Using Bank Supervisory Data to Improve Macroeconomic Forecasts

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Locating the function of bank supervision in the central bank has been a contentious issue, both domestically and internationally. Most discussions of the role of bank supervision in central banking have focused on crisis management and the responsibilities of the central bank as a lender of last resort. However, recent research by Peek, Rosengren, and Tootell (PRT 1999a) has shown that confidential supervisory information garnered through bank examinations potentially can improve the conduct of monetary policy. Forecasting macroeconomic variables is essential to the conduct of monetary policy, since the long lags in the effect of monetary policy ensure that changes in monetary policy today alter the economy only in the future. Thus, an important reason for central banks to have access to confidential supervisory information, and possibly to participate in its collection, is that such information can improve macroeconomic forecasts and in this way improve monetary policy decision-making.

This paper explores further the robustness of the results reported in PRT. In particular, it examines the pattern of the forecast errors of the individual private forecasters studied. The results indicate that all of the major commercial forecasters used in PRT could have substantially improved their forecasts, had they had access to the confidential bank supervisory ratings that are available to the Federal Reserve. Thus, the PRT study's results are not due to large forecast errors produced by one forecaster; rather, all forecasters tended to have forecast errors that were correlated with the information found in bank supervisory ratings. This finding confirms the robustness of the earlier results and is consistent with the highly confidential nature of the data involved.

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 economy. The role of banks in intermediating credit and interest rate risk, as well as their role in the payments system, means that troubles in the overall economy may first become apparent in the banking system, providing 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, such studies have tended to examine publicly available measures such as interest rates and interest rate spreads. (See, for example, Stock and Watson 1989; Bernanke 1990; Friedman and Kuttner 1992, 1998; Estrella and Mishkin 1998.) These studies have not explicitly included comprehensive direct measures of the health of the banking sector, such as confidential bank supervisory ratings.

Recent research has shown that confidential supervisory information garnered through bank examinations potentially can improve the conduct of monetary policy.

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

This research on bank supervisory information has several potential policy implications. One is that the public release of more bank supervisory information could improve the ability of private forecasters and other private sector participants to forecast the paths of inflation and unemployment rates. Releasing aggregated supervisory information that does not compromise the confidentiality of individual institutions might provide useful information that improves economic interactions in the private sector.

Second, the results in this article indicate that supervisory responsibilities provide the Federal Reserve with an informational advantage that can be used to conduct monetary policy (Peek, Rosengren, and Tootell 1999b). Consequently, countries that have reduced their central bank's oversight of banks should be careful not to reduce the flow of supervisory information to the central bank. To the extent that the Federal Reserve has a significant informational advantage, this also has implications for the role of activist monetary policy.

The article proceeds as follows. The first section describes the methodology and data used to reexamine the results in PRT. The following section examines the potential contribution of bank supervisory data to unemployment and inflation rate forecasts for a sample formed by pooling the data for the individual forecasters. The third section provides empirical results for each of the individual forecasters. The final section provides some conclusions.

I. Data and Methodology

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 finding 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.[1]

The measure of confidential supervisory information that we use in this study and in PRT 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: *C*apital, *A*ssets, *M*anagement, *E*arnings, and *L*iquidity.[2] Each bank is rated from 1, the most healthy, to 5, the least healthy, on each of the component categories and given a

[1] 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 CAMEL ratings.

[2] 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.

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.

Testing the hypothesis that bank supervisory data could help in the conduct of monetary policy requires examining the effect on private forecast errors of a variable that serves as a proxy for confidential bank supervisory information. The basic equation takes the following form:

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

where X_{t+i} is the realized future value in period $t+i$ of the macroeconomic variable being forecast, either the unemployment rate or the inflation rate. $E_{t,j}(X_{t+i}:I_{t,j})$ 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 information available to bank supervisors at time t. The variable that serves as the proxy for the confidential bank data available to the Federal Reserve (CAMEL5) is the assets of all commercial and savings banks rated CAMEL 5, measured as a percentage of the total assets of all commercial and savings banks with supervisory ratings. We use the CAMEL5 value as of the end of the month prior to the forecast.

