October, 2009

# How Has Bank Supervision Performed

# And How Might It Be Improved?

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This paper was prepared for the Federal Reserve Bank of Boston's 54th Economic Conference, "After the Fall: Re-evaluating Supervisory, Regulatory and Monetary Policy." October 20-23, 2009. We thank Luis G. Dopico for criticisms and suggestions. The views expressed here are not necessarily those of the FDIC or its staff. Any remaining errors are ours alone.

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### Abstract

Bank supervisors rate individual banks' safety and soundness according to the Uniform Financial Institutions Rating System (UFIRS). Under UFIRS, bank supervisors rate banks' overall safety and soundness based on their capital adequacy, asset quality, management, earnings, liquidity and sensitivity to market risk (CAMELS attributes). Important inputs into supervisors' ratings of banks are banks' financial performance, risk management practices and local economic conditions. We estimate the effects of key financial performance and economic measures on CAMELS by estimating approximate supervisory "Rating Rules." The estimated Rating Rules are similar to regulators' well-known early warning models, whose specifics have not been publicly available.

While maintaining confidentiality about the sizes of estimates of individual coefficients in the ratings models, we document how they have evolved over time. Over 1984-2009, the effective factor weights that our "Rating Rules" place on equity capital and on loan loss allowances fluctuate relatively more than do the factor weights on delinquent loans and earnings. We also show the extent to which movements of the factor weights over time are correlated with developments in banking and in the broader economy.

We next modify the Ratings Rule Model to forecast banks' likely overall conditions (i.e., CAMELS ratings) one to two years hence. We demonstrate that contemporaneously-available forecasts of future statewide economic conditions significantly improve these forecasts of banks' conditions. We conclude by discussing how the more-explicitly-forward-looking forecasts of banks' condition might be used to set a threshold for regulatory intervention for distressed banks. This threshold could serve as an alternative to the single-factor, equity capital threshold specified by the Prompt Corrective Action provisions of the Federal Deposit Insurance Corporation Improvement Act (1991).

## I. Introduction and Overview

The primary indicator of a bank's overall safety and soundness is its capital adequacy.[1] Bankers and bank supervisors assess a bank's capital adequacy based on the bank's ability to absorb unexpected losses, given the risks inherent in its balance sheet and off-balance-sheet activities, local economic conditions and its risk management practices.[2] Banks may become inadequately capitalized because of unexpected credit or other losses, which may stem 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] Weaknesses in bank risk management practices become more transparent to bankers and their supervisors during periods of economic stress. For these reasons, pressures to augment capital buffers, both from bank supervisors and bank managers, typically increase during periods when available resources for obtaining capital—retained earnings or external capital injections—are shrinking. As a result, bank capital pressures may be "pro-cyclical," whereby pressures to

[1] We use to term "bank" to refer to all FDIC-insured depository institutions. This includes commercial banks, savings banks, savings and loan associations and co-operative banks. Our sample of "banks" does not include credit unions insured by the National Credit Union Share Insurance Fund.

[2] Bank earnings and risk management practices should act to absorb expected losses or the "normal" costs of doing business. Under GAAP accounting rules, banks are required to establish loss reserves (also known as allowances for loan and lease losses (ALLL)) that reflect the level of probable and estimable losses in the portfolio but 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 comprised of a set of statutory minimum capital ratios for safe and sound banks and discretionary supervisory requirements that increase required capital ratios as a bank's overall condition deteriorates.

raise capital ratios increase during economic downturns, which then curtail bank lending and thereby exacerbate the downturns.[4]

Prior studies found that capital pressures on banks reduced lending and economic activity. Studies by 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.

In order to reduce the unintended harm to the macroeconomy resulting from pro-cyclical bank capital requirements, various schemes for regulatory flexibility and supervisory discretion have been proposed during previous banking crises, as well as during the current global financial crisis. These schemes typically allow for the temporary suspension of statutory minimum bank capital requirements, as well as greater flexibility in supervisory standards if banks are considered to be under duress temporarily. More recent policy proposals have sought to reduce and even eliminate the procyclicality of bank capital requirements by making statutory minimum capital requirements explicitly counter cyclical, (e.g., proposals for "dynamic" loss provisioning).

In addition, there may be significant opportunities for circumventing regulatory capital requirements. Any regulatory capital requirements can be undermined by excessive financial reporting discretion. For example, the recent Financial Accounting Standards Board amendments to accounting guidance for reporting the "fair value" of infrequently traded securities held in banks' trading books (level 3 asset valuations) may

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

effectively allow banks to avoid recording losses on many of the structured securities whose underlying collateral (commercial and residential mortgages) values have fallen dramatically since 2007.

We propose an alternative to single-factor, book-value of capital-based thresholds for early supervisory intervention at troubled banks. We propose a method for forecasting the likely overall conditions of individual banks, one to two years hence. The method incorporates both factors that predictably affect banks' future conditions and factors that reflect the volatility of banks' future conditions. The efficacy of our proposal depends on two features: 1) having an effective early warning system that indicates what supervisory and management actions might be warranted far enough in advance of adverse economic conditions to reduce the pro-cyclicality of capital pressures and lending, and 2) having an early warning system that is less susceptible to manipulation and mis-measurement than a single-factor, book-equity capital-based.[5] The approach advanced here attempts to provide bank supervision with tools to "assist" banks in taking more prompt, more preventive actions than has been the case too often in the past.

Section II briefly reviews some of the literature on supervisory ratings of bank safety and soundness and the roles therein of banks' accounting data and local economic conditions. Section III shows how similarly accounting, supervisory, and market-based data portray the evolution of banks' conditions over recent decades. Section IV reviews some of the difficulties inherent in modeling supervisory ratings, and presents our model

[5] We acknowledge that there is no system of risk measurement, internal or external to a bank that is impervious to manipulation and, therefore, mis-measurement at some level. However, by making the risk measurement system more forward looking, risk assessment might occur when banks are under less pressure to mask financial difficulties. This might also require that the early warning system not be disclosed too explicitly to bank managements.

specification. Section V presents estimates of CAMELS-rating "rules" that are based on banks' accounting data and local economic conditions. Section VI develops a model for forecasting CAMELS-ratings for individual banks 1 to 2 years hence (hereafter, Intermediate-term Model). The Intermediate-term Model uses contemporaneous information on forecasted state economic conditions and bank financial condition to forecast CAMELS ratings. Section VII proposes how forecasts for a 12 to 24 month horizon of bank condition might be incorporated into current supervisory and management actions and plans. This section also indicates how current estimates of the future volatility of banks' conditions might be used to calculate risk-adjusted CAMELS ratings. It also discusses a possible role for the more-explicitly-forward-looking risk measures in setting capital requirements. Section VIII notes that small banks might impose systemic risks and then discusses how their capital requirements might reflect their contributions to systemic risk. Section IX summarizes our findings and discusses some of their potential applications.

## II. Literature Review

Various aspects of supervisors' ratings of banks have been addressed in empirical studies. Some studies have investigated whether supervisors' judgments, as encapsulated in the CAMELS ratings that they assigned, have been validated, in the sense that the ratings predicted ensuing bank performance or market 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 later on came to be known and was then reflected in banks' share prices. Berger, Davies, and Flannery (2000) reported, for predicting future performances of bank holding companies, that recently-assigned (BOPEC) ratings tended to out-perform market-based measures. O'Keefe, et al. (2003) provided 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 it was to become troubled and to fail. Taken together, these studies suggest that on-site exams and supervisors' judgments provide information beyond that embodied in contemporaneous Call Report or financial market data.

A small number of studies have examined the extent to which banks' future conditions, as indicated by their (composite) CAMELS ratings, were forecastable by Call Report (accounting) 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 SCOR model indicated that it 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. They reported mixed evidence: For some measures of bank conditions and at some horizons, economic conditions contributed appreciably, but for others, the contributions of local economic conditions were negligible. Thus, prior studies have quite consistently pointed toward supervisors' ratings as being informative about banks' conditions. At the same time, there is not 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 1-2 years that we focus on.

## III. Trends in Banking Industry Condition and the Outlook

Figure 1 shows annual data for (gross) charge-offs and for provisions for loan losses (both as a percent of assets) and the ratio of equity capital to assets in the aggregate for U.S. banks during 1960-2008. These data reveal that, 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 global financial crisis in 2007. For instance, until the middle of the 1990s, banks' capital ratios were lower than since. After the early 1990s, reported capital ratios rose markedly.[6] With the advent of the 2007 financial crisis, loan losses rose and capital fell.

Bank supervisors combine information from banks' financial statements and reports and from their on-site examinations and interviews to form their judgments as to the conditions of banks. Under the Uniform Financial Institutions Rating System (UFIRS), supervisors use their judgments to assign integer ratings from 1 to 5 to each of the of CAMELS components (**C**apital, **A**sset quality, **M**anagement, **E**arnings, **L**iquidity, and **S**ensitivity to market risk). They also assign a composite rating for the overall safety and soundness of each bank. CAMELS ratings are lower for banks that are judged to be in better condition. Banks with CAMELS ratings 4 or 5, and some 3-rated banks, for example, comprise the FDIC's list of "problem banks." Typically, CAMELS are revised

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[6] 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 the effective bank capital ratios in the 1990s were very likely even stronger than were reported then.

(or re-iterated) only upon a "fresh" on-site examination of a bank. By statute banks are now examined every 12 to 18 months.[7]

Figure 2 plots the average composite CAMELS ratings across banks for each quarter from 1984:1 through 2009:3. For each quarter, Figure 2 also plots the cross-bank standard deviation of the CAMELS ratings, which moved nearly in tandem through time with the average rating. Note that the averages and standard deviations for each quarter that were plotted in Figure 2 were based on current CAMELS ratings, that is, those that were assigned during the quarter.

