*Preliminary – not for quotation*

# Economic Cycles and Bank Health

John S. Jordan* and Eric S. Rosengren*

4/10/02

## Abstract

Over the past two decades the United States has experienced substantial increases in the number of bank failures, however, surprisingly few banks have failed during the 2001 recession. This paper explores the relationship between economic cycles and bank health. We find that economic forecasts provide little additional information over bank-specific financial data during prosperous times, possibly because bank problems during these times are likely to be idiosyncratic to individual management decisions. However, economic forecasts become relevant during troubled economic periods, with poor economic conditions hindering a broader set of institutions.

---

*Federal Reserve Bank of Boston. The authors would like to thank David Schramm for valuable research assistance. We thank Mark Vaughan and seminar participants of the Federal Reserve Bank Structure Conference for helpful comments.

Economic Cycles and Bank Health

Over the past two decades, troubles in the banking sector have been highly correlated with economic downturns. While relatively few banks failed between 1945 and 1980, in the 1980s and early 1990s, bank failures became increasingly common, with 221 banks failing in 1988 alone. One explanation for the surge in bank failures is that competition increased in the industry, as regulatory barriers to entry were reduced, and banks increased leverage to enhance return on equity (Keeley, 1990). Another explanation is that several regions experienced severe economic troubles over the period, as hardship in particular sectors such as oil, agriculture, and commercial real estate had a disproportionate impact on regions with particular concentrations in these sectors. Despite the apparent correlation between economic conditions and the health of the banking industry, relatively few banks have failed during the 2001 recession despite the high level of bankruptcies and the unusually large decline in corporate profitability. This anomaly raises the question of the role of business cycles in predicting bank failures. This paper examines whether regional economic variables, in particular, forecasts of these variables, provide useful information for assessing bank health.

Assessing the role of regional economic variables is particularly important today, as bank regulators attempt to better understand the impact of a deteriorating economy on the health of the banking industry. Interestingly, surveillance models of bank health among bank supervisors in the United States have focused on bank financial variables, but not included economic forecasts. These models generally use quarterly Call Report data to assess bank health, deriving financial variables from the balance sheet and income statement. The variables chosen are those that most closely mimic the on-site activity of bank examiners, and those that are readily available to the econometrician estimating the model off-site. Cole, Cornyn and Gunther (1995) and Cole and

Gunther (1998) provide a review of such modeling techniques. Others, including Gilbert, Meyer, Vaughan (1999 and 2000), Krainer and Lopez (2001) evaluate possible enhancements to the models.

In this paper, we examine the usefulness of economic forecasts over a four quarter time horizon to model the connection between business cycles and bank health. With the longer forecast horizon, we investigate whether the introduction of regional economic variables into existing surveillance models used by bank supervisors that does not utilize economic variables. Regional economic variables are potentially important in surveillance models of long time horizon for several reasons. First, if accounting conventions, or bank practice, prevent financial statement variables from fully reflecting current and future expected losses, including forecasts of economic variables may provide valuable information about the bank health. Second, existing models do not forecast future balance sheet variables, but these variables are likely to be correlated with future economic conditions.

We find that economic variables add relatively little value to the assessment of current bank health, but that these variables are both economically and statistically significant when forecasting bank health over a four-quarter horizon. The relative timeliness of the release of economic variables and the correlation between future economic conditions and future bank-specific financial data are both plausible explanation of this finding. In addition, we find that economic variables provide little additional information over bank-specific financial data during prosperous times, when most banking problems are idiosyncratic to individual management decisions. However, these variables become relevant during troubled economic periods, when economic conditions hinder many institutions.

If poor economic conditions significantly increase banking problems, why is it that this recession has resulted in so few troubled banks? We find three factors account for the relative health of the banking system during the 2001 recession. First banks were in better financial condition, with substantially higher capital ratios and better asset quality than the period leading up to the 1991 recession. Second, the recession was somewhat milder, as measured by the decline in payroll employment. However, corporate profits declined more and bankruptcies were higher in 2001 than during the 1991 recession. Third, the evidence is consistent with better risk management. Thus, the 2001 recession does not indicate that the link between economic variables and bank health have been severed, in fact, economic variables significantly reduce the errors in identifying problem banks. Rather it shows that bank management had taken actions that positioned banks to avoid difficulties during a mild recession.

The first section of this paper provides a brief review of models of bank surveillance models and discusses how bank supervisors use these models in practice. The second section examines whether forecasting regional economic conditions significantly improve the ability to predict bank health over existing models that forecast bank health. The third section examines the connection between economic variables and bank health during the 2002 recession. The final section draws implications of the analysis for the linkage between economic cycles and bank health.

## *I. Background*

The widespread failure of savings and loan institutions and the large number of commercial bank failures over the past two decades has increased the amount of research into the determinants of bank health. One segment of the literature examines the causes of bank failures

(Cole and Gunther, 1995, 1998; and FDIC's History of the Eighties). Another examines the economic impact of these failures (Bernanke 1982; Slovin, Sushka and Polonchek, 1993). While others examine the role of on-site and off-site bank supervision (Hirtle and Lopez, 1999; Berger, Davies and Flannery, 1998; DeYoung, Flannery, Lang, and Sorescu, 1998) as well as the role and importance of bank regulations (BIS, 2001). The literature on bank failures use bank Call Report data to estimate probabilities of failure (Thomson, 1992, Cole and Gunther 1995, 1998) and to estimate bank ratings (Jones and King 1995; Gilbert, Meyer, Vaughan 1999, 2000). While bank supervisors have long used surveillance screens and financial ratios to monitor banks (Cole, Cornyn, and Gunther, 1995), this academic literature served as the foundation for developing off-site early warning systems used by bank supervisors. These off-site evaluations are used to supplement the on-site bank examinations that verify the financial health of banks.

The information generated from the on-site exams regarding the financial condition of the bank is summarized in confidential supervisory ratings of the bank. Bank supervisors evaluate the bank according to the Capital, Asset quality, Management, Earnings, Liquidity, and Sensitivity to Market Risk (CAMELS). Each component, as well as a composite rating, is given a score from 1 to 5, where 1 is the highest score. Thus, a composite score of 1 would indicate that the bank is sound in every respect while a score of 5 would indicate an extremely high probability of failure.

The off-site early warning system developed by the Federal Reserve System, the System to Estimate Examination Ratings (SEER) was designed to provide an assessment of bank financial condition between on-site exams. SEER consists of two statistical models, the ratings model and the risk rank model. The ratings model uses current Call Report data to estimate banks current composite CAMELS rating. The model is rerun each quarter, and the estimated rating is available to analysts providing off-site surveillance. The risk rank model provides the probability that a bank fails or becomes insolvent in the next two years using variables from the bank Call Report. The coefficients are based on estimates of running the model for the period from 1985 to 1992 when bank failures were prevalent. Thus, the coefficients from the model are not updated.

The SEER model, and most of the previous academic work on bank failures, focus on generating estimates of CAMELS rating for banks in quarters for which no on-site exam is available, and are generated solely based on bank-specific financial data. However, it is important to understand the condition of banks not only in the current quarter, but also in future quarters based on the economic and financial outlook. Bank supervisors have increasingly taken a risk-focused approach to supervision. Targeting reviews and allocating bank examiner resources should reflect not only the current condition of the bank, but also how that condition might change based on the economic outlook. Thus, it may be important to understand the allocation of bank CAMELS ratings based on the economic outlook. Furthermore, the condition of the banking sector can be important in understanding the transmission of monetary policy (Kashyap and Stein, 2000) and the credit conditions firms may expect to finance inventories and producer durable equipment (Kashyap, Stein, and Lamont 1994, Peek, Rosengren, and Tootell1998).

There are reasons why economic variables might not be useful in forecasting bank financial condition. If banks fully factor their economic forecast into determining forward looking banking variables such as loan loss reserves, than the reserves would include any expected future losses. If so, than economic variables might provide little additional information over current bank Call Reports. This would imply that the best estimate of CAMELS ratings over the next four quarters would be no different than the CAMELS ratings that would be assigned for the current quarter based on current bank Call Reports. However, reserving procedures can be affected by accounting conventions, attempts by management to window dress or manage earnings, and tax effects. This would imply that reserves would not fully capture how expected economic conditions will affect bank health over the next four quarters.

