

How Has Bank Supervision Performed And How Might It Be Improved?

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Abstract

Bank supervisors rate an individual bank's overall safety and soundness according to the Uniform Financial Institutions Rating System (UFIRS), which requires that the ratings be based on the bank's financial performance, risk management practices and compliance with laws and regulations. UFIRS ratings assess bank financial performance and risk management practices based on six areas—capital adequacy, asset quality, management, earnings, liquidity, and sensitivity to market risk (hereafter, CAMELS ratings).

To understand how banks' financial performance and local economic conditions influence their CAMELS ratings, we develop and estimate a supervisory Ratings Rule Model. The Ratings Rule Model predicts the CAMELS rating a bank might receive in the near term (quarter) based on its current financial performance and local economic conditions. We investigate how the estimated regression coefficients (factor weights) of the model vary with banking market and economic conditions in order to learn how supervisors' assessments are influenced by these same conditions. We find systematic variation in the model's factor weights and offer reasons for this variation.

We next develop and estimate an Interim-Term Model that forecasts banks' likely CAMELS ratings one to two years hence. We demonstrate that the forecasts of banks' CAMELS ratings are significantly improved if the model includes contemporaneously available forecasts of future statewide economic conditions. We conclude by developing a framework for making more explicitly forward-looking forecasts of banks' conditions and discuss how these forecasts might be used to set a threshold for regulatory intervention at distressed banks. This threshold could serve as an alternative to the equity capital threshold specified by the Prompt Corrective Action provisions of the Federal Deposit Insurance Corporation Improvement Act (1991).

1. Introduction

The primary financial indicator of a bank's overall safety and soundness is its capital adequacy.¹ To assess a bank's capital adequacy, bankers and bank supervisors consider three things: the bank's ability to absorb unexpected losses, given the risks inherent in its balance sheet and off-balance-sheet activities;² the bank's risk management practices; and local economic conditions. Banks may become inadequately capitalized because of unexpected credit or other losses, which may stem either from ordinary business and financing risks or from poor risk-management practices, such as inadequate loan underwriting standards, unduly-risky portfolio concentrations, and underpriced risk.³ Moreover, weaknesses in bank risk-management practices become more transparent to bankers and their supervisors during periods of economic stress. Thus, during periods when available resources for obtaining capital—retained earnings or external capital injections—are shrinking, both bank supervisors and bank managers typically increase the pressure on banks to augment capital buffers. As a result, bank

¹ We use the term “bank” to refer to all FDIC-insured depository institutions. This category includes commercial banks, savings banks, savings and loan associations, and cooperative banks. It does not include credit unions insured by the National Credit Union Share Insurance Fund.

² While equity capital serves as a cushion against unexpected losses, a bank's loss reserves serve as a cushion against expected losses. Under GAAP accounting rules, banks are required to establish loss reserves (also known as allowances for loan and lease losses) that reflect the level of probable and estimable losses in the portfolio—that is, expected or normal losses that have not yet accrued to the bank. When expected losses become actual losses, loss reserves are reduced by the amount of loss actually incurred. Should further losses be expected, the bank would replenish loss reserves through an expense or loan-loss provision shown on the income statement.

³ Bank capital requirements are based on a set of statutory minimum capital ratios for safe and sound banks, and on discretionary supervisory requirements that increase required capital ratios as a bank's overall condition deteriorates.

capital pressures may be “procyclical”: pressures to raise capital ratios increase during economic downturns and curtail bank lending, thereby exacerbating the downturns.⁴

Prior studies have found that capital pressures on banks reduce lending and economic activity. Bernanke and Lown (1991), Peek and Rosengren (1995), Hancock and Wilcox (1994, 1998), and Pennacchi (2005, 2006), along with several others, have documented the depressing effects on U.S. banks and the economy resulting from increased pressures on bank capital.

During previous banking crises, as well as during the early period of the 2007–2009 financial crisis, several proposals were made that would increase regulatory flexibility and supervisory discretion as a way to reduce the unintended harm to the macroeconomy caused by procyclical bank capital requirements. These proposals typically allow for the temporary suspension of statutory minimum bank capital requirements as well as for greater flexibility in supervisory standards if banks are considered to be temporarily under duress. More recent policy proposals have gone further and have sought to reduce and even eliminate the procyclicality of bank capital requirements by making statutory minimum capital requirements explicitly countercyclical (examples are proposals for “dynamic” loss provisioning).

In addition to the possibility of modifying regulatory capital requirements, there may be significant opportunities for banks and their regulators to circumvent them. Any regulatory capital requirements can be undermined by excessive financial reporting discretion exercised by banks and accepted by their regulators. For example, the 2009 Financial Accounting Standards Board amendments to accounting guidance for reporting

⁴ The adverse macroeconomic consequences of procyclical capital pressures are addressed by the literature on credit cycles and, in particular, the literature on the bank lending channel.

the “fair value” of infrequently traded securities held in banks’ trading books (level 3 asset valuations) may effectively allow banks to avoid recording losses on many of the structured securities whose underlying collateral (commercial and residential mortgage) values have fallen dramatically since 2007.

We propose an alternative to capital-based thresholds for early supervisory intervention at troubled banks. Specifically, we propose a method of forecasting the likely overall conditions of individual banks one to two years hence. Our measure of overall bank conditions is the safety and soundness ratings assigned after on-site inspections of banks by their supervisors. Bank supervisors rate an individual bank’s overall safety and soundness according to the Uniform Financial Institutions Rating System (UFIRS), which requires that the ratings be based on the bank’s financial performance, risk management practices and compliance with laws and regulations. UFIRS ratings assess bank financial performance and risk management practices based on six areas—capital adequacy, asset quality, management, earnings, liquidity, and sensitivity to market risk (hereafter, CAMELS ratings).⁵ Bank CAMELS ratings are integer ratings that vary from 1 (best rating) to 5 (worst rating).⁶ As such, our method incorporates factors that affect both the expected value and variance of potential future bank conditions. The efficacy of our proposal depends on two features: (1) an early warning system that is effective—that can indicate what supervisory and management actions might be warranted far enough in advance of adverse economic conditions to

⁵ In addition to the overall bank safety and soundness ratings (also known as composite CAMELS ratings), bank supervisors also assign banks ratings for each of the six areas reviewed during on-site examinations—capital adequacy, asset quality, management, earnings, liquidity and sensitivity to market risk (component CAMELS ratings).

⁶ The UFIRS rating criteria are based on the strength of banks’ financial performance, risk management practices and compliance with laws and regulations relative to the size and complexity of the bank.

reduce the procyclicality of capital pressures and lending, and (2) an early warning system that is less susceptible to manipulation and mis-measurement than an equity capital-based early warning system.⁷ The approach advanced here attempts to provide bank supervision with tools to “assist” banks in taking more prompt and more preventive actions than has been the case too often in the past.

Section 2 briefly reviews the literature on supervisory ratings of bank safety and soundness, with particular attention to studies of the roles played in those ratings by banks’ accounting data and by local economic conditions. Section 3 shows how similarly the accounting, supervisory, and market-based data portray the evolution of banks’ conditions over recent decades. Section 4 presents our CAMELS Ratings Rule Model. Section 5 presents results of our estimates of the Ratings Rule Model. Section 6 develops a model for forecasting CAMELS ratings for individual banks one to two years hence (hereafter, Intermediate-Term Model), using contemporaneous information on forecasted state economic conditions and bank financial condition. Section 7 proposes ways in which forecasts for a one- to two-year horizon of bank condition might be incorporated into current supervisory and management actions and plans; indicates how current estimates of the future volatility of banks’ conditions might be used to calculate risk-adjusted CAMELS ratings; and discusses a possible role for the more explicitly forward-looking risk measures in setting capital requirements. Section 8 notes that small banks as a group might pose systemic risk and then discusses how their capital requirements might

⁷ We acknowledge that there is no system of risk measurement, internal or external to a bank, that is impervious to manipulation and therefore to mis-measurement at some level. However, if the risk measurement system were made more forward looking, risk assessment might occur when banks were under less pressure to mask financial difficulties.

reflect their contributions to such risk. Section 9 summarizes our findings and some of their potential applications.

2. Literature Review

Empirical studies have addressed various aspects of supervisors' ratings of banks. Some of the studies have investigated whether supervisors' judgments, as encapsulated in the CAMELS ratings the supervisors assigned, have been validated in the sense that the ratings predicted ensuing bank financial performance or bank equity share prices. Cole and Guenther (1998) showed that recently-assigned CAMELS ratings (statistically significantly) improved forecasts of bank failures. De Young et al. (1998) found that CAMELS ratings helped to forecast yields on banks' bonds. Berger and Davies (1998) concluded that supervisors' ratings tended 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) reported that, for predicting future performances of bank holding companies, recently-assigned bank holding company examination ratings tended to outperform market-based measures. O'Keefe et al. (2003) and O'Keefe (2009) provide evidence that supervisors' judgments about the caliber of loan underwriting standards helped to predict the future volumes of problem loans at banks. And Bennett et al. (2008) showed that the worse a bank's CAMELS rating, the more likely the bank was to become troubled and fail. Taken together, these studies suggest that on-site exams and supervisors' judgments provide information about banks beyond that embodied in

contemporaneous bank financial statements (Call Reports) and bank debt and equity prices and yields.⁸

A small number of studies have examined the extent to which banks' future conditions, as indicated by their CAMELS ratings, could be forecasted by Call Report or other readily available data. Collier et al. (2003) showed that banks' future conditions, and in particular CAMELS-rating downgrades, were somewhat forecastable with Call Report data. Their testing of the FDIC's Statistical CAMELS Off-site Ratings (SCOR) model indicated that the model had some ability to predict downgrades over a six-month horizon. Nuxoll et al. (2003) investigated whether adding measures of current local economic conditions helped SCOR better forecast banks' conditions. The evidence they reported was mixed: For some measures of bank condition and at some horizons, economic conditions contributed appreciably, but for other measures and at other horizons, the contributions of local economic conditions were negligible. Thus, prior studies have pointed quite consistently toward supervisors' ratings as being informative about banks' conditions. At the same time, there is no strong evidence that economic variables significantly improve forecasts of banks' conditions. Nor is there strong evidence that the same Call Report measures that seem to perform well at very short horizons help to forecast banks' conditions at the considerably longer forecast horizon of one to two years that we focus on.

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.

3. Trends in Banking Industry Condition and the Outlook

The literature discussed in section 2 indicates that bank supervisors poses unique information about banks that can be used to predict future bank performance, including the likelihood of failure. Importantly, the literature also indicates that bank supervisors poses information that provides better forecasts of future bank performance than that provided by bank financial statements and debt and equity prices. This section continues the comparison of the three types of bank information—supervisory, financial and security market—by direct comparisons of trends in each type of information.

Figure 1 shows annual data for (gross) loan charge-offs and for provisions for loan losses (both expressed as a percentage of bank assets) and the ratio of the book value of bank equity capital to assets in the aggregate for U.S. banks during 1960–2008. By these indicators, banking conditions were noticeably weaker before the middle of the 1990s and were markedly stronger after that, at least until the onset of the 2007–2009 global financial crisis. For instance, until the middle of the 1990s, banks' capital ratios were lower than they would be subsequently (until 2007); starting in the mid-1990s they rose markedly,⁹ but with the advent of the 2007–2009 financial crisis, loan losses rose and capital fell.

