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Does the Federal Reserve Have an Informational Advantage?
You Can Bank on It

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Abstract

Even in a world with rational expectations, it has been well established theoretically that if the central bank possesses information superior to that available to the public, there is room for effective and socially beneficial countercyclical monetary policy. This paper tests whether confidential information from bank supervisors could be one source of any such informational advantage. In particular, we examine whether information gained from bank supervision activities could substantially improve the forecasts of macroeconomic variables important for guiding monetary policy. We find that confidential supervisory information on bank ratings significantly improves private forecasts of inflation and unemployment rates, thus providing an informational advantage to the Federal Reserve.

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Once rational expectations were introduced into economics, important questions were raised about the efficacy of monetary policy. Since then, it has been well established theoretically that if the central bank possesses information superior to that available to the public, there is room for effective and socially beneficial countercyclical monetary policy. However, since the public knows the monetary authority's objective function, the central bank's informational advantage must involve variables other than its goals. In particular, it has been postulated that a central bank may have superior information about the nature of economic shocks and/or the consequences of those shocks for the macroeconomy. Despite this extensive theoretical literature, very little effort has been expended attempting to empirically identify the existence and possible sources of any informational advantage that might be possessed by a central bank.

This paper tests whether knowledge derived from its role as a supervisor and regulator of banks could be one source of informational advantage possessed by the Federal Reserve. For this to be the case, bank supervisory information must satisfy two criteria. First, it must be known by the Federal Reserve, but not available to the public. Second, it must provide data that are relevant to the future course of the macroeconomy. On the first point, the Federal Reserve has access to confidential bank supervisory data on individual institutions (CAMELS ratings) through its role as a bank regulator. This information is viewed as extremely confidential by bank regulators. Thus, neither the public nor any private forecasting agency would have access to CAMELS ratings. And in fact, recent research has documented that CAMELS ratings do provide information about banks not contained in publicly available data.

On the second point, bank supervisory information may be useful in predicting macroeconomic variables, either because bank health provides an indicator of emerging problems in the economy or because it plays a more direct role in the transmission of monetary policy. Bank health would be a good leading indicator if economic problems first become apparent through a deterioration of bank balance sheets. For example, emerging credit problems in the overall economy may appear as an increase in nonperforming bank assets. Alternatively, several recent studies have argued that an ailing banking sector may play a causal role insofar as it impedes the transmission of monetary policy, making it more difficult for policymakers to offset adverse shocks.

We examine whether confidential bank supervisory data provide a statistically informative addition to private sector forecasts of the macroeconomic variables of most concern to the Federal Reserve — the unemployment rate and the inflation rate. Information based on confidential supervisory ratings is shown to substantially improve private sector forecasts of these variables. Given the central role of economic forecasting in guiding monetary policy, these results show that bank supervision does produce information useful for the implementation of monetary policy.

Our finding that bank supervisory data significantly improve forecasts of inflation and unemployment has several important policy ramifications. First, evidence of an important informational advantage to the Fed strengthens arguments advocating a role for discretionary monetary policy. Second, since the source of this informational advantage is confidential bank supervisory information, detailed bank supervisory data should be integrated into monetary policy deliberations. Finally, because our evidence shows that supervisory information is useful for economic forecasts even when banking problems are not of crisis proportions, the Federal Reserve needs continuous access to this information.

The next section discusses why confidential bank supervisory information may be useful in forecasting macroeconomic variables of relevance for monetary policy. The second section describes the data. The third section presents the results; confidential supervisory ratings are shown to reduce significantly the errors of forecasts of inflation and unemployment rates by a group of private forecasters. The fourth section presents further evidence that the results are due to an informational advantage enjoyed by the Federal Reserve. The final section discusses some policy implications of our findings.

I. Motivation and Methodology

Kydland and Prescott (1977) and Barro and Gordon (1983a, 1983b) highlighted the costs to discretionary monetary policy. On the other hand, Sargent and Wallace (1975), Barro (1976), Fischer (1977), Rogoff (1985), and Walsh (1995) have modeled potential benefits emanating from discretion in setting monetary policy. One of these benefits is the central bank's ability to offset real shocks if it possesses information superior to that of the public about these disturbances. Yet, despite this theoretical literature, little empirical research has been conducted on the origin of any potential informational advantage the central bank may enjoy.[1] This paper attempts to examine one possible source of any informational advantage the Federal Reserve may possess — confidential banking data available to policymakers through its bank supervisory function.

Bank supervisory information may be useful for evaluating economic conditions and guiding monetary policy because an ailing banking sector may signal emerging weakness in the macroeconomy. The role of banks in intermediating credit and interest rate risk, as well as their role in the payments system, may mean that emerging weaknesses in the overall economy first become apparent in the banking system. Thus, troubles in the banking sector may provide an early indicator of problems outside the banking sector. While numerous studies have found an important role for financial variables as leading indicators for the economy (for example, Stock and Watson 1989; Bernanke 1990; Friedman and Kuttner 1992, 1998; Estrella and Mishkin 1998), such studies have tended to examine publicly available measures such as interest rates and interest rate spreads. Although such measures may be correlated with problems in the banking sector, these studies have not explicitly included comprehensive direct measures of the health of the banking sector, such as confidential bank supervisory ratings. Furthermore, because such studies use publicly available data, they cannot be used to address the important question of whether the Federal Reserve possesses an informational advantage.

A second possibility is that supervisory information may be important because of the role banks play in the economy. A number of studies have shown that the financial health of banks may affect the response of the economy to a change in monetary policy instruments or the availability and terms of credit to borrowers, either of which could have a direct causal role in the performance of the overall economy (for example, Bernanke 1983; Bernanke and Lown 1991; Hancock and Wilcox 1992; Kashyap and Stein 1994; Peek and Rosengren 1995a, 1995b; Stein 1995).