Economic variables may be an important supplement to Call Report data for several reasons. First, if forward-looking bank Call Report data does not fully reflect future economic conditions, than examiners, when determining the appropriate CAMELS rating will incorporate future economic conditions when determining supervisory ratings. This implies that both future and current economic variables are potentially important in predicting bank condition.

A second source of information is that future bank health may be correlated with future economic conditions. While we do not have forecasts of future Call Report items, we do have forecasts of regional economic variables. While economic variables may provide little additional benefit to Call Report data in predicting near-term bank condition, they may nonetheless be useful in predicting bank condition our several quarters. In the subsequent empirical analysis, we focus on testing these two information hypotheses.

## *II. Empirical Analysis*

The first hypothesis is the "examiner information hypothesis." It posits that regional economic variables are useful in determining examiner ratings since, in addition to knowing the current quarter Call Report data, examiners may use economic variables in setting ratings. We estimate the following base regression, and variations of it, to test this hypothesis:

$$CAMELS_t = \alpha + \beta Call_t + \gamma RegionEconomic_t^{forecast\ as\ of\ t} + \varepsilon \tag{1}$$

The dependent variable, $CAMELS_t$ takes on a discrete value between 1 and 5, reflecting the supervisory rating given to an individual bank at time *t*. $Call_t$ is a vector of bank-specific financial variables taken from the Call Report at time t, and $RegionEconomic_t$ is the forecast of regional economic conditions at time *t* for period *t*. By using quarter *t* Call Report data for predicting CAMELS in quarter *t*, we are assuming that examiners can perfectly forecast the end-of-the-period Call Report during the quarter in which they are completing the exam. For the economic variables, we generated a forecast of current quarter economic conditions using a simple autoregressive time-series model.

Our second hypothesis, the "forecast hypothesis," posits that forecasts of regional economic conditions can help predict bank ratings four quarters into the future. We use the following base regression, and variations of it, to test this hypothesis:

$$CAMELS_{t+4} = \alpha + \beta Call_{t-1} + \gamma\, RegionEconomic^{forecast\ as\ of\ t}_{t+1\ through\ t+4} + \varepsilon \qquad (3)$$

The timing of each of the variables in this regression is important. One can think of estimating this regression at the end of period *t*. At the end of period *t*, we are interested in predicting the supervisory rating four quarters ahead, thus, the dependent variable is $CAMELS_{t+4}$. As for the explanatory variables, we use data that would be available at the end of period *t*. For Call Report variables, only the previous quarter's Call Report, $Call_{t-1}$ is available as of the end of period *t*. Large banks have up to 45 days after the end of the quarter to provide bank supervisors with their quarterly Call Report. The processing of the data, as well as verification via edit checks, results in preliminary Call Report data not being available until the end of the subsequent quarter. Thus, we use $Call_{t-1}$. The regional economic variables, $RegionEconomic_{t+1\ through\ t+4}$, are forecasts of economic conditions for the period $t+1$ through $t+4$, made as of period *t*.

All regressions were estimated using an ordered probit technique, with the models estimating the probability of being a "high CAMELS" rating. As with any probit model, the magnitudes of the coefficients are difficult to interpret without translating them into predicted probabilities, but the signs of the coefficients are informative. In all the specifications, a "+" signed coefficient can be interpreted as *increasing* the likelihood that a bank will have a high CAMELS rating (1,2), while a "-" signed coefficient can be interpreted as *decreasing* the likelihood that a bank of will have a high CAMELS rating (1,2). The ordered probit model allows one to estimate the probability of receiving any of the 5 possible CAMELS ratings. For the purposes of this paper, we will focus on the probability of being an "unsatisfactory" rated bank (CAMELS=3, 4, or 5). This allows the interpretation of the results to be more straightforward and highlights the group of banks in the worst financial health.

*The Data*

To estimate the above regressions, we created a database that begins in 1985 Q1 and ends in 2001 Q4. The data starts in 1985 because consistency in financial variables obtained from Call Report becomes very problematic if data is used from the period before 1985. In addition, while supervisors introduced the CAMELS ratings system in the late 1970s, not all banks had a rating until the early 1980s.

The Call Report variables included in the regression include most of the variables used for off-site surveillance under the CAEL system, as well as the variables used in the SEER risk rank model. These variables include the lagged CAMELS rating, the capital to asset ratio, nonperforming loans to asset ratio, net income to assets, liquid assets to assets, the logarithm of total assets, commercial and industrial loans to assets, commercial real estate to assets, residential real estate to assets, other real estate loans to assets, long term deposits to assets, and past-due 30 to assets.

We used several regional economic variables in the analysis. The list includes payroll employment growth, residential housing price appreciation, commercial real estate price appreciation, and total personal income growth; all were measured at the state level. However, since there was strong correlation across all three of these variables, we found that including just a single regional economic variable captured the most of the economic effects. Thus, to make the regression results more tractable, we present only regression results that use forecasts of growth in payroll employment measured at the state level.

*Findings*

Table 1 presents the results of estimating the examiner information hypothesis, where both the economic variables and the Call Report data are contemporaneous with CAMELS rating assigned in the exam quarter. The first column reports the results using only the Call Report data, the second column includes both Call Report data and regional economic forecasts. The regional economic forecast is entered as two variables, forecasts that predict payroll employment growth to be negative and forecasts that predict payroll employment growth to be positive. This variable is entered as two variables to allow the magnitude of the impact of a deteriorating economy on banks to be different from the magnitude of the impact of a prosperous economy. The third column includes variables that interact the percent of assets in commercial real estate, the percent of assets in residential real estate, and the percent of assets in commercial and industrial loans each with the two payroll employment variables.

In the first column of Table 1, all the coefficients on the Call Report variables have the expected sign and are significant at the one percent confidence level, with the exception of commercial real estate and past-due 30 to assets. Table 1b provides some summary statistics for the probit regression. One means of assessing the goodness-of-fit of a probit model is to examine the percent of observations that the model predicted correctly.[1] Specifically, we calculated the percentage of unsatisfactory rated banks that were predicted to be unsatisfactory. Because probit models yield predicted probabilities between 0 and 1, whereas the satisfactory/ unsatisfactory distinction is a discrete 1/0 variable, a threshold has to be chosen to determine whether a bank is predicted to be in the unsatisfactory bucket. We use a threshold of 0.21 (the percentage of banks that were actually unsatisfactory rated during the entire sample period). Those banks that had estimated probabilities in excess of 0.21 were predicted to be unsatisfactory rated, those banks that had estimated probabilities less than of 0.21 where predicted to be satisfactory rated banks.[2] Using this threshold, 87 percent of those classified as unsatisfactory CAMELS rated banks were correctly predicted to be unsatisfactory rated. We also calculated the percentage of satisfactory rated banks that were predicted to be satisfactory, with 90 percent of the satisfactory rated banks correctly predicted to be satisfactory rated.

Another measure that provides an indication of the equation's ability to differentiate between satisfactory and unsatisfactory banks is to compare the mean estimated probability of each of these buckets. The mean fitted probability for unsatisfactory banks is 0.67 compared to a mean estimated probability 0.09 for satisfactory banks. The fact that the difference in these two estimated probabilities is a multiple of 7 indicates that the equation does a good job of distinguishing between high and low CAMELS rated banks.

[1] Ideally, we would want to assess the model's predictive power "out-of-sample." However, given that there was only one recessionary period during the sample period, it was not possible to estimate parameters on a subperiod that included both "good and bad" times, and see how the model performed in another subperiod of "good and bad" times. Thus, we resorted to "in-sample" predictive power.

[2] An alternative threshold of 0.5 is also often used, but because the distribution of CAMELS ratings is not evenly distributed across the 5 ratings, we chose to use the sample proportion of unsatisfactory banks as the threshold. We investigate alternative thresholds later in the paper (see Figures 1-5).

The second column adds the forecast for payroll employment. The coefficients on the Call Report data are qualitatively similar when the regional economic variable is included, with none of the variables changing sign or losing statistical significance, and only the coefficients on commercial real estate to assets and past-due 30 to assets remaining statistically insignificant. Both negative and positive forecasts for payroll employment have the expected positive coefficient and both are highly significant. Interestingly, the magnitude of the coefficient on negative payroll forecasts exceeds the coefficient on positive payroll forecast by a factor of almost 2 to 1.