Figure 2 plots the average CAMELS rating across banks for each quarter from 1984:1 through 2009:3, and for each quarter it also plots the cross-bank standard deviation of the CAMELS ratings, which through time moved nearly in tandem with the average rating. Note that the average and standard deviation for each quarter as plotted in

⁹ See Flannery and Rangan (2008) for an investigation of the reasons for the increase in capital ratios during this period. Stever and Wilcox (2007) indicate that less reporting discretion was likely exercised in the 1990s than previously and that, instead of being over-stated, bank capital ratios in the 1990s were effectively very likely even stronger than were reported then.

Figure 2 are based on contemporaneous CAMELS ratings, that is, those that were assigned during the quarter.¹⁰

We see in Figure 2 that the average and standard deviation of the CAMELS ratings improved (declined) substantially by the middle of the 1990s and also worsened (rose) slightly during and after the 2001 recession. Then, with the onset of the 2007–2009 financial crisis, both the average and the standard deviation of the CAMELS ratings reached their worst (highest) levels since at least 1984. We note in passing that the average CAMELS ratings may change over time because of changes in banking and economic conditions, in bank risk-management practices, and in supervisory standards.

Figure 3 shows monthly data for the expected default frequencies (EDFs) for publicly traded U.S. banking companies from 1990 through the summer of 2009. Moody’s KMV (MKMV) calculated these EDFs using its implementation of the Merton (1974) model of firm equity holders’ put option on the value of firm assets. The KMV/Merton model uses banks’ stock prices, banks’ balance-sheet data, and MKMV’s data on observed debt defaults. The series for large banks is based on the banks that are in the top asset-size quartile of banks; the series for “small” banks is based on the banks that had fewer than the median amounts of assets.¹¹ The average EDFs for small banks were quite highly correlated over time with the EDFs for large banks, but the former were very much smaller. The average EDFs improved (declined) noticeably into the middle of the

¹⁰ The Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991 established examination frequencies for large and small banks. To ease regulatory burden, the examination cycle has been amended over time. As of 2009, all banks with assets under \$250 million and a composite CAMELS rating of 1 or 2 must be examined at least every 18 months by their primary state or federal supervisor. All other banks must be examined at least annually.

¹¹ At the beginning of the sample period there were about 100 small and 50 large banks in the sample; by the end of the period there were about 300 small and 150 large banks. The EDF data for the two series were provided by Moody’s KMV.

1990s, as the average CAMELS did, but unlike the average CAMELS, the average EDFs then worsened (rose) considerably during both the Asian crisis of the latter 1990s (which affected publicly traded banks more than banks on average) and the 2001 recession. After 2001, the average EDFs improved (fell) very sharply, to their best (lowest) levels of the years since 1990. Then, in 2008, the average EDFs worsened (rose) to their highest levels by far in the sample period.

Despite the differences among Figures 1–3 in banks' covered and in approach, all three figures portray U.S. banks (in broad outline) as having been stronger in the middle of each of the two-decades and weaker near each decade's beginning and end.

4. Ratings Rule Model

In this section we develop a short-term forecasting model (Ratings Rule Model) that predicts the CAMELS ratings banks might receive if they are examined in the calendar quarter subsequent to the forecast date (e.g., predict CAMELS ratings for first quarter of 2009 based only on information available as of year-end 2008). The model is based on the FDIC's SCOR model.¹² Specifically, we hypothesize that the CAMELS rating received by a bank during a calendar quarter is determined by measures of the bank's financial CAMELS attributes as of the end of the prior quarter and to lagged measures of state economic conditions (equation 1, below). This Ratings Rule Model uses publicly available data and admittedly does not include crucial information on the practices and quality of bank management.

¹² See Collier et al. (2003) and Nuxoll et al. (2003).

$$1) \text{ CAMELS}_{j,t} = \alpha + \beta' X_{j,t-1} + \lambda' Z_{t-1} + \varepsilon_t$$

In equation 1, $\text{CAMELS}_{j,t}$ is the CAMELS rating received by bank j during an on-site examination during quarter t ; β is a vector of regression coefficients (factor weights); and $X_{j,t-1}$ is a vector of financial ratios reflecting the bank's capital adequacy, asset quality, earnings, liquidity, and sensitivity to market risk as of quarter $t-1$. To control for local economic conditions we include Z_{t-1} , a vector of lagged state economic conditions, with associated factor weights vector, λ , 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.

We estimate equation 1 using Ordinary Least Squares (OLS) regression. We acknowledge that OLS regression is not the correct specification for explaining a discrete, ordinal dependent variable (CAMELS rating); however, the linear approximation greatly simplifies our discussion of the Ratings Rule Model factor weights.¹³

We began by estimating a Ratings Rule Model to approximate the actual process that supervisors use to assign CAMELS to individual banks. For each quarter, we regressed the actual CAMELS rating for each bank on variables from its most recent Call Report. Thus, for example, for the Ratings Rule Model we regressed second-quarter CAMELS ratings on (end of) first-quarter Call Report data. Our cross-section estimation

¹³ Unpublished research conducted by the FDIC during the development its amendments to its risk-related deposit insurance pricing system in 2006 found that both OLS regression models and ordinal logistic regression models produced CAMELS forecasts that rank banks, in terms of risk, very similarly.

sample included only those banks that received a fresh CAMELS rating during that quarter. Our quarter-by-quarter samples averaged around 4,000 banks.

Mimicking SCOR, we used the following 12 variables in our OLS regressions to account for individual banks' CAMELS ratings: equity capital, loans delinquent 30–89 days, loans delinquent over 90 days, 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.¹⁴ In the regressions, each of these variables was expressed as a percentage of each bank's gross assets.¹⁵

We excluded from our sample those banks whose Call Reports reported values far in the tails of the variables' distributions. We otherwise included banks of all sizes. Because the data were not weighted by asset size, the few dozen very large 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 included banks regardless of whether they were part of multibank holding companies.

In addition to the SCOR variables, we also included recent local economic growth, as measured by the first four quarterly lags of the statewide growth rate of economic activity, which we approximated by the one-quarter growth rate of the State Coincident Indexes that are compiled by the Federal Reserve Bank of Philadelphia (2009). We expected recent local economic growth rates to influence supervisors' judgments, and thus CAMELS ratings, in that they serve as a proxy for information that

¹⁴ 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.

¹⁵ Gross assets are defined as total assets gross of the allowance for loan and lease losses.

will likely soon be—but has not yet been—reflected in future Call Reports. Thus, for example, weak 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.

5. Results of Ratings Rule Model Estimations

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 estimates of the coefficients for the explanatory variables (factor weights) of the Ratings Rule Model and offer potential explanations for time variation in factor weights.

5.1 Time Variation in Factor Weights

The OLS coefficient estimates for the explanatory variables of the Ratings Rule Model provide quarterly time-series data for the factor weights. We indexed the values for each series of factor weights to equal 1.00 for 1984:1 in Figures 4 and 5. The factor weights for the index base period (1984:1) for each variable in Figures 4 and 5 had the sign that we expected. Because this indexing procedure makes the factor weights all positive, we can regard the plotted series as the absolute values of the factor weights. Thus, for example, although the factor weights for capital were uniformly negative, its plotted values are all positive (having been normalized by its negative estimate for

1984:1). In Figure 4, then, we should recognize that having more capital tended to lead to better (lower) CAMELS ratings.

The top panel in Figure 4 plots the factor weights for equity capital and for income before taxes (return on assets [ROA]). There we see considerable variation over time in the effect of an additional unit of capital on a bank's predicted CAMELS rating (standard deviation [s.d.] = 0.87). The factor weight on banks' incomes, however, varied relatively much less (s.d. = 0.12). The bottom panel of Figure 4 contains the (indexed) factor weights for gross loan charge-offs and for loan loss provisions, both of which varied relatively less over 1984–2009 (s.d. = 0.26 and 0.29, respectively) than the factor weights on equity capital did but more than the factor weights on bank income.

Historically, some of the largest factor weights for all four variables were clustered around 1990–1991. Between 1990 and 2008 the factor weight on capital dwindled quite steadily; then it rebounded considerably from its lows, but recently it has still been considerably below the peaks observed around 1990. Although more charge-offs and provisions tended to worsen (raise) CAMELS ratings, the factor weights associated with both of these variables have fallen noticeably in recent years.

Figure 5 plots the estimated factor weights for OREO and nonaccrual loans (top panel) and for liquid assets and volatile liabilities (bottom panel). Somewhat surprisingly, the factor weights on OREO plummeted around 1990. The factor weights have been considerably higher ever since and have shown no dramatic changes over the past decade. Nonaccruals have typically been consistently strong contributors, statistically speaking, in the SCOR model, as they are in our Ratings Rule Model: higher nonaccruals quite reliably worsened (raised) CAMELS ratings. Unlike several other variables, the factor

weights on nonaccruals did not change much around 1990. The factor weights did, however, drop around the late 1990s and again during the 2007–2009 financial crisis. Also noteworthy is the apparent tendency of the factor weights on nonaccruals to move in the opposite direction from those on OREO. Given the likely positive correlation in the individual-bank data of OREO and nonaccruals, observing negative correlation in the estimated coefficients due to that pattern of multicollinearity in the data was not particularly surprising.

The factor weights on liquid assets tended to increase around 1990 but then drifted downward substantially, whereas the factor weights on volatile liabilities trended upward, with both series reversing their trends somewhat after the onset of the recent crisis.

The upshot of Figures 4 and 5 is, first, that the factor weights have quite consistently been related to CAMELS ratings and, second, that the factor weights have changed considerably through time. When the banking industry was weak, as in the early 1990s and perhaps most recently, the factor weights were often larger than they had been previously or than they are on average.

5.2 *Reasons for Time Variation in Factor Weights*

There are a number of potential reasons for time variation in the factor weights obtained from quarterly estimations of equation 1. First, the actual “ratings rule” that supervisors used may have contained known, measurable variables other than those that we included in our specification of the rule; two prime examples of variables that supervisors use to evaluate banks but that are missing in our model are the quality and the

risk management practices of bank management. A third example of an explanatory variable we cannot include is a measure of individual banks' loan underwriting standards. Underwriting standards, especially those for residential mortgages, now appear to have undergone large, widespread gyrations over the past decade.¹⁶ Although supervisors might well have obtained valuable information during their on-site exams about banks' underwriting standards, we had no long-running data for individual banks' underwriting standards. The resulting omitted-variables bias may well be substantial and, importantly for present purposes, may well vary substantially over time, thereby causing our estimates of factor weights to vary over time. If the correlation between the included and excluded variables changes over time, we would expect the estimated factor weights to shift relative to the actual factor weights used by supervisors.¹⁷

A second potential reason for time variation in estimated factor weights is that supervisors' judgments about banks' conditions may well reflect information that is not quantified in publicly available data. One virtue of on-site bank examinations is that they enable supervisors to validate and, if necessary, call for adjustments to bank financial statements.¹⁸ (Note that, as a practical matter, we have access only to the finalized financial statements that banks file with their primary federal regulators.)

A third reason for time variation in estimated factor weights might be another form of misspecification error. Although we have included a measure of economic

¹⁶ See O'Keefe (2009) and Wilcox (forthcoming).

¹⁷ As an indication of whether correlations might change considerably over time, we compared the correlations between the included variables over the period 1984–1993 with the correlations for the period 1999–2009. We found, for example, that in our estimation sample of banks, the correlation between the (aggregate) mean capital ratio and bank incomes before taxes fell from +0.30 to -0.11; the correlation between loans delinquent more than 90 days and OREO rose from -0.54 to +0.37.