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. For example, a high percentage of banks with a CAMEL rating of 5, indicating weakness in the banking sector, would provide significant information about a weakening of the economy not included in the commercially available forecasts. For the unemployment rate, we expect α_2 to be positive, indicating that as more banks become troubled and have a CAMEL 5 rating, private forecasters will overpredict the strength of the economy and thus underpredict the unemployment rate. For the inflation rate, we expect α_2 to be negative, indicating that as more banks have CAMEL 5 ratings, private forecasters will overpredict the inflation rate.

It is important to note that the supervisory data on individual institutions are viewed as extremely confidential by each of the bank regulators. In fact, at one time the Federal Deposit Insurance Corporation (FDIC) had a policy of not disclosing a CAMEL rating even to the bank's management. Furthermore, bank management is prohibited from disclosing the CAMEL rating to its customers. 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. (1998) find that CAMEL 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.

Forecasting macroeconomic variables is essential to the conduct of monetary policy, since the long lags in the effect of monetary policy ensure that actions today alter the macroeconomy only in the future.

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.[3]

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 records 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 forecasts 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 begin 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.

The role of banks in intermediating credit and interest rate risk, as well as their role in the payments system, means that troubles in the overall economy may first become apparent in the banking system.

An example will serve to make clear how the timing issues have been resolved. The one-quarter-ahead forecasts for the first quarter of 1990 correspond to forecasts of the unemployment rate and the inflation rate 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.[4]

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.[5] Because of this, 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).

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

[3] 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.

[4] 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.

[5] 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 provide only the consensus forecast. Only annual forecasts are provided for the individual forecasters.

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	.126	.199	.304	.398	.767	1.138*	1.501**
	(.053)	(.127)	(.212)	(.276)	(.237)	(.398)	(.485)	(.559)
Forecast	.979**	.945**	.927**	.910**	.925**	.928**	.922**	.820**
	(.008)	(.019)	(.031)	(.041)	(.029)	(.054)	(.072)	(.083)
CAMEL5	.091**	.175**	.240**	.258**	−.141	−.468**	−.926**	−.997**
	(.013)	(.030)	(.048)	(.060)	(.116)	(.180)	(.199)	(.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.

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.[6] 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.[7]

II. 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.[8] 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 fore-

[6] 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.

[7] 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.

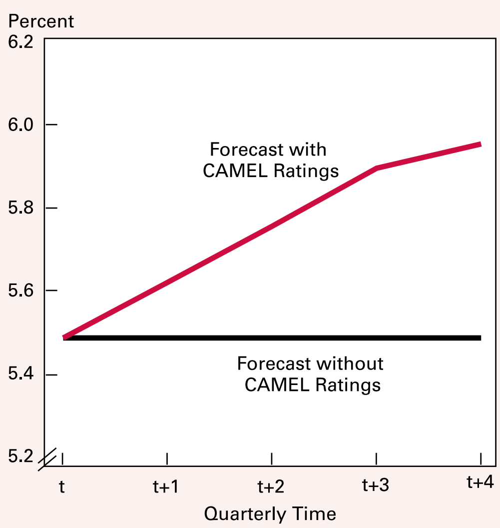
[8] The standard efficiency test of the forecast, testing whether the constant is zero and the coefficient on the forecast is equal to one, is no longer valid for our specification. First, the null hypothesis for this efficiency test would assume that the forecasters have the confidential supervisory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

casts 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. 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.[9]

The size of the estimated coefficients also suggests economic significance, as illustrated in Figure 1. This figure shows the effect an unhealthy banking system would have on the forecast of the unemployment rate if all the other available information pointed to a constant unemployment rate over the next year. The horizontal line in the figure corresponds to a set of private-sector forecasts (at a point in time) of the unemployment rate of 5.5 percent for the one-, two-, three-, and four-quarter-ahead periods. The other line is computed using the estimated coefficients from

Figure 1

Forecasting Unemployment with and without Supervisory CAMEL Ratings



Note: The forecast incorporating CAMEL ratings uses a variable expressing the share of assets in banks with a CAMEL rating equal to 5 as a percent of total assets. This chart uses a constant value of 2.5 percent for that variable. The unemployment forecast without CAMEL data is constrained to be a constant 5.5 percent.