Table 1b provides summary statistics that examine the impact of including the payroll employment forecast in a surveillance model. The results presented in the top panel (full sample) suggest that there is minimal benefit. Both the mean estimated probabilities and the percent correctly predicted are virtually the same between models 1 and 2. However, examining these measures in particular regions suggests that there are potential benefits that the full sample statistics mask. For example, if we look at Mid-Atlantic states and the New England states (panel 2 and 3 in Table 1b) there is evidence that including regional economic variables has a marginal effect on the mean probabilities as well the percent correctly predicted. However, few other regions had substantive effects, and states such as California and Texas where we might expect an effect (panel 4 and 5 in Table 1b) show virtually no impact at all.

The third column allows portfolio exposure variables to interact with the forecast of payroll employment. The coefficients all have the expected sign, with the exceptions of the interacted coefficient of positive employment growth forecasts and commercial and industrial loans as a percent of assets and the interacted coefficient of positive employment growth and commercial real estate, but both are not statistically significant. Interestingly, the coefficient on interacted variable of commercial real estate and negative forecasts of employment growth is highly significant. Remember, in model 1, the coefficient on commercial real estate was insignificant. Comparing these results suggests that assuming that exposure variables have a single effect on bank health (as is assumed in model 1) regardless of whether the prices of the underlying assets of the exposure are rising or falling is problematic. If the exposure had a positive impact on bank health during prosperous times, but a negative impact during difficult times, then by including forecasts of economic conditions into the model, one can allow the impact of exposure variables on bank health to vary with economic conditions (as is assumed in model 3).

However, as with model 2, model 3's summary statistics presented in Table 1b indicates that the additional variables add little to the ability of the equation to distinguish between healthy and unhealthy banks. Both the mean fitted probabilities and the percent of observations correctly identified are virtually the same as the model that only includes Call Report data, with exceptions in the Mid-Atlantic and New England regions. Overall, Table 1 confirms the results of earlier studies (Cole, Cornyn and Gunther (1995)) that suggest that the inclusion of economic variables provides little additional information over bank-specific variables.

Table 2 presents the results of the analysis examining the forecast hypothesis, which examines alternative models predicting CAMELS at the end of period t+4, using only information available at time t. Comparing the results of Table 2 with those in Table 1 shows the increase in imprecision as one attempts to predict CAMELS several quarters out. For example, the predictive power of model 4 deteriorates relative to model 1. This can be seen comparing the results of Table 1b and Table 2b. The percent correctly identified as being troubled banks declines from .871 for model 1 (panel 1 of Table 1b) to .818 for model 2 (panel 1 of Table 2b).

In the first column of Table 2 (model 4), all the coefficients on the Call Report financial variables have the expected sign and are significant at the one percent confidence level. The coefficient estimates on these same Call Report variables in models 5 and 6 are virtually unchanged, despite including the forecast of payroll employment. This is similar to the findings in Table 1. Also similar to Table 1, the marginal impact of including economic variables is fairly modest when examining the impact on the full sample of banks. Model 6 shows a slight improvement in the percent of observations correctly identified as troubled, rising to .824 from .818 (as measured in model 4). While the economic variables do improve the classification of satisfactory and unsatisfactory banks, the impact is still relatively small.

The effect of including the economic variables is illustrated in Figure 1, which depicts the type 1/type 2 error tradeoff. Type 1 error refers to the percentage of troubled banks that were categorized as having a satisfactory rating when in fact they received unsatisfactory CAMELS rating. Type 2 error refers to the percent of satisfactory CAMELS rated banks that were categorized as having unsatisfactory CAMELS ratings when the banks actually were rated as being in satisfactory condition. Figure 1 provides the type 1 and type 2 trade-off as one varies the threshold that classifies a bank as being unsatisfactory. Thus, one can assure zero type 2 error if the threshold is set very high, since no banks will ever reach the threshold, and thus no satisfactory bank would be rated unsatisfactory. However, with such a high threshold, one can be assured that type 1 error will be 100%, since all banks are rated satisfactory, even though some will end up unsatisfactory. Thus, by lowering the threshold, one will improve the identification of unsatisfactory banks, but at a cost of misclassifying satisfactory banks. When comparing two models, if one of the models has lower type 1 and type 2 error for all thresholds, it can be considered superior. Graphically, superior models have type1/type2 tradeoff curve closer to the origin. Figure 1 shows that model 6 is superior over model 3, as the inclusion of the economic variables results in a lower type 1 error, for a given type 2 error, indicated by curve for model 6 being closer to the origin.

In contrast to the results for models 1 through 3, the results for models 4 through 6 suggests that, at times, including forecasts of regional economic variables can significantly improve the predicative power of the surveillance model. For example, Table 2b shows that in the Mid-Atlantic states, the mean fitted probability for unsatisfactory banks increases to .512 in model 6 from .465 in model 3. Similar results hold for New England states and for California. Figures 2, 3 and 4 also show significant improvements in the type 1/type 2 tradeoff for these regions. This is especially true for New England and the Mid-Atlantic states.

One explanation for the divergent results across regions is that during prosperous economic times, the inclusion of economic variables into surveillance models provides little improvement in predictive power. During such prosperous times, most failures are likely the result of idiosyncratic problems at particular banks. Thus, it is not surprising that economic variables provide minimal additional information in differentiating between troubled and sound banks. In good times, economic variables often are not the risk that causes bank problems, rather specific risks associated with individual bank characteristics, such as a extremely strong risk appetite or fraud often are the cause of bank problems.

The results shown in Table 2b and figures 2, 3, and 4 suggest that the greatest divergence between models with economic variables and those without economic variables occurs in regions that experience very difficult economic times (the exception in Texas). Further investigation revealed that within those regions, the greatest divergence occurred during recessionary periods. It is perhaps not surprising that the greatest impact of economic variables is generated during economic slowdowns, since all banks will be affected by deterioration in asset quality and collateral valuations.

## *III. Bank Health and the 2001 recession*

That economic variables significantly improve forecasts of deteriorating bank health during recessions would seem to be contradicted by the recent experience in the 2001 recession. Despite very poor corporate profits and very high bankruptcies, very few banks were downgraded to an unsatisfactory CAMELS rating. In fact, of those banks with a 1 or 2 CAMELS rating prior to the recession, only 2 percent of the banks were downgraded to an unsatisfactory rating during the recession. The continued health of the banking industry during this recession raises the possibility of a breakdown of the correlation between bank health and economic activity. To examine this linkage, using the econometric model in Table 2, we compare the role of economic variables in explaining the 1991 and 2001 recessions.

Table 3 examines the impact of economic variables in forecasting CAMELS 1 and 2 banks receiving an unsatisfactory CAMELS rating during the 1991 recession. The top panel splits the banks into quartiles, based on the growth of payroll employment in that state that the bank is headquartered. Those banks in hard hit regions of the country experienced an average decline in payroll employment of 2.45 percent, a decline of 9.61 percent in commercial real estate prices, and an increase in residential housing prices of 1.4 percent. In contrast, banks located in the regions least impacted by the recession had positive payroll employment growth, less severe declines in commercial real estate prices and stronger growth in residential housing prices.

The second panel examines the financial health of banks in the fourth quarter of 1990. Banks with CAMEL ratings of 1 or 2, in all regions of the country, had capital to asset ratios of approximately 8.5 percent. However, banks in the lowest quartile, regions hardest hit by the recession, already had 50 percent more nonperforming loans to assets and had almost double the concentration of commercial real estate loans than the other three quartiles.

The third panel shows the results of using model 4, the model that does not include economic variables, to forecast movement to unsatisfactory status of banks with a CAMELS rating of 1 or 2 as of the end of 1990. The first column shows that 30 percent of banks located in the lowest quartile for growth in payroll employment received an unsatisfactory rating by the end of 1991. However, the mean probability of having an unsatisfactory rating by the end of 1991 was only 13 percent for these banks, and the model had a type 1 error of 44 percent. In contrast, banks in the other three quartiles had approximately 10 percent of their CAMELS 1 and 2 banks downgraded to unsatisfactory. In addition, the type 1 error is greater than 50 percent for all three of the quartiles in the regions less impacted by the recession.