To distinguish whether banking problems exacerbate problems in the real economy or they are only leading indicators of problems in the real economy is beyond the scope of this paper. Rather, the goal of this research is to examine whether confidential bank supervisory information provides an informational advantage to the Federal Reserve that could improve the conduct of discretionary monetary policy.

If confidential supervisory information substantially reduces the forecast errors made by private forecasters who do not have access to this information, then supervisory information may be one source of any informational advantage useful to a central bank in conducting monetary policy. Note that this informational advantage does not imply that private forecasters are making inefficient forecasts. Private forecasts still may be efficient, given the information available to them. However, the importance of bank supervisory data for macroeconomic forecasts would suggest that those private forecasts could have been improved, had they had the information set available to the central bank.[2]

Testing the hypothesis that bank supervisory data could be one source of any informational advantage possessed by the Federal Reserve requires examining the effect on private forecast errors of a variable that serves as a proxy for those supervisory data. The basic equation takes the following form:

$$X_{t+i} = \alpha_0 + \alpha_1 E_{t,j}(X_{t+i}:I_{t,j}) + \alpha_2 Z_t + \epsilon_t , \qquad \textbf{(1)}$$

where X_{t+I} is the realized future value in period t+I of the macroeconomic variable being forecast, $E_{t,j}(X_{t+i}:I_{t,j})$ is the expectation of that variable by forecaster j at time t conditioned on publicly available information at time t when the forecast is made, and Z_t is a proxy variable for the confidential supervisory data available to bank supervisors at time t. If confidential supervisory data provide no additional information to that used by private forecasters, α_2 would equal zero. If α_2 differs significantly from zero, then the confidential bank supervisory data available to the

Federal Reserve would provide statistically significant information in addition to that used by private forecasters.

The measure of confidential supervisory information that we use is based on the CAMEL ratings used by bank examiners to rate individual banks. The CAMEL scores given to banks are based on the five categories supervisors analyze when evaluating the health of a bank — Capital, Assets, Management, Earnings, and Liquidity.[3] Each bank is rated from 1, the highest, to 5, the lowest, on each of the component categories and given a composite rating. Banks with a rating of 1 (sound in every respect) or 2 (fundamentally sound) are not likely to be constrained in any way by supervisory oversight. Banks with a 3 rating (flawed performance) are likely to have potential problems raised by examiners, but these problems are usually viewed as being correctable. Banks with a CAMEL rating of 4 (potential of failure, impaired viability) have a significant risk of failure. Banks with a CAMEL rating of 5 (high probability of failure, severely deficient performance) represent the set of banks with the most severe problems.

It is also important to note that the supervisory data on individual institutions are viewed as extremely confidential by each of the bank regulators. Until recently, the Federal Deposit Insurance Corporation (FDIC) had a policy of not disclosing the CAMEL rating even to bank management.[4] Thus, neither the public nor any private forecasting agency would have access to data on individual institutions. These data are the primary confidential assessments of individual bank health, the public release of which could be very damaging to an institution, particularly if it became widely known that examiners thought a bank had a very high probability of failure. While some assessment of banking problems can be deduced from publicly available financial statements, bank examiners have access to proprietary bank information that is more comprehensive and more timely than the publicly available information. For example, DeYoung et al. (1997) find that CAMELS ratings contain useful private information uncovered during the course of bank exams that is not known to the public. Similarly, Berger and Davies (1994) find that a CAMEL rating downgrade contains substantial private information about the bank's health.

II. The Data

The macroeconomic variables that are the focus of this study are the unemployment rate and the inflation rate as measured by the Consumer Price Index (CPI). Most models of the Federal Reserve objective function, from Theil (1964) to Kydland and Prescott (1977) and Walsh (1995), include these two variables. The use of these two variables has an added benefit. The CPI is not revised subsequently, and the unemployment rate is revised only marginally, when seasonals are updated.[5]

This study examines the one-, two-, three-, and four-quarter-ahead forecast errors of inflation and unemployment rates of three major commercial forecasters: Data Resources, Inc.-McGraw Hill (DRI), Georgia State University (GSU), and the University of Michigan Research Seminar in Quantitative Economics (RSQE). All three forecasters sell their forecasts commercially and have generally been among those with the best forecast record for the macroeconomic variables examined in this study (McNees 1992). Both RSQE and GSU provide quarterly forecasts that generally are released in the middle month of each quarter. DRI provides forecasts monthly, and we use their forecast for the middle month of each quarter so that all forecasters possess roughly the same information set. The sample period begins in 1978:I, since the CAMEL data first became available only in late 1977, and ends in 1996:II. Only two of the individual forecasters, DRI and RSQE, have forecasts available as far back as 1978:I. The GSU forecasts begin in 1980:III.

An example will serve to make clear how the timing issues have been resolved. The one-quarter-ahead forecasts would correspond to forecasts of the unemployment rate and the inflation rate for the first quarter of 1990 made as of the middle of 1990:I (the within-quarter forecast) or, in the case of the monthly DRI forecasts, as of February 1990. The two-quarter-ahead forecasts made as of the middle of the first quarter of 1990 would be for values of the unemployment rate and the inflation rate in 1990:II, and so on. It should be emphasized that each forecast is for a single quarter, with the one-, two-, three-, and four-quarter-ahead forecasts differing in their distance from the date at which the forecast is made, not in the length of the period being forecast.

