08 (2.65)***	0.05 (1.59)	0.00 (-0.69)
2004 & 2009	0.00 (-0.07)	0.01 (0.30)	0.02 (0.60)	0.02 (0.55)	0.00 (0.04)
2005 & 2009	0.00 (-0.18)	0.08 (1.74)*	0.11 (3.06)***	0.08 (2.09)**	0.00 (-0.69)
2006 & 2009	0.02 (0.89)	0.10 (2.44)**	0,09 (2.69)***	0.05 (1.18)	-0.00 (-1.19)

*Mean values of interaction effects and Z score for banks in each problem bank probability range.
Note: ***, **, * denote significance levels of 1%, 5% and 10%, respectively.[25]

[25] The critical values of the Z score for 1%, 5% and 10% significance levels are 2.58, 1.96 and 1.64, respectively.

Table 4.
Interaction of Liquid Assets and Crisis Period Dummy
Average Marginal Effect (Z score) on Probability of Being a Problem Bank*
(AME in Percentage Points)

Year-ends	Probability of Problem Bank = 1 Range				
	0 - .2	**.2 - .4**	**.4 - .6**	**.6 - .8**	**.8 – 1**
1988 & 1997	-0.00 (-1.24)	-0.00 (-1.22)	-0.00 (-1.14)	-0.00 (-1.00)	-0.00 (-0.74)
1989 & 1997	-0.00 (-1.36)	-0.00 (-1.12)	-0.00 (-0.78)	-0.00 (-0.41)	-0.00 (0.03)
1990 & 1997	-0.00 (-1.83)*	-0.00 (-1.81)*	-0.00 (-1.63)	-0.00 (-1.33)	-0.00 (-0.85)
1991 & 1997	-0.00 (-2.39)**	-0.00 (-2.09)**	-0.00 (-1.15)	-0.00 (-0.89)	-0.00 (-0.10)
1992 & 1997	-0.00 (-2.43)**	-0.00 (-2.10)**	-0.00 (-1.57)	-0.00 (-0.92)	-0.00 (-0.15)
1988 & 1998	-0.00 (-1.06)	-0.00 (-1.00)	-0.00 (-0.90)	-0.00 (-0.77)	-0.00 (-0.58)
1988 & 1999	-0.00 (-0.17)	-0.00 (-0.23)	-0.00 (-0.29)	-0.00 (-0.35)	-0.00 (-0.39)
1988 & 2000	0.00 (0.30)	0.00 (0.25)	0.00 (0.19)	0.00 (0.14)	0.00 (0.07)
1988 & 2001	-0.00 (-1.30)	-0.00 (-1.41)	-0.00 (-1.45)	-0.00 (-1.43)	-0.00 (-1.19)
2002 & 2009	-0.00 (-0.40)	0.00 (0.11)	0.00 (0.29)	0.00 (0.44)	0.00 (0.58)
2003 & 2009	-0.00 (-0.86)	-0.00 (-1.01)	-0.00 (-1.12)	-0.00 (-1.07)	-0.00 (-0.82)
2004 & 2009	-0.00 (-1.16)	-0.00 (-1.35)	-0.00 (-1.53)	-0.00 (-1.49)	-0.00 (-1.10)
2005 & 2009	-0.00 (-0.99)	-0.00 (-1.15)	-0.00 (-1.32)	-0.00 (-1.39)	-0.00 (-1.12)
2006 & 2009	-0.00 (-0.70)	-0.00 (-0.71)	-0.00 (-0.64)	-0.00 (-0.51)	-0.00 (-0.34)

*Mean values of interaction effects and Z score for banks in each problem bank probability range.
Note: ***, **, * denote significance levels of 1%, 5% and 10%, respectively.[26]

[26] The critical values of the Z score for 1%, 5% and 10% significance levels are 2.58, 1.96 and 1.64, respectively.