The fourth panel shows the results of using model 6, the model with economic variables, to forecast movement to unsatisfactory status of banks with a CAMELS rating of 1 or 2 as of the end of 1990. Inclusion of regional economic variables significantly improves the model performance. For banks located in the quartile with the slowest growth in payroll employment, the mean probability of receiving an unsatisfactory rating was 25 percent. This is close to the 30 percent for banks in that quartile, and almost double the mean probability of model 4. Also particularly striking is the type 1 error for this quartile is substantially lower than for model 4, reducing the type 1 error from 44 percent to only 10 percent.

Table 4 repeats the experiment for the 2001 recession. The top panel shows that, as measured by payroll employment growth, the 2001 recession was milder than the 1991 recession. However, the economic conditions for banks in the lowest quartile in the 2001 recession had quite similar economic conditions to banks in the second quartile in the 1991 recession. The lowest quartile in 2001 has a payroll employment decline of 1.24 percent and a decline in commercial real estate prices of 7.02 percent. Similarly, banks in the second lowest quartile in the 1991 recession had a decline of 1.31 percent in payroll employment and a decline of 7.77 percent in commercial real estate prices. Thus, while the recession was milder in 2001 than 1991, it is possible to make comparisons across quartiles with similar economic outcomes.

The second panel shows that CAMEL 1 and 2 rated banks going into the 2001 recession were in better financial condition than banks going into the 1991 recession. The banks in 2001 had more than a full percentage point of capital compared to banks in 1991. Similarly, asset quality was much better, with nonperforming loans to assets for all four quartiles of only 0.5 percent. Interestingly, the concentration of commercial real estate lending was similar across all four quartiles and was approximately the same as the lowest quartile of banks during the 1991 recession.

The third panel shows the results of using model 4, the model excluding economic variables. Particularly striking is how few banks that were rated CAMELS 1 or 2 received an unsatisfactory rating by the end of 2001. If one compares the first quartile of banks in 2001 to the second quartile of banks in 1991, the downgrades were 2 percent compared to 11 percent, despite very similar economic conditions. Also, the type 1 error when economic variables are excluded is quite high at 72 percent.

The fourth panel shows the results of using model 6, that includes economic variables, to forecast the unsatisfactory status of banks. The mean probability of receiving an unsatisfactory rating is roughly the same for all four quartiles and somewhat overestimates the likelihood of an unsatisfactory rating. For banks in the first quartile of 2001, the model predicts that 8 percent of CAMEL 1 and 2 banks would become unsatisfactory. This predication is less than the 13 percent predicted, and the 11 percent that actually became unsatisfactory, for second quartile banks in 1991. Thus, despite similar economic conditions between the two quartiles, the model anticipated less unsatisfactory ratings than was estimated or occurred during the 1991 recession. This lower probability of receiving a downgrade reflects the better average financial condition of the banks. However, the model overpredicts the probability of receiving an unsatisfactory rating, which indicates that after controlling for economic conditions and financial conditions and the higher concentration in commercial real estate, fewer banks were downgraded than expected. This is consistent with banks being better diversified or having better risk management than during the previous recession.

The 2001 recession does not indicate that the link between economic conditions and bank health has been broken. Inclusion of economic variables continues to reduce type I errors during recessions. It also shows that a combination of better financial condition of banks going into the recession and a milder recession can partly explain how few banks have become troubled. However, there is some support that even after controlling for these factors that the number of downgrades to unsatisfactory is low, consistent with increased diversification and better risk management at many banks.

## *IV. Conclusion*

Forecasts of regional economic conditions were shown to be statistically significant predictors of bank health. However, the economic significance only occurs for forecasts extending well beyond the current quarter, and during cyclical downturns. At times, the magnitude of the economic significant is quite large, reducing type 1 errors by as much as 10 percentage points. It is precisely those errors that are of most relevance to bank supervisors, since the costs of failing to identify a troubled bank is likely to be costly to the deposit insurance fund, and reflect poorly on the supervisor that did not allocate more resources to turning around a troubled institution. Of course, there are also costs associated with type 2 errors, allocating resources to institutions that are not troubled, however, these may be of somewhat less concern to policymakers during economic downturns.

The results of this paper suggest that developers of off-site surveillance models should consider the inclusion of forecasts of regional economic conditions into their models. In prosperous times, the inclusion of these variables do not materially detract from the existing surveillance models, but in difficult times, these variables potentially can enhance the predicative power of the model.

The inclusion of economic variables reduced type 1 errors during the 2001 recession, and the robust condition of most banks during this recession does not indicate that there is no longer linkage between economic conditions and bank health. Rather, the benign outcome during this recession can be attributed to a mild downturn, better financial conditions of banks going into the downturn, and possibly, improvements in bank risk management.

Bibliography


Cole, Rebel A., Barbara G. Cornyn and Jeffrey W. Gunther. 1995. "FIMS: A New Monitoring System for Financial Institutions. Federal Reserve Bulletin. Vol. 81, pp. 1-15.

Cole, Rebel A. and Jeffrey W. Gunther. 1998. "A Comparison of On- and Off-Site Monitoring Systems." Journal of Financial Research. Vol. 13, pp. 103-17.

Gilbert, Alton, R., Meyer, Andrew P., and Mark D. Vaughan. 1999. "The Role of Supervisory Screens and Econometric Models in Off-Site Surveillance. Federal Reserve Bank of St. Louis Review. Vol. 81, pp. 31-56.

Gilbert, Alton, R., Meyer, Andrew P., and Mark D. Vaughan. 2000. "The Role of A CAMELS Downgrade Mode in Bank Surveillance." Working paper 2000-021A.

Hirtle, Beverly J. and Jose A. Lopez. 1999. "Supervisory Information and the Frequency of Bank Examinations." Federal Reserve Bank of New York. Vol. 5 (1), pp. 1-19.

Kashyap, Anil K., and Jeremy C.Stein. 2000. "What Do A Million Banks Have to Say About the Transmission of Monetary Policy?" The American Economic Review.

Kashyap, Anil K., Jeremy C. Stein, and Owen A. Lamont. 1994. "Credit Conditions and the Cyclical Behavior of Inventories." The Quarterly Journal of Economics, vol. 109, August, pp. 565-92.

Keeley, Michael C. 1990. "Deposit Insurance, Risk, and Market Power in Banking." American Economic Review. December,

Krainer John and Jose A. Lopez. 2001. "Incorporating Equity Market Information into Supervisory Models. August unpublished working paper.

Jones, David S. and Kathleen Kuester King. "The Implementation of Prompt Corrective Action: An Assessment" Journal of Banking and Finance. 19 (1995), 491-510.

Peek, Joe, Eric S. Rosengren, and Geoffrey M.B. Tootell. 1999 "Is Bank Supervision Central to Central Banking?" The Quarterly Journal of Economics, vol. 114. May, pp. 629-53.

Slovin, Myron B., Marie E. Sushka, and John A. Polonchek. "The Value of Bank Durability: Borrowers as Bank Stakeholders." Journal of Finance 48 (1993), 247-266.

Thomson, James B. 1992. "Modeling the Bank Regulator's Closure Option: A Two-Step Logit Regression Approach." Journal of Financial Services Research. May, pp. 5-23.