¹⁸ See Dahl et al. (1998).

activity for the state in which each bank was headquartered, for some banks the relevant region was much larger than the home state, and for other banks it was much smaller. To the extent that banks' states differed from banks' relevant regions, whether the relevant region was multistate or countywide, there is some scope for (time-varying) bias in estimated rating-rule factor weights.

Fourth, there may be a sort of time-varying "Lucas Critique" bias associated with the lagged local economic activity variables that we included in the model. If the time-series process for economic activity changed, then the implied optimal factor weights for forecasting current and future activity would change, and so—probably—would the judgment about the implications of currently observed values of included variables. Thus, for example, when economic growth was more strongly autocorrelated, larger extrapolations of the effects of additional recent economic growth on banks' conditions (e.g., on loan delinquencies or earnings) would be warranted.¹⁹

A fifth reason for observing changing factor weights over time might be (non)linearity. We applied a linear estimation technique (OLS) to a linear specification of the variables. A nonlinear estimation method, such as ordered logit, is preferable. (We did find considerable time variation in factor weights estimated via ordered-logit as well). At the same time, it might well have been the case that supervisors put more weight on a particular variable when a bank generally, or that particular variable, was worryingly weak. Thus, judgments reflected in CAMELS ratings might have responded more to capital when capital was low than when it was abundant. This sort of judgment might impart a systematic variation to factor weights.

¹⁹ During the moderation of economic growth rates after the 1980s, the volatility of growth rates plummeted. Before then, economic growth rates had been less forecastable.

Sixth and last, quite apart from the possibilities mentioned above, there may have been shifts over time in the effective stringency of supervisory judgments. Bankers have occasionally decried such shifts, most vocally during the period around 1990 and perhaps again currently. Regardless, though we document the time variation in factor weights, disentangling how much of the variation should be attributed to each of the sources noted above is outside the scope of this paper.

5.3 *Systematic Patterns in the Ratings Rule Model*

In this section we investigate whether quarterly values of the Ratings Rule Model factor weights were related to lagged quarterly values of the same factor weights and to measures of banking market and local economic conditions. To do this we regressed the quarterly values of factor weights on local economic growth rates (summed across four lags), equity capital, loans delinquent more than 90 days, nonaccrual loans, allowance for loan and lease losses, volatile liabilities, income before taxes, and the model intercept on the following variables: (1) one-quarter lagged values of the dependent variables, (2) one-quarter lagged values of the financial ratio corresponding to the factor weight, computed for the total sample of banks, (hereafter, portfolio shares of that variable, lagged one quarter), (3) one-quarter lagged values of the mean CAMELS rating for the sample of banks, (4) the prior-quarter's spread between the 10-year Treasury yield and the federal funds interest rate and (5) the average of the national economic growth rate over the prior four quarters.²⁰ The results of these regressions are shown in Table 1.

²⁰ In addition, we found that a number of other macroeconomic variables were generally statistically insignificant, such as the unemployment rate, the gap between actual and potential GDP, real home prices, and a linear time trend.

Interpreting the coefficients on the factor weights in Table 1 requires some care. The estimated factor weights come, of course, from the Ratings Rule Model regression with 12 banking variables, plus the four lags of economic activity. Thus, the factor weights reflect the effects on CAMELS ratings, holding constant a dozen or more other conditions. Though we might have suppositions about many of the simple correlations, intuition about the partial effects of the variables in Table 1 on the factor weights may be harder to come by.

Row 2 of Table 1 shows that (own) prior-quarter factor weights (i.e., the dependent variables lagged) in general significantly predicted current values of the factor weights. The estimated coefficients on the (own) lagged dependent variables averaged about 1/3 and were statistically significant (except for the factor weight on loans past due 90 days or more). Thus, the current factor weights can be regarded as partly reflecting past factor weights and partly reflecting gradual adjustments to changed conditions.

The negative coefficients on the lagged bank capital ratio for the sample, shown in row 3 (lagged portfolio shares) of Table 1, indicate that the factor weight for equity capital (column 2) was higher when the overall sample capitalization was lower, as we might hope and expect. Similarly, row 3 of Table 1 shows that the factor weights on delinquent loans (column 3) rose significantly when the overall delinquencies for the sample of banks (as a percent of gross assets) were higher. Despite nonaccrual loan's strong statistical showing in the Ratings Rule Model, no such relation to high nonaccruals is seen in the nonaccrual loans factor weights. The positive relation did show up again, however, in column 6, for the factor weights on volatile liabilities: When those liabilities were higher, so too was the weight applied to them. Less intuitively, the factor weights on

bank income before taxes also tended to rise, not when earnings were low but, rather, when they were high.

Row 4 of Table 1 shows that the Ratings Rule Model intercepts were positively related to the lagged quarterly mean CAMELS rating, which presumably captured well the overall health of the banking system. The factor weights on the loan loss allowance and volatile liabilities were significantly lower when mean CAMELS ratings were higher (worse).

Row 5 of Table 1 shows that only the factor weights associated with equity capital and loan delinquencies were significantly associated with our measure of monetary policy, as measured by the difference (yield spread) between the yield on U.S. Treasury securities with maturities of 10-years and the federal funds interest rate. Table 1 indicates that monetary easing of credit availability, as indicated by wider yield spreads, is associated with lower factor weights on equity capital and on delinquent loans.

Row 6 of Table 1 shows that the factor weights on equity capital, on delinquent loans, and on the loan loss allowance were significantly higher when recent actual economic growth was lower. These effects may well suggest that the supervisory process was significantly incorporating the otherwise-unmeasured effects of the economy on bank conditions (that is, the effects beyond those already measured by a dozen Call Report variables).

Thus, Table 1 helps us to better understand how rating factor weights have shifted over time. Among the most significant associations that we found were that specific factor weights tended to rise as specific conditions worsened (as in the case of equity capital) and that worse recent economic performance tended to raise the factor weights

applied to several bank variables. In that regard, Table 1 is at least consistent with the view that supervisors' concerns, as reflected in their assignments of CAMELS ratings, tended to move in the direction that we might hope.

6. An Intermediate-Term Model

In this section we expand on the Ratings Rule Model in two important ways. First, we extend the forecast horizon from one quarter to one to two years into the future. We chose this horizon on the ground that it balances extra lead time for bank management and supervisors (to reduce the likelihood and severity of bank problems) against the loss of forecast accuracy as the horizon lengthens. Second, we add forecasts of local economic conditions to the original set of twelve financial ratios used by the Ratings Rule Model (and omit lagged values of state economic conditions from the model). The resulting expanded version of the Ratings Rule Model is our Interim-Term Model. Equation 2 presents our Interim-Term Model in general form.

$$2) \text{ CAMELS}_{j,t+4 \text{ to } t+8} = \alpha + \beta' X_{j,t} + \lambda_1 G_{t+1}^* + \lambda_2 G_{t+2}^* + \lambda_3 G_{t+3}^* + \lambda_4 G_{t+4}^* + \varepsilon_t$$

In equation 2, $\text{CAMELS}_{j,t+4 \text{ to } t+8}$ is the CAMELS rating received by bank j between quarters $t+4$ and $t+8$ (i.e., between one and two years in the future), $X_{j,t}$ is the same vector of bank financial ratios as was used in the Ratings Rule Model (equation 1), the forecasts of state economic growth are given by the quarterly values of G^* , and ε_t is the normally distribute error term. We estimate equation 2 using OLS regression. We next discuss our methodology for forecasting local economic conditions.

6.1 *Forecasts of Local Economic Conditions*

To predict local (state) economic conditions we used the Federal Reserve Bank of Philadelphia's State Coincident Index. Specifically, we computed a quarterly average of the monthly coincident index for each state, and used the change in the logarithm of quarterly average values of the indexes as our measure of the state economic growth rate. Next, using OLS regression we regressed the most recent quarterly state economic growth rate on lagged quarterly state economic growth rates for the prior four quarters and a time trend.

$$3) \quad G_t = \alpha + \beta_1 G_{t-1} + \beta_2 G_{t-2} + \beta_3 G_{t-3} + \beta_4 G_{t-4} + \beta_5 T_t + \varepsilon_t$$

Equation 3 presents our model for state economic growth (subscripts indicating the state are omitted for simplicity). In equation 3, G_t is the state economic growth rate between quarters t and $t-1$ (lagged values of G_t are defined similarly), the time trend is indicated by T_t , and ε_t is the normally distribute error term. We estimated equation 3 beginning in the fourth quarter of 1983 (using data on state economic growth starting in the first quarter of 1980) and re-estimated the model on a quarterly basis through the third quarter of 2009, adding one more quarter of data on state economic growth to the estimation sample at each successive re-estimation of the model.

Forecasts of state economic growth were computed as follows. A one-quarter forecast of state economic growth was computed based on estimates of equation 3 as of the current quarter and actual values of state economic growth available as of the current

quarter. For example, we forecast state economic growth for the first quarter of 1991 using beginning of first quarter of 1991 estimates of equation 3 regression coefficients and data on state economic growth from the first quarter of 1990 through the fourth quarter of 1990. Forecasts of state economic growth beyond one quarter were obtained by using the most recently available estimates of equation 3 regression coefficients and by substituting forecasts of state economic growth for the currently unavailable interim future values of state economic growth. For example, a two-quarter forecast of state economic growth was obtained using estimates of equation 3 as of current quarter, actual data on state economic growth for quarters $t-2$ to $t-4$ and a one-quarter forecast of state economic growth for quarter $t-1$. Three and four quarter forecasts of state economic growth were computed similarly to two quarter forecasts, using additional forecasts of state economic growth as needed to move the forecast horizon further into the future. As such, our forecasts of state economic growth for two to four quarters into the future are conditional on actual state economic growth and interim forecasts of state economic growth.

6.2 *The Value of Forecasts of State Economic Growth*

To show the statistical significance of the forecasts of state economic growth in the Interim-Term Model, Figure 6 plots the square roots of the F-statistics (i.e., the t-statistics) calculated for the test of the joint significance of the four economic-forecast variables included in the model. Figure 6 also displays the square roots of the F-statistics for the significance for three of the twelve bank financial ratios included in the model: (1) capital, (2) nonaccrual loans, and (3) the loan loss allowance.

The top panel of Figure 6 plots the square root of the F-statistics for omitting the four economic forecast variables from the Interim-Term Model. For convenience, we included a horizontal line at 1.54, the square-root of the critical value for the relevant F-statistic at a 5 percent significance level. In the bottom panel, we present standard t-statistics that we obtained by deleting the other variables, one by one. There we also plot a horizontal line, this one at 1.96, the critical value for t-statistics for a 5 percent significance level.

The top panel shows that economic forecasts were typically statistically significant at the 5 percent level, with square-roots of calculated F's that were less than the critical value of 1.54 for only 9 quarters—during 1997–1998, 2000–2001, and 2007. For the other 87 quarters, the statistics were above, and often well above, the critical value of 1.54. Apart from one quarter in 2007, when CAMELS for 2008 were being forecasted, the forecasts maintained their statistical significance throughout the most recent period.²¹ Thus, we regard the economic forecasts, which were based only on past data, as being able to contribute significantly to predicting banks' CAMELS ratings.

For comparison with the results for the economic forecasts, in the bottom panel of Figure 6 we present the t-statistics for the bank financial ratios for equity capital, for nonaccrual loans, and for the loan loss allowance. In forecasting banks' conditions one to two years ahead, we found that equity capital typically had a large t-statistic, often in the range of 10. Ever since 1990, however, the t-statistic on equity capital has been, in general, declining. The t-statistics on capital dropped considerably in 2005 and then

²¹ Because we are forecasting, the last forecast equation was estimated through the end of 2007 so that we could forecast out of sample for the period after 2008.

rebounded. Even at their lowest points, however, the t-statistics almost always exceeded 1.96.

