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DOES CURRENT-QUARTER INFORMATION IMPROVE QUARTERLY FORECASTS FOR THE U.S. ECONOMY?

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Abstract

This paper presents new evidence on the benefits of conditioning quarterly model forecasts on monthly current-quarter data. On the basis of a quarterly Bayesian vector error corrections model, the findings indicate that such conditioning produces economically relevant and statistically significant improvement. The improvement, which begins as early as the end of the first week of the second month of the quarter, is largest in the current quarter, but in some cases, extends beyond the current quarter. Forecast improvement is particularly large during periods of recessions but generally extends to other periods as well. Overall, the findings suggest that it is rational to update one's quarterly forecast in response to incoming monthly data.

1. Introduction

Many business analysts, economists, and policymakers pay close attention to monthly releases of economic data. Business periodicals, such as the *Wall Street Journal*, are filled with experts' commentaries on the previous day's data and what such data may portend for the future health of the U.S. economy. And forward-looking financial markets often react strongly to new data that are reported at unexpected levels, suggesting that such data carry important information about near-term economic fundamentals. However, one need only follow the regular cycle of news releases for a short period of time to realize that the implications of these data can be ambiguous. Experts may disagree about whether yesterday's data suggest stronger or weaker economic growth in the future, higher or lower inflation, or tighter or looser monetary policy. Even more striking, expert commentary on the economy's near-term outlook can change from day to day in response to the release of additional monthly data. Such disagreement naturally begs the question: How useful are the new data reported in monthly statistical releases for forecasting broad measures of U.S. economic performance over the next few quarters? More fundamentally, should an analyst revise his near-term outlook on the basis of such data?

On first thought, monthly data seem very useful. After all, two of the most important measures of economic performance—real GDP and the associated price level—are released only once per quarter. For this reason, most macroeconomic forecasting models are estimated on quarterly data, and, thus, can provide an updated forecast only when a new quarter of data is available. However, if the data contained in monthly statistical releases contain useful information about yet-to-be-released quarterly data, such information may be used to update a quarterly model's forecast before the additional quarterly data are released. For example, the

Bureau of Labor Statistics releases, in February, data on the level of employment in January. To the extent that first-quarter real GDP reflects, in part, the average level of employment over the quarter, knowledge of the level of employment for January may improve the accuracy of a quarterly model's forecast for first-quarter real GDP. Since macroeconomic time series tend to be related intertemporally, such an improvement may even enhance forecast accuracy beyond the first quarter. Statistical procedures used to update a quarterly model's forecasts on the basis of the high-frequency, current-quarter data reported in monthly news releases are known as current-quarter models.

The ambiguity surrounding the implications of monthly data, noted above, suggests an alternative view. In this view, the monthly data are too noisy and not reliably related to quarterly data to be of much use for updating and improving a quarterly model's forecast. According to this view, an analyst would be better to ignore—or, at least, downplay—many of the monthly data releases. This view suggests that the analyst's quarterly forecast should remain roughly unchanged in response to incoming monthly data.

Of course, one need not take an either/or stance on the benefits of the monthly statistical releases because a host of intermediate results are possible: some monthly data may be of use for updating the quarterly forecasts for some variables but not for others. Ultimately, the issue is one that can be settled only by an empirical exercise. This paper conducts such an exercise, by running horse races between forecasts for quarterly variables that incorporate no current-quarter information and forecasts that incorporate increasing amounts of such information. Several questions are of interest. First, does the use of current-quarter information improve the accuracy of a quarterly model's current-quarter forecasts? In the example cited above, does the use of data for the level of employment in January produce a more accurate prediction of first-quarter real GDP than a forecast that ignores the employment data? Second, if the current-quarter quarterly forecast is more accurate, does such improvement extend beyond the current quarter? Third, if there is evidence of forecast improvement, on average, is the improvement largely the result of increased accuracy in a few isolated periods—such as recessions—or, can one be confident in assuming that the use of current-quarter data almost always yields more accurate forecasts?

These questions are addressed within the context of the quarterly Bayesian vector error corrections model described in Stark (1998). The model applies the Bayesian VAR methodology of Litterman (1986) and the idea of cointegration [Engle and Granger (1987)] to a system of seven equations in real GDP, the GDP price index, the rate of unemployment, the M2 money stock, the import price index, and the rates of interest on federal funds and 10-year Treasury bonds. Following Miller and Chin's (1996) methodology, I select a group of 11 variables, all available at a monthly frequency, and combine those variables into an 11-equation monthly Bayesian vector error corrections model. The monthly model generates forecasts for the current-quarter quarterly averages of the monthly data, which are then used to update the quarterly model's forecasts. Formal hypothesis tests of forecast improvement, stemming from the use of increasing amounts of current-quarter monthly data, are based on the recent work of Diebold and Mariano (1995) and Harvey, Leybourne and Newbold (1997).

Formal statistical procedures for incorporating current-quarter data into quarterly forecasting models have been developed by Corrado and Greene (1988), Corrado and Haltmaier (1988), Fitzgerald and Miller (1989), Trehan (1989), Braun (1990), Howrey, Hymans, and Donihue (1991), Rathjens and Robins (1993), and Miller and Chin (1996). In this paper, the procedure of Miller and Chin (1996) is used. The procedures differ in the degree of statistical complexity required to extract the information contained in monthly data and the degree to which they are applicable to multi-equation systems. In this paper, the Miller and Chin procedure is used because it is relatively easy to implement, applicable to multi-equation systems, and easily modified to incorporate varying amounts of current-quarter information.

Thus, the present analysis is related most closely to that of Miller and Chin because both use Bayesian VAR methodologies, with one key difference. The latter is based upon a baseline model—the Minneapolis Fed's quarterly Bayesian VAR—that is specified in the levels of the model's variables. However, a mounting body of research suggests there may be forecasting benefits to specifying statistical models for standard macroeconomic variables in first-differences [Franses and Kleibergen (1996), Christoffersen and Diebold (1997), Duy and Thoma (1998), and Stark (1998)]. To the extent that models specified in levels produce less accurate forecasts, it is possible that there is a bias in favor of finding benefits to the use of current-quarter information in such models. Thus, it seems worthwhile to search for such benefits in a model that is specified in first-differences. The quarterly model mentioned above represents such a model. The present analysis also differs from Miller and Chin's by considering the possibility that forecast improvement may be confined to a few isolated periods, and may not be a general phenomenon.

The results suggest statistically and economically meaningful benefits to updating a quarterly forecast on the basis of incoming monthly data, thus justifying at least some of the attention paid to monthly news releases. To a large degree, most of the benefits of updating appear to cumulate during periods of recessions, but positive benefits also accrue during less turbulent times. These findings appear robust to several experiments, including an extension to an analysis of real-time forecasts.

The remainder of the paper is organized as follows. Section 2 provides a description of the baseline quarterly statistical model that is used to assess the advantages of updating quarterly forecasts with current-quarter information. The section also presents some evidence on how well the model forecasts in the absence of current-quarter information. Section 3 describes the procedure used to update the quarterly forecasts, and Section 4 provides a discussion of some technical details related to estimation and hypothesis testing. The paper's primary results are discussed in Section 5, and Section 6 discusses the robustness of those results to some experiments. Section 7 concludes.

2. A Baseline Quarterly Model: The QBVEC

Model Overview

To test whether current-quarter data can be used to improve on the forecasts of a quarterly model, one needs to have in hand a quarterly model. Stark (1998) presents such a model, consisting of seven equations in log real GDP, the log of the GDP price index, the rate of unemployment, the log of the real M2 money stock, the log of real import prices, and the rates of interest on federal funds and 10-year Treasury bonds. With one exception, the model's specification assumes all variables are integrated of order one. The exception is that the log price level is assumed to be integrated of order two. A cointegration constraint is imposed on the two interest rates, implying that their difference is a stationary variable, and a typical equation in the model—which is estimated in the Bayesian tradition, using Litterman (1986)-like priors—is given by

$$\Delta \log RGDP_t = c + \rho*(RFF - RTB10)_{t-1} + \beta(L)*[\ Q_{t-1}\ ] + e_t$$

where Δlog indicates a log first-difference; RGDP is real GDP; RFF is the rate on federal funds; RTB10 is the rate on 10-year Treasury bonds; Q is a 7 x 1 vector of the model's seven quarterly variables, appropriately differenced; e is a random disturbance; c is the equation's constant; ρ is the error-corrections parameter, which is attached to the error-corrections term representing the spread between the two interest rates; and, $\beta(L)$ is a coefficient polynomial in the lag operator, representing five lags. Taken together, the system of equations is called the QBVEC, to denote the model's quarterly frequency, its Bayesian estimator, and its vector error-corrections structure.

Forecasting Properties

For the purpose of analyzing the benefits of using current-quarter data, one would like some assurance that the chosen baseline quarterly model has reasonable forecasting properties. Otherwise, inference drawn from a model not possessing such properties might be biased in favor of finding benefits to the use of current-quarter data. If the QBVEC forecasts are very inaccurate, it is likely that the use of current-quarter monthly indicator data will yield large benefits in accuracy, benefits that, perhaps, would not exist in a better quarterly model. Stark analyzed the QBVEC's dynamic behavior and forecasting performance and concluded that it possesses reasonable properties on both fronts. However, one shortcoming of that analysis is that it was undertaken on the basis of the most recent (as of that time) data, disregarding the emphasis placed by many macroeconomists on assessing forecast performance in *real* time—that is, using only those data that would have been available to a forecaster when the forecast was made.