**Table 1: Ordered Probit Results**

Dependent Variable: Composite CAMEL Rating for **period t**, Exam Quarters Only, Contemporaneous Call Report Data and Economic Forecast

$$CAMEL_t = \alpha + \beta Call_t + \gamma\, RegionEconomic_t^{forecast\ as\ of\ t} + \varepsilon$$

| | Model 1 | | | Model 2 | | | Model 3 | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Estimate** | **Std Error** | **Significance** | **Estimate** | **Std Error** | **Significance** | **Estimate** | **Std Error** | **Significance** |
| **Intercept** | -1.2699 | 0.0414 | <.0001 | -1.4528 | 0.0423 | <.0001 | -1.4552 | 0.0437 | <.0001 |
| **Lag CAMEL 2** | -1.5772 | 0.0094 | <.0001 | -1.5914 | 0.0094 | <.0001 | -1.5908 | 0.0094 | <.0001 |
| **Lag CAMEL 3** | -2.7030 | 0.0138 | <.0001 | -2.7353 | 0.0139 | <.0001 | -2.7368 | 0.0139 | <.0001 |
| **Lag CAMEL 4** | -3.6109 | 0.0193 | <.0001 | -3.6619 | 0.0194 | <.0001 | -3.6673 | 0.0194 | <.0001 |
| **Lag CAMEL 5** | -4.7457 | 0.0385 | <.0001 | -4.8028 | 0.0386 | <.0001 | -4.8124 | 0.0386 | <.0001 |
| **K/A $_t$** | 0.0590 | 0.0011 | <.0001 | 0.0593 | 0.0011 | <.0001 | 0.0594 | 0.0011 | <.0001 |
| **NPL/A $_t$** | -0.2665 | 0.0028 | <.0001 | -0.2556 | 0.0028 | <.0001 | -0.2544 | 0.0028 | <.0001 |
| **NIA/A $_t$** | 0.4207 | 0.0060 | <.0001 | 0.4122 | 0.0060 | <.0001 | 0.4115 | 0.0060 | <.0001 |
| **LIQ/A $_t$** | 0.0079 | 0.0003 | <.0001 | 0.0082 | 0.0003 | <.0001 | 0.0082 | 0.0003 | <.0001 |
| **Log of Assets $_t$** | 0.0997 | 0.0030 | <.0001 | 0.1043 | 0.0030 | <.0001 | 0.1053 | 0.0030 | <.0001 |
| **CI/A $_t$** | -0.0055 | 0.0005 | <.0001 | -0.0053 | 0.0005 | <.0001 | -0.0071 | 0.0009 | <.0001 |
| **Commercial Real Estate/A $_t$** | 0.0005 | 0.0004 | 0.215 | 0.0003 | 0.0004 | 0.561 | 0.0012 | 0.0008 | 0.1277 |
| **Residential Real Estate/A $_t$** | 0.0046 | 0.0004 | <.0001 | 0.0056 | 0.0004 | <.0001 | 0.0058 | 0.0007 | <.0001 |
| **OREO $_t$** | -0.1834 | 0.0035 | <.0001 | -0.1805 | 0.0035 | <.0001 | -0.1792 | 0.0035 | <.0001 |
| **Large Time/A $_t$** | -0.0172 | 0.0005 | <.0001 | -0.0167 | 0.0005 | <.0001 | -0.0169 | 0.0005 | <.0001 |
| **Past-due 30/A $_t$** | -0.0001 | 0.0001 | 0.4268 | -0.0001 | 0.0001 | 0.3853 | -0.0001 | 0.0001 | 0.399 |
| **Forecast for Payroll Employment Growth in $_t$ (< 0)** | -- | -- | -- | 0.3830 | 0.0214 | <.0001 | 0.0948 | 0.0571 | 0.0969 |
| **Forecast for Payroll Employment Growth in $_t$ (>= 0)** | -- | -- | -- | 0.2006 | 0.0116 | <.0001 | 0.1673 | 0.0280 | <.0001 |
| **Interactive Residential Real Estate/A $_t$ (< 0)** | -- | -- | -- | -- | -- | -- | 0.0086 | 0.0016 | <.0001 |
| **Interactive Residential Real Estate/A $_t$ (>= 0)** | -- | -- | -- | -- | -- | -- | 0.0006 | 0.0011 | 0.5905 |
| **Interactive Commercial Real Estate/A $_t$ (< 0)** | -- | -- | -- | -- | -- | -- | 0.0153 | 0.0023 | <.0001 |
| **Interactive Commercial Real Estate/A $_t$ (>= 0)** | -- | -- | -- | -- | -- | -- | -0.0008 | 0.0012 | 0.5056 |
| **Interactive CI/A $_t$ (< 0)** | -- | -- | -- | -- | -- | -- | -0.0026 | 0.0025 | 0.2909 |
| **Interactive CI/A $_t$ (>= 0)** | -- | -- | -- | -- | -- | -- | 0.0028 | 0.0014 | 0.0413 |
| **Intercept 2** | 2.6135 | 0.0085 | -- | 2.6277 | 0.0086 | -- | 2.6296 | 0.0086 | -- |
| **Intercept 3** | 4.1852 | 0.0132 | -- | 4.2106 | 0.0133 | -- | 4.2143 | 0.0133 | -- |
| **Intercept 4** | 6.4000 | 0.0247 | -- | 6.4210 | 0.0247 | -- | 6.4271 | 0.0247 | -- |
| ***Observations*** | | *139,981* | | | *139,981* | | | *139,981* | |
| ***Log Likelihood*** | | *-92,013* | | | *-91,571* | | | *-91,518* | |
| ***Obs where CAMEL = 1, or 2 (satisfactory)*** | | *110,178* | | | *110,178* | | | *110,178* | |
| ***Obs where CAMEL = 3, 4, or 5 (unsatisfactory)*** | | *29,803* | | | *29,803* | | | *29,803* | |
| ***Proportion of Obs = unsatisfactory*** | | *0.213* | | | *0.213* | | | *0.213* | |
| ***Mean fitted probability of being sat, when obs = sat*** | | *0.666* | | | *0.669* | | | *0.669* | |
| ***Mean fitted probability of being unsat, when obs = unsat*** | | *0.086* | | | *0.086* | | | *0.085* | |

**Table 2: Ordered Probit Results**

Dependent Variable: Composite CAMEL Rating in **period t+4**, Exam Quarters Only, Call Report Data Lagged One Quarter, Economic Forecast for the period t+1 through t+4

$$CAMEL_{t+4} = \alpha + \beta Call_{t-1} + \gamma RegionEconomic_{t+1 through\, t+4}^{forecast\ as\ of\ t} + \varepsilon$$