Table 1, using the 5.5 percent value for the private forecasts of the unemployment rate and assuming that CAMEL5 has a value of 2.5 percent, which is near the high end of the range attained in our sample period. Adding such supervisory information to the forecast would suggest that the unemployment rate would rise almost one-half percentage point over the course of the year. Such a large difference in the forecasts could easily justify a change in the path of monetary policy.

Supervisory data appear to provide information that can improve upon private forecasts of the unemployment rate and the CPI inflation rate.

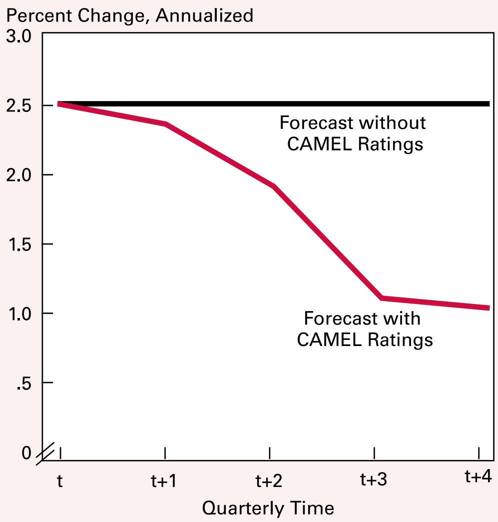
The results are qualitatively similar for the inflation forecast equations (Table 1). For the one-quarter-ahead inflation forecast, the estimated coefficient on CAMEL5 is negative, as predicted, but is not significant. However, when the forecast horizon shifts to the more distant two-, three-, and four-quarter-ahead forecasts, the estimated coefficients are each significant. As was the case with the unemployment forecast equations, the estimated effect of CAMEL5 is larger, the more distant the quarter being forecast, with the increase in the size of the coefficient (in absolute value) even more dramatic than the increase for the unemployment rate equations. The estimated 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.

Figure 2 illustrates the same experiment as Figure 1, except it is now based on inflation forecasts. The horizontal line in the figure represents a set of private-sector forecasts (at a point in time) of inflation of 2.5 percent for each of the one-, two-, three-, and four-quarter-ahead periods. The other line is constructed

[9] 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.

Figure 2

Forecasting Inflation with and without Supervisory CAMEL Ratings



Note: The forecast incorporating CAMEL ratings uses a variable expressing the share of assets in banks with a CAMEL rating equal to 5 as a percent of total assets. This chart uses a constant value of 2.5 percent for that variable. The inflation forecast without CAMEL data is constrained to be a constant 2.5 percent.

using the estimated coefficients from Table 1, maintaining the private forecasts of inflation of 2.5 percent and assuming a value for CAMEL5 of 2.5 percent. The figure clearly shows that knowledge of the poor health of the banking system would substantially lower the forecast of inflation over the next four quarters—again, by enough (nearly 1.5 percentage points) to justify altering monetary policy.

One 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 of those coefficients. OLS estimation ignores the potential contemporaneous correlations across individual forecast errors due to unanticipated shocks to the economy. For example, an unanticipated oil shock that occurs just after the forecasts are made will result in all forecasters having large positive errors in their inflation forecasts. 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 substantially 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.[10]

III. Evidence from Individual Forecasters

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. 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, rather than having the results driven by the errors of a single forecaster. 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. Thus, the results would be more compelling if all forecasts would be similarly improved by inclusion of the supervisory data. We explore this issue below.

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

[10] 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.

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.

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, 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.[11] 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

[11] 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.

Table 3A

Unemployment Rate Results, Disaggregated by Individual Forecasters

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

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

	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.

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 confidential information contained in CAMEL5 does appear to add to the explanatory power of the information sets used by individual private sector forecasters.