The loan loss allowance has historically been an indifferent performer, both in SCOR and in our Ratings Rule Model. Here, similarly, we see that its t-statistics were more often below 1.96 than above it, and since 1993 have been above it only briefly. In some ways, that is not surprising. A larger allowance may signal that upcoming losses have already been provided for, or it may indicate that there are more losses to come, which may not have been sufficiently provided for. On the other hand, having more nonaccrual loans is more likely unalloyed bad news. And, not surprisingly given their track record in SCOR, nonaccrual loans always made strong statistical showings in our ratings rule estimates. In Figure 6, nonaccruals continued to show strong performance, with t-statistics averaging about 10 and varying little over the entire 1984–2007 forecast estimation period.

To measure the contribution that our forecasts of state economic conditions make to the Intermediate-Term Model, we compare the changes in adjusted R^2 due to deleting (or adding) the set of economic variables with the changes in adjusted R^2 due to adding the other typically included (Call Report) variables. Figures 7 and 8 plot the increases in adjusted R^2 attributable to the same variables that are shown in Figure 5. The top panel in Figure 7 plots the improvements in adjusted R^2 (in percentage points) attributable to the economic forecast variables and attributable to equity capital for the entire 1984–2007 period.²² To highlight the more-recent performances of growth and of capital, the bottom panel repeats the data from the top panel but only for 1995–2007.

²² The adjusted R^2 s for the forecasting models, when all variables were included, averaged about 35 percent.

Until the late 1980s and since 2003, the economic forecast variables added more to adjusted R^2 s than capital did. (Given the long list of included variables, perhaps no one variable added enormous amounts to adjusted R^2 s, either in sample or out of sample.) Perhaps it was the apparently abundant bank capital in the middle of the 2000s that reduced the factor weights, the t-statistics, and the adjusted R^2 s associated with capital. On average over the entire period, economic forecasts added somewhat more by this measure than capital did. Over the shorter period shown in the bottom panel, capital added somewhat more.

Figure 8 shows a comparison of the additions to adjusted R^2 's attributable to economic forecasts with the additions attributable to nonaccrual loans (top panel) and to the loan loss allowance (bottom panel). Economic forecasts added much more than the allowance, but much less than nonaccruals.

Given these measures of statistical and practical significance, we consider local growth to be worth including in the forecasting model. Overall, the improvements in forecasts of CAMELS ratings that were attributable to forecasts of economic growth were on a par with the improvements to CAMELS Ratings forecasts attributable to capital. Together, then, Figures 6–8 suggest that adding forecasts of economic growth to intermediate-term CAMELS forecasting models would be expected to provide additional information to supervisors and perhaps to their banks (which might have already sized up the likely effects of economic growth).

With the resulting CAMELS predictions in hand, supervisors and their banks would have more information about whether a bank should consider altering its current actions and plans. Supervisors are unlikely to reveal the estimated coefficients of the

contemporaneous Ratings Rule Model estimated above, which in principle would indicate how much more capital or how many fewer nonaccrual loans would likely be needed to achieve a different rating. Nor would they be likely to reveal the estimated coefficients in the Intermediate-Term Model.

7. Ways to Incorporate Intermediate-Term Forecasts into Bank Supervision

In this section we develop a conceptual framework for improving off-site bank supervision that is based on one- to two-year forecasts of bank condition. Next, we discuss how a more forward looking measure of bank risk might be incorporated into bank supervisory and management actions and plans. Finally, we propose the more forward-looking risk measure be used to set regulatory capital requirements for banks.

7.1 A Conceptual Framework for Improved Off-site Bank Supervision

As noted, a one- to two-year forecast of a CAMELS rating that was based on a bank's financial condition and on forecasts of local economic growth (in turn, based on observed [lags of] actual local economic growth) would be valuable to bank supervisors and managers. Suppose that at time t a bank received a CAMELS rating of 2 from its supervisor. Suppose also that this bank's predicted CAMELS rating for time t based on a previously estimated Ratings Rule Model was 2.38, as shown in Figure 9. With a forecasted CAMELS rating of 2.38, we might view this bank as currently a "weak 2."²³

At time t , we could use the Intermediate-Term Model to calculate a forecast of the CAMELS rating that the bank would get at time $t+1$, a horizon that we took to be one to

²³ Since the forecast horizon of the Ratings Rule Model is only one quarter, the model's predicted CAMELS ratings are effectively "second opinions" on banks' CAMELS ratings based on bank financial ratios and local economic conditions.

two years. Suppose that the same bank had, as of time t , an Interim-Term Model predicted CAMELS rating of 3.14 for time $t+1$. That is, the bank's condition in this case was expected to worsen. Such a prediction might well spur both the bank and its supervisors to take measures in order to avoid the currently forecasted future outcome.²⁴

To supplement the time t point forecast of the bank's time $t+1$ CAMELS rating, \hat{C}_{t+1} , we would also like to have a measure of the range of its "likely" outcomes (CAMELS ratings) at time $t+1$. More specifically, we wish to measure a bank's potential future condition based on both the mean and likely range of future outcomes as shown in Figure 9. The probability distribution of potential values for CAMELS ratings at time $t+1$ shown in Figure 9 would depend on the process generating CAMELS ratings.

Currently, bank supervisors' off-site early warning systems (e.g., the FDIC's SCOR model) focus on point estimates of predicted CAMELS ratings and, importantly, on predictive accuracy. To allocate supervisory resources efficiently bank supervisors focus their attention on those banks whose conditions are *most likely* to deteriorate in the near future. In practical terms this means that bank supervisors focus their attention on a small subset of all banks with the subset of banks (off-site review list) chosen based on measures of their likelihood of deterioration. The criteria for inclusion in an off-site review list typically means that a bank's predicted CAMELS rating must exceed a certain threshold value (i.e., the bank has a high probability of receiving a poorer CAMELS rating at its next on-site examination), where the threshold value is chosen based on a trade-off between type 1 and type 2 predictive errors. Since overall predictive accuracy

²⁴ According to Barr (2009), SNL Financial calculated that 29 banks had been issued Prompt Corrective Action letters in 2009 through August, up from 7 for the same period in 2008. Of the 29 banks, two-thirds had failed as of October 2009.

decreases as the likely range of future outcomes increases, a consequence of current supervisory practices for forming off-site review is that as a bank's future outcome becomes more uncertain (greater range of likely outcomes), the likelihood of the bank being included on an off-site review list decreases, all other things being equal.

While we acknowledge the need to consider predictive accuracy in supervisory early warning systems, we propose that supervisors also include a separate, explicit measure of the likely range of future outcomes in their early warning systems. This dispersion measure might allow supervisors to distinguish between two banks that at first glance appear to be equally risky (e.g., both banks have Interim-Term Model predicted CAMELS ratings of say 3.14) but that have very different probability distributions associated with their future CAMELS ratings.

To continue our example, suppose the two banks come from very different industry subgroups, for example, one bank might be an agricultural lender and the other bank a well diversified retail bank. If the interim-term model were estimated separately for these two industry groups, we might find the model predicts CAMELS ratings at time $t+1$ more accurately for retail banks than it does for agricultural banks. Suppose also that agricultural banks' high loan concentrations (relative to those of retail banks) might make them more susceptible to weather conditions, agricultural price fluctuations and other market forces than are retail banks. The result would be a greater likely range in agricultural banks' CAMELS ratings relative to that of retail banks. While bank supervisors might wish to discount our hypothetical agricultural bank's predicted CAMELS rating (3.14) due to greater forecast error relative to that of retail lenders, we

argue that supervisors should also weigh the greater uncertainty about agricultural banks' future conditions relative to that of retail lenders, in their decisions.

7.2 *Measures of Uncertainty about Future Outcomes*

How might we obtain measures of the likely range of future outcomes (likely CAMELS ratings at time $t+1$)? One candidate for a measure of this range would be an estimated range of future outcomes for some given level of confidence (or forecast confidence interval), as exemplified by the distance from D to E in Figure 9.

The size of that range for an individual bank will depend on a number of factors. Predictability narrows the range: The more predictable the future local economic conditions and the more predictable the future values of the bank's financial statements (i.e., Call Report variables), the tighter the range. The greater the uncertainty about future GDP growth, about future loan delinquency rates, or about future capital, the greater the chances that the future outcomes will deviate more from the point estimate of forecasted future condition for a bank. Concomitantly, the more confident we are about the future values of banks' financial ratios (e.g., capitalization) the more confidence we can have that the bank will be near its forecasted condition at time $t+1$. In addition, the range of likely outcomes would also depend on the uncertainty about how closely the estimated regressions approximate the unknown actual process generating CAMELS ratings.

We denote an estimate for the range of likely future outcomes as S , whose size would depend on the standard error of the forecast. S would likely vary across individual banks (j) and over time (t). We next discuss factors that can influence the value of $S_{j,t}$.

7.3 *Sources of Uncertainty about Future Outcomes*

The extent to which the factors used by supervisors to assign CAMELS ratings to banks are correlated can affect the dispersion of likely future outcomes. Developments in one part of a bank, whether positive or negative, can reverberate within other parts of a bank. For example, a weakening of local economy might lead to increases in loan defaults, loan loss provisions and charge-offs, ultimately resulting in lower net income and capital. The degree to which a bank is exposed to local economic fluctuations depends on the degree to which its balance sheet and off-balance-sheet activities are diversified and on the bank's risk management practices.

The stronger the covariance of negative (or positive) movements in the factors that are used to assess banks' conditions (e.g., the Call Report variables and the local economy), the greater the likelihood that more things will go wrong (or right) for the bank at the same time. Thus, the larger the reinforcing covariances of a bank's performance measures, the larger the dispersion of future outcomes that we should expect to see. To the extent that a bank is more diversified in its business activities, we expect the covariances—and therefore the resulting range of likely outcomes, $S_{j,t}$ —to be smaller.

To begin to assess how much $S_{j,t}$ varies across banks at any given time, we might consider estimating the Intermediate-Term Models over subsamples of banks that are judged likely to have similar dispersions of outcomes. For example, higher $S_{j,t}$ might be typically signaled by larger concentrations of commercial real estate loans or agricultural loans, or by larger shares of bank income that arise from noninterest revenues. To the extent that such factors can be somewhat systematically associated with higher (or lower)

$S_{j,t}$, the more likely it is that supervisors will be able to assign appropriately different S's at different times and to different banks.

Further, it may be that combinations of factors, and not just individual factors, more effectively signal the likely range of future outcomes. For example, it may be that banks that have both more volatile liabilities and more commercial real estate loans have particularly high $S_{j,t}$ (or maybe low $S_{j,t}$).²⁵ To the extent that banks become more seriously troubled as a result of the positive covariance between the troubles associated with the several individual factors, combinations of factors are more likely to be effective signals of the likely range of future outcomes.²⁶

Although there may well be identifiable factors that systematically signal risk, much more analysis would be necessary before we could judge whether these factors might satisfactorily approximate the risks (volatility) of individual banks.

7.4 *An Estimated Risk-Adjusted CAMELS Rating*

An empirical measure of the likely range of future outcomes for an individual bank j at time t , $S_{j,t}$, might be used in several ways. One way would be to forecast an Estimated Risk-Adjusted CAMELS rating (ERAC) as follows:

$$4) \quad ERAC_{j,t} = \hat{C}_{j,t+1} + rS_{j,t}$$

²⁵ Neither the mean nor the volatility of commercial real estate assets, for example, typically appears in regressions that explain CAMELS ratings or that forecast them for a short horizon.