We see in Figure 2 that the average and standard deviation of the composite CAMELS ratings both declined substantially by the middle of the 1990s and increased slightly during and after the 2001 recession. Then, with the onset of the 2007 financial crisis, both the average and the standard deviation of the composite CAMELS ratings rose to their 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, bank risk management practices, and changes 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.[8] These EDFs were calculated by Moody's KMV using their implementation of the Merton

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[7] The Federal Deposit Insurance Corporation Improvement Act (FDICIA) 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 composite CAMELS of 1 or 2 may be examined every 18 months by their primary state or federal supervisor. All other banks are examined annually.

[8] The small bank series that is plotted in Figure 3 was based on the banking companies who had fewer than the median amount of assets. The large bank series was based on the banking companies that were in the top quartile by asset size. At the beginning of the sample there were about 100 small and 50 large banks in the sample; by the end of the sample period there were about 300 small and 150 large banks. The EDF data for the two series was kindly provided by MKMV.

(1973) model of firm equity holders' put option on the value of firm assets. The KMV/Merton model uses banks' stock prices, their 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. The average EDFS for small banks were quite highly correlated over time with the EDFs for large banks, but were very much smaller. The average EDFs declined noticeably into the middle of the 1990s, as the average CAMELS did, but then rose considerably during the Asian crisis of the latter 1990s (which affected publicly-traded banks more than banks on average) and the 2001 recession, unlike the CAMELS. After 2001, the average EDFs fell very sharply, to their lowest levels of the years since 1990. Then, in 2008, the average EDFs rose to their highest levels of the sample period, by far.

Despite their differences in banks' covered and approaches, in broad outline, each of Figures 1-3 portray U.S. banks as having been stronger in the middles of these decades and weaker near the ends of these decades.

## IV. Ratings Rule Model

In this section we develop approximations to the composite CAMELS ratings process, akin to the FDIC's off-site early warning system SCOR.[9] Specifically, we hypothesize that a bank's composite CAMELS ratings is determined by its recent income and condition data, bank management practices and quality, local economic conditions

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[9] The FDIC's Statistical Off-site Ratings System (SCOR) uses a considerably shorter prediction horizon than that used by our Ratings Rule. However, SCOR and the Ratings Rule use the same explanatory variables to predict CAMELS Ratings. In addition, SCOR uses a stepwise ordinal logistic regression to model composite CAMELS ratings, whereas our Ratings Rule Model uses an Ordinary Least Squares regression. See Collier, et.al. (2003) and Nuxoll, et.al. (2003).

and supervisory standards. In this section we approximate this process using a simple Ratings Rule Model wherein the composite CAMELS ratings received during a calendar quarter is related to measures of a bank's financial CAMELS attributes as of the end of the prior quarter and to lagged measures of state economic conditions (equation 1). This Ratings Rule uses publicly available data and admittedly does not include crucial information on bank management practices and the quality of bank management.

1) $$CAMELS_t = \beta' X_{t-1} + \lambda' Z_{t-1} + \varepsilon_t$$

In equation 1, $CAMELS_t$ is the composite CAMELS rating received during a full-scope on-site examination during quarter $t$, $\beta$ is a vector of regression coefficients (factor weights) and $X_t$ 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, λ. 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 ratings); however, the linear approximation greatly simplifies our discussion of the Rating Rules factor weights. However, prior research conducted by the FDIC during development of risk-related insurance premiums indicates a linear approximation to SCOR produces very similar ordinal rankings of banks, based on predicted CAMELS.

To preview, our estimates of equation 1 suggest that the rules significantly incorporated both bank and economic conditions and that the factor weights varied, sometimes considerably, over time and varied somewhat systematically with bank and economic conditions. Later we discuss how the Ratings Rule Model might be modified to forecast bank conditions 1 to 2 years hence. We also discuss and demonstrate how incorporating more-explicitly-forward-looking measures of economic conditions can improve those forecasts.

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 rule that supervisors used may have contained known, measurable variables other than those that we included in our specification of the rule; bank management quality and risk management practices are two prime examples of factors used by supervisors to evaluate banks that are missing in our model. Another example of a factor that we cannot include is a measure of individual banks' loan underwriting standards. Underwriting standards, especially those for residential mortgages, appear now to have undergone large, widespread gyrations over the past decade.[10] Although supervisors might well obtain 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 might well be substantial and, importantly for our purposes here, might 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 change over time, so too

[10] See O'Keefe (2009) and Wilcox (2009).

would we expect the estimated factor weights to shift relative to the actual factor weights used by supervisors.[11]

Second, supervisors may well have embodied in their judgments about banks' conditions information that is not quantified in publicly-available data. One virtue of on-site bank examinations is to validate and, if necessary, call for adjustments to bank financial statements.[12] (Note that, as a practical matter, we have access only to the finalized financial statements banks file with their primary federal regulatory, also known as Call Reports.)

A third reason time-variation in estimated factor weights might be another form of mis-specification error. While we have included a measure of economic activity for the state in which each bank was headquartered, for some banks their relevant regions are much larger than their home states and for some banks their relevant regions are much smaller than their home states. To the extent that their states differed from banks' relevant regions, whether they were multi-state or countywide, there is some scope for (time-varying) bias in estimated ratings-rule factor weights.

Further, there may be a sort of time-varying, "Lucas Critique" bias associated with the lagged, local economic activity variables that we included. If the time-series process for economic activity changes, then the implied, optimal factor weights for forecasting current and future activity would change, as likely would the judgment about the implications of currently observed values of included variables. Thus, for example,

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[11] As an indication of whether correlations might change considerably over time, we compared the correlations between the included variables over 1984-1993 with their correlations over 1999-2009. For example, 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.

[12] See Dahl, et al. (1998).

when economic growth is more strongly autocorrelated, larger extrapolations of the effects on banks' conditions (e.g., loan delinquencies or earnings) of additional recent economic growth would be warranted.[13]

Yet another 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 estimate considerable time-variation in factor weights estimated via ordered-logit as well, and their implied marginal effects might have varied just as much as those implied by OLS estimates.) At the same time it may well be the case that supervisors put more weight on a particular variable when banks generally, or that particular variable, was worrisomely weak. Thus, judgments reflected in CAMELS ratings may have responded more to capital when capital was low than when it was abundant. This sort of judgment might impart a systematic variation to estimated (and actual) factor weights.

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

<u>Estimating a Ratings Rule Model</u>

We began by estimating an "as-if" Ratings Rule Model to approximate the actual process that supervisors used to assign (composite) CAMELS to individual banks. For

[13] During the Great Moderation of economic growth rates after the 1980s, the volatility of growth rates plummeted. Before then, economic growth rates were less forecastable.

each quarter, we regressed the actual CAMELS rating for each bank on variables from its most recent Call Report. Thus, for example, the Ratings Rule Model regressed second-quarter CAMELS ratings on (end of) first-quarter Call Report data. Our cross-section estimation sample included only those banks that received a "fresh" CAMELS rating during that quarter. Our quarter-by-quarter samples averaged around four thousand banks.

Mimicking SCOR, we used the following 12 variables in our OLS regressions to account for individual banks' composite CAMELS ratings: equity capital, loans delinquent 30-89 days, loans delinquent over 90 days, nonaccrual loans, allowance for loan and lease losses (ALLL), 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 percent of each bank's gross assets.[15]

Our estimation sample included only banks that were examined and received a CAMELS rating during the forecast window. We also trimmed from our sample those banks who reported values in their Call Reports that were far in the tails of the variables' distributions. We did include banks of all sizes (unless "trimmed out"). 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.

[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 & 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.

Because each bank was separately examined and rated, we included banks regardless of whether they were part of multi-bank 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 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 is not included in the Call Reports. For example, 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. In addition, there may be some tendency for bank data revisions to be correlated with economic conditions: When the economy weakens, there may be an increased tendency to under-report problems. Mentally judgmentally-adjusting reported data for such extra information might occur and improve CAMELS ratings.

## V. Accounting for CAMELS with Bank and Economic Data

<u>Estimated Time-Variation in Factor Weights</u>

The coefficient estimates provide quarterly time series data for the (estimated) factor weights for each of the explanatory variables in equation 1. We indexed the values for each series of factor weights to equal 1.00 for 1984:2 in Figures 4 and 5. The estimated factor weights for the index base period (1984:2) for each variable in Tables 4 and 5 had the sign that we expected. Because this indexing procedure renders the factor weights all positive, we can regard the plotted series as the absolute values of the estimated coefficients. Thus, for example, while the estimated weight for capital was uniformly negative, its plotted values are all positive (having been normalized by its negative estimate for 1984:2). 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 (estimated) factor weights for equity capital and for ROA (before taxes). 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 varied.

Historically, some of the largest factor weights for all four of variables were clustered around 1990-1991. Until 2008, the weight on capital dwindled quite steadily; then it rebounded considerably from its lows, but recently it was still considerably below the peaks observed around 1990. While more charge-offs and provisions tended to raise (worsen) CAMELS ratings, the factor weights associated with both of these two variables fell 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 were 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 and in our Ratings Rule: Higher nonaccruals quite reliably raised (worsened) 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 U.S. crisis more recently. Also of note is the apparent tendency of the factor weights on nonaccruals to move in the opposite direction of those on OREO. Given the likely positive correlation in the data for individual banks of OREO and nonaccruals, observing negative correlation in the estimated coefficients due to that pattern of multicollinearity in the data was not particularly surprising.