In a series of papers, Croushore and Stark (1999a, b, c) describe the construction of a real-time data set, called RTDSM, that can be used to assess the real-time forecasting ability of models like the QBVEC. The data set contains a sequence of vintages or snapshots, each vintage containing the exact time series that would have been available to a forecaster at each point in time in the past, starting with the fourth quarter of 1965. Using that data set, Croushore and Stark (1999a) show that the QBVEC's real-time output-growth forecasts outperform those of simple autoregressive specifications. So, in a horse race against such a simple specification, the QBVEC wins. But many forecasts exist, some better than others, and one wonders how the QBVEC's forecasts compare with those of the professionals—namely, the panelists of the Philadelphia Fed's *Survey of Professional Forecasters.*

To address this question, I used RTDSM to generate a sequence of real-time QBVEC one-year-ahead four-quarter-average forecasts for output growth, inflation, and the rate of unemployment for the period 1992Q1 to 1999Q3.[1] In each quarter, estimation and forecast calculations are based upon the vintage of data that the professionals would have had at their

[1]To minimize the slight current-quarter advantage that the professional forecasters have, I construct the four-quarter averages as the average of forecast steps two through five, not one through four, where the one-step-ahead forecast is that for the current quarter.

disposal when they made their forecasts, and the corresponding forecast errors (actual minus predicted) are constructed using the history associated with the last vintage prior to a NIPA benchmark revision. For example, the one- through five-step-ahead quarterly forecasts that I imagine to have been made in the first quarter of 1992 are based on estimation on RTDSM's February 1992 vintage, and the implied four-quarter-average forecasts are evaluated on the basis of the November 1995 vintage, the last vintage available prior to the late-1995 NIPA benchmark revision.

Figures 1 to 3 compare the QBVEC's forecast errors with those of 14 *Survey of Professional Forecasters'* (SPF) panelists, chosen on the basis of their (nearly) continuous survey participation in the 1990s. All of the panelists are involved in forecasting as a major part of their responsibilities.[2] Each panel of the figures plots quarterly forecast errors, with the QBVEC error plotted first (solid bar), followed by a given forecaster's error (open bar). [Note that some initial observations are missing for some of the SPF panelists.]

Keeping the analysis relatively casual, the general impression one gets from the figures is that there are periods over which the QBVEC does relatively worse than the SPF forecasters, periods over which the QBVEC does better, and periods over which it would be hard to pick a clear-cut winner. Typically, the QBVEC is outperformed in the early 1990s, a consequence of very dramatic overpredictions for output growth (Figure 1), underpredictions for the unemployment rate (Figure 2), and underpredictions for inflation (Figure 3): the figures show that the QBVEC predicted a much stronger recovery from the 1990 recession than was seen at

[2]Confidentiality agreements with the forecasters precludes a listing of the panelists by name.

the time by the SPF forecasters. However, the relative ranking is reversed over the late-1990s, with the QBVEC generally producing more accurate forecasts for all variables. Over the 1990s as a whole, QBVEC appears to yield forecasts that are about as accurate as those of the professional forecasters, suggesting that the model represents a reasonable baseline from which to analyze the benefits of current-quarter information.[3]

3. A Current-Quarter Forecasting Procedure

The Miller and Chin (1996) Procedure

According to the Miller and Chin procedure, one begins by generating a sequence of one-step-ahead forecasts from the baseline quarterly model, in this case the QBVEC. By construction, these forecasts incorporate no current-quarter information. For use below, one can represent these forecasts as $Q_{j,t|t-1}$, where j indicates the variable, and t|t-1 indicates the forecast is for quarter t, made on the basis of information through quarter t-1.

The second step is to specify a monthly statistical model for variables—a set of monthly indicators—that are thought to carry information about each of the variables in the quarterly model. Presumably, the monthly indicators will carry information about the quarterly model's

[3]Though a comparison with individuals' forecasts seems more relevant for the present analysis, I also conducted a similar comparison with the SPF *median* forecasts and found no economically meaningful differences between the two forecasts. Using a longer sample period, the results are as follows: over the period 1980Q1 to 1999Q2, the SPF root-mean-square-errors associated with the median inflation and unemployment forecasts are 1.17 percent and 0.59 percent, respectively. The corresponding root-mean-square-errors for the QBVEC forecasts are 1.04 percent and 0.64 percent. A slightly shorter sample (1982Q3 to 1999Q2) was used for the output-growth forecasts because such forecasts were not included in early surveys: the root-mean-square-errors are 1.72 percent for the SPF median forecast and 1.66 percent for the corresponding QBVEC forecasts.

variables, $Q_{j,t}$, that is not contained in $Q_{j,t|t-1}$. Though many different sets of monthly indicators are possible, and analysts are unlikely to agree on the best set, the choices described below were based on intuition and on a desire to include many of the variables that seem to generate the most attention among analysts. In some cases, the choices are pretty obvious. For example, the QBVEC contains the quarterly average of the monthly values of the federal funds rate, the 10-year Treasury rate and the unemployment rate, so prime candidates for inclusion in the monthly model are, simply, the monthly values of these variables. The QBVEC also contains the quarterly average of M2, so monthly M2 is included in the monthly model, too. Some of the quarterly data, however, do not have exact monthly counterparts, and, in these cases, an analyst must choose from among a number of monthly indicators. In the QBVEC, real GDP and the GDP price index are the quarterly variables without monthly counterparts. For real GDP, reasonable monthly indicators are: the industrial production index, monthly real personal consumption expenditures, housing starts, retail sales, and nonfarm payroll employment. And for the GDP price index, reasonable monthly counterparts are the CPI and PPI. A suitable monthly indicator for the quarterly import price index is somewhat harder to find: A monthly series on import prices is available, but that series does not have enough historical observations to provide for reasonable parameter estimates for use in forecasting over the early part of the sample period that I analyze. So, I do not use the current-quarter procedure to update the import-price forecasts. Together, the monthly model contains 11 variables and is estimated using the Bayesian VAR methodology described above and a cointegrating relation between the rates of interest on Federal funds and 10-year Treasuries.

In the third step, one uses the monthly model to generate sequences of current-quarter quarterly-average forecasts for the monthly indicators, with the quarterly averages constructed from a combination of current-quarter monthly history and monthly forecasts. The exact combination depends on when in the quarter one makes the forecast and on the monthly indicator being forecast. For example, at the end of the first week of the second month of the quarter, the first month's historical values are available for the unemployment rate, nonfarm payrolls, and the two interest rates, but not for the remaining variables. Thus, to compute forecasts for the current-quarter quarterly averages, one needs first-month forecasts for the remaining seven variables and second- and third-month forecasts for all variables: the first is generated by taking a block triangular factorization of the monthly model's innovation variance-covariance matrix and using that factorization to compute first-month forecasts for the remaining seven variables, conditioning those forecasts on the available first-month history; the second is computed in the normal dynamic fashion, by conditioning on the first-month values.

By redefining the dimension of the first block of the triangular factorization—to correspond to the normal staggering of monthly data releases—one can use the procedure at any point during the current quarter to generate quarterly-average forecasts. The results presented below consider six such cases, depending on whether one has one, two, or three months of current-quarter history for interest rates, employment, and the unemployment rate and on whether one also has one, two, or three months of history for the remaining variables, excluding monthly real personal consumption expenditures. Recognizing that the previous month's observations for the first group of variables are available at the end of the first week of each month and that the same is true by the end of the third week for the observations in the second group, these cases correspond to forecasts made early in the month and late in the month, for the second and third months of the current quarter and the first month of the following quarter. In the tables presented below, I refer to these cases as 1.1, 1.2, 2.1, 2.2, 3.1, and 3.2, the first number indicating the number of months of current-quarter history available for the two interest rates, employment and the unemployment rate, and the second indicating whether the forecast is made early in the month (1) or late in the month (2). Table 1 summarizes the information structure represented by these cases.

Armed with quarterly-average monthly indicator forecasts, one forms an updated estimate of the quarterly model's current-quarter forecast, $Q_{j,t|t-1}$, by estimating and forecasting equations of the form

$$Q_{j,t} = \alpha_j^{(k)} + \beta_j^{(k)} Q_{j,t|t-1} + \delta_j^{(k)} M_{j,t|k} + e_{j,t} \qquad (1)$$

where k represents one of the six cases described above; $M_{j,t|k}$ represents a vector of quarterly-average monthly indicator forecasts associated with case k; $e_{j,t}$ is an error term; and $\alpha_j^{(k)}$, $\beta_j^{(k)}$, and $\delta_j^{(k)}$ are parameters. The equation says that each variable in the quarterly model is regressed on a constant, the corresponding one-step-ahead quarterly-model forecast, and on a vector of quarterly-average monthly indicator forecasts. The superscripts on the parameters indicate that the parameters are allowed to vary with k, and the forecast from this equation is denoted $Q_{j,t|(t-1,k)}$. Given a $Q_{j,t|(t-1,k)}$ for each variable in the QBVEC, one uses the quarterly model to generate dynamic multi-step-ahead forecasts in the usual fashion, by conditioning on the updated current-quarter forecasts.

Of particular interest is whether $Q_{j,t|(t-1,k)}$ is a better forecast than $Q_{j,t|t-1}$. Interest also centers on the relative merits of the corresponding multi-step forecasts, given by $Q_{j,\tau|(t-1,k)}$ and $Q_{j,\tau|t-1}$ for $\tau \rangle$ t.

A Simple Current-Quarter Specification

Equation (1) allows one to use a wide variety of current-quarter information because one is free to specify the vector of current-quarter predictors, $M_{j,t|k}$, narrowly or broadly. After some initial experimentation, I found that a broad specification tends to add very little to forecasting performance—suggesting that simple, parsimonious specifications may be sufficient to extract the information contained in the monthly data releases. Indeed, for all quarterly-model variables except real GDP, I've specified $M_{j,t|k}$ to include the forecast of just one monthly indicator.