One benefit of this timing of the forecasts is that by the middle of the quarter, forecasters know the actual values of the unemployment rate and the inflation rate for the prior quarter. This timing convention eliminates any concern about introducing a moving-average process into the forecast errors for the one-quarter-ahead forecasts, although the possibility of a moving-average term in the error of equation 1 still exists for the more distant quarters most relevant to monetary policy: the two-, three-, and four-quarter-ahead forecasts.[6]

In addition to the three individual forecasts, we also examine the Blue Chip consensus forecast, which is an average of 50 individual forecasts. Since these forecasts are provided monthly, like DRI's, the Blue Chip forecast for the middle month of each quarter is used. These forecasts begin in 1980:I. As Keane and Runkle (1990) point out, ordinary least squares (OLS) estimation produces inconsistent estimates of the standard errors when forecast errors are correlated across forecasters within a consensus forecast.[7] As a result, the Blue Chip consensus is used only as a standard for comparison, since its mean squared error has been found to be comparable to those of the best individual forecasts (McNees 1992).

The variable that serves as a proxy for the confidential bank data available to the Federal Reserve (CAMEL5) is the percentage of assets of all commercial and savings banks rated CAMEL 5 relative to the total assets of all commercial and savings banks with supervisory ratings, as of the end of the month prior to the forecast. If weakness in the banking sector, as indicated by a high percentage of banks with a CAMEL rating of 5, contains significant information about the economy not included in the commercially available forecasts, the estimated coefficient on CAMEL5 should be positive in the unemployment rate equation and negative in the inflation rate equation.

One problem with examining forecasts over this period is the presence of substantial oil price shocks. Since the unemployment rate exhibits substantial inertia, these oil supply shocks introduce little unexpected variation in the series. However, movements in the quarterly CPI inflation rate measure immediately reflect the sharp increases in oil prices associated with the second OPEC supply shock in 1979 and the Gulf War in 1990, as well as the collapse in oil prices in 1986. Ideally, we would examine the core rate of inflation, since bank supervisory information is unlikely to be useful in explaining externally generated supply shocks. Unfortunately, several forecasters do not report core inflation rates back to the late 1970s. Thus, comparing the forecast error for the total CPI to the measure of supervisory information is a stringent test, since the supervisory data will not explain any of the largest CPI errors — those when oil prices changed unexpectedly due to external factors. Consequently, we reestimated each of the regressions including a set of dummy variables for those observations when oil prices rose or fell sharply.

However, the results presented here do not include the oil shock dummy variables, because identifying the precise quarters when the oil shocks occurred is somewhat subjective.[8] For the inflation equations, including these oil shock dummy variables tended to strengthen the significance levels on the estimated coefficients for the variable of interest here, CAMEL5.[9]

III. Empirical Results

Table 1 provides the ordinary least squares (OLS) regression results for the unemployment rate and the CPI inflation rate for a sample formed by pooling the data for the three individual forecasters (DRI, GSU, and RSQE). For the unemployment rate, the estimated coefficient on the forecast has a statistically significant value close to one for each of the four quarters.[10] The estimated coefficient on the proxy for supervisory information (CAMEL5) is also both positive and significant in each equation. The positive sign on the estimated coefficient indicates that as a larger share of bank assets is accounted for by CAMEL 5-rated banks, the unemployment rate rises relative to private forecasts of it; that is, private forecasters would overpredict the strength of the economy.

The significance of the CAMEL5 estimated coefficients indicates that supervisory data appear to provide information that can improve upon private forecasts of the unemployment rate at all four horizons. In fact, the estimated coefficients rise (in absolute value) as the quarter being forecast becomes more distant. For example, the estimated coefficient on CAMEL5 for the two-quarter-ahead forecast is nearly twice that for the equation based on the one-quarter-ahead forecast, and the estimated coefficients for the three- and four-quarter-ahead forecasts are almost three times that of the one-quarter-ahead forecast. This pattern is consistent with the initial effect of an economic shock growing over time as it feeds through the economy.[11]

The size of the estimated coefficients also suggests economic significance. For example, a one-standard-deviation (0.84 percentage point) increase in CAMEL5 would account for an error in the private sector four-quarter-ahead unemployment rate forecast of one-quarter of a percentage point. Given that the standard deviation of the private sector four-quarter-ahead forecast error is 0.7, the informational advantage provided by CAMEL5 is substantial.

The results are qualitatively similar for the inflation forecast equations. For the one-quarter-ahead inflation forecast, the estimated coefficient on CAMEL5 is negative, as predicted, but is not significant. However, when the forecast horizon shifts to the more distant two-, three-, and four-quarter-ahead forecasts, the estimated coefficients are each significant. As was the case with the unemployment forecast equations, the estimated coefficient on CAMEL5 is larger, the more distant the quarter being forecast, with the increase in the size of the coefficient even more dramatic than the increase for the unemployment rate equations. The coefficient on the measure of supervisory information for the two-quarter-ahead forecast is more than three times as large as that for the one-quarter-ahead forecast, and those for the three- and four-quarter-ahead forecasts are more than six times as large. Furthermore, the fact that the effect appears to be delayed slightly more in the inflation equations than in the unemployment equations is consistent with a large number of models: for example, standard estimates of the Phillips curve imply that the real economy tends to react earlier than do prices.

In terms of economic significance, a one-standard-deviation (0.84 percentage point) increase in CAMEL5 would account for an error in the private sector four-quarter-ahead inflation rate forecast of 0.8 percentage point. Given that the standard deviation of the private sector four-quarter-ahead forecast error is 2.5, the informational advantage provided by CAMEL5 is again substantial.