| | Model 4 | | | Model 5 | | | Model 6 | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Estimate** | **Std Error** | **Significance** | **Estimate** | **Std Error** | **Significance** | **Estimate** | **Std Error** | **Significance** |
| **Intercept** | -1.5834 | 0.0394 | <.0001 | -1.8182 | 0.0402 | <.0001 | -1.8252 | 0.0415 | <.0001 |
| **Lag CAMEL 2** | -1.3892 | 0.0089 | <.0001 | -1.4119 | 0.0089 | <.0001 | -1.4104 | 0.0089 | <.0001 |
| **Lag CAMEL 3** | -2.1758 | 0.0131 | <.0001 | -2.2180 | 0.0132 | <.0001 | -2.2185 | 0.0132 | <.0001 |
| **Lag CAMEL 4** | -2.7143 | 0.0181 | <.0001 | -2.7742 | 0.0182 | <.0001 | -2.7793 | 0.0183 | <.0001 |
| **Lag CAMEL 5** | -2.9965 | 0.0360 | <.0001 | -3.0718 | 0.0361 | <.0001 | -3.0831 | 0.0361 | <.0001 |
| **K/A $_{t-1}$** | 0.0321 | 0.0009 | <.0001 | 0.0331 | 0.0009 | <.0001 | 0.0333 | 0.0009 | <.0001 |
| **NPL/A $_{t-1}$** | -0.1860 | 0.0025 | <.0001 | -0.1781 | 0.0025 | <.0001 | -0.1770 | 0.0025 | <.0001 |
| **NIA/A $_{t-1}$** | 0.2365 | 0.0070 | <.0001 | 0.2292 | 0.0071 | <.0001 | 0.2281 | 0.0071 | <.0001 |
| **LIQ/A $_{t-1}$** | 0.0144 | 0.0003 | <.0001 | 0.0144 | 0.0003 | <.0001 | 0.0143 | 0.0003 | <.0001 |
| **Log of Assets $_{t-1}$** | 0.1186 | 0.0029 | <.0001 | 0.1250 | 0.0029 | <.0001 | 0.1261 | 0.0029 | <.0001 |
| **CI/A $_{t-1}$** | -0.0094 | 0.0005 | <.0001 | -0.0091 | 0.0005 | <.0001 | -0.0115 | 0.0008 | <.0001 |
| **Commercial Real Estate/A $_{t-1}$** | 0.0026 | 0.0004 | <.0001 | 0.0022 | 0.0004 | <.0001 | 0.0029 | 0.0008 | 0.0003 |
| **Residential Real Estate/A $_{t-1}$** | 0.0082 | 0.0004 | <.0001 | 0.0094 | 0.0004 | <.0001 | 0.0106 | 0.0006 | <.0001 |
| **OREO $_{t-1}$** | -0.1140 | 0.0033 | <.0001 | -0.1192 | 0.0033 | <.0001 | -0.1195 | 0.0033 | <.0001 |
| **Large Time/A $_{t-1}$** | -0.0238 | 0.0004 | <.0001 | -0.0226 | 0.0004 | <.0001 | -0.0227 | 0.0004 | <.0001 |
| **Past-due 30/A $_{t-1}$** | -0.0006 | 0.0002 | 0.0005 | -0.0006 | 0.0002 | 0.0003 | -0.0006 | 0.0002 | 0.0003 |
| **Forecast for Payroll Employment Growth in $_{t+1\ through\ t+4}$ (< 0)** | -- | -- | -- | 0.1478 | 0.0050 | <.0001 | 0.0245 | 0.0138 | 0.0749 |
| **Forecast for Payroll Employment Growth in $_{t+1\ through\ t+4}$ (>= 0)** | -- | -- | -- | 0.0722 | 0.0027 | <.0001 | 0.0626 | 0.0066 | <.0001 |
| **Interactive Residential Real Estate/A $_t$ (< 0)** | -- | -- | -- | -- | -- | -- | 0.0028 | 0.0004 | <.0001 |
| **Interactive Residential Real Estate/A $_t$ (>= 0)** | -- | -- | -- | -- | -- | -- | -0.0003 | 0.0003 | 0.1908 |
| **Interactive Commercial Real Estate/A $_t$ (< 0)** | -- | -- | -- | -- | -- | -- | 0.0064 | 0.0005 | <.0001 |
| **Interactive Commercial Real Estate/A $_t$ (>= 0)** | -- | -- | -- | -- | -- | -- | 0.0002 | 0.0003 | 0.5136 |
| **Interactive CI/A $_t$ (< 0)** | -- | -- | -- | -- | -- | -- | 0.0000 | 0.0006 | 0.9909 |
| **Interactive CI/A $_t$ (>= 0)** | -- | -- | -- | -- | -- | -- | 0.0010 | 0.0003 | 0.0016 |
| **Intercept 2** | 2.2910 | 0.0074 | -- | 2.3164 | 0.0075 | -- | 2.3192 | 0.0075 | -- |
| **Intercept 3** | 3.4209 | 0.0101 | -- | 3.4657 | 0.0103 | -- | 3.4721 | 0.0103 | -- |
| **Intercept 4** | 4.7229 | 0.0161 | -- | 4.7864 | 0.0163 | -- | 4.7987 | 0.0164 | -- |
| ***Observations*** | | *141,592* | | | *141,592* | | | *141,592* | |
| ***Log Likelihood*** | | *-110,867* | | | *-109,737* | | | *-109,590* | |
| ***Obs where CAMEL = 1, or 2 (satisfactory)*** | | *110,178* | | | *110,178* | | | *110,178* | |
| ***Obs where CAMEL = 3, 4, or 5 (unsatisfactory)*** | | *29,803* | | | *29,803* | | | *29,803* | |
| ***Proportion of Obs = unsatisfactory*** | | *0.213* | | | *0.213* | | | *0.213* | |
| ***Mean fitted probability of being sat, when obs = sat*** | | *0.561* | | | *0.568* | | | *0.569* | |
| ***Mean fitted probability of being unsat, when obs = unsat*** | | *0.115* | | | *0.113* | | | *0.113* | |

**Table 1b: Ordered Probit Results**

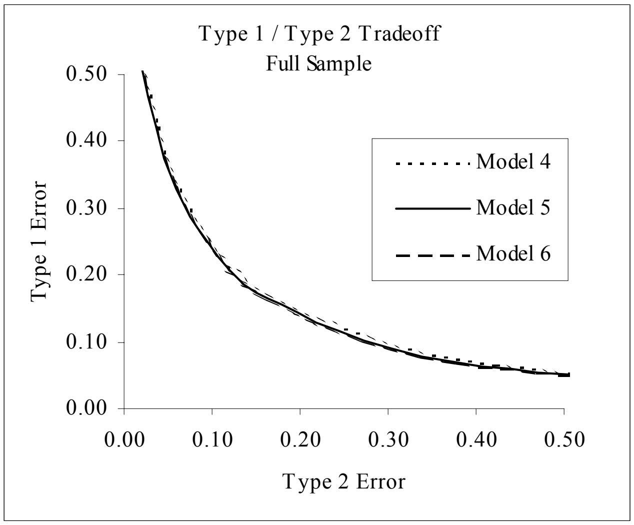
Goodness-of-Fit Measures

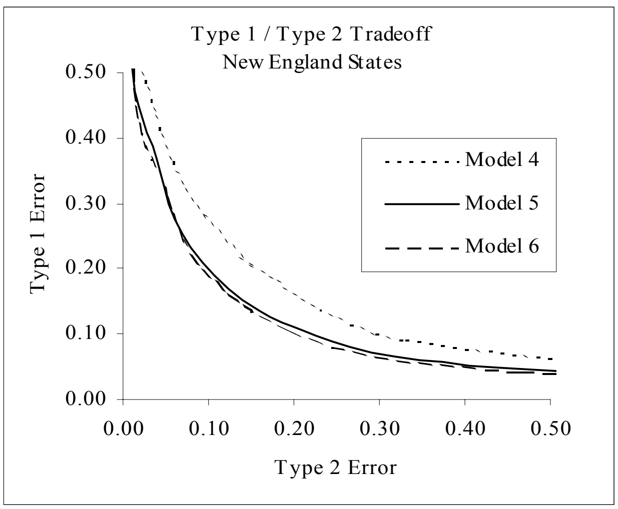
| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| | | ***Full Sample*** | |
| *Number of Obs* | 139,981 | 139,981 | 139,981 |
| *Proportion of Obs = unsatisfactory* | 0.213 | 0.213 | 0.213 |
| *Mean fitted probability of being sat, when obs = sat* | 0.666 | 0.669 | 0.669 |
| *Mean fitted probability of being unsat, when obs = unsat* | 0.086 | 0.086 | 0.085 |
| *Predicted = unsat, Actual = unsat* | 0.871 | 0.873 | 0.873 |
| *(Type 1 Error) Predicted = sat, Actual = unsat* | **0.129** | **0.127** | **0.127** |
| *Predicted = sat, Actual = sat* | 0.900 | 0.900 | 0.900 |
| *(Type 2 Error) Predicted = unsat, Actual = sat* | **0.100** | **0.100** | **0.100** |
| | | ***Mid-Atlantic States*** | |
| *Number of Obs* | 6,600 | 6,600 | 6,600 |
| *Proportion of Obs = unsatisfactory* | 0.148 | 0.148 | 0.148 |
| *Mean fitted probability of being sat, when obs = sat* | 0.590 | 0.611 | 0.614 |
| *Mean fitted probability of being unsat, when obs = unsat* | 0.068 | 0.072 | 0.072 |
| *Predicted = unsat, Actual = unsat* | 0.864 | 0.879 | 0.880 |
| *(Type 1 Error) Predicted = sat, Actual = unsat* | **0.136** | **0.121** | **0.120** |
| *Predicted = sat, Actual = sat* | 0.898 | 0.889 | 0.889 |
| *(Type 2 Error) Predicted = unsat, Actual = sat* | **0.102** | **0.111** | **0.111** |
| | | ***New England States*** | |
| *Number of Obs* | 3,572 | 3,572 | 3,572 |
| *Proportion of Obs = unsatisfactory* | 0.302 | 0.302 | 0.302 |
| *Mean fitted probability of being sat, when obs = sat* | 0.697 | 0.724 | 0.738 |
| *Mean fitted probability of being unsat, when obs = unsat* | 0.092 | 0.096 | 0.099 |
| *Predicted = unsat, Actual = unsat* | 0.837 | 0.872 | 0.886 |
| *(Type 1 Error) Predicted = sat, Actual = unsat* | **0.163** | **0.128** | **0.114** |
| *Predicted = sat, Actual = sat* | 0.913 | 0.902 | 0.890 |
| *(Type 2 Error) Predicted = unsat, Actual = sat* | **0.087** | **0.098** | **0.110** |
| | | ***California*** | |
| *Number of Obs* | 4,519 | 4,519 | 4,519 |
| *Proportion of Obs = unsatisfactory* | 0.393 | 0.393 | 0.393 |
| *Mean fitted probability of being sat, when obs = sat* | 0.741 | 0.745 | 0.746 |
| *Mean fitted probability of being unsat, when obs = unsat* | 0.165 | 0.165 | 0.165 |
| *Predicted = unsat, Actual = unsat* | 0.835 | 0.840 | 0.842 |
| *(Type 1 Error) Predicted = sat, Actual = unsat* | **0.165** | **0.160** | **0.158** |
| *Predicted = sat, Actual = sat* | 0.874 | 0.873 | 0.873 |
| *(Type 2 Error) Predicted = unsat, Actual = sat* | **0.126** | **0.127** | **0.127** |
| | | ***Texas*** | |
| *Number of Obs* | 14,222 | 14,222 | 14,222 |
| *Proportion of Obs = unsatisfactory* | 0.378 | 0.378 | 0.378 |
| *Mean fitted probability of being sat, when obs = sat* | 0.727 | 0.729 | 0.729 |
| *Mean fitted probability of being unsat, when obs = unsat* | 0.113 | 0.113 | 0.113 |
| *Predicted = unsat, Actual = unsat* | 0.834 | 0.839 | 0.839 |
| *(Type 1 Error) Predicted = sat, Actual = unsat* | **0.166** | **0.161** | **0.161** |
| *Predicted = sat, Actual = sat* | 0.904 | 0.901 | 0.902 |
| *(Type 2 Error) Predicted = unsat, Actual = sat* | **0.096** | **0.099** | **0.098** |