When a variable appears in both the monthly and quarterly models (the rate of unemployment and the two interest rates), one gives up very little in forecasting performance by imposing the restrictions $\alpha_j^{(k)} = 0$, $\beta_j^{(k)} = 0$, and $\delta_j^{(k)} = 1.0$. For these variables, the updated current-quarter forecast is simply that given by the monthly model, as in Miller and Chin.

For (real) M2 forecasts, I use a variation of this approach: quarterly average *nominal* M2 forecasts are taken from the monthly model, and the updated quarterly forecasts are obtained by dividing the nominal forecasts by the updated forecasts for the GDP price index.

The current-quarter specifications for the GDP price index and real GDP are given in the following equations:

$$\Delta^2 \log PGDP_t = \alpha_1^{(k)} + \beta_1^{(k)} \Delta^2 \log PGDP_{t|t-1} + \delta_1^{(k)} \Delta^2 \log CPI_{t|k} + e_{1,t} \qquad (2)$$

$$\Delta \log RGDP_t = \alpha_2^{(k)} + \beta_2^{(k)} \Delta \log RGDP_{t|t-1} + \delta_{21}^{(k)} \Delta \log RPCE_{t|k} + \delta_{22}^{(k)} \Delta \log N_{t|k} + \delta_{23}^{(k)} \Delta \log IP_{t|k} + e_{2,t} \quad (3)$$

Equation (2) indicates that the first-difference of the GDP inflation rate ($\Delta^2 \log PGDP_t$) is regressed on a constant, the quarterly model's one-step-ahead forecast for the change in the inflation rate ($\Delta^2 \log PGDP_{t|t-1}$), and on the monthly model's current-quarter quarterly-average forecast for the first-difference of the CPI inflation rate ($\Delta^2 \log CPI_{t|k}$), where the CPI forecast is conditioned on the number of months of current-quarter data available, as indexed by k, and on the lags in the monthly model. Equation (3) indicates that real GDP growth ($\Delta \log RGDP_t$) is regressed on a constant, the quarterly model's one-step-ahead forecast ($\Delta \log RGDP_{t|t-1}$), and on a vector of current-quarter quarterly-average monthly indicator forecasts for: the rate of growth in quarterly-average real personal consumption expenditure ($\Delta \log RPCE_{t|k}$), the rate of growth in quarterly-average nonfarm payroll employment ($\Delta \log N_{t|k}$), and the rate of growth in the quarterly-average industrial production index ($\Delta \log IP_{t|k}$). This specification is closely related to that of Ingenito and Trehan (1996). In both equations, superscripts on the coefficients allow the coefficients to vary with the amount of available current-quarter monthly history.

Of the six current-quarter specifications, only those for inflation and real GDP have potentially interesting parameter estimates because estimates of the remaining equations' parameters are derived by constraint. Tables 2.A and 2.B show the parameter estimates and t-statistics associated with these two specifications, using the sample period 1970Q1 to 1998Q2 for each of the six cases indexed by k. Using conventional statistical tests, both tables show that there are significant correlations between the monthly indicator forecasts and the quarterly model's variables. Table 2.A shows that quarterly- and monthly-model inflation forecasts carry significant coefficients in the GDP price equation, though the quarterly-model forecasts have a coefficient about four times larger than that associated with the monthly-model forecasts: Regardless of the number of months of current-quarter information, the quarterly-model forecast has a coefficient of about 0.8 and the monthly-model CPI forecast carries a coefficient of about 0.2. As the number of months of current-quarter information increases—toward three months of CPI data, in case 3.2—the t-statistic on the coefficient attached to the monthly-model forecast rises.

Table 2.B shows that, in general, the monthly model's forecasts enter significantly in the GDP equation. Indeed, the monthly model's forecasts dominate the quarterly model's forecast, with the latter entering in an insignificant fashion—and with a negative sign. The coefficients on the real personal consumption expenditure and nonfarm payroll forecasts are positive, (mostly) increasing in k, and (mostly) increasing in significance as k increases.

These results hint that monthly data releases may carry important information for use in updating a quarterly model's forecasts. But these are in-sample results, and important questions remain about whether monthly data releases carry information for improving out-of-sample forecast accuracy and about the magnitude of such improvement.

4. Technical Issues

In assessing the empirical benefits of updating a quarterly forecast, one would like to use real-time data for estimation and forecasting and a formal statistical test for assessing relative performance. Unfortunately, though RTDSM can be used for the data in the QBVEC and for some of the data in the monthly model, such data have not been assembled for many of the key monthly indicators—in particular, nonfarm payrolls, industrial production, retail sales, monthly real personal consumption expenditures, and housing starts. Thus, the results presented below are based on the data as they existed on August 1, 1998. However, an element of realism is added to the analysis by estimating the models, at each time period, on the *number* of observations that would have been available to a forecaster in real time: a rolling regression procedure, described below, is used at all stages of the analysis. The Diebold and Mariano (1995) test is used to assess the relative forecast performance of one- through eight-step-ahead forecasts that, alternatively, exclude and include current-quarter information.

A Rolling Regression Procedure

To mimic the information structure represented by case 1.1, the rolling regression procedure begins by estimating the monthly model on data over the period January 1959 to December 1969 and generating the 1970Q1 current-quarter quarterly-average forecast for each monthly indicator. The sample is then advanced by three months, the model is reestimated, and a second type-1.1 quarterly-average forecast, for 1970Q2, is generated. The procedure is repeated until a sequence of 1.1-type forecasts is generated over the period 1970Q1 to 1998Q2.[4] A similar procedure is used for the remaining cases, but to mimic the information structure of cases 2.1 and

[4]To ease the computational burden of the procedure, *each* element of the forecast sequence is generated on the basis of estimation through the period before the forecast date. For this reason, the forecast sequence may incorporate less information than a sequence generated in real time because it is computationally easier to generate, in real time, a new historical sequence of forecasts each quarter than it is to do so after the fact.

2.2, the first estimation ends in January 1970, reflecting the fact that, in these cases, the January value is observed for all variables in the monthly model, as shown in Table 1. An analogous sample extension is used in cases 3.1 and 3.2.

Armed with sequences of type 1.1 through type 3.2 monthly indicator forecasts, the current-quarter specifications, represented by equation (1), are estimated on data beginning with 1970Q1, the first quarter for which the forecasts are available, and the first rolling sample ends in 1979Q4, from which the first sequence of one- through eight-step-ahead updated quarterly-model forecasts incorporating current-quarter information are generated (for the period 1980Q1 to 1981Q4). A competing set of forecasts that do not incorporate current- quarter information is also generated.

Using this procedure, I generate 74 one-step-ahead forecasts for the period 1980Q1 to 1998Q2, 73 two-step-ahead forecasts for the period 1980Q2 to 1998Q2, and so on. The sample periods were chosen to permit enough observations for reliable parameter estimation, leaving enough forecast periods from which to analyze the benefits of current-quarter information over a few recessions.

Assessing Statistical Significance With the S_1 Statistic

Economists often analyze the forecasting performance of competing models by comparing the values of forecast-error statistics—such as the mean-absolute-error or the root-mean-square-error—with no allowance for randomness. The problem with such an approach is that it does not account for the possibility that differences in error statistics can occur by chance. A formal statistical test is required to account for such possibilities. So why have economists adopted the approach? According to Diebold and Mariano (1995), the answer is that forecast errors are characterized by several features that hamper the construction of a statistically valid test. For example, the errors associated with multi-step forecasts can be shown to follow moving average processes, indicating that such errors are serially correlated—a fact that must be accounted for in the design of a test statistic. Also, reflecting the existence of macroeconomic shocks, the errors associated with competing forecasts tend to be correlated contemporaneously, invalidating the use of traditional F-statistics constructed from the ratio of cumulative squared forecast errors. Finally, forecast errors may be non-Gaussian, which also complicates traditional statistical inference.

Diebold and Mariano showed that it is possible to construct a test statistic that accounts for these features of forecast errors. The statistic (called S_1), which takes its asymptotic properties from a version of the central limit theorem extended to the case of serially correlated but stationary random variables, is quite general and can be employed under a variety of loss functions. Here, I use the statistic to test for a statistically significant difference in mean-square-errors, using the null hypothesis H_0: $MSE(0)_{1,S} = MSE(k)_{2,S}$, where $MSE(0)_{1,S}$ denotes the QBVEC's S-step-ahead mean-square-error based on zero months of current-quarter information, and $MSE(k)_{2,S}$ denotes the same for the QBVEC when current-quarter information of type k is used to condition the forecast, for k = case 1.1, 1.2,..., 3.2, and S= 1 (current quarter), 2,...,8.

If one denotes the period-t loss differential by $d_t = (e_{1t})^2 - (e_{2t})^2$, where e_1 and e_2 are the competing forecast errors, the estimated mean loss differential by d, the estimated asymptotic variance of d by v(d), and the estimated jth autocovariance of d_t by γ_j, the test statistic is given by

$$S_1 = d[v(d)]^{-½} \rightarrow N(0,1)$$

where $\rightarrow$ N(0,1) indicates that the statistic behaves, asymptotically, as a normally distributed random variable with a mean of zero and a variance of unity under the null hypothesis. Diebold and Mariano recommend using a rectangular lag window for the construction of v(d) such that, for a sample of size T,

$$v(d) = T^{-1}[\ \gamma_0 + 2\ (\ \gamma_1 + \gamma_{2\ +} \ldots + \gamma_{S(T)}\ )] \qquad (4)$$

where S(T) represents the truncation lag. Following Diebold and Mariano, I set the truncation lag, S(T), to S-1 to reflect the fact that optimal S-step-ahead forecast errors follow MA(S-1) stochastic processes.