A problem with the estimates presented in Table 1 is that when the data are pooled, OLS estimation produces consistent estimates for the coefficients, but inconsistent estimates for the standard errors. OLS estimation ignores the potential contemporaneous correlations across individual forecast errors due to unanticipated shocks to the economy. Consistent estimates of the standard errors require that the estimation account for this property of the covariance structure of the forecast errors. Furthermore, as noted earlier, the two-, three-, and four-quarter-ahead forecasts might be expected to have forecast errors that follow a moving-average process.

Table 2 contains the coefficient estimates from Table 1 with the associated standard error estimates corrected for the moving-average and contemporaneous correlations in the equation errors resulting from the pooling of the individual forecasts. The covariance matrices are adjusted to achieve efficient estimates using the procedure described by Keane and Runkle (1990). The consistent estimates of the standard errors are significantly larger than those produced by the OLS estimation. Still, the estimated coefficients on the measure of supervisory information remain statistically significant in the unemployment rate equations for each of the four forecast horizons, as in Table 1. The estimated coefficients on CAMEL5 for the three- and four-quarter-ahead inflation rate forecast equations also remain significant.[12]

IV. Corroborating Evidence

Table 2 provides evidence that supervisory information could be a source of a significant informational advantage to the Federal Reserve. However, additional corroborating evidence would make the case even more compelling. First, if it is the confidentiality of bank supervision data that is giving rise to the Fed's informational advantage, then each forecaster should suffer from the same degree of informational asymmetry. Thus, it should be the case that CAMEL5 adds valuable information to the forecasts of each individual forecaster, since confidential information should be similarly unavailable to each of the private forecasters. Second, confidence in the result would be enhanced by finding that bank supervisory information is important even during periods not characterized by a banking crisis: that is, the results shown in Table 2 do not emanate solely from one extreme episode. And finally, the case would be strengthened by a finding that bank supervisory information contained useful information independent of that contained in financial variables that are publicly available and found by others to be leading indicators. Each of these issues is explored in this section.

Supervisory Information, Forecaster by Forecaster

The much larger sample size generated by pooling the individual forecaster data enhances the power of the test. Nonetheless, one might still want to consider the results obtained by estimating separate equations for each individual forecaster. Even though the much smaller sample size is likely to substantially reduce the t-statistics on the estimated coefficients, the size of the estimated coefficients can provide a feel for the extent to which the results in Table 2 might be generated primarily by aberrations associated with the data from only one of the forecasters. It would be reassuring if each of the individual forecasts, as well as the Blue Chip consensus forecasts, provided similar point estimates for the CAMEL5 coefficients.

Table 3A provides the results for the unemployment rate, with separate equations estimated for each individual forecaster included in the pooled results in Table 2 as well as for the consensus Blue Chip forecasts. The standard errors are adjusted for the relevant moving-average processes. Since the data for the individual forecasters are not pooled, the contemporaneous cross-correlations are no longer an issue. The results are strikingly similar across forecasters. The estimated coefficients on CAMEL5 are significant for each of the four forecasters for the one-quarter-ahead forecasts of the unemployment rate. Furthermore, the separately estimated coefficients for each forecaster are of a similar magnitude, indicating that the pooled results in Table 2 reflect a consistency across the individual private forecasters.

For the equations based on the two-, three- and four-quarter-ahead unemployment rate forecasts, the estimated coefficient patterns for the measure of supervisory information are also quite consistent, both across forecasters and compared to the estimates in Table 2.[13] The coefficient estimates are significant for three of the four forecasters for the two-quarter-ahead forecasts, and for all four of the three-quarter-ahead forecasts. For the four-quarter-ahead forecasts, the RSQE and Blue Chip equations have CAMEL5 effects that are significant at traditional levels, while that for DRI is significant at the 10 percent level. Furthermore, the coefficient estimates for each of the forecasters exhibit the same pattern as shown in Table 2, with the coefficients generally rising as the quarter being forecast becomes more distant. These estimates highlight the finding that the significant coefficients on CAMEL5 in Table 2 are not due to a single forecaster. Rather, the coefficient patterns are produced consistently across each of the separate sources of private forecasts.

Table 3B shows the results for the inflation rate when separate equations are estimated for each of the individual forecasters. With only one exception, the coefficients on the measure of supervisory information for each forecaster at each horizon are correctly signed. The coefficients for the individual forecasters also exhibit the same pattern as those in the pooled regressions, increasing in magnitude as the forecast quarter becomes more distant. However, the estimated coefficients on CAMEL5 are significantly different from zero only for the three- and four-quarter-ahead horizons for GSU and for the four-quarter-ahead horizon for DRI. Nevertheless, the results for the individual forecasters confirm the patterns shown in the regressions based on the pooled sample. The confidential information contained in CAMEL5 does appear to add to the explanatory power of the information set used by private sector forecasters, although, as expected, the t-statistics are weaker when the sample size is so sharply reduced by estimating separate equations for each forecaster.

The consistency in the size of the estimated CAMEL5 coefficients across individual forecasters in Tables 3A and 3B suggests that each of the forecasters omits the information contained in CAMEL5 to the same degree. This is consistent with the relevant supervisory information contained in CAMEL5 being confidential. Thus, it appears that all the private forecasters are limited to the same degree in their access to information about bank health.

Supervisory Data and Bank Crises

Several earlier studies have indicated that the late 1980s and early 1990s were an unusual period for banking, with bank failure rates not seen since the Great Depression. Thus, one might wonder whether the explanatory power found for the supervisory data is derived only from this banking crisis. In other words, while it may be very important to have such bank supervisory information during a banking crisis, it might be less important during periods when fluctuations in bank health are less extreme.