The similarity 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 not being available to any one forecaster and the results not being driven by one particularly inefficient forecast. Consequently, it appears that all the private forecasters are limited to the same degree in their access to information about bank health.

These results corroborate those reported in PRT and indicate that confidential supervisory information can improve on macroeconomic forecasts, potentially providing the central bank with an information advantage. PRT provide more specific evidence of why these results may be relevant to the case for bank supervision responsibilities being retained by the central bank. They find that supervisory information does not seem to be incorporated into internal Fed staff forecasts, possibly because the highly confidential CAMEL ratings are not provided to staff involved in the macroeconomic forecast. However, they find that the information does have an impact on the votes of the governors and presidents of the regional banks. Governors and presidents are actively involved in bank supervisory issues, and they use this knowledge to alter the forecasts provided by internal staff forecasts. Not only do PRT show that CAMEL ratings can potentially be used to improve forecasts and that supervisory information is correlated with FOMC votes, they also provide some evidence that it may be important to be directly involved in bank supervision rather than a passive recipient of the data. They show suggestive evidence that CAMEL ratings may vary by size of institution and that knowledge of how the rating is being applied, as well as the actual rating given, may be information relevant for monetary policy.

IV. Conclusion

This paper provides evidence that the finding in PRT, that information about banks' CAMEL ratings improves on commercial macroeconomic forecasts, applies consistently to individual forecasts as well as pooled forecasts. The robustness of the result indicates that confidential bank supervisory information, of which CAMEL ratings are a subset, should be utilized by a central bank to improve on macroeconomic forecasts. This also implies that important synergies may exist between the information gathered in bank exams and the central bank's responsibility for conducting monetary policy. Loss of bank supervisory responsibilities may reduce the ability of the central bank to understand the nuances in supervisory data, making the data potentially less useful in quantitatively or qualitatively adjusting forecasts of the economy. Thus, removing bank supervisory responsibilities from a central bank, as has been done in some other countries, including England, potentially can have costs to other central bank responsibilities such as the conduct of monetary policy.

While this study examines only one possible cost to the central bank of having no supervisory authority, the possible loss to macroeconomic forecasts used for monetary policy, many other areas of central bank responsibility might also be affected. For example, operating the discount window, serving as a lender of last resort, is also likely to benefit from having "hands-on" knowledge of banks obtained through bank supervision. The central bank may also be able to better control risk in the payments system and be better prepared for a systemic crisis if it has some bank supervisory responsibilities. These are important issues for central bank operations that are not addressed in this paper.

That the confidential supervisory information can improve macroeconomic forecasts suggests that the private sector could also benefit from enhanced disclosure of this information. Supervisory assessments of individual banks are not released in most countries because of concerns that the data might prove destabilizing to individual banks or to the banking system. However, this research indicates that even highly aggregated information could be useful to private forecasters. Greater release of aggregate assessments of the banking system, based on confidential micro data, might improve macroeconomic forecasts without revealing details that would affect individual financial institutions.

Important synergies may exist between the information gathered in bank exams and the central bank's responsibility for conducting monetary policy.

This research also indicates numerous avenues for future research. To be useful for monetary policy, supervisory information may be most valuable if the content remains useful for a relatively long time. Peek, Rosengren, and Tootell (1999b), in some preliminary work, have found that even supervisory data entered with a substantial lag would still measurably improve macroeconomic forecasts. Furthermore, they find that most of the information content of the aggregate CAMEL ratings is derived from non-publicly traded banks. This is consistent with the information about bank health that improves private-sector forecasts not being publicly available, insofar as much of the information about non-publicly traded banks remains private.

The information content of supervisory information may also provide useful insights into the role of banks in the transmission of monetary policy. If supervisory information is useful because reductions in bank lending reduce macroeconomic activity, then sectors of the economy most affected by bank credit should be the areas most influenced by banking problems. Ongoing research suggests that there may be a causal link, and that this information is not merely a leading indicator. This result provides further evidence that banks may be an important factor in the transmission of monetary policy in the United States and may have an even greater effect in countries where the financing is primarily provided by banks.

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