After tending to swell around 1990, afterwards the factor weights on liquid assets drifted downward substantially, while the factor weights on volatile liabilities trended upward, with both series reversing their trends somewhat since the onset of the recent crisis.

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

Systematic Patterns in the Ratings Rule Model

Next, we investigated whether the Ratings Rule Model factor weights were reliably related to aggregate values of various banking and economic variables. We regressed the estimated factor weights for eight variables (including the estimated intercepts of the Ratings Rule) on their own lags (i.e., lagged dependent variables), on the (aggregate) mean of banks' portfolio shares of that variable (lagged one quarter), on the mean CAMELS rating (lagged one quarter), on the spread between the 10-year Treasury yield and the federal funds interest rate, and on a moving average of recent, national, economic growth rates.[16] The eight dependent variables, listed in the columns of Table 1, were the factor weights (summed across all four lags) on local economic growth rates, equity capital, loans delinquent more than 90 days, nonaccrual loans, the allowance for loan and lease losses (ALLL), volatile liabilities, income before taxes, and the intercepts. Table 1 shows the results.

Interpreting the coefficients on the factor weights in Table 1 requires some care. The estimated factor weights come, of course, from a 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 shows that (own) prior-quarter factor weights (i.e., the dependent variables lagged) significantly predicted current values of many of the factor weights. The estimated coefficients on the (own) lagged dependent variables averaged about 1/3 and were often significant, though typically far below one. Thus, the current factor weights can be regarded as partially reflecting past factor weights and partially reflecting gradual adjustments to changed conditions.

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

The negative coefficients on the (aggregate) bank capital ratio, shown in row 3, indicate that the weight on equity capital (column 2) was higher when (aggregate) capital was lower, as we might hope and expect. Similarly, row 3 shows that the factor weights on delinquent loans (column 3) rose significantly when (aggregate) delinquencies were higher. Despite its strong statistical showing in the Ratings Rule Model, no such relation to high nonaccruals showed up in the accrual 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 earnings (as measured by income before taxes) also tended to rise, not when earnings were low, but rather when they were high (however, this coefficient was not significant at the usual, five percent significance level).

Row 4 shows that only the estimated intercepts responded significantly (and positively) to a higher 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.

Row 5 shows that only the factor weights associated with equity capital and loan delinquencies were significantly associated with the measure of easy monetary policy, as measured by the difference between the yield on 10-year Treasurys and the federal funds interest rate. The estimated effects of easier monetary policy were to reduce the factor weights on equity capital and on delinquent loans.

Row 6 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 might well suggest the supervisory process was significantly incorporating the otherwise-unmeasured effects (beyond those already measured by a dozen Call Report variables) of the economy on bank conditions.

Thus, Table 1 helps us to better understand how ratings 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 worsened 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.

## VI. An Intermediate-term Model: The Value of Economic Forecasts

In this section we extend the Ratings Rule Model to a longer forecast horizon of 1 to 2 years. The purpose of using this longer horizon is to test whether forecasts of future, local, economic conditions add explanatory power to an intermediate-term variation of the Ratings Rule Model (hereafter, Intermediate-term Model) .

We seek to improve forecasts of future bank conditions by adding variables that are explicitly forward looking. In particular, we added forecasts of the growth rate of the local (i.e., state) economy for each bank for each of the next four quarters (including the current quarter for which data would not yet be available). For a horizon of 1 to 2 years, we regarded local growth rates over the next four quarters as being most relevant, especially in light of the time that might take for economic conditions to affect banks and their CAMELS ratings.

We again used the same bank financial variables that are included in the SCOR and Ratings Rule models, but re-specified our models to forecast over a longer horizon of

1-2 years. We chose this horizon on the argument 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. Having a longer lead time and having information about the source of the forecasted deterioration in a bank's CAMELS rating is intended to reduce the probability and severity of bank distress and losses imposed on the FDIC. In that regard, the goal is to promote "more prompt, more preventive actions."

For each quarter, we generated conditional forecasts of the one-quarter (not annualized) growth rate of local economic activity for the current and for each of the three ensuing quarters. Again, as our measure of local economic conditions, we used the FRB Philadelphia's State Coincident Indexes. For each quarter, we estimated an auto-regression with four lags (and a constant and a linear trend) for each state. The sample period was lengthened quarter by quarter to include the most recent, lagged economic growth rate. So, for each state for each quarter we forecasted local growth for the current and three ensuing quarters, using all of the then-available observations on local growth. The forecasts for the ensuing quarters were conditional on the forecasts for the prior quarters.

Thus, to predict the CAMELS ratings that would be assigned 1-2 years in the future for each freshly examined and CAMELS-assigned bank, we used the current values of its (same as before) Call Report variables, plus the four local-economic-forecast variables, one for the current and each of the ensuing three quarters for its home state.

One advantage of including each of the four forecasted growth rates without coefficient restrictions is that then the data can choose the combinations that have been most informative for future CAMELS. Regardless of whether of which lags were empirically most relevant, of whether it is the level of growth or its acceleration that was most relevant, or whether it was cumulative growth that was most relevant, the estimates are free to reflect the relevant specification.

To show how consistently the economic forecasts significantly affected forecasts of banks' conditions (i.e., future CAMELS ratings), Figure 6 plots the square roots of the F-statistics calculated for the test of the joint significance of the four economic forecast variables. Figure 6 also displays the square roots of the F-statistics (i.e., the t-statistics) for the significance for capital, for nonaccrual loans, and for the loan loss allowance. We follow these with comparisons of the economic significance of having added the economic forecasts with other variables to the CAMELS forecasting specifications. As our measure of economic significance, we used the change in the adjusted $R^2$ that resulted from deleting the economic forecast variables as a group. We then compare the changes in adjusted $R^2$ due to deleting the economic forecast with the changes due to deleting, one by one, other variables.

The top panel of Figure 6 plots the square root of the F-statistics for omitting the four economic forecast variables from the CAMELS-forecasting specification. 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% 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 at 1.96, the standard cut-off level for t-statistics for a 5% significance level.

The top panel shows that economic forecasts were typically significant, with square-roots of calculated F's that were less than the critical value of 1.54 for only nine 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.[17] Thus, we regard the economic forecasts, which were based only on past data, as being able to contribute significantly to predicting bank troubles.

For comparison with the results for the economic forecasts, in the bottom panel of Figure 6, we present the t-statistics for equity capital, for nonaccrual loans, and for the loan loss allowance. In forecasting banks' conditions 1-2 years ahead, equity capital typically had a huge t-statistic, often in the range of 10. Ever since 1990, however, the t-statistic on equity capital has been drifting downward. The estimated t-statistics on capital dropped considerably in 2005, and then rebounded most recently. 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 than above 1.96, and only briefly above 1.96 since 1993. 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 provided for sufficiently. On the other hand, having more nonaccrual loans is more likely unalloyed bad news. And, not surprisingly given their track record in SCOR,

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[17] 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.

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.

How much do economic forecasts add to CAMELS forecasts?

We measure the contribution of our forecasts of state economic conditions to the intermediate-term CAMELS prediction model by comparing the changes in adjusted $R^2$ due to deleting (or adding) the set of economic variables to 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 were 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.[18] 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.

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 added. Over the shorter period shown in the bottom panel, capital added somewhat more.

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

Figure 8 shows a comparison of the additions to adjusted $R^2$'s attributable to economic forecasts with the additions due 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 that were attributable to forecasts of economic growth were on a par with those 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 may have already sized up the likely effects of economic growth).

With the resulting CAMELS prediction 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 fewer real estate loans it would likely take to achieve a different rating. Nor are they likely to reveal the estimated coefficients in the Intermediate-term Model that forecast CAMELS.

Nonetheless, informed discussions about the forecasted CAMELS ratings might well help guide a bank toward a better trajectory. Such discussions might give both the supervisor and the bank a better understanding of why a CAMELS deterioration was in the offing, as well as how to avert it. If the current predictions were sufficiently dire, then the forecasts would seem to provide supervisors with cause for considering whether the bank ought to be under greater regulatory scrutiny, and perhaps, subjected currently to memoranda of understanding (MOUs) or Cease and Desist Orders (C&Ds).

## VII. Estimating Banks' Future Outcomes and Their Risks

A 1-to-2-year-ahead forecast of a composite CAMELS rating that is 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 receives a CAMELS rating of 2. Suppose also that this bank's estimated CAMELS rating for time t based on a previously estimated Ratings Rule Model is 2.38, as shown in Figure 9. With a model-estimated CAMELS rating of 2.38, we might view this as a "weak 2" bank currently.

At time t, we could use the Intermediate-term Model to calculate an estimate of the future CAMELS rating that the bank will get at time t+1, a horizon that we took to be 1-2 years. Suppose that same bank had, as of time t, an estimated CAMELS rating of 3.14 for time t+1. That is, the bank's condition in this case is expected to worsen. Such a prediction might well spur both the bank and its supervisors into "more prompt, more preventive actions", in order to avoid the currently-estimated future outcome.[19] If supervisors do act sooner to help avoid the predicted outcome, their more-anticipatory actions might be termed as "supervisory preventive actions" (SPA).[20]

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[19] Barr (2009) reported that SNL Financial calculated that 29 banks had been issued PCA letters in 2009 through August, up from 7 for the same period in 2008. Of the 29 banks, 2/3 have already failed.