Is such information useful when banking problems are moderate? To answer this question, we reestimated the equations reported in Table 2, excluding data for the period from 1988:II to 1991:III. These end-points were chosen because the value of CAMEL5 began to climb in 1988:II and 1991:III marks the end of the recession, as designated by the NBER Business Cycle Dating Committee; by that time banks had begun to show improved financial health. Omitting this subperiod removes the largest CAMEL5 values. Nonetheless, the economy before 1988:II experienced banking problems in the oil-producing and agricultural states, while after 1991:III the banking sector had problems in California.

The effects of supervisory data on the forecast errors for the unemployment rate over this restricted sample, shown in Table 4, are similar to the effects reported in Table 2. Even when the subperiod containing the most severe banking problems is excluded, the estimated coefficients on CAMEL5 for the one-quarter-ahead and two-quarter-ahead forecasts are 0.091 and 0.174, respectively, virtually identical to the results over the entire period of 0.091 and 0.175. Although the standard errors are now larger than those in Table 2, the estimated coefficients are still significant. The coefficients for the three- and four-quarter-ahead forecasts are smaller than those shown in Table 2, although they remain larger than that on the one-quarter-ahead forecast, and the standard errors are larger, perhaps because of the reduced sample size, so that the coefficients are no longer significant at the 5 percent level.

The results for the inflation rate equations are somewhat stronger when the period of the most severe banking problems is excluded. The CAMEL5 coefficient for the one-quarter-ahead forecast equation changes from -0.141 to -0.227, while that for the two-quarter-ahead forecast equation changes from -0.468 to -0.731. For the three- and four-quarter-ahead forecasts, the coefficients also are larger (in absolute value) than those in Table 2. The measure of supervisory information adds significantly to the forecasting ability of the equations at the two-, three-, and four-quarter-ahead forecast horizons. Thus, the results for inflation are actually stronger in Table 4 than in Table 2, in part because the period omitted includes the Gulf War oil shock, which produced some of the largest forecast errors for inflation during the 1978:I to 1996:II period under consideration.

It is reassuring to find such similarity in the coefficient patterns between Tables 2 and 4, and to find that the statistical significance was not seriously eroded by the exclusion of so much of the data, particularly since the excluded subperiod contained the most severe banking problems and the most extreme values of CAMEL5. These results, like those for the unemployment rate equations, indicate that bank supervisory information may be useful for the conduct of monetary policy even when the economy is not experiencing severe banking problems.

Contribution of Supervisory Information Beyond That of Leading Financial Indicators

Recent studies investigating a similar time period have found a role as leading indicators for a number of financial variables (see, for example, Stock and Watson 1989; Bernanke 1990; Bernanke and Blinder 1992; Friedman and Kuttner 1992, 1998; Estrella and Mishkin 1998). Consequently, to investigate the extent to which CAMEL5 provides information for forecasts of unemployment and inflation rates independent of that provided by financial leading indicators, we include three such variables in our equations: the federal funds rate, the quarterly growth rate of M2, and the commercial paper — Treasury bill interest rate spread.

The results, shown in Table 5, indicate that the inclusion of these variables has little impact on the overall results. The size and significance of the coefficients on CAMEL5 are qualitatively similar to those reported in Table 2, and our finding of a significant impact of CAMEL ratings on forecasts of inflation and unemployment rates is robust to the inclusion of these additional financial variables.[14] This should not be a surprising result, since these financial variables are known to the public, while CAMEL5 remains confidential.

IV. Conclusion

This study has shown that confidential bank supervisory information is highly correlated with the errors of private forecasters who do not have access to bank CAMEL ratings. Periods with a high percentage of bank assets in CAMEL 5-rated banks are associated with private forecasters underpredicting the unemployment rate and overpredicting the inflation rate. The results appear to be related to the confidentiality of the CAMEL5 information, since the results are consistent across the individual forecasters and the CAMEL5 contribution is independent of that of publicly available financial market leading indicators. Furthermore, this information advantage is valuable even in periods not characterized by a banking crisis.

The importance of supervisory information in improving forecasts has several potentially important policy implications. First, supervisory information should be available to monetary policymakers that depend on macroeconomic forecasts. In fact, bank supervisory information appears to be one source of an informational advantage possessed by the Federal Reserve. Access to bank supervisory information can improve forecasts of variables critical in guiding monetary policy and thus increase any benefit provided by discretionary monetary policy.

Second, central banks need continuous access to this information. While severe banking crises like those experienced here during the Great Depression and currently in Japan and Southeast Asia are widely viewed as contributing to the severity of economic problems, we find that bank supervisory information is useful even during more moderate fluctuations in bank health. Because the conduct of monetary policy requires timely information on bank health and because policymakers must understand the data sufficiently to identify nuances in its movements, it may be important for central banks to have hands-on bank supervisory responsibility.

Third, while bank supervisory information should be valuable for guiding monetary policy in developed as well as developing countries, it is particularly valuable in countries with less developed capital markets especially hard hit by the simultaneous occurrence of banking and economic crises (Caprio and Klingebiel 1996). The relative importance of supervisory information in those countries arises in large part from the much larger role played by banks in their credit markets.

References

Barro, Robert J. 1976. "Rational Expectations and the Role of Monetary Policy." Journal of Monetary Economics, 2, January, 1-32.

Barro, Robert J. and D.P. Gordon. 1983a. "A Positive Theory of Monetary Policy in a Natural Rate Model." Journal of Political Economy, 91, 589-610.

____. 1983b. "Rules, Discretion, and Reputation in a Model of Monetary Policy." Journal of Monetary Economics, 12, 101-21.