²⁶ Two considerations suggest that supervisors are sensitive to covariances: one is that composite CAMELS ratings differ from linear weighted averages of the component ratings, and the other is that deposit insurance premiums have been set via an asymmetric pricing matrix.

where \hat{C}_{t+1} is the CAMELS rating that is forecasted as of time t for time $t+1$, and r is a scalar that “prices” or “risk-weights” bank j ’s measured outcome volatility, $S_{j,t}$. The more weight bank supervisors put on volatility (presumably because of their heightened aversion to adverse outcomes), the larger the r they should choose. To the extent that larger variances and covariances of the risk factors translate into more estimated volatilities, equation 4 then serves to “price,” in the form of a higher ERAC, the effects of those variances and covariances. In that sense, equation 4 rewards risk reductions due, for example, to having fewer risky assets or liabilities or to being more diversified. To the extent that a bank has operations, assets, and liabilities whose performances tend to offset each other, that bank would have a lower $S_{j,t}$ than otherwise and would then be rewarded with a smaller ERAC.

Explicit consideration of the uncertainty associated with likely future bank conditions is intended to promote preventive actions. In that regard, another use for ERAC might be to have the various stages of Prompt Corrective Action (PCA) be triggered—either explicitly via a change in the law or implicitly via supervisory practice and agreements—when the ERAC for a bank, $ERAC_{t,j}$, rises to various levels. Although CAMELS ratings have so far been bound by an integer constraint, neither ERAC calculations nor PCA-like triggers nor supervisory agreements need necessarily be integers.

This perspective on bank risk is intended to promote awareness that the amounts of uncertainty about future bank conditions can vary across time and across banks. Risk can also vary across banks whose current conditions might be regarded as similar: For example, some banks with CAMELS ratings of 3 might have much less risk than others.

Consider a bank whose current CAMELS rating is 3 and whose predicted rating for time $t+1$ is, say, 3.22. Suppose that, because of its risks, the bank has an ERAC adjustment of 0.54 and thus an ERAC = 3.76. That bank may be subjected to more stringent supervisory actions than a bank with a current CAMELS rating of 4 but a predicted CAMELS rating of 3.30 and an ERAC add-on of 0.10.

8. The Systemic Importance of Small Banks

In recent policy discussions about the causes and consequences of the 2007–2009 financial crisis policymakers have focused on the risk large and complex financial institutions pose to markets and the overall U.S. economy (systemic risk). Absent from these discussions is the risk smaller banks *collectively* pose to markets and the economy. We believe the collective risk posed by small banks is important, especially given the rather recent experience of the U.S. during the thrift and banking crises of the 1980s and early 1990s. We next discuss small banks' contribution to systemic risk and offer suggestions for pricing this risk in the form of supplemental capital requirements. Our pricing proposal builds on the concept of measuring a bank's likely range of future outcomes and shows how the framework we developed in section 7 can be extended to other areas of bank supervision and regulation.

8.1 Small Banks' Contribution to Systematic Risk

In 1989, Alamo Federal Savings Association failed.²⁷ Alamo was one of thousands of (all too) similar thrift institutions. The thrifts' difficulties engendered a

²⁷ The FDIC reported that the San Antonio, Texas, thrift, with about \$600 million in assets, imposed a loss on the FDIC of \$700 million.

crisis because, in effect, thousands of small institutions were quite similar and, when hit by large common shocks, became troubled similarly and almost simultaneously. Thus, collectively, the thrifts were large banks. In other words, what produced the thrift crisis and its associated credit and economic disruptions was not so much that large thrifts became troubled but, rather, that so much of the thrift industry became troubled. The extent of the difficulties imposed on the aggregate financial and real sectors of the U.S. economy by the thrift crisis was not as large as the extent of the difficulties imposed by the current crisis. But still, the difficulties were very extensive. Thus, when enough smaller institutions are similar enough and therefore co-vary enough, they may also be systemically important.

8.2 *Pricing Systemic Risk*

One way to address otherwise unpriced systemic risks that might arise from the similarity of small institutions (called “banks” here for simplicity) might be to impose a capital charge for the systemic risks that each bank engenders. Of course, for many and probably most smaller banks, this extra capital charge might be trivial, largely because of the small size of such banks and their concomitantly small contributions to systemic risk. For all but the largest banks, as exemplified by the 19 systemically important banks in the 2009 Supervisory Capital Assessment Program, the capital charge might be proportional to a bank’s share of the relevant banking sector.²⁸ For the largest banks, as suggested by

²⁸ In 2009, federal bank regulators joined in a comprehensive assessment of the capital adequacy of 19 large banking organizations determined to be systemically important. This assessment, known as the Supervisory Capital Assessment Program, involved the use of credit stress tests designed to show institutions ability to withstand further deterioration in the U.S. economy. See Board of Governors of the Federal Reserve System (2009) for details on the program.

Borio et al. (2009), a capital charge might rise appreciably more than proportionally with bank size.

The extra capital charge for a bank would also depend on how much the bank's outcomes co-vary with the outcomes for the banking industry: The larger the covariance, the larger the capital charge. (In the calculations above of the estimated risk-adjusted CAMELS rating, ERAC, it is the covariances of outcomes within each bank that are relevant. Here, for systemic risk, it is the covariances across banks that are relevant.) Thus, a systemic-risk capital add-on might depend on a bank's size, its covariance with the relevant banking sector, and the capital price per unit of systemic risk. Choosing which outcomes would be good measures on which to base calculations of beta would not be trivial. For the thousands of small banks that are not publicly traded, there is unlikely to be a market-price-based measure that would suffice. One possibility to consider as a measure of the beta for relevant outcomes—given that much of our concern about systemic risk involves shifts in the aggregate supply of (bank) credit—would be a bank's credit beta, perhaps calculated as the sensitivity of its changes in credit supplied to changes in aggregate credit supplied.

Equation 5 shows how minimum capital requirements at time t for bank j , $K_{j,t}$, then might be built up from a flat-rate minimum, k_{\min} , plus a charge, g , per unit of individual bank uncertainty, $S_{j,t}$, plus a systemic risk charge, b , per unit of systemic risk, $SR_{j,t}$.

$$5) \quad K_{j,t} = k_{\min} + gS_{j,t} + bSR_{j,t}$$

In equation 5, k_{\min} could be set at the current regulatory minimum leverage ratio [3%], and $S_{j,t}$ might be taken from the bank risk calculation described in section 7. $SR_{j,t}$ measures how much the individual bank contributes to systemic risk.²⁹ $SR_{j,t}$ might then be calculated as the product of the relative size of the bank—as measured, say, by its share of total assets for the relevant banking sector—and the covariance between the outcomes of the bank and the sector as a whole (or some other measure of the bank’s interconnectiveness with the industry). If a bank wanted to reduce the systemic risk capital charge, it might alter its size or alter its operations and balance sheet so as to reduce its contribution to systemic risk. In that way, diversification in the form of having different cross-bank exposures to aggregate shocks would be valuable to each institution. The reward for such diversification—that is, the reduction in the bank’s capital requirement—would dilute the incentives to be “too similar to fail” or to find “safety in similarity.”³⁰

9. Conclusion

Over the past 25 years, banks, their regulation, and their regulators have changed considerably. One change has been the increased emphasis on bank capital requirements. Another has been the increased recognition that the economy affects banks, and vice versa. This latter change is reflected in the increased attention bank supervisors have placed on macro-prudential supervision and stress testing of banks and of the financial sector as a whole in recent years.

²⁹ Acharya et al. (forthcoming) and Borio et al. (2009) have recently suggested methods for calculating the contributions, SR, of individual institutions to systemic risk.

³⁰ See Stever and Wilcox (2007) for a discussion of safety in similarity.

Our estimates of the Ratings Rule Model show that the estimated factor weights that supervisors put on various factors have changed over time, sometimes by large amounts and sometimes in connection with developments in banking and in the broader economy. The estimated factor weights on capital, for example, rose and fell with concerns about banks' having too little capital.

We then demonstrated that current forecasts of upcoming local economic growth consistently improved forecasts of banks' future conditions. The improvements are similar in magnitude to the amounts by which capital helps forecast bank conditions.

We then noted how models of future CAMELS ratings might guide the construction of forward-looking measures of individual banks' risks. Potential uses of measures of bank risk might be to calculate risk-adjusted CAMELS ratings or to risk-adjust capital requirements. A more forward-looking assessment of conditions and risks might enable supervisors and bank managements to take actions and make plans that are more anticipatory than those engendered by the current PCA system. In this way, the forward-looking assessments might reduce the likelihood and severity of banking problems and of losses to the FDIC.

Finally, we discussed how large groups of smaller but quite-similar banks might collectively engender systemic risks. We noted, too, that the capital requirements for these banks might appropriately include systemic risk charges.

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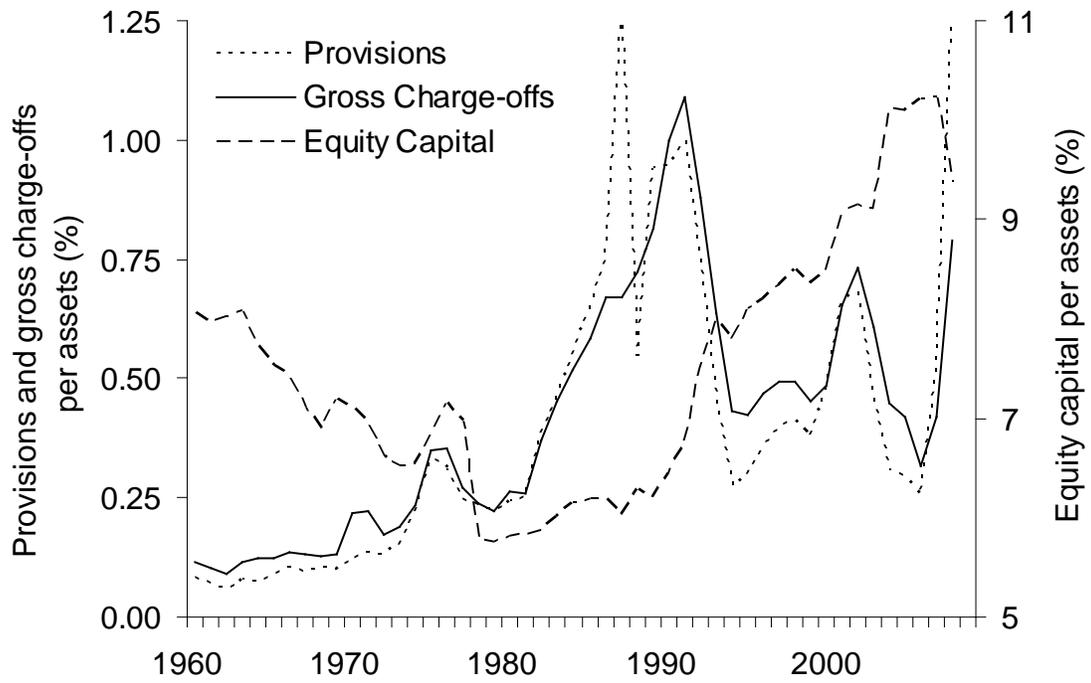
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Figure 1
 Provisions, Gross Charge-offs, and Equity Capital Ratios
 All Commercial Banks, as a Percentage of Assets, 1960–2008



Source: FDIC, annually, 1960–2008.