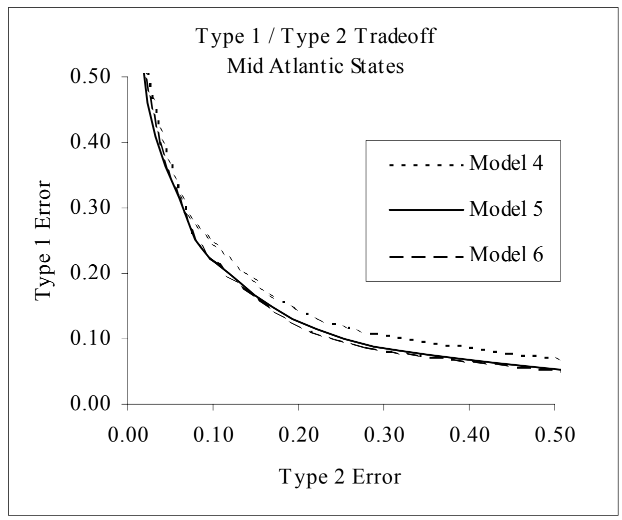
**Table 2b: Ordered Probit Results**

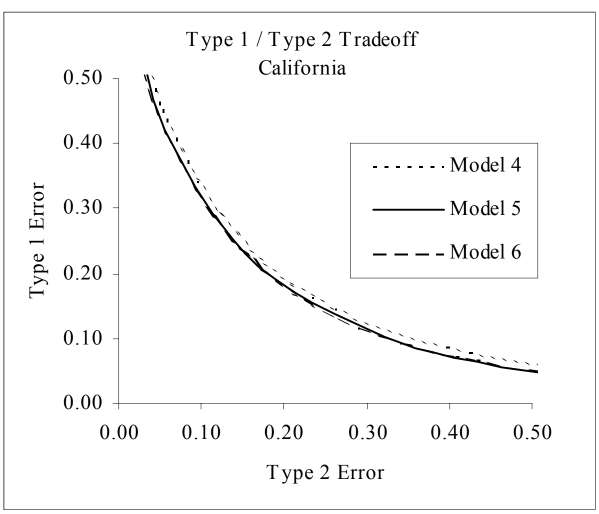
Goodness-of-Fit Measures

| | Model 4 | Model 5 | Model 6 |
|---|---|---|---|
| | | ***Full Sample*** | |
| *Number of Obs* | 139,981 | 139,981 | 139,981 |
| *Proportion of Obs = unsatisfactory* | 0.213 | 0.213 | 0.213 |
| *Mean fitted probability of being sat, when obs = sat* | 0.666 | 0.669 | 0.669 |
| *Mean fitted probability of being unsat, when obs = unsat* | 0.086 | 0.086 | 0.085 |
| *Predicted = unsat, Actual = unsat* | 0.818 | 0.825 | 0.824 |
| *(Type 1 Error) Predicted = sat, Actual = unsat* | **0.182** | **0.175** | **0.176** |
| *Predicted = sat, Actual = sat* | 0.847 | 0.850 | 0.851 |
| *(Type 2 Error) Predicted = unsat, Actual = sat* | **0.153** | **0.150** | **0.149** |
| | | ***Mid-Atlantic States*** | |
| *Number of Obs* | 6,600 | 6,600 | 6,600 |
| *Proportion of Obs = unsatisfactory* | 0.148 | 0.148 | 0.148 |
| *Mean fitted probability of being sat, when obs = sat* | 0.465 | 0.506 | 0.512 |
| *Mean fitted probability of being unsat, when obs = unsat* | 0.082 | 0.088 | 0.088 |
| *Predicted = unsat, Actual = unsat* | 0.810 | 0.854 | 0.852 |
| *(Type 1 Error) Predicted = sat, Actual = unsat* | **0.190** | **0.146** | **0.148** |
| *Predicted = sat, Actual = sat* | 0.855 | 0.836 | 0.839 |
| *(Type 2 Error) Predicted = unsat, Actual = sat* | **0.145** | **0.164** | **0.161** |
| | | ***New England States*** | |
| *Number of Obs* | 3,572 | 3,572 | 3,572 |
| *Proportion of Obs = unsatisfactory* | 0.302 | 0.302 | 0.302 |
| *Mean fitted probability of being sat, when obs = sat* | 0.549 | 0.616 | 0.645 |
| *Mean fitted probability of being unsat, when obs = unsat* | 0.109 | 0.114 | 0.118 |
| *Predicted = unsat, Actual = unsat* | 0.721 | 0.811 | 0.832 |
| *(Type 1 Error) Predicted = sat, Actual = unsat* | **0.279** | **0.189** | **0.168** |
| *Predicted = sat, Actual = sat* | 0.906 | 0.893 | 0.884 |
| *(Type 2 Error) Predicted = unsat, Actual = sat* | **0.094** | **0.107** | **0.116** |
| | | ***California*** | |
| *Number of Obs* | 4,519 | 4,519 | 4,519 |
| *Proportion of Obs = unsatisfactory* | 0.393 | 0.393 | 0.393 |
| *Mean fitted probability of being sat, when obs = sat* | 0.659 | 0.669 | 0.671 |
| *Mean fitted probability of being unsat, when obs = unsat* | 0.227 | 0.222 | 0.222 |
| *Predicted = unsat, Actual = unsat* | 0.781 | 0.795 | 0.798 |
| *(Type 1 Error) Predicted = sat, Actual = unsat* | **0.219** | **0.205** | **0.202** |
| *Predicted = sat, Actual = sat* | 0.820 | 0.826 | 0.822 |
| *(Type 2 Error) Predicted = unsat, Actual = sat* | **0.180** | **0.174** | **0.178** |
| | | ***Texas*** | |
| *Number of Obs* | 14,222 | 14,222 | 14,222 |
| *Proportion of Obs = unsatisfactory* | 0.378 | 0.378 | 0.378 |
| *Mean fitted probability of being sat, when obs = sat* | 0.617 | 0.623 | 0.622 |
| *Mean fitted probability of being unsat, when obs = unsat* | 0.143 | 0.143 | 0.143 |
| *Predicted = unsat, Actual = unsat* | 0.752 | 0.757 | 0.757 |
| *(Type 1 Error) Predicted = sat, Actual = unsat* | **0.248** | **0.243** | **0.243** |
| *Predicted = sat, Actual = sat* | 0.888 | 0.879 | 0.880 |
| *(Type 2 Error) Predicted = unsat, Actual = sat* | **0.112** | **0.121** | **0.120** |


Type 1 / Type 2 Tradeoff
Full Sample
Type 1 Error
Type 2 Error
Model 4
Model 5
Model 6
0.00
0.10
0.20
0.30
0.40
0.50