The S_1 statistic is constructed, simply, as the ratio of an average to the average's standard error. However, there are two empirical problems associated with the statistic. First, Diebold and Mariano report results suggesting that the statistic's empirical size tends to exceed its nominal size, especially in small samples—that is, the test rejects the null hypothesis too often. Noting the problem, Harvey, Leybourne, and Newbold (1997), (HLN), suggest a small-sample correction obtained by multiplying S_1 by a scalar that depends on the forecast step and sample size, and they recommend using a Student's t distribution with (T-1) degrees of freedom for assessing statistical significance. I calculated the HLN variant, used the t distribution, and found no important differences compared with the original formulation—an indication that the sample sizes under consideration are too large for the corrections to have much effect.

A second problem is that the asymptotic variance estimate given in (4) need not be positive, as noted by Diebold and Mariano. When a nonpositive estimate occurs, I reconstruct S_1, using a Bartlett lag window for v(d) and the same truncation parameter.[5] These cases are indicated by an "a" in the tables that follow.

[5]See Hamilton (1994) for a discussion of this window.

5. Results

The paper's primary results appear in Tables 3.A to 3.F. For the first-difference and level of each variable in the QBVEC, the tables show, in bold, the root-mean-square-error (RMSE) statistics associated with the baseline QBVEC forecast and each of the six forecasts that incorporate current-quarter information. Statistics are shown for the one- through four-step-ahead forecast and for the eight-step-ahead forecast.[6] The last six columns show, in parentheses, the value of the S_1 statistic and the associated two-tailed p-value for the test of equality of mean-square-errors (MSE). As noted, each test is a test of equality between the MSE corresponding to the column labeled "base" and that corresponding to one of the remaining columns. When S_1 takes a positive value, the corresponding MSE is less than that of the baseline, indicating that the incorporation of current-quarter information produces a more accurate forecast. Low p-values—say, less than 0.10—indicate a statistically significant difference between the competing forecasts' MSEs and hence a rejection of the null hypothesis of equality.

Since there are a large number of test results to digest, I'll first summarize the broad conclusions. A more detailed analysis of the findings for each variable appears below.

- In most cases, the incorporation of current-quarter information yields a lower RMSE and hence an improvement in forecast accuracy. In general, the differences are statistically

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[6]The RMSE is shown rather than the MSE, on which the tests are based, because the former preserves the units of the data and because the RMSE may be more familiar. The RMSE also provides a more direct (rough) guide to assessing the economic significance of differences in forecast performance: one can use the rule-of-thumb that a two standard error confidence interval for the forecasts is approximated by ±2RMSE and then compare the size of the competing confidence intervals.

significant. In those cases in which the RMSE is higher, there is rarely a statistically significant difference in the corresponding MSEs, with one prominent exception.

- Surprisingly, the forecasts for GDP inflation tend to be *less* accurate when conditioned on the within-quarter monthly CPI forecasts, though in most cases, the differences are not statistically significant. When a statistically significant difference occurs, the magnitude of the difference is of little economic significance.
- In most cases, the improvement in accuracy for the forecasts for first-differences afforded by the incorporation of current-quarter data extends only to the current-quarter. For the forecasts for the corresponding levels, statistically (and economically) significant differences in forecast accuracy can extend beyond the current quarter.
- In broad terms, the use of current-quarter information appears to improve forecast accuracy. This implies that some revision to a quarterly model's forecast represents a reasonable response to incoming monthly statistical releases.

Real GDP Forecasts

Table 3.A shows the results for the real GDP forecasts. As an example in interpreting the reported numbers, consider the first cell in the column labeled 1.1 (upper panel). The RMSE of one-step-ahead forecast for real GDP growth, given one month of current-quarter data on interest rates, employment, and the unemployment rate, is 2.41. The next two numbers are the S_1 test statistic (2.51) and the two-tailed p-value (0.01) for the null hypothesis of no difference between the squared RMSE in the first column (3.04^2) and that in the second column.

For the forecasts for the growth in real GDP (upper panel), the use of current-quarter information yields a statistically significant difference in one-step-ahead forecast accuracy, and the improvement reaches a maximum once two months of current-quarter information are incorporated into the forecast, as can be seen by looking across the top row. Looking down a given column, one sees no economically meaningful difference in forecast accuracy beyond that of the current quarter. In contrast, the lower panel shows statistically significant effects on the forecasts for the level of real GDP through the three-step-ahead horizon.

GDP Inflation Forecasts

Table 3.B shows that the use of current-quarter information on the CPI tends to worsen the GDP inflation (and price level) forecasts relative to the base forecasts that do not incorporate the information: In all cases, the test statistic is negative, though a comparison of the RMSEs suggests there's not much economic significance to the differences. It's worth noting that even when three months of CPI observations are known (column 3.2), the difference in RMSEs remains negative and negligible, even at the one-quarter horizon. These results are quite surprising given the previous finding that CPI forecasts tend to enter the current-quarter equation in a statistically significant manner. Below, I describe a robustness check on these results.

Unemployment Rate Forecasts

Table 3.C shows that the use of current-quarter data for the monthly unemployment rate has large, statistically significant, and relatively long-lived effects on the accuracy of the quarterly forecasts. With just one month of current-quarter data, the RMSE is reduced by half, from 0.27 to 0.12 (top row, column 1.1). Though economically significant effects do not extend past the one-quarter horizon in first-differences, such effects extend through the three-quarter horizon, in levels. Note that the one-step-ahead RMSEs associated with columns 3.1 and 3.2 are zero because all three current-quarter monthly values of the unemployment rate are known, as shown in Table 1.

Interest Rate Forecasts

An interesting contrast arises in connection with the two interest rate forecasts. For the 10-year Treasury-rate forecasts (Table 3.E), the use of one-month of current-quarter data has a statistically significant effect on the MSE, reducing the associated RMSE from 0.68 to 0.35 (first row, column 1.1). In levels, a statistically significant effect exists through the four-step horizon, though the economic significance of the effect diminishes somewhat at the longer horizons. In contrast, having one month of current-quarter data on the funds rate does not yield a statistically significant effect on the one- and two-step-ahead MSEs (Table 2.D), even though the corresponding reduction in the one-step-ahead RMSE, from 1.18 to 0.83, appears large.

Not surprisingly, having two months of current-quarter data yields sizeable (and significant) increases in the accuracy of the forecasted level of both rates (column 2.1), which extends through the four-step-ahead horizon.

Real M2 Forecasts

Table 3.F shows that the use current-quarter information yields a statistically significant effect on the accuracy of forecasts for the growth in real M2. Indeed, with only one month of history for interest rates and labor-market measures, the RMSE falls from 2.89 to 2.33, and this is associated with a statistically significant reduction in the MSE (upper panel, column 1.1). With the incorporation of additional current-quarter data, the increase in accuracy extends beyond the one-quarter horizon, as shown in columns 2.1 and 2.2. At the three-, four-, and eight-step horizons, there is a reduction in forecast accuracy, but that reduction is not statistically significant.

Summary

Taken as a whole, the statistical results suggest that one can improve upon the accuracy of a quarterly model's forecasts by conditioning those forecasts on current-quarter information. With the exception of the forecasts for quarterly GDP inflation, there is evidence of economically meaningful and statistically significant forecast improvement in the current quarter and, in some cases, in the quarters beyond the current quarter. In many cases, the improvement begins with forecasts generated as early as the end of the first week of the second month of the quarter.

6. Robustness Checks

Economists know that statistical results can be fragile and that it's often desirable to subject such results to various robustness checks. In the present analysis, the most obvious source of concern is the lack of real-time data, a concern that is only partially—and unsatisfactorily—analyzed below. But there are some other concerns as well. This last section addresses those concerns and concludes that the main findings are robust to the checks described below.

Excess Serial Correlation

In applying the Diebold and Mariano test, I used a rectangular lag window and set the value of the truncation parameter to the number of forecast steps minus one, a choice motivated by Diebold and Mariano's observation that an optimal S-step-ahead forecast error follows an MA(S-1) stochastic process. But in practice, forecast errors may exhibit a degree of serial correlation in excess of that implied by an optimal forecast—for a variety of reasons, including parameter instability, nonlinear data generating processes and omitted variables. In such cases, the S_1 statistic, so computed, may give misleading results, and it is advisable to increase the number of autocovariances used to estimate v(d) and recompute the statistic.

For each of the tests conducted in Tables 3.A to 3.F, I plotted the autocorrelations of the period-t loss differential along with two-standard-error Bartlett confidence intervals [Granger and Newbold (1986), p. 81] and checked for the existence of a significant autocorrelation at a lag that would not have been accounted for by Diebold and Mariano's rule-of-thumb for setting the value of the truncation parameter. I detected about 50 such instances.

Figure 4 depicts a typical situation, associated with the three-step-ahead forecast for the growth in real GDP. The first three rows show the forecast sequences and corresponding historical values associated with the baseline forecast (left side) and the current-quarter-information-inclusive forecast for case 1.2 (right side), the associated forecast errors, and the squared errors. The fourth row plots the period-t loss differential (left side) and its autocorrelations and two-standard-error bands (right side). With a minor exception at the third lag, the autocorrelations are not statistically significant, and I do not recompute the S_1 statistic in a case like this. Figure 5 shows a more pronounced violation: The two-step-ahead loss differential for the federal funds rate displays a significant (and relatively large) autocorrelation at the third lag, a lag not reflected in the computation of the S_1 statistic. In this situation, the statistic must be recomputed to account for the influence of the correlation.

In recomputing the S_1 statistics, I found no reversals of the broad findings listed above. The main effect of the correction is to make some of the results a bit less significant than is suggested in Tables 3.A to 3.F. For example, only four tests of the forecasts for real GDP are affected by the presence of significant autocorrelations at lags not already accounted for in the statistics presented in Table 3.A: the two-step-ahead forecasts for the first-difference and level associated with cases 3.1 and 3.2. The new p-values for the first-difference forecasts are 0.53 and 0.54, slightly larger than the original p-values of 0.39 and 0.40. However, note that the null hypothesis is not rejected under either the old or new p-values. The new p-values associated with the level forecasts are 0.02 and 0.02, also slightly larger than the original values of 0.00 and 0.00, indicating that the null hypothesis is rejected under both sets of p-values, at conventional levels of significance. In this example, the new p-values do not alter the conclusions.