Figure 2
Average and Standard Deviation of Cross-Sectional CAMELS Ratings
(All Recently-Examined FDIC-Insured Institutions, Quarterly, 1984:1–2009:3)

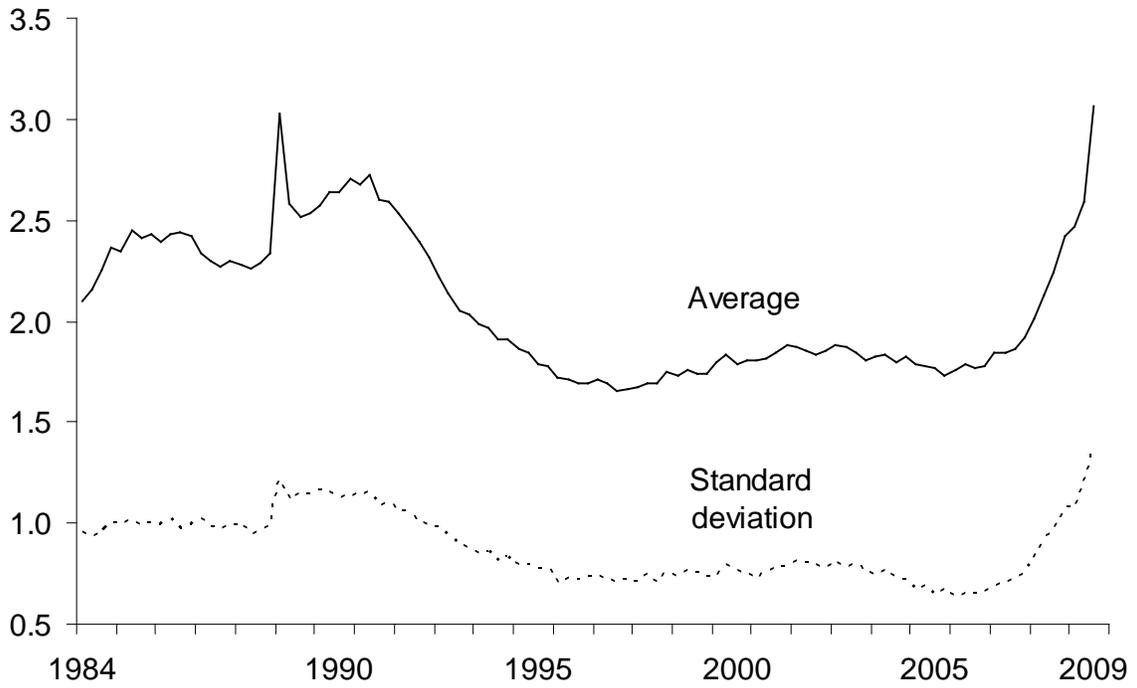


Figure 3
Average of EDFs for Large and Small (Publicly Traded) U.S. Banking Companies
(Percentage, One-Year Horizon, Monthly, 1990:1–2009:8)

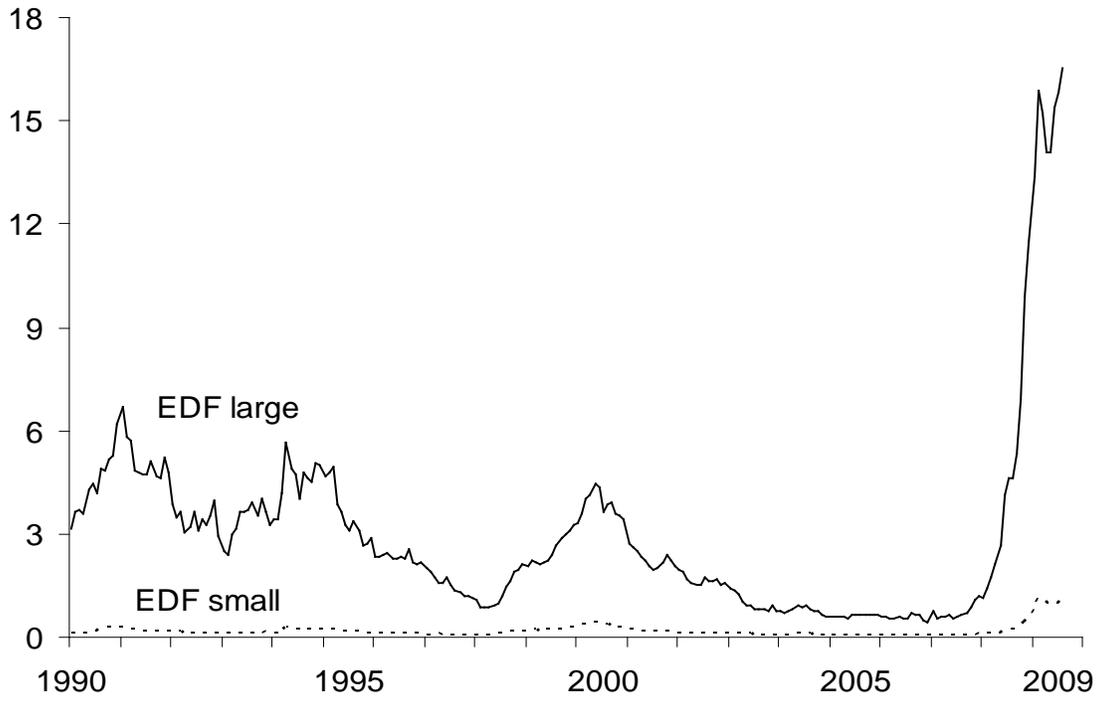


Figure 4
 Estimated Factor Weights in the Ratings Rule Model:
 Equity Capital, Income before Tax, Gross Charge-offs, and Provisions for Loan Losses
 (Quarterly, 1984:2–2009:2; Indexed: 1984:2 = 1) Eight-quarter trailing moving averages
 of factor weights are shown for charge-offs and provisions.

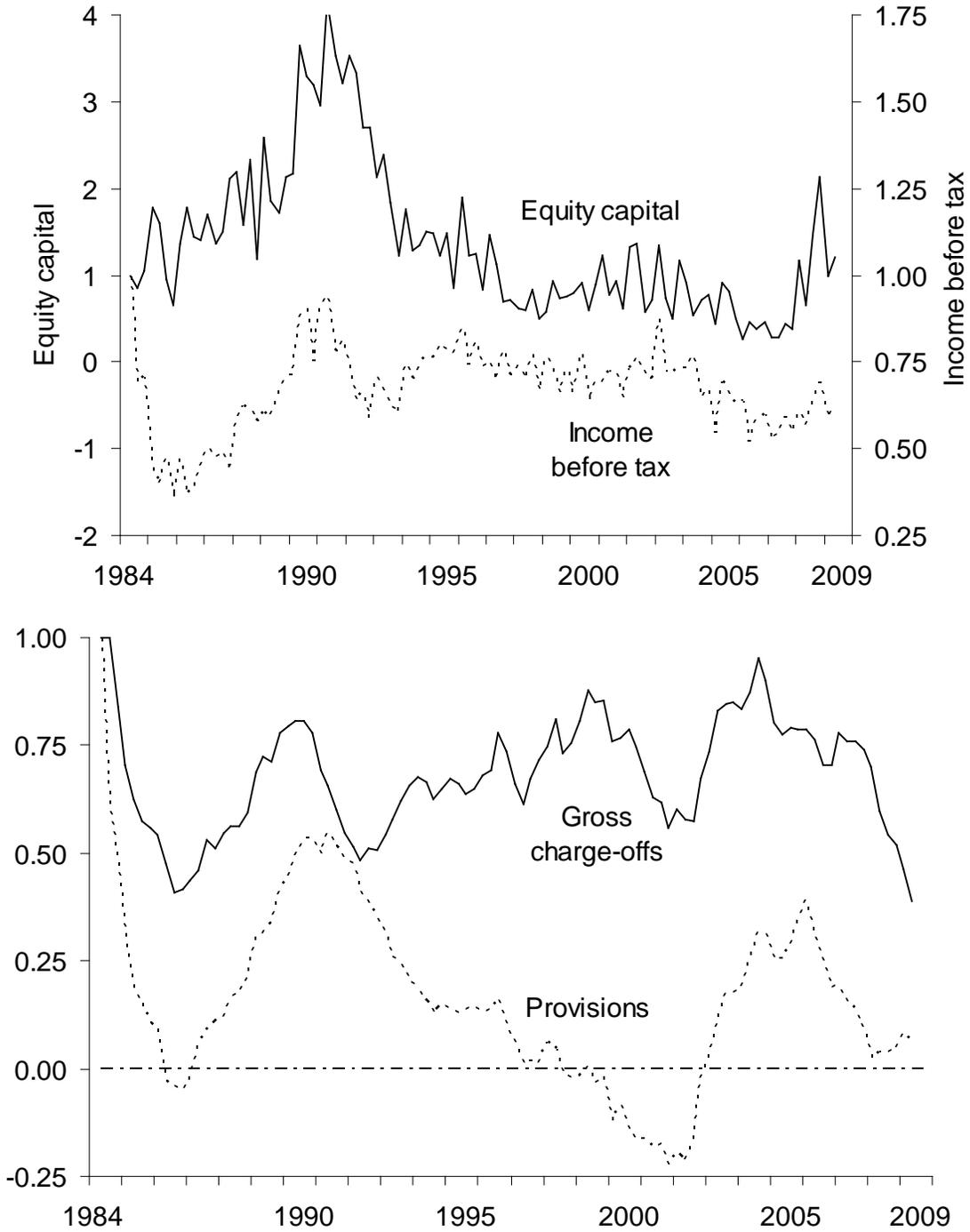


Figure 5
 Estimated Factor Weights in the Ratings Rule Model:
 OREO, Nonaccrual Loans, Volatile Liabilities, and Liquid Assets
 (Quarterly, 1984:2–2009:2; Indexed: 1984:2 = 1)
 Eight-quarter trailing moving averages of factor weights are shown.