Table 5.
Interaction of Volatile Liabilities and Crisis Period Dummy
Average Marginal Effect (Z score) on Probability of Being a Problem Bank*
(AME in Percentage Points)

Year-ends	Probability of Problem Bank = 1 Range				
	0 - .2	**.2 - .4**	**.4 - .6**	**.6 - .8**	**.8 – 1**
1988 & 1997	-0.00 (-0.41)	-0.00 (-0.25)	-0.00 (-0.10)	0.00 (0.05)	0.00 (0.22)
1989 & 1997	-0.00 (-1.44)	-0.00 (-1.19)	-0.00 (-0.88)	-0.00 (-0.55)	-0.00 (-0.17)
1990 & 1997	0.00 (2.18)**	0.00 (2.14)**	0.01 (1.99)*	0.00 (1.73)*	0.00 (1.22)
1991 & 1997	-0.00 (-0.27)	-0.00 (-0.15)	-0.00 (-0.02)	0.00 (0.11)	0.00 (0.27)
1992 & 1997	0.00 (0.83)	0.00 (0.82)	0.00 (0.80)	0.00 (0.76)	0.00 (0.68)
1988 & 1998	-0.00 (-0.60)	-0.00 (-0.49)	-0.00 (-0.37)	-0.00 (-0.25)	-0.00 (-0.11)
1988 & 1999	-0.00 (-2.18)**	-0.00 (-2.35)**	-0.01 (-2.46)**	-0.01 (-2.40)**	-0.00 (-1.78)*
1988 & 2000	-0.00 (-2.44)**	-0.00 (-2.66)***	-0.01 (-2.79)***	-0.01 (-2.70)***	-0.00 (-1.90)*
1988 & 2001	-0.00 (-0.31)	-0.00 (-0.08)	0.00 (0.14)	0.00 (0.34)	0.00 (0.59)
2002 & 2009	0.00 (2.36)**	0.01 (2.91)***	0.01 (3.12)***	0.01 (2.94)***	0.00 (1.98)*
2003 & 2009	0.00 (1.33)	0.00 (1.54)	0.00 (1.56)	0.00 (1.48)	0.00 (1.20)
2004 & 2009	0.00 (1.30)	0.00 (1.52)	0.00 (1.50)	0.00 (1.39)	0.00 (1.06)
2005 & 2009	0.00 (2.29)**	0.01 (2.84)***	0.01 (2.81)***	0.01 (2.47)**	0.00 (1.65)*
2006 & 2009	0.00 (0.52)	0.00 (0.75)	0.00 (0.89)	0.00 (0.94)	0.00 (0.90)

*Mean values of interaction effects and Z score for banks in each problem bank probability range.
Note: ***, **, * denote significance levels of 1%, 5% and 10%, respectively.[27]

[27] The critical values of the Z score for 1%, 5% and 10% significance levels are 2.58, 1.96 and 1.64, respectively.

Table 6.
Interaction of Nonaccrual Loans and Crisis Period Dummy
Average Marginal Effect (Z score) on Probability of Being a Problem Bank*
(AME in Percentage Points)

Year-ends	Probability of Problem Bank = 1 Range				
	0 - .2	**.2 - .4**	**.4 - .6**	**.6 - .8**	**.8 – 1**
1988 & 1997	0.01 (2.31)**	0.01 (0.67)	-0.03 (-0.72)	-0.07 (-2.23)**	-0.02 (-1.94)*
1989 & 1997	0.02 (2.91)***	0.02 (1.15)	-0.02 (-0.47)	-0.07 (-2.19)**	-0.03 (-2.11)**
1990 & 1997	0.03 (3.82)***	0.07 (3.05)***	0.05 (1.34)	-0.01 (-0.43)	-0.02 (-2.06)**
1991 & 1997	0.02 (3.32)***	0.05 (2.11)**	0.02 (0.53)	-0.03 (-1.04)	-0.02 (-2.14)**
1992 & 1997	0.01 (2.39)**	0.01 (0.63)	-0.02 (-0.64)	-0.06 (-2.07)**	-0.02 (-1.99)*
1988 & 1998	0.00 (0.77)	-0.04 (-0.98)	-0.08 (-2.12)**	-0.10 (-3.15)***	-0.02 (-1.22)
1988 & 1999	0.01 (1.51)	-0.00 (0.04)	-0.04 (-1.06)	-0.07 (-2.30)**	-0.02 (-1.73)*
1988 & 2000	0.01 (1.62)	0.01 (0.66)	-0.01 (-0.24)	-0.03 (-1.19)	-0.01 (-1.53)
1988 & 2001	0.02 (2.31)**	0.03 (1.25)	0.00 (0.10)	-0.03 (-1.10)	-0.01 (-1.75)*
2002 & 2009	-0.01 (-1.29)	-0.04 (-1.30)	-0.03 (-1.01)	-0.01 (-0.37)	0.00 (0.82)
2003 & 2009	-0.01 (-1.21)	-0.07 (-1.98)**	-0.07 (-2.35)**	-0.04 (-1.47)	-0.00 (0.57)
2004 & 2009	-0.02 (-1.09)	-0.09 (-2.20)**	-0.10 (-2.78)***	-0.06 (-1.78)*	-0.00 (0.91)
2005 & 2009	0.00 (0.49)	0.00 (0.16)	-0.01 (-0.17)	-0.02 (-0.57)	-0.00 (-0.50)
2006 & 2009	-0.01 (-1.21)	-0.06 (-1.75)*	-0.06 (-1.83)*	-0.03 (-0.93)	0.00 (0.80)