The federal funds rate loss differentials are particularly prone to excess serial correlation. Though no conclusions are overturned in the new tests, it is worth noting that the p-values for the one-step-ahead tests, in cases 2.1 and 2.2, rise from 0.01 (in both cases) to 0.09 (in both cases).[7] This is a surprising result because cases 2.1 and 2.2 assume two months of current-quarter data are available for the funds rate. It's hard to explain why current-quarter data on the funds rate seem to yield such relatively weak test results, but one suspects the monthly VAR specification, in combination with the lack of real-time monthly indicator data, is to blame—a guess bolstered by Rudebusch's (1998) observation that VAR-based funds-rate forecasts are particularly poor. In this regard, it is worth noting that excess serial correlation does not appear to be a problem for the 10-year-rate loss differentials.

The Influence of Recessions

In the introduction, I asked whether the benefits of using current-quarter data are uniform over the sample or whether the benefits appear to be concentrated solely around particularly turbulent periods of time—such as recessions. While the ability to forecast with more accuracy around periods of recessions is important, it is also important to know whether such benefits come at the expense of poorer forecasts during periods of time when the risk of recession seems minimal. One way to address this question is to examine a series of time-series plots of the period-t loss differential, d_t, associated with the mean-square-error criterion. To keep the analysis manageable, I only examine one-step-ahead loss differentials for one of the six cases: Figures 6.A to 6.F show the loss differentials (and components) associated with case 1.2, the case that assumes the availability of one month of current-quarter historical values for all monthly

[7]The associated autocovariance estimates, at lags zero through two, are: for case 2.1, 22.605, -1.056, 13.264; and, for case 2.2, 22.612, -1.050, 13.272. The sample size (T) is 74, and the mean loss differential is 1.356 (in both cases).

indicators, except real personal consumption expenditures. The forecasts associated with this case are those assumed to have been made at the end of the third week of the second month of the current quarter, and the panels are constructed in the same manner as those shown in Figures 4 and 5. In particular, note that the loss differentials are constructed by subtracting the type-1.2 squared error from the baseline squared error, implying that positive differentials are associated with positive benefits to the use of current-quarter data.

The figures show much larger (positive) benefits to current-quarter data usage during periods of recession (1980Q1 to 1980Q3, 1981Q3 to 1982Q4, and 1990Q3 to 1991Q1) than during periods of relative stability. Figure 6.A, for real GDP growth, shows huge benefits over the period 1980 to 1982 and somewhat smaller—but still relatively large—benefits in 1990. [These benefits can also be seen in the top row, which plots the forecasts (baseline on the left side; current-quarter-information-inclusive on the right side) and historical values.] Most importantly, even though the bulk of the total benefit accrues during periods of recessions, it is clear that there are positive benefits throughout the entire sample.

In contrast, there are no obvious benefits to using current-quarter data to modify the inflation forecasts (Figure 6.B).

The unemployment loss differential displays a pattern similar to that of the real GDP loss differential (Figure 6.C). There are big positive benefits during periods of recession, particularly during the first two recessions, and smaller benefits throughout the non-recession periods. Indeed, isolated periods in which the use of current-quarter data harms forecast accuracy are rare and the differential losses small.

In figures 6.D and 6.E, one sees, again, an interesting contrast between the benefits to using current-quarter data to modify the forecasts for the federal funds rate and those to modify the forecasts for the 10-year rate. For the funds rate, the benefits accrue largely during the two recessions in the 1980s (Figure 6.D); the benefits are more evenly distributed for the 10-year rate (Figure 6.E). In both cases, the benefits are mostly positive throughout the sample.

Figure 6.F shows that the loss differentials associated with the forecasts for real M2 growth are large and positive during recessions. And on average, there are positive benefits during the non-recession periods.

Taken together, the results suggest there are disproportionately large benefits to using current-quarter data during periods of recessions and smaller—though positive—benefits during other periods of time.

CPI Forecasts

One of the most surprising results in the paper is that the use of current-quarter information for the CPI appears to have no significant positive effect on the accuracy of quarterly forecasts for GDP inflation. Since the two measures are based on different sets of goods, one might expect any such effect to be small, but still positive—especially since it is well known that most measures of inflation track each other well over long periods of time. Even more mysterious is the fact that financial markets often react strongly to new releases of data for the CPI, possibly because these data may portend changes in broader measures of inflation, like that associated with the GDP price index.

There are a number of explanations for why the empirical results seem at odds with the financial market's reaction. First, the simple specifications used here may not adequately capture the relation between the CPI and GDP measures of inflation. Second, the financial markets might believe, correctly or incorrectly, that monetary policy decisions hinge more on the behavior of the CPI than on the GDP price index, and price assets accordingly. Third, financial markets may be able to process incoming data on the CPI in ways not modeled here. In particular, as a result of frequent large changes in the relative prices of the food and energy components of the CPI, period-to-period movements in the total CPI are often erratic and not matched by similar swings in the GDP price index. One of the ways in which analysts process data on the CPI is to abstract from the volatile food and energy components and focus, instead, on the so-called core rate of inflation. This suggests replacing the total CPI with the core CPI in the monthly model.

I recomputed the tests associated with the inflation forecasts in Table 3.B, replacing the total CPI with the core measure and found no difference in the results. Even with the core measure, there is no benefit to updating the quarterly model's forecast for GDP inflation on the basis of incoming information from the monthly CPI report. Thus, the original results appear robust to an important alternative measure of CPI inflation.

Real-Time Forecasts

As noted above, the present analysis is not based on real-time data, and this represents a serious limitation on the results. How much of a difference can this make? Research by Koenig and Dolmas (1997) suggests the distinction may be important, though, as noted in Croushore and Stark (1999a), Koenig and Dolmas' real-time data sets are constructed in an unusual manner, so it's hard to know how to interpret their results.

The forecasting procedures described above have been in place since November 1998, so it's possible to extend the analysis, over a few quarters, to the real time. The results of such an exercise, shown in Table 4, suggest no reason to alter the broad conclusions outlined above. The table shows, for the period 1998Q4 to 1999Q3, historical values and one-step-ahead (i.e., current-quarter) forecasts from the baseline model and from the model with current-quarter information of type 1.2. Also shown are the squared forecast errors, the associated period-t loss differentials, and the mean-square-errors (MSE). Since these real-time results are based on just four current-quarter forecasts, it's not reasonable to push them too hard. In general, the current-quarter-information-inclusive forecasts appear more accurate, and when such a forecast is less accurate than the baseline, the margin of difference is small. It's interesting to note that when there's a big quarter-to-quarter swing in the historical value, that swing seems matched by the current-quarter-information-inclusive forecast, but not by the baseline forecast—as shown by the forecast for growth in real GDP in 1999Q2 and by the forecast for growth in real M2 in 1999Q1. In most instances, the mean-square-error is lower for the current-quarter-information-inclusive forecasts, suggesting little reason to qualify any previous results.

7. Summary and Conclusions

This paper presents new evidence on the benefits of conditioning quarterly-model forecasts on the within-quarter information contained in monthly data releases. The results—which are based on three separate statistical models, a quarterly model, a monthly model, and a set of current-quarter forecasting equations—suggest that quarterly forecasts are more accurate when they are conditioned on monthly data. There is also evidence to suggest that the improvement extends beyond the current quarter, particularly for forecasts for the levels of variables. Using a statistical test developed by Diebold and Mariano (1995), I find that the point estimates of differential forecast accuracy are generally significant. Though much of the gain in forecast accuracy accrues during periods of recession, the evidence suggests that additional—though smaller—gains accumulate during non-recessionary time periods, too.

The findings appear robust to several experiments, the most important of which is an extension to a real-time analysis. Though the real-time analysis covers just four quarters, the results are generally encouraging.

The paper's primary shortcoming is that the bulk of its analysis is not based on the use of real-time data, a constraint dictated by the lack of such data for almost all the monthly series analyzed. The Federal Reserve Bank of Philadelphia plans to augment its quarterly real-time data set in that direction, making it possible to conduct better analyses of the benefits of using current-quarter data to improve quarterly forecast accuracy.

Table 1
Information Structure:
Number of Months of Current-Quarter Information Available

Case	RFF	RTB10	N	U	M2	SALES	IP	PPI	CPI	STARTS	RPCE
QBVEC baseline	0	0	0	0	0	0	0	0	0	0	0
1.1	1	1	1	1	0	0	0	0	0	0	0
1.2	1	1	1	1	1	1	1	1	1	1	0
2.1	2	2	2	2	1	1	1	1	1	1	1
2.2	2	2	2	2	2	2	2	2	2	2	1
3.1	3	3	3	3	2	2	2	2	2	2	2
3.2	3	3	3	3	3	3	3	3	3	3	2

Notes. The table shows the number of months of current-quarter monthly indicator data available for forecasting the current-quarter quarterly averages of the variables listed in the columns. The definitions of the variables used in the monthly model are: RFF (rate on Federal funds); RTB10 (rate on 10-year Treasury bonds); N (nonfarm payroll employment); U (rate of civilian unemployment); M2 (M2 money stock); SALES (real retail sales, deflated by the CPI); IP (industrial production index); PPI (producer price index); CPI (consumer price index); STARTS (housing starts); RPCE (real monthly personal consumption expenditures). Taking the first quarter as a reference, case 1.1 corresponds to the information available at the end of the first week of February, case 1.2 to the information available at the end of the third week of February, case 2.1 to the information available at the end of the first week of March, etc.