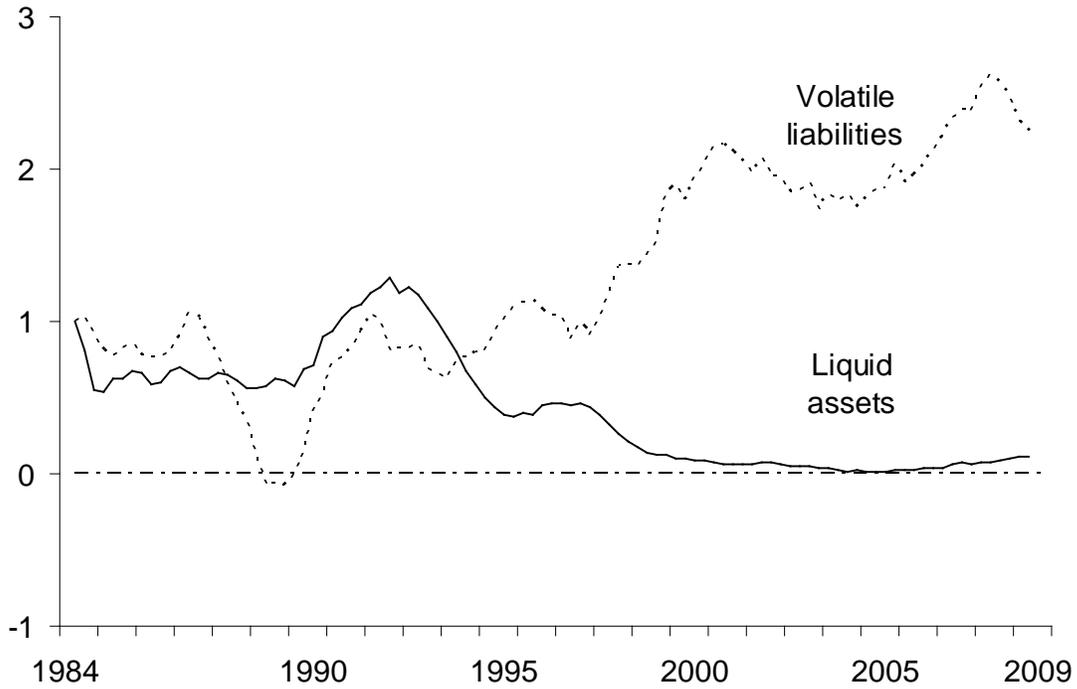
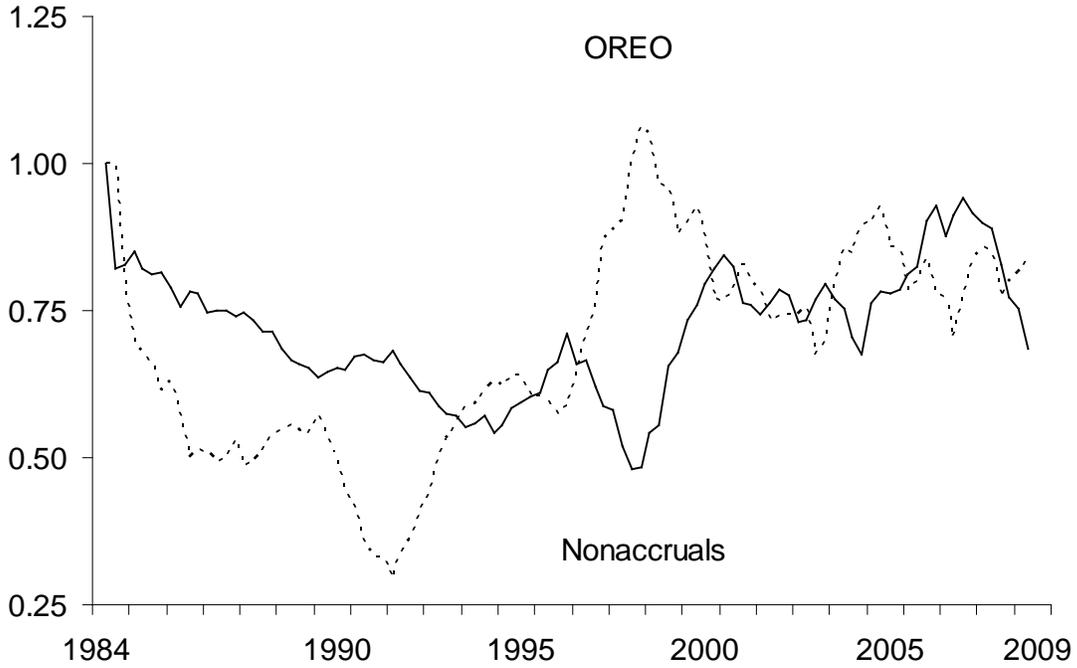


Figure 6
 Statistical Significance for Forecasting Banks' Conditions:
 Economic Forecasts, Nonaccruals, Equity Capital,
 and Allowance for Loan and Lease Losses
 (square-root of F-statistics, log scale, quarterly, 1984:2–2008:1, as of forecast date)

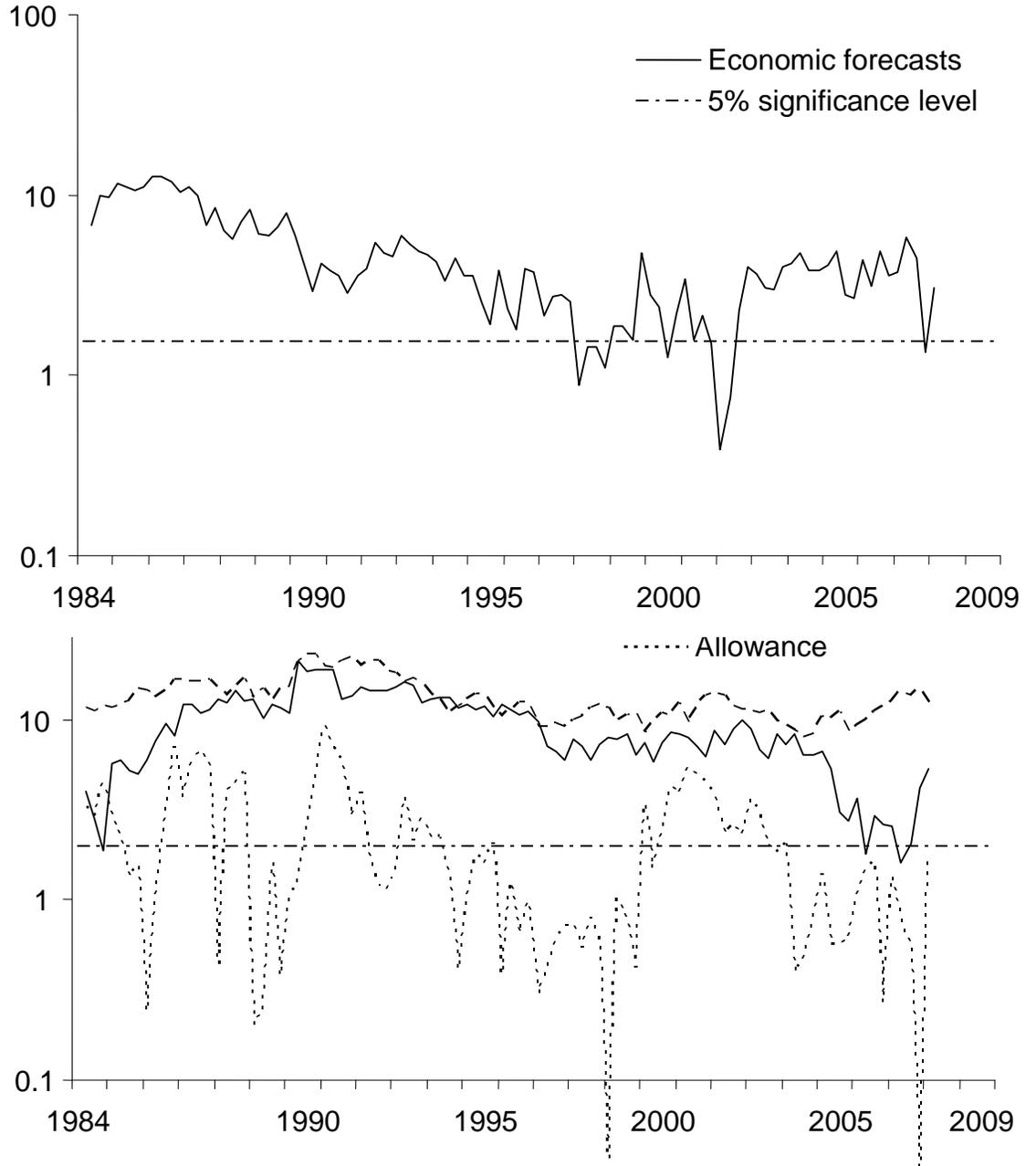


Figure 7
 Improvements in Adjusted R^2 in Forecasting Banks' Conditions:
 Economic Forecasts and Equity Capital
 (Percentage Points, Quarterly, 1985:1–2008:1 and 1995:1–2008:1)
 As of forecast date, four-quarter trailing averages are shown.

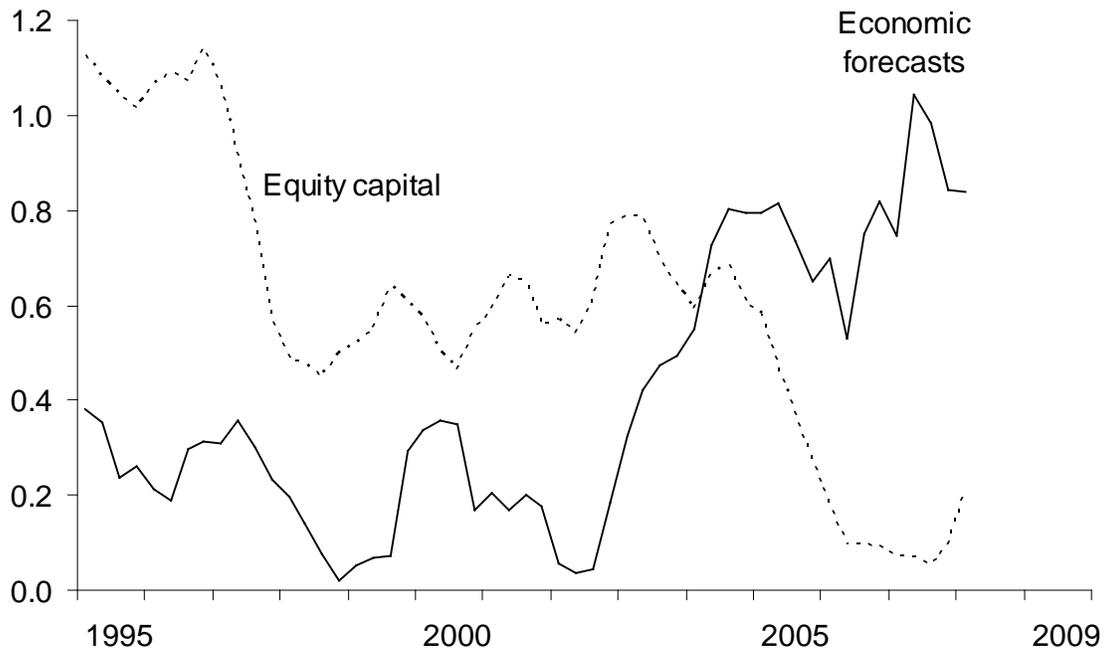
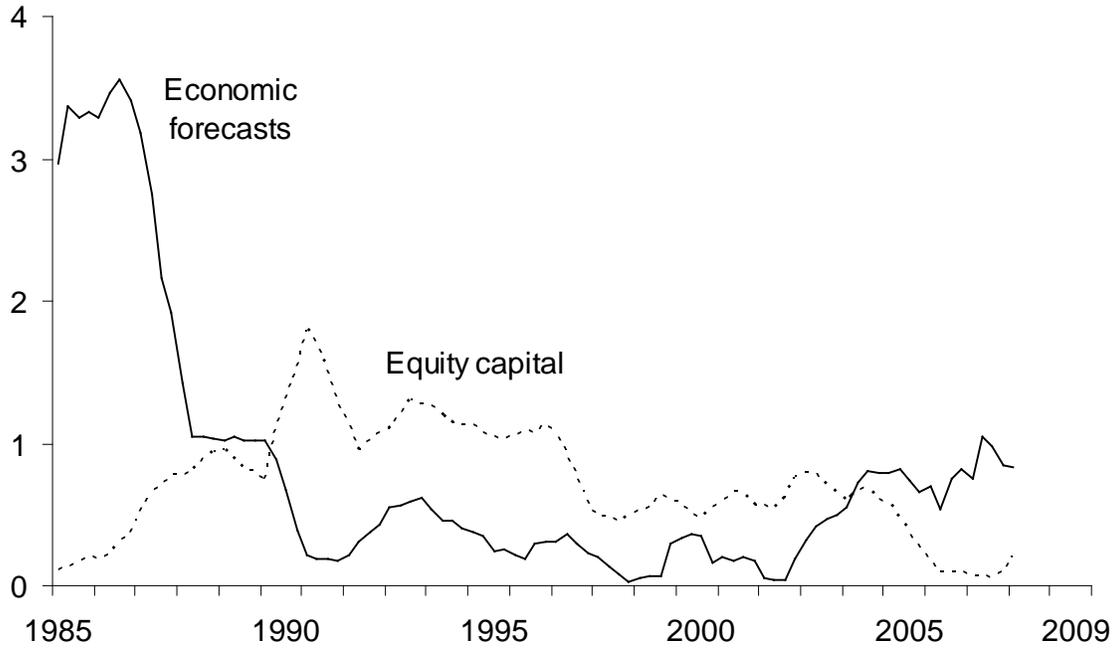


Figure 8
 Improvements in Adjusted R^2 in Forecasting Banks' Conditions:
 Economic Forecasts, Nonaccrual Loans, and Allowance for Loan and Lease Losses
 (Percentage Points, Quarterly, 1985:1–2008:1)
 As of forecast date, four-quarter trailing averages are shown.