[20] Bank supervisors compare forecasts of (near-future) CAMELS ratings to actual ratings as part of their off-site supervision programs. The Federal Reserve Board's Supervision and Regulation Statistical Assessment of Bank Risk Model (SR-SABR) and the FDIC's Statistical CAMELS Off-site Ratings (SCOR) provide such comparisons. Banks' whose predicted CAMELS ratings diverge significantly and adversely from current CAMELS ratings are targeted for additional off-site review and potentially an accelerated on-site examination date. To avoid unnecessary and burdensome oversight, supervisors

The regression estimates upon which the estimated future outcome is based are influenced by the reactions that bank managers and supervisors have taken in the past. As a result, current estimates of future outcomes essentially embody those typical reactions. As another example of a Lucas-critique-like effect, if bank managers or supervisors were to react differently, perhaps more prompt and more corrections actions, then the estimates would come to embody those revised reactions. The more effective such reactions to estimated outcomes are in avoiding adverse outcomes, the more difficult it would be to estimate future outcomes that would result in the absence of such reactions. Consider an extreme case: If the reactions were sufficiently effective in their timing, scope and magnitude that they averted bank problems, then on the basis of the resulting data, it might be much more difficult to discern early warnings of future problems. The reason is that the heretofore useful signals would essentially have been exploited and thereby broken the connection between those signals and future outcomes. In the meantime, we might expect that reactions would not be so effective as to turn the signals into noise.

To supplement the time t point estimate of the bank's time t+1 CAMELS rating, $C_{t+1}$, we also would like a measure of a bank's risk, or the range of its "likely" outcomes at time t+1. We refer here to a bank's being riskier, not when its recent performance or its current condition are considered weak (which would indeed connote a higher probability, or risk, of failure), but when it has a larger dispersion (or volatility or "likely range") of future outcomes, as measured by CAMELS ratings, all other things being equal.[21] Thus,

"triage" banks flagged by early warning systems, focusing only on the most significant CAMELS downgrade forecasts.

[21] The risk-focused on-site examination process and UFIRS rating system may incorporate uncertainty in future outcomes in CAMELS ratings to some extent, especially with regard to the timing and frequency of on-site exams. One of the sources of risk may in fact be deficiencies in banks' abilities to identify measure,

we refer to a bank's risk in the same way that textbooks use the term "risk" and that they incorporate the volatility of asset-price outcomes as a risk factor in the pricing assets. We distinguish between the risk, or probability, of default and a forward-looking assessment about the likelihood of various outcomes. Sometimes banks in weaker conditions, due perhaps to reduced capital or earnings, are referred to as being riskier (and, again, such banks are more likely to fail and impose costs on the FDIC). We associate risk with the volatility of (uncertain, future) outcomes, and, thus, rather than referring to current problems or to probabilities of failure, one might say that by "risk," we mean variance.

How might we obtain measures of the dispersion of future outcomes (actual, future CAMELS ratings at time t+1)? One candidate for a measure of this risk 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, or the bank's risk, will depend on a number of factors. Predictability narrows the range: The more predictable are future local economic conditions and the more predictable are 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 estimated future condition for a bank. Concomitantly, the more confident that we are about the future values of OREO or ROA, for example, the more confidence we can have that the bank will be near its estimated condition at time t+1. In addition, the range would also depend, perhaps importantly, on the uncertainty about how closely the estimated

monitor, and control risk: Stronger bank managements may reduce the dispersion of future outcomes, as well as generally improve average performance at their banks.

regressions approximate the unknown, actual parameters that connect the measured Call Report variables with banks' CAMELS ratings.

We denote an estimate for the range of future outcomes as $S_1$, whose size would depend on the standard error of the forecast. $S_1$ would likely vary over time and across individual (j) banks ($S_{1t,j}$). Estimating $S_{1t,j}$ precisely seems problematic, but we may be able to provide estimates that are sufficiently informative that they provide positive net benefits.

Covariance Counts, or "When It Rains, …"

The extent to which the factors used to rate banks are correlated can also importantly affect the dispersion of future outcomes. Some developments in one part of a bank, whether positive or negative, may typically reverberate, whether causally or coincidentally for other reasons, with other parts of a bank. Having more nonaccrual loans or OREO, or a weaker local economy, may tend to be correlated with reduced ROA, higher non-interest expenses, and lower capital. The stronger the covariance of adverse (or positive) movements in the factors that are used to assess banks' conditions (e.g., the Call Report variables and the local economy), the more likely that more things go wrong (or right) at the same time. Thus, the larger the reinforcing covariances at a bank, the larger the dispersion of future outcomes that we should see and expect. To the extent that a bank is more diversified, we expect the covariances, and thus the resulting range of likely outcomes, $S_{1t,j}$, to be smaller. In that regard, such a bank is less risky.

To begin to assess how much bank risk varies across banks at any given time, we might, we might consider estimating the Intermediate-Term Models over subsamples of banks that are judged likely to have similar dispersions. For example, higher risk might be typically signaled by banks' having larger concentrations of commercial real estate loans or of agricultural loans, or by having larger shares of their income arising from noninterest revenues. To the extent that such factors can be somewhat systematically associated with more (or with less) bank risk, the better able supervisors would be to assign appropriately different $S_1$'s at different times and to different banks.

Further, it may be that combinations of, and not just individual, factors more effectively signal bank risk. For example, it may be that banks that have both more volatile liabilities and more commercial real estate loans are particularly high risk (or maybe low risk).[22] Combinations of factors are more likely to be effective signals to the extent that banks become more seriously troubled as a result of the positive covariance between the troubles associated with the individual factors.[23]

Although there may well be identifiable factors that systematically signal risk, much more analysis would be required to judge whether they would likely satisfactorily approximate the risks (volatility) of individual banks.

Uses for Risk Measures

An empirical measure of the risk of an individual bank j at time t, $S_{1t,\,j}$, might be used in several ways. One way would be to forecast an Estimated Risk-Adjusted CAMELS rating (ERAC) as follows:

$$2)\qquad ERAC_{t,\,j} = \hat{C}_{t+1,\,j} + r{*}S_{1t,\,j}$$

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

[23] That composite CAMELS ratings differ from linear weighted averages of the component ratings and that deposit insurance premiums have been set via an asymmetric pricing matrix suggest that supervisors are sensitive to covariances.

where $\hat{C}_{t+1}$ is the CAMEL rating that is forecasted as of time t for time t+1 and *r* is a scalar that "prices" or "risk-weights" banks' measured outcome volatility, $S_{1t,\,j}$. The more weight that bank supervisors put on volatility, presumably because of their heightened aversion to adverse outcomes, the larger the *r* that they should choose. To the extent that larger variances and covariances of the risk factors translate into more estimated volatilities, equation 2 then serves to "price," in the form of a higher ERAC, the impacts of those variances and covariances. In that sense, equation 2 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 $S_{1t,\,j}$ than otherwise and would then be rewarded with a smaller ERAC.

This perspective 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), either explicitly via a change in the law or implicitly via supervisory practice and agreements, be triggered when the ERAC for a bank, $ERAC_{t,j}$, rises to various levels. While CAMELS have so far been bound by an integer constraint, neither ERAC calculations nor PCA-like triggers or supervisory agreements need be constrained to be integers. (That discussions of CAMELS ratings being "weak" or "strong" 2's, for example, suggests that implicitly the integer constraint is in effect not binding now.)

This forward-looking perspective on banks is intended to promote awareness that the amounts of uncertainty (or risk) can vary across time and across banks. Risk can also vary across banks that currently might be regarded as being in similar condition: Some banks with CAMELS ratings of 3 might have much less risk than others. Consider a bank whose current CAMELS rating was 3 and whose estimated rating for time t+1 was, say, 3.22. Suppose that, because of its risks, the bank had an ERAC adjustment of 0.54, and thus an ERAC = 3.76. That bank might be subjected to more stringent supervisory actions than a bank that currently had a CAMELS rating of 4, but had an estimated future CAMELS rating of 3.30 and an ERAC add-on of 0.10.

## VIII. Systemically-Important Small Banks? , Or "Covariance, Priced Again"

Remember the Alamo (Federal Savings Association)!

In 1989, Alamo Federal Savings Association failed.[24] Alamo was one of thousands of (all-too-) similar thrift institutions. The thrifts' difficulties engendered a 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 S&Ls were large banks. Thus, it was not so much that large thrifts became troubled, but rather that too much of the thrift industry became troubled that produced the S&L crisis and its associated credit and economic disruptions. The extent of the difficulties imposed by the thrift crisis on the aggregate financial and real sectors of the U.S. economy was not as large as in the current crisis. But, they were large. Thus, when enough smaller institutions are similar enough, and thus co-vary sufficiently, they may also be systemically important.

Systematically 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 engenders. Of course, for many, and

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

probably most, smaller banks, this extra capital charge might be trivial, in large part because of their small sizes and concomitantly small contributions to systemic risk. For all but the largest banks, as exemplified by the 19 systemically-important banks in the recent SCAP program, the capital charge might be proportional to a bank's share of the relevant banking sector. For the largest banks, as suggested by 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 calculating the estimated risk-adjusted CAMELS rating, ERAC, above, 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, on its covariance with the relevant banking sector, and the capital-price per unit of systemic risk. Choosing which outcome(s) would be good measures upon which to base calculations of beta will not be trivial. For the thousands of small, not-publicly-traded banks, there is unlikely to be a market-price-based measure that will 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 would be a bank's credit beta, perhaps calculated as the sensitivity of its changes in credit supplied to changes in aggregate credit supplied.