Table 2.A
Parameter Estimates For The Current-Quarter GDP Inflation Equation
1970Q1 to 1998Q2
Dependent Variable: Δ^2log GDP Price Index

	1.1	1.2	2.1	2.2	3.1	3.2
constant	-0.000 (-0.015)	-0.000 (-0.168)	-0.000 (-0.191)	-0.000 (-0.248)	-0.000 (-0.217)	-0.000 (-0.317)
Δ^2log $PGDP_{t\|t-1}$	0.764 (4.439)	0.777 (4.746)	0.772 (4.730)	0.729 (4.530)	0.729 (4.535)	0.731 (4.575)
Δ^2log $CPI_{t\|k}$	0.165 (2.611)	0.190 (3.632)	0.189 (3.745)	0.221 (4.434)	0.222 (4.475)	0.223 (4.590)

Table 2.B
Parameter Estimates For The Current-Quarter Real GDP Equation
1970Q1 to 1998Q2
Dependent Variable: Δlog Real GDP

	1.1	1.2	2.1	2.2	3.1	3.2
constant	0.002 (1.397)	0.001 (0.754)	0.001 (1.388)	0.000 (0.159)	0.000 (0.313)	0.000 (0.200)
Δlog $RGDP_{t\|t-1}$	-0.115 (-0.863)	-0.154 (-1.401)	-0.117 (-1.275)	-0.061 (-0.685)	-0.016 (-0.177)	-0.008 (-0.093)
Δlog $RPCE_{t\|k}$	0.314 (2.147)	0.499 (4.288)	0.445 (4.963)	0.496 (5.993)	0.446 (5.589)	0.458 (5.922)
Δlog $N_{t\|k}$	0.211 (1.000)	0.233 (1.373)	0.246 (1.650)	0.371 (2.574)	0.393 (2.658)	0.419 (2.893)
Δlog $IP_{t\|k}$	0.287 (3.594)	0.278 (4.606)	0.266 (4.935)	0.225 (4.329)	0.217 (4.053)	0.204 (4.068)

Notes. The tables show parameter estimates and associated t-statistics (in parentheses) for the inflation and real GDP current-quarter specifications. The column headers denote the number of months of current-quarter history available for forecasting the quarterly average of the monthly indicators. t|t-1 indicates a one-step-ahead forecast from the quarterly model, and t|k denotes a current-quarter quarterly-average forecast from the monthly model.

Table 3.A

Diebold/Mariano Test Results For Real GDP, 1980Q1 to 1998Q2, Various Forecast Steps

Growth Rate: 400*Δ Log (Real GDP)

	Base	1.1	1.2	2.1	2.2	3.1	3.2
1-Step-Ahead	**3.04**	**2.41** (2.51) (0.01)	**2.05** (3.39) (0.00)	**1.76** (3.51) (0.00)	**1.78** (3.53) (0.00)	**1.82** (3.35) (0.00)	**1.80** (3.30) (0.00)
2-Step-Ahead	**2.89**	**2.93** (-0.43) (0.67)	**2.91** (-0.26) (0.79)	**3.01** (-0.77) (0.44)	**3.00** (-0.70) (0.48)	**3.01** (-0.86) (0.39)	**3.01** (-0.85) (0.40)
3-Step-Ahead	**3.07**	**3.01** (0.50) (0.62)	**2.99** (0.87) (0.39)	**2.78** (1.00) (0.32)	**2.75** (1.12) (0.26)	**2.75** (1.15) (0.25)	**2.75** (1.15) (0.25)
4-Step-Ahead	**3.14**	**3.29a** (-1.10) (0.27)	**3.30a** (-1.23) (0.22)	**3.14a** (0.03) (0.98)	**3.11a** (0.21) (0.84)	**3.16a** (-0.19) (0.85)	**3.16a** (-0.17) (0.87)
8-Step-Ahead	**3.07**	**3.07** (0.05) (0.96)	**3.04** (1.01) (0.31)	**3.10** (-0.38) (0.71)	**3.11** (-0.44) (0.66)	**3.07** (-0.03) (0.98)	**3.07** (-0.01) (0.99)

Log Level: 100*Log (Real GDP)

	Base	1.1	1.2	2.1	2.2	3.1	3.2
1-Step-Ahead	**0.76**	**0.60** (2.51) (0.01)	**0.51** (3.39) (0.00)	**0.44** (3.51) (0.00)	**0.45** (3.53) (0.00)	**0.45** (3.35) (0.00)	**0.45** (3.30) (0.00)
2-Step-Ahead	**1.24**	**1.01** (2.47) (0.01)	**0.97** (2.58) (0.01)	**0.91** (2.70) (0.01)	**0.88** (3.13) (0.00)	**0.87** (3.00) (0.00)	**0.87** (2.97) (0.00)
3-Step-Ahead	**1.60**	**1.48** (1.17) (0.24)	**1.43** (1.58) (0.11)	**1.38** (2.08) (0.04)	**1.35** (2.42) (0.02)	**1.33** (2.41) (0.02)	**1.32** (2.43) (0.01)
4-Step-Ahead	**1.87**	**1.90** (-0.21) (0.83)	**1.84** (0.24) (0.81)	**1.74** (1.10) (0.27)	**1.70** (1.40) (0.16)	**1.71** (1.04) (0.30)	**1.71** (1.03) (0.30)
8-Step-Ahead	**3.04**	**2.95** (1.49) (0.14)	**2.88** (2.63) (0.01)	**2.81** (2.68) (0.01)	**2.79** (3.08) (0.00)	**2.75** (2.75) (0.01)	**2.75** (2.76) (0.01)

Notes. The cells record the root-mean-square-error in bold and (excluding the first column) the Diebold/Mariano test statistic and associated two-tailed p-value in parentheses. Each p-value is for the null hypothesis that the corresponding mean-square-error in a given column equals that in the first column. An "a" indicates that the Bartlett lag window is used to construct the corresponding test statistic. The first column corresponds to the baseline QBVEC; the remaining columns correspond to increasing amounts of current-quarter information, as described in the text.

Table 3.B
Diebold/Mariano Test Results For GDP Price Index, 1980Q1 to 1998Q2, Various Forecast Steps

Growth Rate: 400*Δ Log (GDP Price Index)

	Base	1.1	1.2	2.1	2.2	3.1	3.2
1-Step-Ahead	**0.80**	**0.81** (-0.35) (0.72)	**0.83** (-0.50) (0.62)	**0.83** (-0.46) (0.64)	**0.84** (-0.47) (0.64)	**0.84** (-0.47) (0.64)	**0.84** (-0.44) (0.66)
2-Step-Ahead	**1.05**	**1.06** (-0.60) (0.55)	**1.13** (-1.23) (0.22)	**1.10** (-2.03) (0.04)	**1.08** (-1.69) (0.09)	**1.07** (-4.90) (0.00)	**1.06** (-1.49) (0.14)
3-Step-Ahead	**1.03**	**1.08** (-0.78) (0.43)	**1.13** (-1.00) (0.32)	**1.16** (-1.08) (0.28)	**1.18** (-0.97) (0.33)	**1.19** (-0.99) (0.32)	**1.18** (-0.95) (0.34)
4-Step-Ahead	**1.16**	**1.18** (-0.43) (0.67)	**1.18** (-0.40) (0.69)	**1.19** (-0.52) (0.61)	**1.20** (-0.76) (0.45)	**1.20** (-0.81) (0.42)	**1.19** (-0.70) (0.48)
8-Step-Ahead	**1.75**	**1.77** (-0.18) (0.86)	**1.79** (-0.58) (0.56)	**1.80** (-0.87) (0.38)	**1.76** (-0.20) (0.84)	**1.77** (-0.45) (0.65)	**1.76** (-0.07) (0.95)

Log Level: 100*Log (GDP Price Index)

	Base	1.1	1.2	2.1	2.2	3.1	3.2
1-Step-Ahead	**0.20**	**0.20** (-0.35) (0.72)	**0.21** (-0.50) (0.62)	**0.21** (-0.46) (0.64)	**0.21** (-0.47) (0.64)	**0.21** (-0.47) (0.64)	**0.21** (-0.44) (0.66)
2-Step-Ahead	**0.41**	**0.42** (-1.05) (0.29)	**0.45** (-1.92) (0.05)	**0.44a** (-0.91) (0.36)	**0.44a** (-0.71) (0.48)	**0.43a** (-0.63) (0.53)	**0.43a** (-0.52) (0.60)
3-Step-Ahead	**0.58**	**0.61** (-0.94) (0.35)	**0.66** (-1.05) (0.30)	**0.64** (-1.01) (0.31)	**0.65** (-0.94) (0.35)	**0.65** (-0.93) (0.35)	**0.64** (-0.83) (0.40)
4-Step-Ahead	**0.80**	**0.83** (-1.10) (0.27)	**0.87** (-1.03) (0.30)	**0.86** (-1.01) (0.31)	**0.87** (-0.99) (0.32)	**0.87** (-0.98) (0.32)	**0.86** (-0.88) (0.38)
8-Step-Ahead	**2.16**	**2.22** (-0.47) (0.64)	**2.30** (-0.89) (0.37)	**2.29** (-0.91) (0.36)	**2.26** (-0.72) (0.47)	**2.26** (-0.77) (0.44)	**2.24** (-0.56) (0.58)

See notes to Table 3.A.