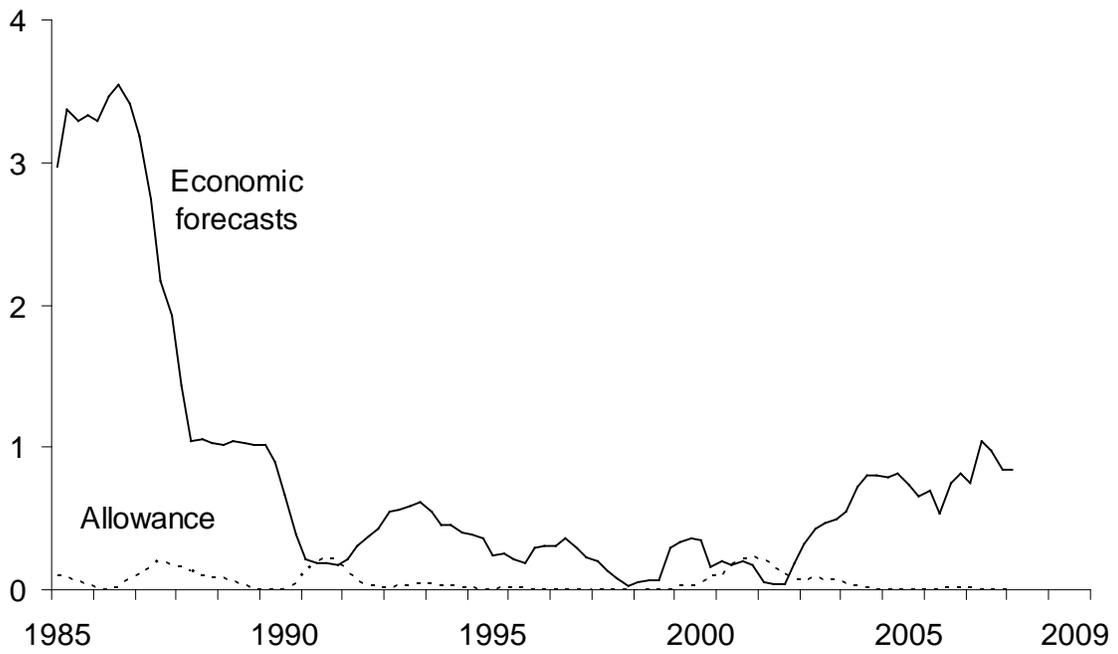
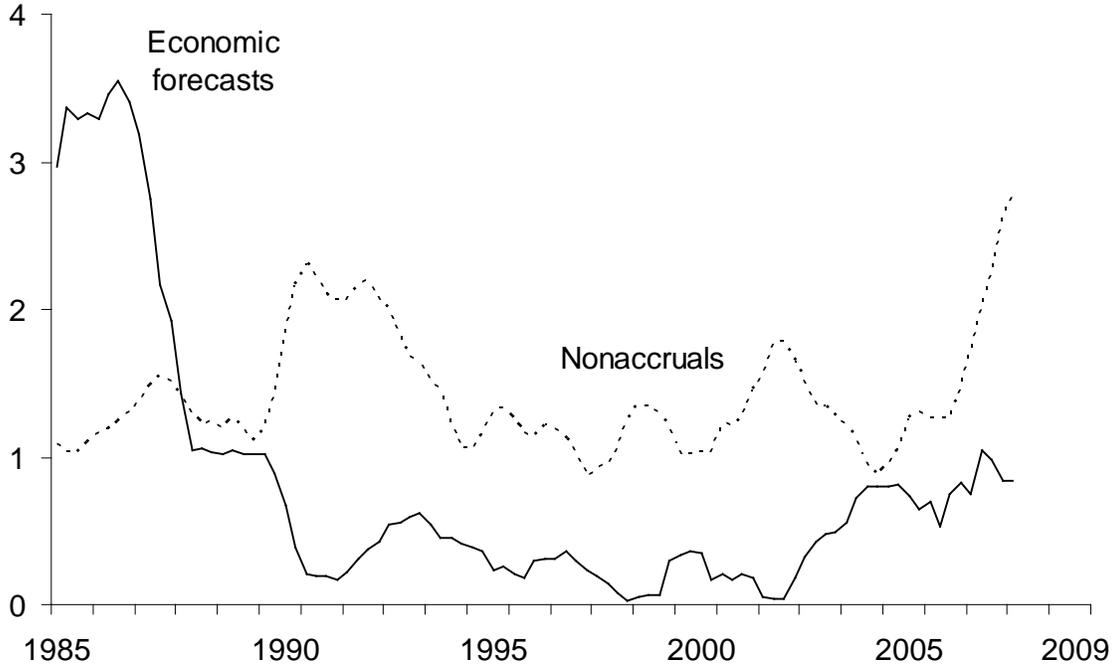


Figure 9
Forecasted CAMELS Rating and Range of Potential Ratings:
Hypothetical One-Period Example

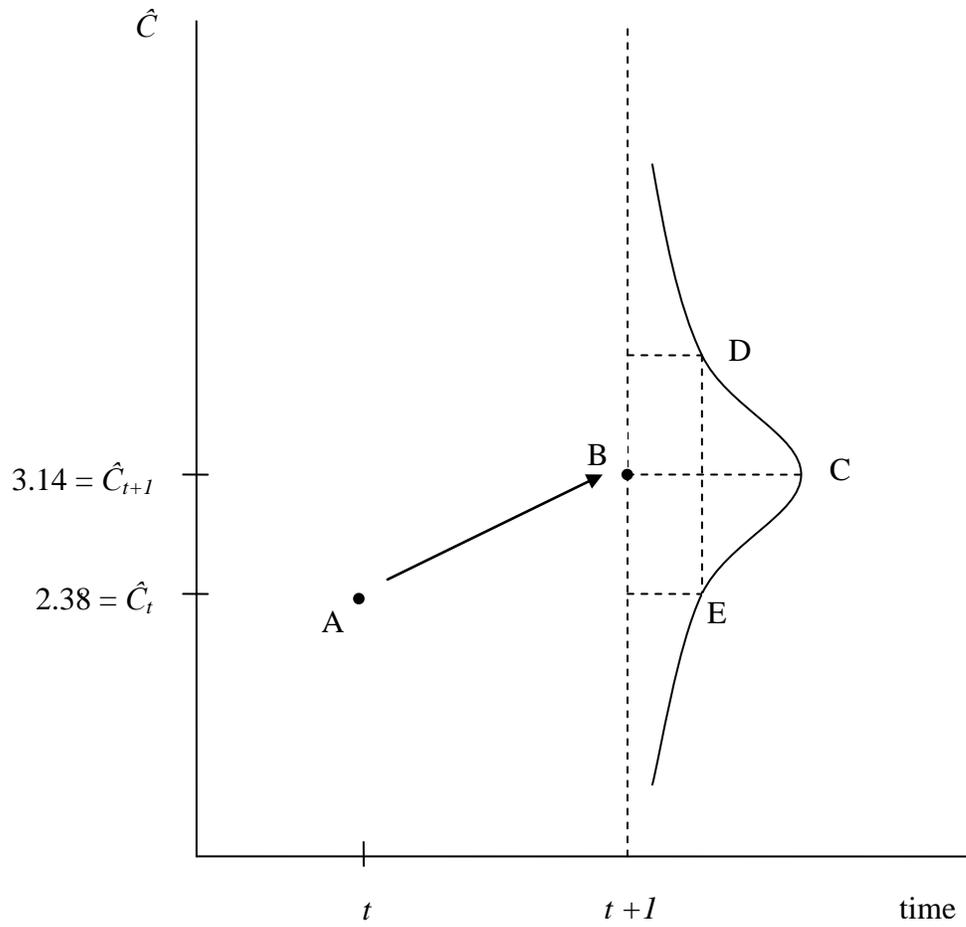


Table 1
Effects of Banking and Economic Developments
on Factor Weights in CAMELS Ratings Rule
(Quarterly, 1984:2–2009:2)

	ESUM (1)	EQUITY (2)	DEL90 (3)	NONACC (4)	ALLL (5)	VOLIAB (6)	ROAB4T (7)	INTRCPT (8)
1. Constant	1.41* (1.69)	4.41** (2.21)	0.91*** (3.73)	0.55*** (3.31)	3.04*** (2.78)	0.88 (0.97)	0.02 (0.21)	-0.54*** (-3.77)
2. Prior-quarter weight (dep. var. lagged)	0.71*** (9.43)	0.35*** (3.08)	0.08 (0.81)	0.27*** (2.75)	0.18* (1.70)	0.30*** (3.07)	0.70*** (8.86)	0.53*** (6.26)
3. Own portfolio share (lagged)	-	-0.37*** (-2.84)	0.80*** (3.29)	-0.17 (-1.41)	-0.14 (-0.13)	0.07*** (3.12)	0.09* (1.82)	-
4. CAMELS (mean, lagged)	-0.50 (-1.43)	0.30 (1.01)	-0.14 (-1.15)	0.07 (0.66)	-0.41* (-1.81)	-0.44* (-1.78)	0.06 (1.44)	0.39*** (4.79)
5. 10-yr Treasurys minus fed funds	0.04 (0.43)	-0.08* (-1.84)	-0.08*** (-3.52)	-0.02 (-1.50)	-0.06 (-1.01)	-0.04 (-0.66)	-0.01 (-1.06)	0.004 (0.32)
6. Economic growth (recent average)	-0.30 (-1.00)	-0.49*** (-2.66)	-0.16* (-1.89)	-0.05 (-1.00)	-0.86*** (-3.68)	-0.18 (-0.80)	-0.04 (-1.39)	0.04 (0.98)
7. Mean of dep. var.	0.65	1.38	0.71	0.70	1.65	1.35	0.67	0.66
8. S.E. E.	0.98	0.43	0.25	0.16	0.70	0.58	0.07	0.16
9. R-squared	0.63	0.77	0.27	0.18	0.28	0.59	0.65	0.78

Note: t-statistics in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent level.

The dependent variables are the factor weights in the estimated CAMELS Ratings rule for recent local economic growth (ESUM), equity capital (EQUITY), loans delinquent over 90 days (DEL90), nonaccrual loans (NONACC), the allowance for loan and lease losses (ALLL), volatile liabilities (VOLIAB), net income before taxes (ROAB4T), and the coefficient on the intercept in the estimated CAMELS Ratings rule (INTRCPT).