Type 1 / Type 2 Tradeoff
New England States
Type 1 Error
Type 2 Error
Model 4
Model 5
Model 6
0.00
0.10
0.20
0.30
0.40
0.50


Type 1 / Type 2 Tradeoff
Mid Atlantic States
Type 1 Error
Type 2 Error
Model 4
Model 5
Model 6
0.00
0.10
0.20
0.30
0.40
0.50


Type 1 / Type 2 Tradeoff
California
Type 1 Error
Type 2 Error
Model 4
Model 5
Model 6
0.00
0.10
0.20
0.30
0.40
0.50

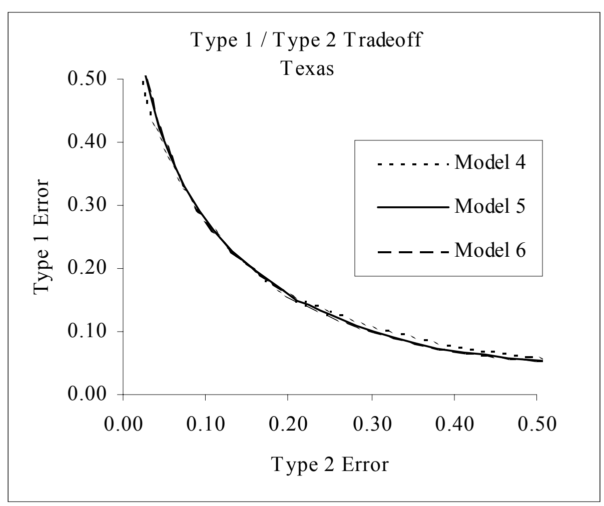

Type 1 / Type 2 Tradeoff
Texas
Type 1 Error
Type 2 Error
Model 4
Model 5
Model 6
0.00
0.10
0.20
0.30
0.40
0.50

**Table 3: The Impact of the 1991 Recession on Healthy Banks**
Sample: Banks with CAMEL Ratings equal to 1 or 2 as of the 4th quarter of 1990

| Quartile for growth in nonfarm-employment | State-level Macroeconomic Performance for 1991: Growth in nonfarm employment | Growth in residential real estate prices | Growth in commercial real estate prices |
|---|---|---|---|
| 1 | -2.45 | 1.40 | -9.61 |
| 2 | -1.31 | 4.30 | -7.77 |
| 3 | -0.10 | 4.10 | -2.80 |
| 4 | 0.96 | 5.00 | -7.94 |

| Quartile for growth in nonfarm-employment | CAMEL 1 and 2 Rated Banks as of the 4th quarter of 1990: Capital to Assets Ratio, 1 year earlier | Nonperforming loans to Assets Ratio, 1 year earlier | ROA, 1 year earlier | Liquid Assets to Assets Ratio, 1 year earlier | C&I Loans to Assets Ratio, 1 year earlier | Commercial Real Estate to Assets Ratio, 1 year earlier |
|---|---|---|---|---|---|---|
| 1 | 8.47 | 1.26 | 0.76 | 30.79 | 12.08 | 17.76 |
| 2 | 8.64 | 0.87 | 1.01 | 38.79 | 10.33 | 9.69 |
| 3 | 8.42 | 0.76 | 0.97 | 39.92 | 10.23 | 9.42 |
| 4 | 8.74 | 0.80 | 0.98 | 39.33 | 11.23 | 8.93 |

| Quartile for growth in nonfarm-employment | Predictions from Model 4 for the fourth quarter of 1991: % of CAMEL 1 and 2 banks that become unsatisfactory banks | Predicted Probability of being unsatisfactory | Predicted Probability of being unsatisfactory for those that became unsatisfactory | Predicted Probability of being satisfactory for those that became satisfactory | Type I error (missed unsatisfactory) | Type II error (false satisfactory) |
|---|---|---|---|---|---|---|
| 1 | 0.30 | 0.13 | 0.22 | 0.08 | 0.44 | 0.13 |
| 2 | 0.11 | 0.08 | 0.20 | 0.07 | 0.51 | 0.06 |
| 3 | 0.10 | 0.08 | 0.16 | 0.07 | 0.67 | 0.06 |
| 4 | 0.09 | 0.09 | 0.15 | 0.08 | 0.65 | 0.11 |

| Quartile for growth in nonfarm-employment | Predictions from Model 6 for the fourth quarter of 1991: % of CAMEL 1 and 2 banks that become unsatisfactory banks | Predicted Probability of being unsatisfactory | Predicted Probability of being unsatisfactory for those that became unsatisfactory | Predicted Probability of being satisfactory for those that became satisfactory | Type I error (missed unsatisfactory) | Type II error (false satisfactory) |
|---|---|---|---|---|---|---|
| 1 | 0.30 | 0.25 | 0.38 | 0.19 | 0.10 | 0.52 |
| 2 | 0.11 | 0.13 | 0.27 | 0.11 | 0.26 | 0.25 |
| 3 | 0.10 | 0.10 | 0.18 | 0.09 | 0.52 | 0.12 |
| 4 | 0.09 | 0.08 | 0.14 | 0.08 | 0.68 | 0.10 |

**Table 4: The Impact of 2001 Recession on Healthy Banks**
Sample: Banks with CAMEL Ratings equal to 1 or 2 as of the 4th quarter of 2000

| Quartile for growth in nonfarm-employment | State-level Macroeconomic Performance for 2001: Growth in nonfarm employment | Growth in residential real estate prices | Growth in commercial real estate prices |
|---|---|---|---|
| 1 | -1.24 | 5.92 | -6.52 |
| 2 | -0.49 | 8.05 | -7.02 |
| 3 | -0.10 | 6.81 | -7.54 |
| 4 | 1.53 | 6.81 | -4.46 |

| Quartile for growth in nonfarm-employment | CAMEL 1 and 2 Rated Banks as of the 4th quarter of 2000: Capital to Assets Ratio, 1 year earlier | Nonperforming loans to Assets Ratio, 1 year earlier | ROA, 1 year earlier | Liquid Assets to Assets Ratio, 1 year earlier | C&I Loans to Assets Ratio, 1 year earlier | Commercial Real Estate to Assets Ratio, 1 year earlier |
|---|---|---|---|---|---|---|
| 1 | 9.66 | 0.52 | 1.06 | 29.25 | 10.03 | 16.53 |
| 2 | 9.78 | 0.54 | 1.14 | 29.18 | 11.49 | 17.11 |
| 3 | 9.78 | 0.52 | 1.07 | 32.96 | 10.94 | 18.69 |
| 4 | 9.64 | 0.51 | 1.18 | 33.52 | 10.80 | 17.62 |

| Quartile for growth in nonfarm-employment | Predictions from Model 4 for the fourth quarter of 2001: % of CAMEL 1 and 2 banks that become unsatisfactory banks | Predicted Probability of being unsatisfactory | Predicted Probability of being unsatisfactory for those that became unsatisfactory | Predicted Probability of being satisfactory for those that became satisfactory | Type I error (missed unsatisfactory) | Type II error (false satisfactory) |
|---|---|---|---|---|---|---|
| 1 | 0.02 | 0.05 | 0.17 | 0.05 | 0.72 | 0.03 |
| 2 | 0.02 | 0.06 | 0.21 | 0.05 | 0.44 | 0.05 |
| 3 | 0.03 | 0.05 | 0.15 | 0.05 | 0.72 | 0.04 |
| 4 | 0.02 | 0.05 | 0.13 | 0.05 | 0.62 | 0.04 |

| Quartile for growth in nonfarm-employment | Predictions from Model 6 for the fourth quarter of 2001: % of CAMEL 1 and 2 banks that become unsatisfactory banks | Predicted Probability of being unsatisfactory | Predicted Probability of being unsatisfactory for those that became unsatisfactory | Predicted Probability of being satisfactory for those that became satisfactory | Type I error (missed unsatisfactory) | Type II error (false satisfactory) |
|---|---|---|---|---|---|---|
| 1 | 0.02 | 0.08 | 0.23 | 0.08 | 0.32 | 0.15 |
| 2 | 0.02 | 0.07 | 0.24 | 0.07 | 0.28 | 0.09 |
| 3 | 0.03 | 0.05 | 0.16 | 0.05 | 0.64 | 0.05 |
| 4 | 0.02 | 0.04 | 0.12 | 0.04 | 0.79 | 0.02 |