Minimum capital requirements, $\underline{K}$, then might be built up from a base minimum, $k_{min}$, plus a charge for individual bank risk as discussed above, $g* S_1$, plus a systemic risk charge, $b$ * SR, as follows:

3) $$\underline{K} = k_{min} + g * S_1 + b * SR$$

$k_{min}$ is the base minimum capital ratio (say, the lowest minimum ratio (3%) in current law. $g$ is the extra capital required per additional unit of individual-bank risk, $S_1$). $g$ is the price per unit of individual bank risk as measured by $S_1$, where $S_1$ might be taken from the bank risk calculation described above. (We offer no suggestion here about how g should be calculated.)

$b$ is the extra capital required per unit that a bank contributes to systemic risk. SR measures how much the individual bank contributes to systemic risk.[25] SR 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 "beta" between the outcomes of the bank and the sector as a whole.

To reduce the systemic risk add-on to its capital requirement, a bank might alter its size or alter its operations and balance sheet so as to reduce its covariance, and thus its contribution to systemic risk. In that way, diversification in the form of having different cross-bank exposures to aggregate shocks will be valuable to each institution. The reward to such diversification will dilute the incentives to be "too similar to fail," or "safety in similarity" (see Stever and Wilcox [2007] for a discussion of safety in similarity).

## IX. Looking Forward to Forward-Looking Assessments of Banks' Conditions

Over the past 25 years, banks, their regulation, and their regulators have changed considerably. One change has been the increased emphasis on capital. Another change has been increased recognition that the economy affects banks, and vice versa. This year,

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

the SCAP program stressed the importance of forward-looking assessments of bank conditions.

Our estimates show that the effective 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 that capital helps forecast bank conditions.

We then noted how models of future CAMELS ratings might guide 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' actions and plans to be more anticipatory than those engendered by the current PCA system. As such, 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 that the capital requirements for these banks too might appropriately include systemic risk charges.

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Figure 1

Provisions, Gross Charge-offs, and Equity Capital Ratios

(all commercial banks, per assets (%), source: FDIC, annually, 1960-2008)

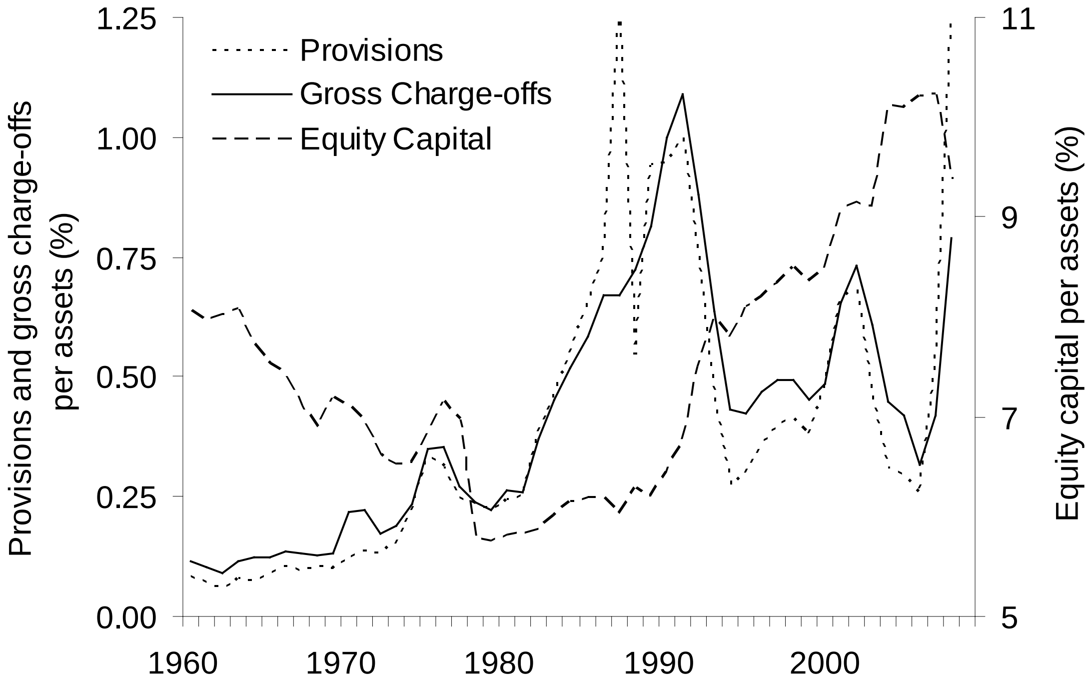


Figure 2
Average and Standard Deviation of Cross-Sectional Composite CAMELS Ratings
(all recently-examined FDIC-insured institutions, quarterly, 1984:1-2009:3)

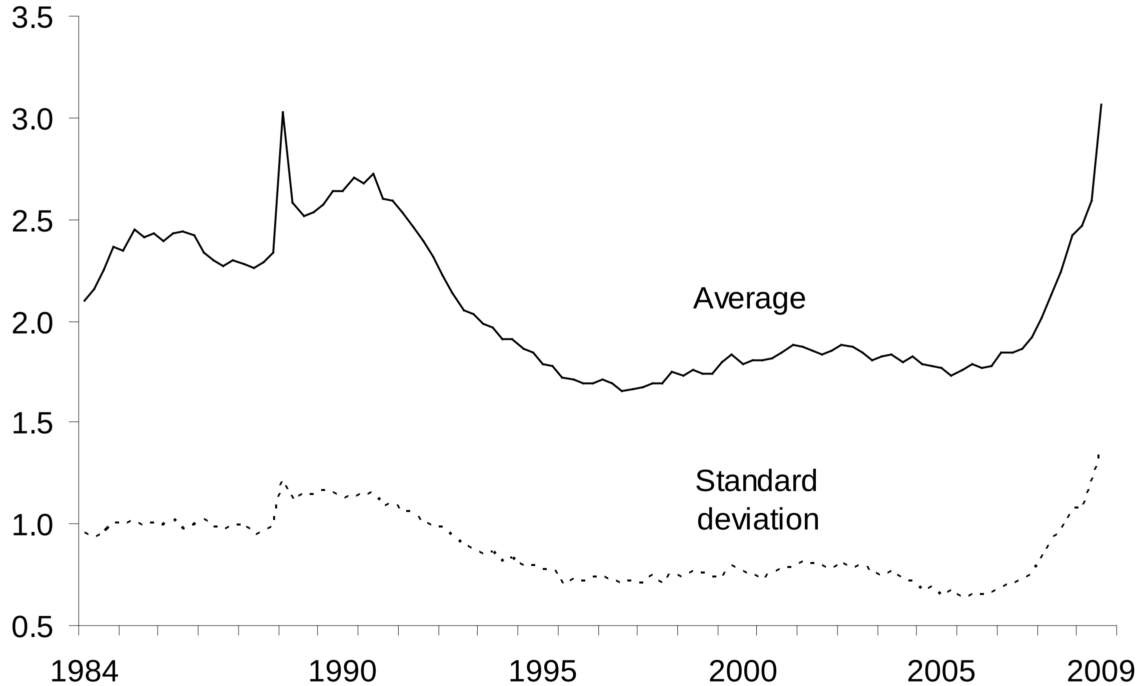



Figure 3
Average of EDFs for Large and for Small (Publicly-traded) U.S. Banking Companies
(percent, one-year horizon, monthly, 1990:1-2009:8)

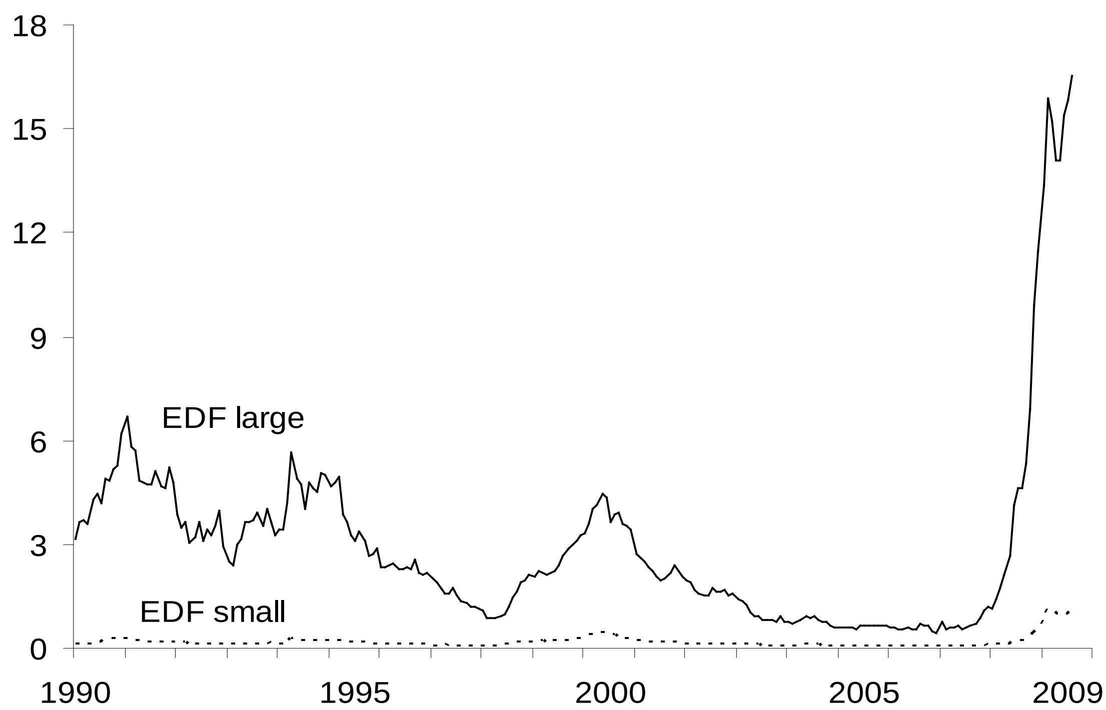


Figure 4
Estimated Factor Weights in the Ratings Rule Model:
Equity Capital, Income before Tax, Gross Charge-offs, and Provisions for Loan Losses
(quarterly, 1984:2 – 2009:2, indexed: 1984:2 = 1, 8-quarter trailing moving averages of factor weights are shown for charge-offs and provisions)