Berger, Allen N. and Sally M. Davies. 1994. "The Information Content of Bank Examinations." In The Declining Role of Banking, Proceedings of the 30th Annual Conference on Bank Structure and Competition, Federal Reserve Bank of Chicago, 615-28.

Bernanke, Ben S. 1983. "Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression." The American Economic Review, 73, June, 257-76.

____. 1990. "On the Predictive Power of Interest Rates and Interest Rate Spreads." New England Economic Review, November/December, 51-68.

Bernanke, Ben S., and Alan S. Blinder. 1992. "The Federal Funds Rate and the Channels of Monetary Transmission." The American Economic Review, 82, 901-21.

Bernanke, Ben S., and Cara S. Lown. 1991. "The Credit Crunch." Brookings Papers on Economic Activity, No. 2, 205-48.

Caprio, Gerard, Jr., and Daniela Klingebiel. 1996. "Bank Insolvencies: Cross Country Experiences." The World Bank Policy Research Working Paper No. 1620, July.

DeYoung, Robert, Mark J. Flannery, William W. Lang, and Sorin M. Sorescu. 1997. "Could Publication of Bank CAMELS Ratings Improve Market Discipline?" Manuscript, December.

Estrella, Arturo, and Mishkin, Frederic S. 1998. "Predicting U.S. Recessions: Financial Variables as Leading Indicators." The Review of Economics and Statistics, 80 (1), February, 45-61.

Fischer, Stanley. 1977. "Long-Term Contracts, Rational Expectations, and the Optimal Money Supply Rule." Journal of Political Economy, 85(1), 191-205.

Friedman, Benjamin M., and Kuttner, Kenneth N. 1992. "Money, Income, Prices, and Interest Rates." The American Economic Review, 82, June, 472-92.

____. 1998. “Indicator Properties of the Paper-Bill Spread: Lessons from Recent Experience.” The Review of Economics and Statistics, 80 (1), February, 34-44.

Hancock, Diana, and James A. Wilcox. 1992. "The Effects on Bank Assets of Business Conditions and Capital Shortfalls." In Credit Markets in Transition, Proceedings of the 28th Annual Conference on Bank Structure and Competition, Federal Reserve Bank of Chicago, 502-20.

Hansen, L. P., and R. J. Hodrick. 1980. “Forward Exchange Rates As Optimal Predictors of Future Spot Rates: An Econometric Analysis.” Journal of Political Economy, 88, 829-53.

Kashyap, Anil K. and Jeremy C. Stein. 1994. “The Impact of Monetary Policy on Bank Balance Sheets.” Carnegie-Rochester Conference Series on Public Policy, 42, June, 151-95.

Keane, Michael P. and David E. Runkle. 1990. “Testing the Rationality of Price Forecasts: New Evidence from Panel Data.” The American Economic Review, 80, September, 714-35.

Kydland, Finn and Edward Prescott. 1977. “Rules Rather than Discretion: The Inconsistency of Optimal Plans.” Journal of Political Economy, 85(3), June, 473-91.

McNees, Stephen K. 1992. “How Large Are Economic Forecast Errors?” New England Economic Review, July/August, 25-42.

Peek, Joe and Eric S. Rosengren. 1995a. “Bank Regulation and the Credit Crunch.” Journal of Banking and Finance, 19(1), June, 679-92.

____. 1995b. “The Capital Crunch: Neither a Borrower nor a Lender Be.” Journal of Money, Credit, and Banking, 27(3), August, 625-38.

Rogoff, Kenneth. 1985. “The Optimal Degree of Commitment to an Intermediate Monetary Target.” The Quarterly Journal of Economics, 100, 1169-90.

Romer, Christina D. and David H. Romer. 1996. “Federal Reserve Private Information and the Behavior of Interest Rates.” NBER Working Paper No. 5692, July.

Sargent, Thomas J., and Neil Wallace. 1975. “‘Rational’ Expectations, the Optimal Monetary Instrument, and the Optimal Money Supply Rule.” Journal of Political Economy, 83(2), 241-54.

Stein, Jeremy C. 1995. "An Adverse Selection Model of Bank Asset and Liability Management with Implications for the Transmission of Monetary Policy." NBER Working Paper No. 5217, August.

Stock, James, and Watson, Mark. 1989. “New Indexes of Coincident and Leading Indicators.” In Olivier Blanchard and Stanley Fischer (eds.), NBER Macroeconomic Annual 4, 351-94.

Theil, Henri. 1964. Optimal Decision Rules for Government and Industry, 2nd ed. Amsterdam: North-Holland.

Walsh, Carl E. 1995. “Optimal Contracts for Central Bankers.” The American Economic Review, 85(1), March, 150-67.

Endnotes

1. Romer and Romer (1996) is an exception. However, they do not examine the role of bank supervisory information as a potential source of any informational advantage possessed by the Federal Reserve.

2. Disclosure practices for supervisory information vary substantially across countries. While banks in the United States provide much greater disclosure of financial information than in most countries, the supervisory agencies do not release CAMELS ratings. Some countries have begun releasing significantly more information about supervisory assessments. For example, New Zealand now requires supervisory ratings to be made public.

3. On January 1, 1997, the CAMEL rating system was expanded to CAMELS. The S stands for "sensitivity to market risk," and is intended to measure how well prepared a bank is to handle changes in interest rates, exchange rates, and commodity or equity prices. The sample period for this study ends in 1996:II, however.

4. The CAMEL rating is revealed only to the top management of the bank, and they are not allowed to disseminate this information to other employees, bank customers, or financial market participants (DeYoung et al. 1997).