*Mean values of interaction effects and Z score for banks in each problem bank probability range.
Note: ***, **, * denote significance levels of 1%, 5% and 10%, respectively.[28]

[28] The critical values of the Z score for 1%, 5% and 10% significance levels are 2.58, 1.96 and 1.64, respectively.

Table 7.
Interaction of Loan Charge-offs and Crisis Period Dummy
Average Marginal Effect (Z score) on Probability of Being a Problem Bank*
(AME in Percentage Points)

Year-ends	Probability of Problem Bank = 1 Range				
	0 - .2	**.2 - .4**	**.4 - .6**	**.6 - .8**	**.8 – 1**
1988 & 1997	0.02 (2.52)***	0.03 (0.93)	-0.04 (-0.63)	-0.11 (-2.30)**	-0.03 (-1.99)*
1989 & 1997	0.01 (1.24)	-0.03 (-0.50)	-0.10 (-1.82)*	-0.15 (-3.35)***	-0.04 (-2.08)**
1990 & 1997	0.01 (0.99)	-0.01 (-0.08)	-0.06 (-1.04)	-0.11 (-2.10)**	-0.04 (-2.13)**
1991 & 1997	-0.00 (0.03)	-0.05 (-0.99)	-0.10 (-1.80)*	-0.14 (-2.72)***	-0.04 (-2.26)**
1992 & 1997	0.01 (1.40)	-0.01 (-0.06)	-0.06 (-1.10)	-0.11 (-2.32)**	-0.04 (-2.11)**
1988 & 1998	0.02 (1.99)	0.03 (0.90)	-0.00 (-0.06)	-0.05 (-1.20)	-0.02 (-1.73)*
1988 & 1999	0.02 (1.75)	0.02 (0.56)	-0.02 (-0.39)	-0.07 (-1.51)	-0.02 (-1.78)*
1988 & 2000	0.01 (1.35)	0.01 (0.39)	-0.03 (-0.48)	-0.06 (-1.40)	-0.02 (-1.54)
1988 & 2001	0.02 (1.44)	-0.01 (-0.05)	-0.08 (-1.40)	-0.13 (-2.83)***	-0.03 (-1.66)*
2002 & 2009	-0.03 (-2.15)**	-0.11 (-2.30)**	-0.13 (-2.36)**	-0.10 (-2.21)**	-0.02 (-1.51)
2003 & 2009	-0.04 (-2.48)**	-0.14 (-2.75)***	-0.16 (-2.99)***	-0.13 (-2.76)***	-0.02 (-1.70)*
2004 & 2009	0.01 (0.91)	0.04 (0.93)	0.06 (0.93)	0.05 (0.91)	0.01 (0.75)
2005 & 2009	-0.00 (-0.31)	-0.02 (-0.60)	-0.04 (-0.60)	-0.04 (-0.74)	-0.01 (-0.45)
2006 & 2009	-0.03 (-1.92)*	-0.12 (-2.06)**	-0.14 (-2.18)**	-0.10 (-2.11)**	-0.02 (-1.50)
*Mean values of interaction effects and Z score for banks in each problem bank probability range. Note: ***, **, * denote significance levels of 1%, 5% and 10%, respectively.[29]					

[29] The critical values of the Z score for 1%, 5% and 10% significance levels are 2.58, 1.96 and 1.64, respectively.