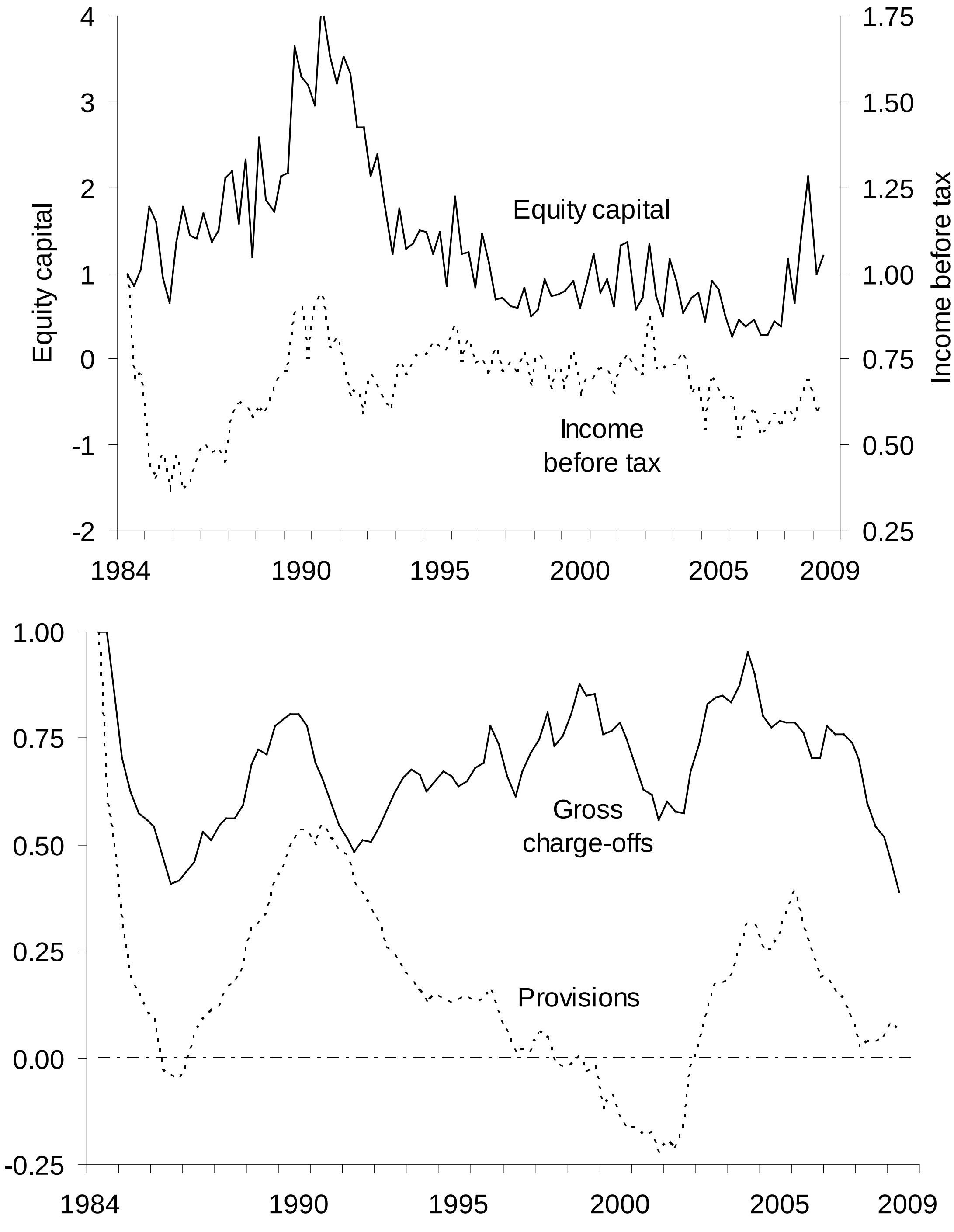
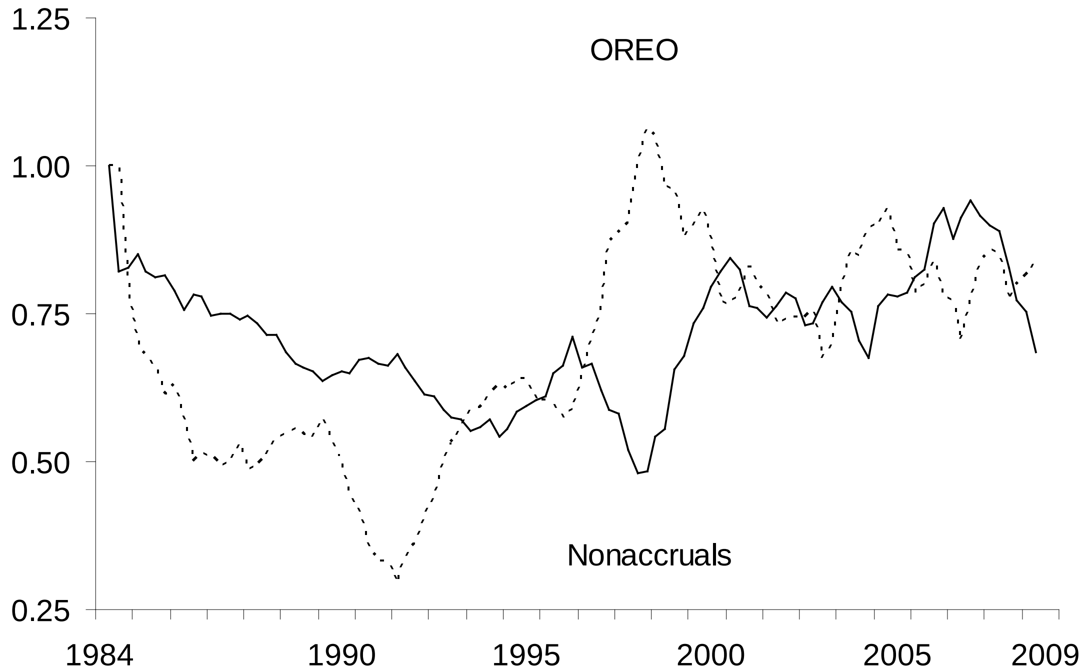


Figure 5
Estimated Factor Weights in Ratings Rule Model:
OREO, Non-accrual Loans, Volatile Liabilities, and Liquid Assets
(quarterly, 1984:2 – 2009:2, indexed: 1984:2 = 1,
8-quarter trailing moving averages of factor weights are shown)



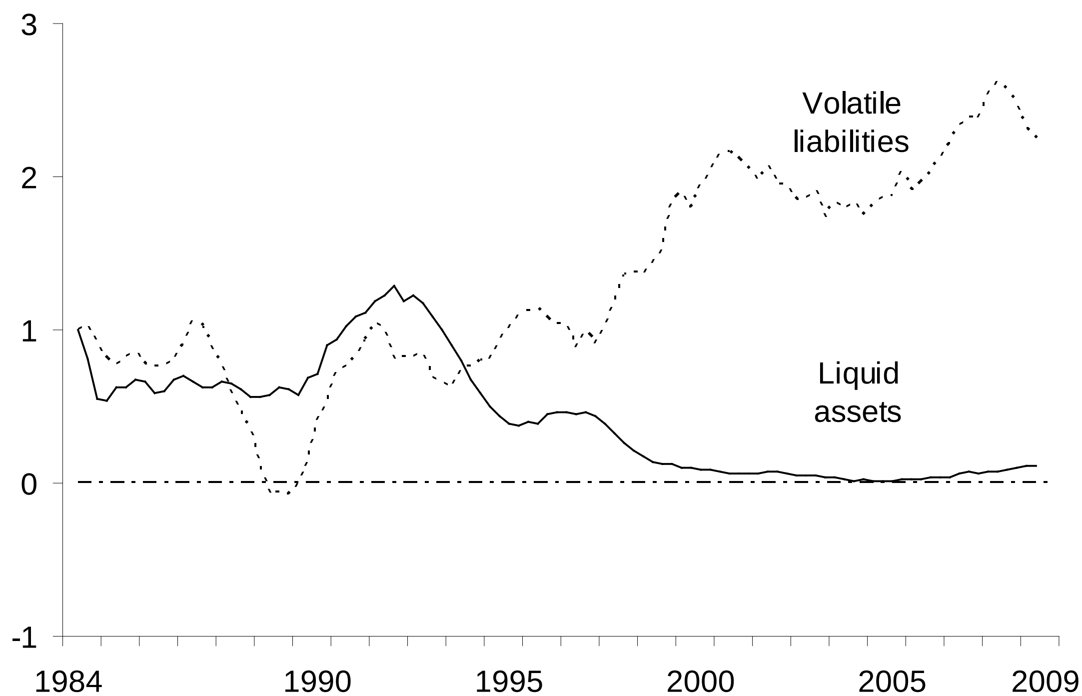
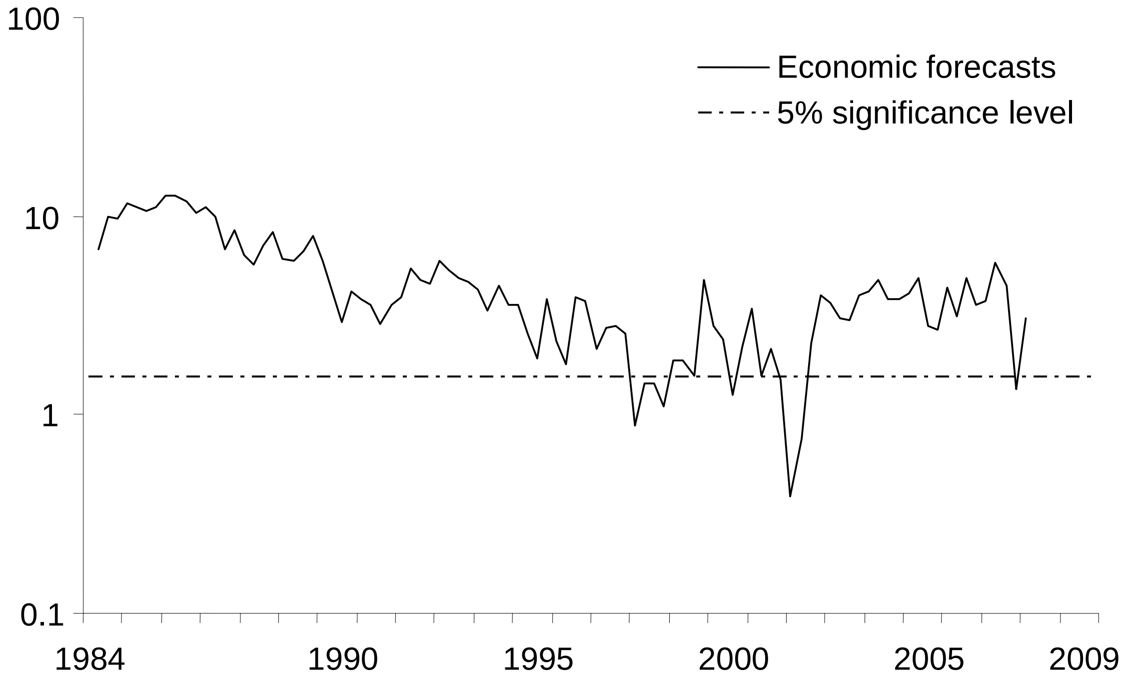