5. These two series avoid the serious problem of forecasting a variable using one set of base year relative prices and comparing it to an actual realization that uses another set, which occurs with the GDP forecasts when the base year changes.

6. Hansen and Hodrick (1980) point out that the errors over longer forecast horizons should follow predictable moving-average processes. In this study, since the forecasts are for nonoverlapping quarters, the moving-average process is not introduced by construction. Rather, the moving-average processes occur because a shock that arises subsequent to the time at which the quarterly forecasts are made is likely to have persistent effects.

7. The inconsistency caused by this correlation across forecasters could be corrected if each forecaster's quarterly forecast were given in the Blue Chip. Unfortunately, the quarterly forecasts are provided only for the consensus forecast. Only the annual forecasts are provided for the individual forecasters.

8. We included two dummy variables to control for oil shocks. The first one had a value of one associated with forecasts of unemployment and inflation rates for 1979:I through 1979:IV and for 1990:III, the periods of large oil price increases associated with the second OPEC price shock and the outbreak of the Gulf War, and zero otherwise. The second dummy variable had a value of one associated with forecasts for 1986:I, when oil prices collapsed, and zero otherwise. To avoid concerns that the results are predicated on the periods we selected, we simply provide the results from the regressions that do not include the oil shock dummy variables. Omitting the dummy variables only increases the probability that the results would find no effect for the supervisory information.

9. In addition, we found that the moving-average terms tend to be less important when controlling for the oil shocks, much of whose effect was not anticipated by forecasters and accounts for most of the largest forecast errors in the inflation equation.

10. The standard efficiency test of the forecast, testing whether the constant is zero and the coefficient on the forecast is equal to one, is no longer valid for our specification. First, the null hypothesis for this efficiency test would assume that the forecasters have the confidential supervisory information, which is false. Second, as will be discussed later, the standard error estimates are inconsistent.

11. It should be emphasized that each of the forecasts is for a one-quarter horizon. Thus, the two-quarter-ahead forecast made in the first quarter (a February forecast) would cover the period from April to June, and the corresponding three-quarter-ahead forecast would cover the period from July to September.

12. If one includes the oil supply shock dummy variables in the inflation forecast equations, the CAMEL5 coefficient in the two-quarter-ahead forecast equation also is significant.

13. Note that some of the differences in the coefficient estimates across forecasters may be attributable to the fact that they differ in the sample period they cover. The DRI and RSQE samples begin in 1978:I, while Blue Chip and GSU begin in 1980:I and 1980:III, respectively.

14. Note that because we are including information not available to forecasters, the partial correlation coefficients on the additional financial variables do not necessarily imply inefficient forecasts.

Table 1
Contribution of Confidential Bank Supervisory Information to the Forecast Accuracy for the Unemployment and Inflation Rates
Estimation Method: Ordinary Least Squares

	Unemployment Rate				Inflation Rate (CPI)			
Variable	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Constant	.018 (.053)	.126 (.127)	.199 (.212)	.304 (.276)	.398 (.237)	.767 (.398)	1.138* (.485)	1.501** (.559)
Forecast	.979** (.008)	.945** (.019)	.927** (.031)	.910** (.041)	.925** (.029)	.928** (.054)	.922** (.072)	.820** (.083)
CAMEL5	.091** (.013)	.175** (.030)	.240** (.048)	.258** (.060)	-.141 (.116)	-.468** (.180)	-.926** (.199)	-.997** (.215)
R^2	.988	.933	.831	.736	.851	.642	.522	.426
SSR	4.22	24.16	62.05	98.43	341.7	821.2	1,057.0	1,222.7
SER	.142	.340	.545	.686	1.279	1.982	2.249	2.419

Standard errors are in parentheses.
* Significant at the 5 percent level.
**Significant at the 1 percent level.

Table 2
Contribution of Confidential Bank Supervisory Information to the Forecast Accuracy for the Unemployment and Inflation Rates, Corrected for Moving Average and Contemporaneous Correlations

	Unemployment Rate				Inflation Rate (CPI)			
Variable	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Constant	.018	.126	.199	.304	.398	.767	1.138	1.501
	(.078)	(.252)	(.477)	(.564)	(.325)	(.682)	(.910)	(1.073)
Forecast	.979**	.945**	.927**	.910**	.925**	.928**	.922**	.820**
	(.012)	(.038)	(.071)	(.082)	(.038)	(.089)	(.132)	(.155)
CAMEL5	.091**	.175**	.240*	.258*	-.141	-.468	-.926*	-.997*
	(.019)	(.059)	(.103)	(.125)	(.161)	(.314)	(.380)	(.414)

Note: The standard errors in the two-quarter-ahead-forecast equation are corrected for MA(1) errors; the three-quarter-ahead-forecast equation is corrected for MA(1) and MA(2) errors; and the four-quarter-ahead forecast equation is corrected for MA(1), MA(2), and MA(3) errors.

Standard errors are in parentheses.
* Significant at the 5 percent level.
**Significant at the 1 percent level.