Table 8.
Interaction of Provisions for Loan Losses and Crisis Period Dummy
Average Marginal Effect (Z score) on Probability of Being a Problem Bank*
(AME in Percentage Points)

Year-ends	Probability of Problem Bank = 1 Range				
	0 - .2	**.2 - .4**	**.4 - .6**	**.6 - .8**	**.8 – 1**
1988 & 1997	-0.03 (-2.34)**	-0.07 (-2.08)**	-0.07 (-1.46)	-0.04 (-0.74)	-0.00 (-0.10)
1989 & 1997	-0.02 (-1.98)*	-0.07 (-1.92)*	-0.08 (-1.68)*	-0.07 (-1.34)	-0.01 (-0.99)
1990 & 1997	0.00 (0.03)	0.01 (0.14)	0.01 (0.25)	0.02 (0.35)	0.01 (0.42)
1991 & 1997	0.00 (0.39)	0.01 (0.17)	-0.00 (-0.05)	-0.01 (-0.28)	-0.01 (-0.59)
1992 & 1997	0.00 (0.40)	0.02 (0.48)	0.03 (0.54)	0.03 (0.58)	0.01 (0.56)
1988 & 1998	-0.03 (-2.24)**	-0.08 (-2.04)**	-0.09 (-1.69)*	-0.07 (-1.27)	-0.01 (-0.93)
1988 & 1999	-0.05 (-3.54)***	-0.17 (-3.83)***	-0.23 (-4.00)***	-0.21 (-3.89)***	-0.04 (-2.45)**
1988 & 2000	-0.03 (-2.52)***	-0.10 (-2.59)***	-0.12 (-2.50)**	-0.10 (-2.30)**	-0.02 (-1.77)*
1988 & 2001	-0.04 (-3.01)***	-0.12 (-3.18)***	-0.15 (-2.96)***	-0.13 (-2.56)**	-0.02 (-1.83)*
2002 & 2009	-0.03 (-2.31)**	-0.12 (-2.41)**	-0.13 (-2.48)**	-0.10 (-2.18)**	-0.01 (-1.19)
2003 & 2009	-0.03 (-2.32)**	-0.12 (-2.44)**	-0.15 (-2.66)***	-0.12 (-2.53)**	-0.02 (-1.53)
2004 & 2009	0.01 (1.01)	0.05 (1.06)	0.06 (1.08)	0.06 (1.05)	0.01 (0.79)
2005 & 2009	0.01 (0.61)	0.03 (0.73)	0.03 (0.86)	0.05 (0.92)	0.01 (0.74)
2006 & 2009	-0.04 (-2.26)**	-0.15 (-2.42)**	-0.16 (-2.63)***	-0.12 (-2.30)**	-0.01 (-2.11)**

*Mean values of interaction effects and Z score for banks in each problem bank probability range.
Note: ***, **, * denote significance levels of 1%, 5% and 10%, respectively.[30]

[30] The critical values of the Z score for 1%, 5% and 10% significance levels are 2.58, 1.96 and 1.64, respectively.

Table 9.
Interaction of Financial Variables and Crisis Period Dummies: Results Summary

Financial Variables	**Direction of Average Marginal Effect of Interaction Term on Probability of Problem Bank = 1**	
	1980s – 1990s Crises	**2007 – 2010 Crisis**
Equity	**–**	Not Significant
Loan Loss Reserve	**–**	Not Significant
Return on Assets	Mixed	Weakly **+**
Liquid Assets	Weakly **–**	Not Significant
Volatile Liabilities	Mixed	Weakly **+**
Nonaccrual Loans	Mixed	Weakly **–**
Gross Loan Charge-offs	**–**	**–**
Loan Loss Provision	**–**	**–**
Loans Delinquent 30-89 Days	Not Significant	Not Significant
Loans Delinquent 90 Days or More	Not Significant	Not Significant
Other Real Estate Owned	Not Significant	Not Significant
Loans and long-term Securities	**+**	**+**