Figure 6

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)



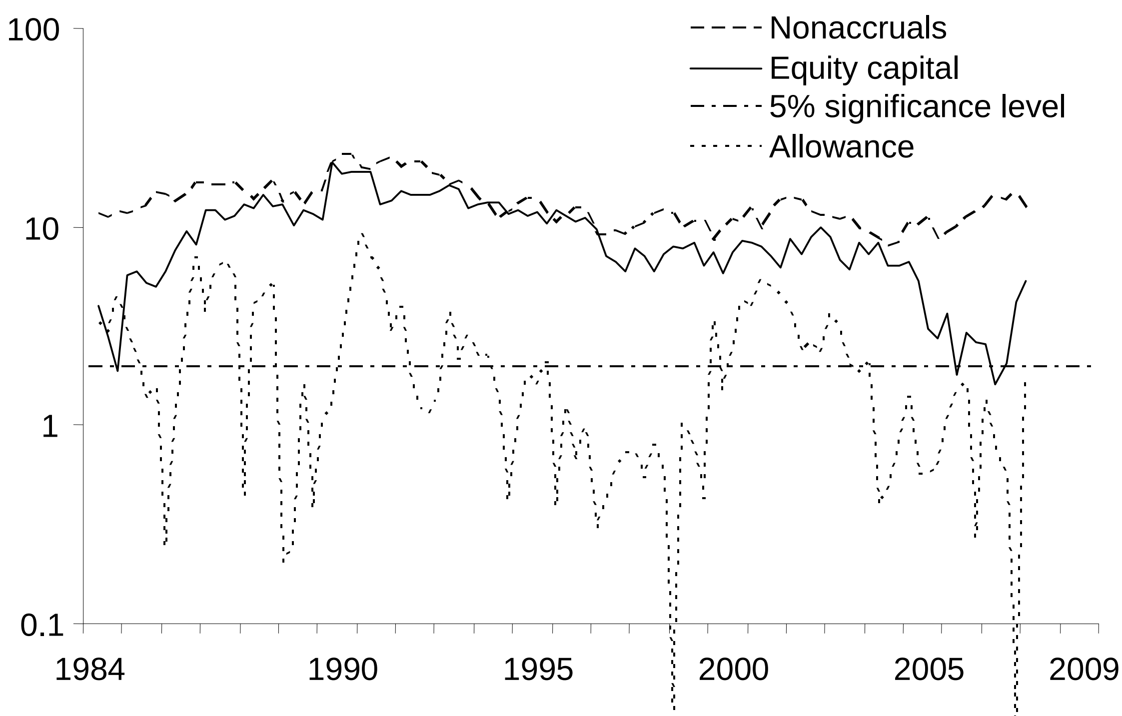



Figure 7
Improvements in Adjusted $R^2$ in Forecasting Banks' Conditions:
Economic Forecasts and Equity Capital
(percentage points, quarterly, 1985:1-2008:1 and 1995:1-2008:1,
as of forecast date, four-quarter trailing averages are shown)

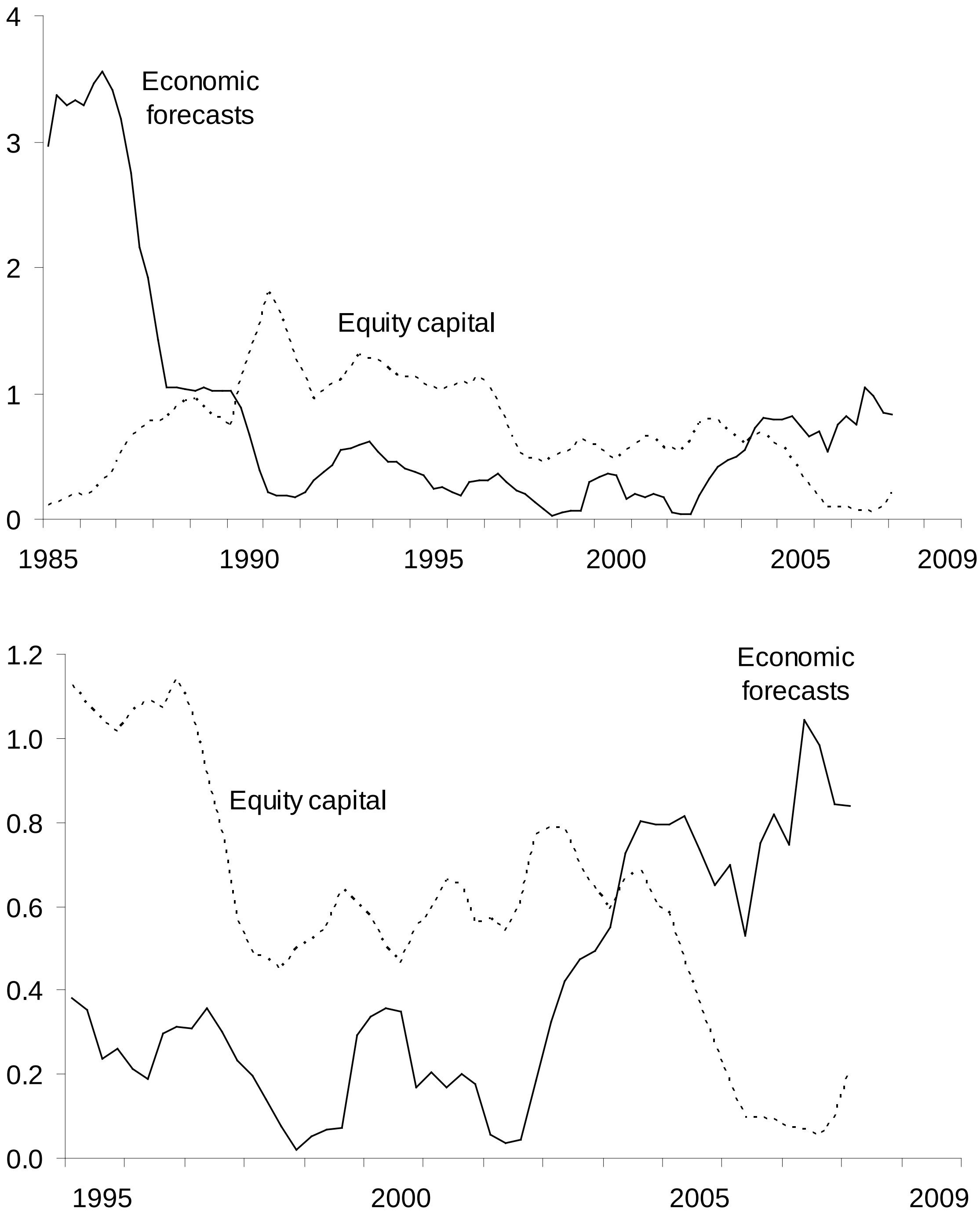
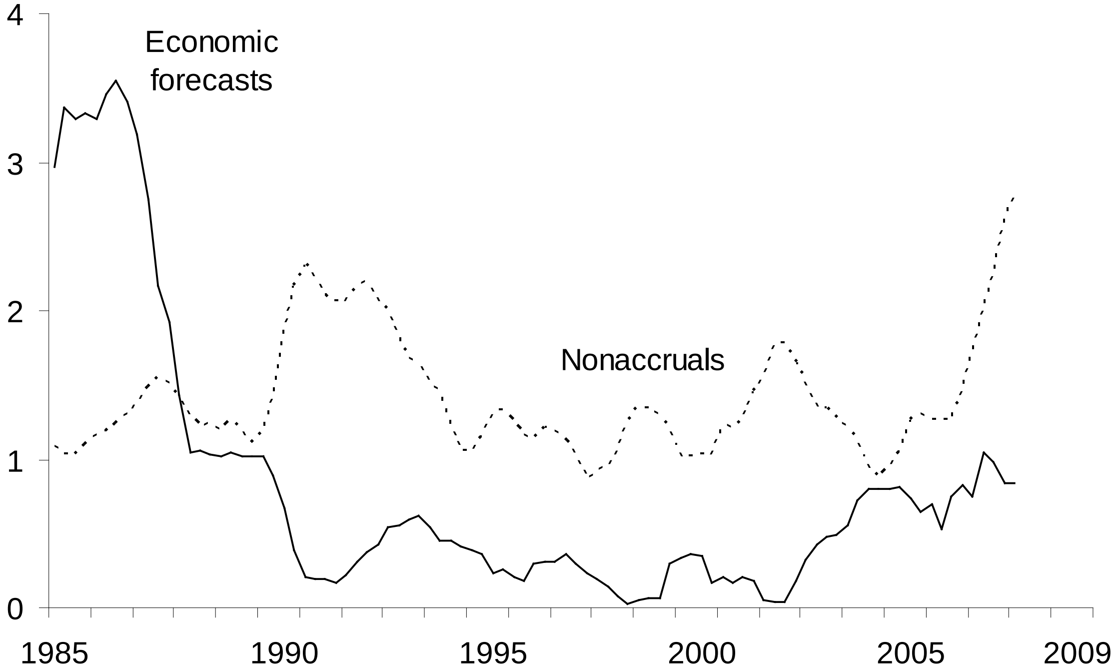