Table 3A
Unemployment Rate Results, Disaggregated by Individual Forecasts

	DRI				GSU			
	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Constant	-.059 (.082)	-.046 (.274)	-.056 (.406)	.183 (.595)	.154 (.083)	.397 (.445)	.558 (.415)	.850 (.525)
Forecast	.991** (.012)	.972** (.041)	.965** (.060)	.926** (.088)	.963** (.013)	.918** (.067)	.889** (.062)	.849** (.079)
CAMEL5	.084** (.019)	.156* (.061)	.195* (.087)	.220 (.122)	.086** (.020)	.154 (.108)	.216* (.098)	.204 (.124)

	RSQE				Blue Chip			
	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Constant	-.082 (.109)	-.095 (.294)	-.076 (.651)	-.471 (.639)	-.092 (.087)	-.139 (.316)	-.223 (.440)	-.123 (.576)
Forecast	.984** (.016)	.956** (.042)	.942** (.094)	.993** (.093)	.992** (.013)	.977** (.046)	.975** (.064)	.958** (.085)
CAMEL5	.115** (.019)	.247** (.072)	.342* (.149)	.396** (.139)	.107** (.021)	.205** (.074)	.297** (.099)	.329** (.124)

Note: The standard errors in the two-quarter-ahead-forecast equation are corrected for MA(1) errors; the three-quarter-ahead-forecast equation is corrected for MA(1) and MA(2) errors; and the four-quarter-ahead forecast equation is corrected for MA(1), MA(2), and MA(3) errors.

Standard errors are in parentheses.
* Significant at the 5 percent level.
**Significant at the 1 percent level.

Table 3B
Inflation Rate (CPI) Results, Disaggregated by Individual Forecasts

	DRI				GSU			
	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Constant	-.117	.025	.189	.921	.112	.748	1.833	1.858
	(.333)	(.838)	(1.234)	(1.407)	(.348)	(.900)	(1.116)	(1.447)
Forecast	1.018**	1.091**	1.169**	1.040**	1.001**	.969**	.878**	.816**
	(.039)	(.112)	(.189)	(.218)	(.041)	(.117)	(.159)	(.205)
CAMEL5	-.052	-.325	-.876	-1.038*	-.153	-.587	-1.285**	-1.295*
	(.158)	(.365)	(.463)	(.518)	(.169)	(.404)	(.487)	(.543)

	RSQE				Blue Chip			
	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Constant	1.102*	1.201*	.898	1.369	-.528	-.128	.402	.467
	(.464)	(.543)	(.669)	(.721)	(.309)	(.597)	(.785)	(.954)
Forecast	.668**	.666**	.684**	.540**	1.803**	.965**	.872**	.865**
	(.063)	(.079)	(.104)	(.112)	(.043)	(.090)	(.128)	(.159)
CAMEL5	.070	-.112	-.178	-.188	-.032	-.102	-.324	-.471
	(.244)	(.271)	(.295)	(.300)	(.147)	(.259)	(.308)	(.347)

Note: The standard errors in the two-quarter-ahead-forecast equation are corrected for MA(1) errors; the three-quarter-ahead-forecast equation is corrected for MA(1) and MA(2) errors; and the four-quarter-ahead forecast equation is corrected for MA(1), MA(2), and MA(3) errors.

Standard errors are in parentheses.
* Significant at the 5 percent level.
**Significant at the 1 percent level.

Table 4
Determinants of Forecasts of Unemployment and Inflation Corrected for Moving Average and Contemporaneous Correlations - Excluding 1988:II - 1991:III

	Unemployment Rate				Inflation Rate (CPI)			
	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Constant	.064 (.111)	.165 (.351)	.168 (.621)	-.052 (.732)	.415 (.364)	.714 (.706)	1.063 (.941)	1.432 (1.126)
Forecast	.973** (.017)	.941** (.054)	.936** (.094)	.973** (.111)	.930** (.042)	.950** (.091)	.944** (.136)	.841** (.163)
CAMEL5	.091** (.028)	.174* (.086)	.201 (.146)	.125 (.177)	-.227 (.201)	-.731* (.360)	-1.184** (.442)	-1.273** (.486)

Note: The standard errors in the two-quarter-ahead-forecast equation are corrected for MA(1) errors; the three-quarter-ahead-forecast equation is corrected for MA(1) and MA(2) errors; and the four-quarter-ahead forecast equation is corrected for MA(1), MA(2), and MA(3) errors.

Standard errors are in parentheses.
* Significant at the 5 percent level.
**Significant at the 1 percent level.

Table 5
Specification Tests of Confidential Bank Supervisory Information to the Forecast Accuracy for the Unemployment and Inflation Rates, Corrected for Moving Average and Contemporaneous Correlations

	Unemployment Rate				Inflation Rate (CPI)			
Variable	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
Constant	.009 (.057)	-.094 (.246)	-.094 (.468)	.002 (.498)	.228 (.270)	1.080 (.778)	1.498 (.945)	1.105 (1.104)
Forecast	.986** (.009)	.947** (.040)	.890** (.077)	.838** (.086)	.823** (.040)	.906** (.124)	1.140** (.187)	1.029** (.213)
FedFund	-.001 (.004)	.024 (.015)	.083** (.025)	.149** (.030)	.165** (.040)	.038 (.108)	-.183 (.129)	-.267* (.135)
M2	-.004 (.003)	-.020 (.013)	-.040* (.020)	-.071** (.025)	-.066* (.027)	.043 (.067)	.088 (.076)	.133 (.081)
Commercial Paper - Treasury Bill Rate	-.010 (.028)	.180 (.110)	.091 (.182)	-.116 (.205)	-.256 (.245)	-1.094 (.625)	-.855 (.714)	.961 (.742)
CAMEL5	.088** (.013)	.193** (.055)	.288** (.095)	.333** (.110)	-.230* (.116)	-.538 (.328)	-.876* (.377)	-.923* (.423)

Note: The standard errors in the two-yquarter-ahead-forecast equation are corrected for MA(1) errors; the three-quarter-ahead-forecast equation is corrected for MA(1) and MA(2) errors; and the four-quarter-ahead forecast equation is corrected for MA(1), MA(2), and MA(3) errors.

Standard errors are in parentheses.

* Significant at the 5 percent level.
**Significant at the 1 percent level.