Table 3.C
Diebold/Mariano Test Results For Unemployment, 1980Q1 to 1998Q2, Various Forecast Steps

First Difference: Δ Unemployment Rate

	Base	1.1	1.2	2.1	2.2	3.1	3.2
1-Step-Ahead	**0.27**	**0.12** (4.57) (0.00)	**0.12** (4.60) (0.00)	**0.05** (5.38) (0.00)	**0.05** (5.36) (0.00)	**0**	**0**
2-Step-Ahead	**0.28**	**0.26** (2.68) (0.01)	**0.26** (2.86) (0.00)	**0.27** (0.97) (0.33)	**0.26** (1.13) (0.26)	**0.26** (1.24) (0.21)	**0.26** (1.27) (0.20)
3-Step-Ahead	**0.28**	**0.29** (-1.23) (0.22)	**0.29** (-0.93) (0.35)	**0.28a** (0.52) (0.60)	**0.27a** (0.78) (0.44)	**0.28a** (0.36) (0.72)	**0.28a** (0.37) (0.71)
4-Step-Ahead	**0.28**	**0.29a** (-0.89) (0.37)	**0.28a** (-0.66) (0.51)	**0.27** (0.69) (0.49)	**0.27** (0.75) (0.46)	**0.28** (-0.74) (0.46)	**0.28** (-0.73) (0.47)
8-Step-Ahead	**0.32**	**0.31** (0.54) (0.59)	**0.31** (2.07) (0.04)	**0.31** (0.58) (0.56)	**0.31** (0.56) (0.57)	**0.31** (0.94) (0.35)	**0.31** (0.94) (0.35)

Level: Unemployment Rate

	Base	1.1	1.2	2.1	2.2	3.1	3.2
1-Step-Ahead	**0.27**	**0.12** (4.57) (0.00)	**0.12** (4.60) (0.00)	**0.05** (5.38) (0.00)	**0.05** (5.36) (0.00)	**0**	**0**
2-Step-Ahead	**0.47**	**0.32** (4.13) (0.00)	**0.31** (4.15) (0.00)	**0.28** (3.95) (0.00)	**0.28** (3.97) (0.00)	**0.26** (3.83) (0.00)	**0.26** (3.84) (0.00)
3-Step-Ahead	**0.64**	**0.52** (2.38) (0.02)	**0.52** (2.47) (0.01)	**0.48** (2.98) (0.00)	**0.47** (3.01) (0.00)	**0.46** (3.09) (0.00)	**0.46** (3.10) (0.00)
4-Step-Ahead	**0.77**	**0.71** (1.26) (0.21)	**0.69** (1.48) (0.14)	**0.65** (3.31) (0.00)	**0.64** (3.38) 0.00)	**0.64** (3.49) (0.00)	**0.64** (3.46) (0.00)
8-Step-Ahead	**0.99**	**1.01** (-0.49) (0.62)	**1.00** (-0.27) (0.79)	**0.90** (1.92) (0.06)	**0.89** (1.99) (0.05)	**0.91** (1.98) (0.05)	**0.91** (1.99) (0.05)

See notes to Table 3.A.

Table 3.D

Diebold/Mariano Test Results For Federal Funds Rate, 1980Q1 to 1998Q2, Various Forecast Steps

First Difference: Δ Federal Funds Rate

	Base	1.1	1.2	2.1	2.2	3.1	3.2
1-Step-Ahead	**1.18**	**0.83** (1.56) (0.12)	**0.83** (1.55) (0.12)	**0.20** (2.45) (0.01)	**0.20** (2.45) (0.01)	**0**	**0**
2-Step-Ahead	**1.29**	**1.29** (0.05) (0.96)	**1.28** (0.30) (0.76)	**1.22** (0.88) (0.38)	**1.22** (0.96) (0.34)	**1.22** (0.94) (0.34)	**1.21** (0.98) (0.33)
3-Step-Ahead	**1.28**	**1.27** (0.16) (0.87)	**1.27** (0.11) (0.91)	**1.25** (0.62) (0.53)	**1.25** (0.59) (0.56)	**1.26** (0.45) (0.65)	**1.26** (0.47) (0.64)
4-Step-Ahead	**1.26**	**1.25** (1.23) (0.22)	**1.25** (1.90) (0.06)	**1.28** (-0.69) (0.49)	**1.27** (-0.48) (0.63)	**1.29** (-1.11) (0.27)	**1.29** (-1.10) (0.27)
8-Step-Ahead	**0.92**	**0.88** (1.18) (0.24)	**0.88** (1.13) (0.26)	**0.85** (1.04) (0.30)	**0.85** (1.05) (0.29)	**0.83** (1.07) (0.29)	**0.83** (1.07) (0.29)

Level: Federal Funds Rate

	Base	1.1	1.2	2.1	2.2	3.1	3.2
1-Step-Ahead	**1.18**	**0.83** (1.56) (0.12)	**0.83** (1.55) (0.12)	**0.20** (2.45) (0.01)	**0.20** (2.45) (0.01)	**0**	**0**
2-Step-Ahead	**1.88**	**1.67** (1.23) (0.22)	**1.66** (1.30) (0.19)	**1.23** (2.84) (0.00)	**1.23** (2.83) (0.00)	**1.22** (3.01) (0.00)	**1.21** (3.00) (0.00)
3-Step-Ahead	**2.13**	**1.90** (3.54) (0.00)	**1.88** (3.26) (0.00)	**1.86a** (1.31) (0.19)	**1.86a** (1.31) (0.19)	**1.86a** (1.19) (0.23)	**1.86a** (1.20) (0.23)
4-Step-Ahead	**2.53**	**2.33a** (2.36) (0.02)	**2.31a** (2.52) (0.01)	**2.18a** (2.17) (0.03)	**2.17a** (2.21) (0.03)	**2.13a** (2.31) (0.02)	**2.13a** (2.31) (0.02)
8-Step-Ahead	**3.28**	**3.26** (0.24) (0.81)	**3.24** (0.43) (0.67)	**3.18** (3.39) (0.00)	**3.17** (3.68) (0.00)	**3.16a** (0.96) (0.34)	**3.16** (22.05) (0.00)

See notes to Table 3.A.

Table 3.E
Diebold/Mariano Test Results For 10-Year Treasury Rate, 1980Q1 to 1998Q2, Various Forecast Steps

First Difference: Δ 10-Year Rate

	Base	1.1	1.2	2.1	2.2	3.1	3.2
1-Step-Ahead	**0.68**	**0.35** (3.89) (0.00)	**0.34** (3.95) (0.00)	**0.10** (4.63) (0.00)	**0.10** (4.63) (0.00)	**0**	**0**
2-Step-Ahead	**0.67**	**0.66** (0.83) (0.41)	**0.67** (0.64) (0.52)	**0.67** (0.51) (0.61)	**0.66** (0.70) (0.49)	**0.67** (0.44) (0.66)	**0.67** (0.46) (0.64)
3-Step-Ahead	**0.65**	**0.64** (1.42) (0.15)	**0.64** (1.42) (0.16)	**0.66** (-0.56) (0.58)	**0.66** (-0.62) (0.54)	**0.66** (-0.40) (0.69)	**0.66** (-0.40) (0.69)
4-Step-Ahead	**0.66**	**0.66** (0.20) (0.84)	**0.66** (0.23) (0.82)	**0.66** (1.18) (0.24)	**0.66** (1.22) (0.22)	**0.65** (1.50) (0.13)	**0.65** (1.49) (0.14)
8-Step-Ahead	**0.63**	**0.63a** (-1.69) (0.09)	**0.63** (-2.47) (0.01)	**0.64** (-1.64) (0.10)	**0.64** (-1.67) (0.09)	**0.64** (-1.83) (0.07)	**0.64** (-1.84) (0.07)

Level: 10-Year Rate

	Base	1.1	1.2	2.1	2.2	3.1	3.2
1-Step-Ahead	**0.68**	**0.35** (3.89) (0.00)	**0.34** (3.95) (0.00)	**0.10** (4.63) (0.00)	**0.10** (4.63) (0.00)	**0**	**0**
2-Step-Ahead	**1.07**	**0.83** (3.69) (0.00)	**0.83** (3.85) (0.00)	**0.70** (3.75) (0.00)	**0.70** (3.78) (0.00)	**0.67** (3.79) (0.00)	**0.67** (3.79) (0.00)
3-Step-Ahead	**1.36**	**1.19** (2.65) (0.01)	**1.19** (2.62) (0.01)	**1.09** (2.69) (0.01)	**1.08** (2.72) (0.01)	**1.07** (2.77) (0.01)	**1.07** (2.77) (0.01)
4-Step-Ahead	**1.67**	**1.52** (3.18) (0.00)	**1.51** (2.81) (0.00)	**1.39** (3.19) (0.00)	**1.39** (3.26) (0.00)	**1.37** (3.30) (0.00)	**1.37** (3.30) (0.00)
8-Step-Ahead	**2.26**	**2.26** (0.06) (0.95)	**2.25** (0.17) 0.86)	**2.20** (1.01) (0.31)	**2.19** (1.04) (0.30)	**2.19** (1.11) (0.27)	**2.19** (1.11) (0.27)

See notes to Table 3.A.