Figure 8
Improvements in Adjusted $R^2$ in Forecasting Banks' Conditions:
Economic Forecasts, Nonaccrual Loans, and Allowance for Loan and Lease Losses:
(percentage points, quarterly, 1985:1-2008:1,
as of forecast date, four-quarter trailing averages are shown)



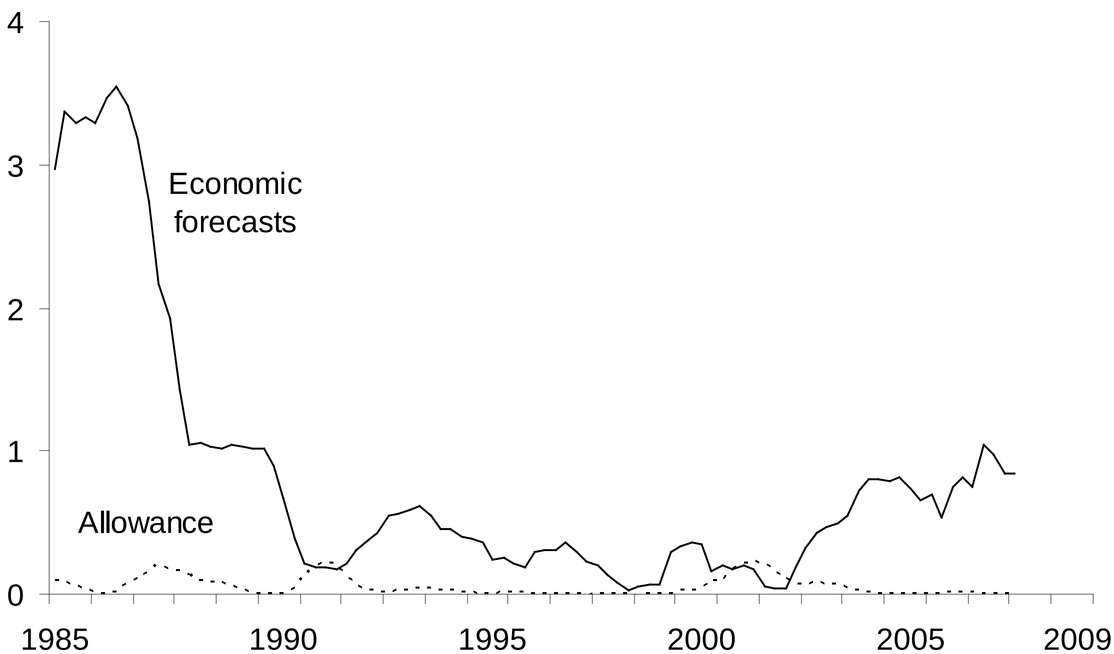



Figure 9

Forecasted CAMELS Rating and a Range of Potential Ratings:

A Hypothetical, One-Period Example

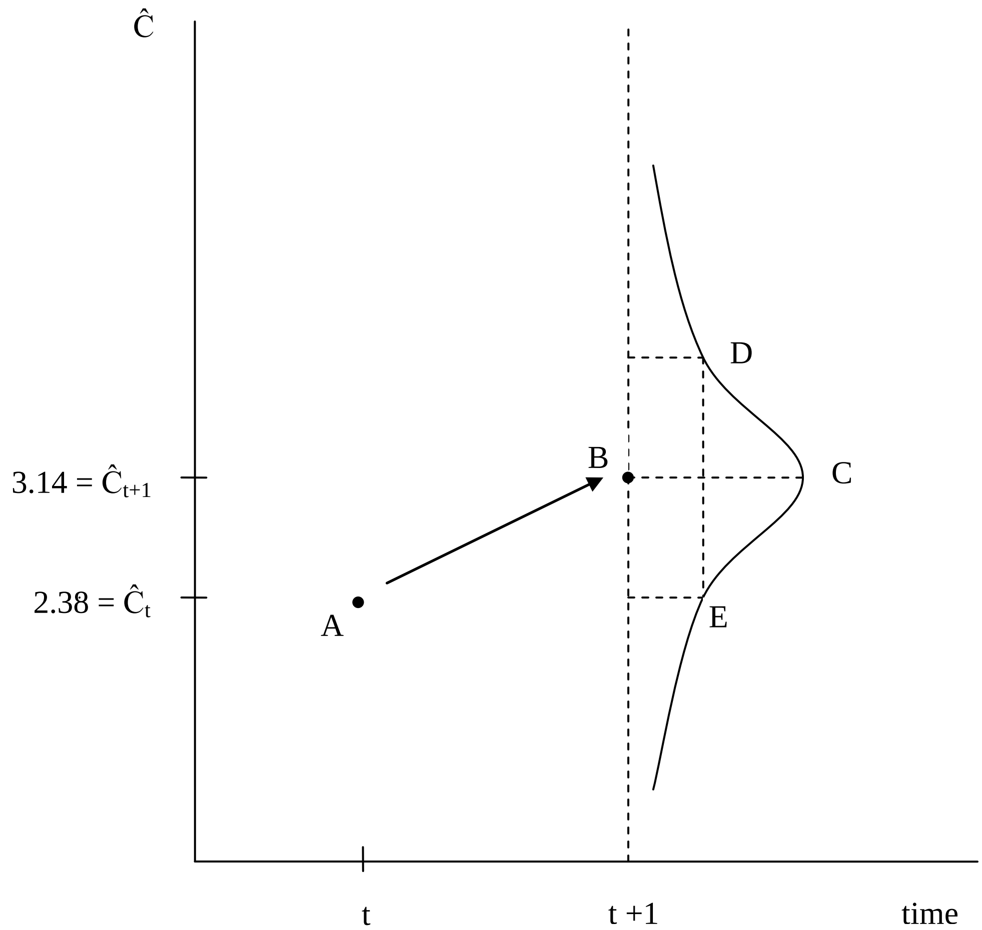


Table 1

Effects of Banking and Economic Developments
on Factor Weights in CAMELS Rating Rules

(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* | 4.41** | 0.91*** | 0.55*** | 3.04*** | 0.88 | 0.02 | -0.54*** |
| | | (1.69) | (2.21) | (3.73) | (3.31) | (2.78) | (0.97) | (0.21) | (-3.77) |
| 2. | Prior-quarter weight (dep. var. lagged) | 0.71*** | 0.35*** | 0.08 | 0.27*** | 0.18* | 0.30*** | 0.70*** | 0.53*** |
| | | (9.43) | (3.08) | (0.81) | (2.75) | (1.70) | (3.07) | (8.86) | (6.26) |
| 3. | Own portfolio share (mean, lagged) | - | -0.37*** | 0.80*** | -0.17 | -0.14 | 0.07*** | 0.09* | - |
| | | | (-2.84) | (3.29) | (-1.41) | (-0.13) | (3.12) | (1.82) | |
| 4. | CAMELS (mean, lagged) | -0.50 | 0.30 | -0.14 | 0.07 | -0.41* | -0.44* | 0.06 | 0.39*** |
| | | (-1.43) | (1.01) | (-1.15) | (0.66) | (-1.81) | (-1.78) | (1.44) | (4.79) |
| 5. | 10-yr Treasurys minus fed funds | 0.04 | -0.08* | -0.08*** | -0.02 | -0.06 | -0.04 | -0.01 | 0.004 |
| | | (0.43) | (-1.84) | (-3.52) | (-1.50) | (-1.01) | (-0.66) | (-1.06) | (0.32) |
| 6. | Economic growth (recent average) | -0.30 | -0.49*** | -0.16* | -0.05 | -0.86*** | -0.18 | -0.04 | 0.04 |
| | | (-1.00) | (-2.66) | (-1.89) | (-1.00) | (-3.68) | (-0.80) | (-1.39) | (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 |

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 Rating Rules 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 Rating Rules (INTRCPT).