Table 3.F
Diebold/Mariano Test Results For Real M2, 1980Q1 to 1998Q2, Various Forecast Steps

Growth Rate: 400*Δ Log (Real M2)

	Base	1.1	1.2	2.1	2.2	3.1	3.2
1-Step-Ahead	**2.89**	**2.33** (2.44) (0.01)	**1.24** (4.26) (0.00)	**1.21** (4.27) (0.00)	**0.92** (4.69) (0.00)	**0.92** (4.68) (0.00)	**0.84** (4.74) (0.00)
2-Step-Ahead	**3.85**	**3.77** (0.41) (0.69)	**3.61** (1.26) (0.21)	**3.24** (5.75) (0.00)	**3.15** (7.27) (0.00)	**3.09** (7.79) (0.00)	**3.02** (7.36) (0.00)
3-Step-Ahead	**3.81**	**3.84** (-0.21) (0.83)	**3.81** (0.03) (0.98)	**3.98** (-0.60) (0.55)	**3.96** (-0.52) (0.61)	**4.05** (-0.68) (0.50)	**4.03** (-0.63) (0.53)
4-Step-Ahead	**3.82**	**3.83a** (-0.08) (0.94)	**3.76a** (0.70) (0.48)	**3.90a** (-0.63) (0.53)	**3.90a** (-0.55) (0.58)	**3.88** (-1.62) (0.11)	**3.86** (-1.22) (0.22)
8-Step-Ahead	**3.80**	**3.97** (-1.37) (0.17)	**3.97** (-1.42) (0.16)	**4.02** (-1.46) (0.14)	**4.04** (-1.58) (0.11)	**4.04** (-1.59) (0.11)	**4.04** (-1.56) (0.12)

Log Level: 100* Log (Real M2)

	Base	1.1	1.2	2.1	2.2	3.1	3.2
1-Step-Ahead	**0.72**	**0.58** (2.44) (0.01)	**0.31** (4.26) (0.00)	**0.30** (4.27) (0.00)	**0.23** (4.69) (0.00)	**0.23** (4.68) (0.00)	**0.21** (4.74) (0.00)
2-Step-Ahead	**1.49**	**1.36** (2.68) (0.01)	**1.11** (3.97) (0.00)	**1.00** (5.01) (0.00)	**0.92** (5.95) (0.00)	**0.90** (5.80) (0.00)	**0.83** (5.76) (0.00)
3-Step-Ahead	**2.17**	**2.07** (1.14) (0.26)	**1.85** (3.40) (0.00)	**1.77** (5.20) (0.00)	**1.70** (5.94) (0.00)	**1.70** (4.84) (0.00)	**1.64** (4.82) (0.00)
4-Step-Ahead	**2.86**	**2.78** (1.70) (0.09)	**2.53** (3.86) (0.00)	**2.49** (3.44) (0.00)	**2.42** (3.29) (0.00)	**2.42** (3.03) (0.00)	**2.36** (3.19) (0.00)
8-Step-Ahead	**5.68**	**5.77** (-0.54) (0.59)	**5.46** (1.31) (0.19)	**5.42** (1.80) (0.07)	**5.38** (1.62) (0.10)	**5.34** (2.00) (0.05)	**5.28** (2.16) (0.03)

See notes to Table 3.A.

Table 4
Real-Time Forecast Evaluation, 1998Q4 to 1999Q3

	Actual	**Forecasts (current quarter)**		**Squared Errors**		**Loss Differential**
Real GDP Growth		**Baseline**	**1.2**	**Baseline**	**1.2**	
98Q4	5.59	3.23	3.67	5.570	3.686	1.883
99Q1	4.49	4.49	3.09	0.000	1.960	-1.960
99Q2	2.29	4.99	2.87	7.290	0.336	6.954
99Q3	4.82	3.75	3.65	1.145	1.369	-0.224
MSE				3.501	1.838	
GDP Inflation						
98Q4	0.85	0.56	0.69	0.084	0.026	0.059
99Q1	1.44	1.21	1.13	0.053	0.096	-0.043
99Q2	1.59	1.40	2.10	0.036	0.260	-0.224
99Q3	0.96	1.50	1.22	0.292	0.068	0.224
MSE				0.116	0.112	
Unemployment Rate						
98Q4	4.40	4.57	4.62	0.029	0.048	-0.020
99Q1	4.30	4.28	4.29	0.000	0.000	0.000
99Q2	4.27	4.23	4.29	0.002	0.000	0.001
99Q3	4.23	4.22	4.32	0.000	0.008	-0.008
MSE				0.008	0.014	

Table 4 (continued)
Real-Time Forecast Evaluation, 1998Q4 to 1999Q3

	Actual	Forecasts (current quarter)		Squared Errors		Loss Differential
Federal Funds Rate		**Baseline**	**1.2**	**Baseline**	**1.2**	
98Q4	4.86	4.96	4.83	0.010	0.001	0.009
99Q1	4.73	4.88	4.71	0.023	0.000	0.022
99Q2	4.75	5.00	4.67	0.063	0.006	0.056
99Q3	5.09	4.80	4.90	0.084	0.036	0.048
MSE				0.045	0.011	
10-Year Rate						
98Q4	4.67	5.20	4.57	0.281	0.010	0.271
99Q1	4.98	4.72	4.78	0.068	0.040	0.028
99Q2	5.54	5.08	5.10	0.212	0.194	0.018
99Q3	5.88	5.60	5.70	0.078	0.032	0.046
MSE				0.160	0.069	
Real M2 Growth						
98Q4	11.12	5.88	12.05	27.458	0.865	26.593
99Q1	5.89	8.44	6.74	6.503	0.723	5.780
99Q2	4.18	4.37	4.71	0.036	0.281	-0.245
99Q3	4.10	3.77	3.51	0.109	0.348	-0.239
MSE				8.526	0.554	

Notes. The table shows historical values (actual) and the forecasts corresponding to the baseline QBVEC with no current-quarter information (baseline) and to the QBVEC with current-quarter information of type 1.2 (denoted 1.2). All forecasts are those for the current-quarter and are based on the data available on the following dates: November 21, 1998; February 20, 1999; May 22, 1999; and, August 19, 1999 . The actual values are those available on the following dates: February 6, 1999; May 8, 1999; August 9, 1999; and, November 9, 1999. Also shown are the squared forecast errors (actual minus forecast) and the associated loss differential, the latter constructed as the difference between the squared errors (baseline minus 1.2). The row labeled MSE shows the mean-square-error statistic for each forecast.

References

Braun, Steven N. "Estimation Of Current-Quarter Gross National Product By Pooling Preliminary Labor-Market Data," *Journal of Business & Economic Statistics* 8 (1990), pp. 293-304.

Christoffersen, Peter F. and Francis X. Diebold. "Cointegration and Long-Horizon Forecasting," Federal Reserve Bank of Philadelphia Working Paper No. 97-14, (September 1997).

Corrado, Carol and Mark Greene. "Reducing Uncertainty in Short-term Projections: Linkage of Monthly and Quarterly Models," *Journal of Forecasting 7* (1988), pp. 77-102.

Corrado, Carol and Jane Haltmaier. "The Use Of High-Frequency Data In Model-Based Forecasting At The Federal Reserve Board," Federal Reserve Board, Finance and Economic Discussion Series Paper 24 (April 1988).

Croushore, Dean and Tom Stark. "A Real-Time Data Set For Macroeconomists," Federal Reserve Bank of Philadelphia Working Paper No. 99-4, June 1999a.

Croushore, Dean and Tom Stark. "Does Data Vintage Matter For Forecasting?" Federal Reserve Bank of Philadelphia Working Paper No. 99-15, October 1999b.

Croushore, Dean and Tom Stark. "A Real-Time Data Set For Macroeconomists: Does The Data Vintage Matter?," Federal Reserve Bank of Philadelphia Working Paper No. 99-21, December 1999c.

Diebold, Francis X. and Roberto S. Mariano. "Comparing Predictive Accuracy," *Journal of Business & Economic Statistics* 13 (July 1995), pp. 253-263.

Duy, Timothy A. and Mark A Thoma. "Modeling and Forecasting Cointegrated Variables: Some Practical Experience," *Journal of Economics and Business* 50 (1998), pp. 291-307.

Engle, Robert F. and C.W.J. Granger. "Co-Integration and Error Correction: Representation, Estimation, and Testing," *Econometrica* 55 (March 1987), pp. 251-276.

Fitzgerald, Terry J. and Preston J. Miller. "A Simple Way To Estimate Current-Quarter GNP," Federal Reserve Bank of Minneapolis *Quarterly Review* (Fall 1989), pp. 27-31.

Franses, Philip Hans, and Frank Kleibergen. "Unit Roots in the Nelson-Plosser Data: Do They Matter For Forecasting?" *International Journal of Forecasting* 12 (1996), pp. 283-288.

Granger, C.W.J. and Paul Newbold. *Forecasting Economic Time Series, Second Edition*, Orlando, Florida: Academic Press, Inc., 1986.

Hamilton, James D. *Time Series Analysis*, Princeton, New Jersey: Princeton University Press, 1994.

Harvey, David, Stephen Leybourne, and Paul Newbold. "Testing The Equality Of Prediction Mean Squared Errors," *International Journal of Forecasting* 13 (June 1997), pp. 281-291.

Howrey, Philip E., Saul H. Hymans, and Michael R. Donihue. "Merging Monthly and Quarterly Forecasts: Experience With MQEM," *Journal of Forecasting* 10 (1991), pp.255-268.

Ingenito, Robert and Bharat Trehan. "Using Monthly Data To Predict Quarterly Output," Federal Reserve Bank of San Francisco *Economic Review* (1996), pp.3-11.

Koenig, Evan F. and Sheila Dolmas. "Real-Time GDP Growth Forecasts," Federal Reserve Bank of Dallas Working Paper 97-10 (December 1997).

Litterman, Robert B. "Forecasting With Bayesian Vector Autoregressions—Five Years of Experience," *Journal of Business & Economic Statistics* 4 (January 1986), pp. 25-38.

Miller, Preston J. And Daniel M. Chin. "Using Monthly Data to Improve Quarterly Model Forecasts," Federal Reserve Bank of Minneapolis *Quarterly Review* (Spring 1996), pp. 16 - 33.

Rathjens, Peter and Russell P. Robins. "Forecasting Quarterly Data Using Monthly Information," *Journal of Forecasting* 12 (1993), pp. 321-330.

Rudebusch, Glenn D. "Do Measures Of Monetary Policy In A VAR Make Sense?" *International Economic Review* 39 (November 1998), pp. 907-931.

Stark, Tom. "A Bayesian Vector Error Corrections Model Of The U.S. Economy," Federal Reserve Bank of Philadelphia Working Paper No. 98-12, June 1998.

Trehan, Bharat. "Forecasting Growth In Current Quarter Real GNP," Federal Reserve Bank of San Francisco *Economic Review* (1989), pp. 39-52.

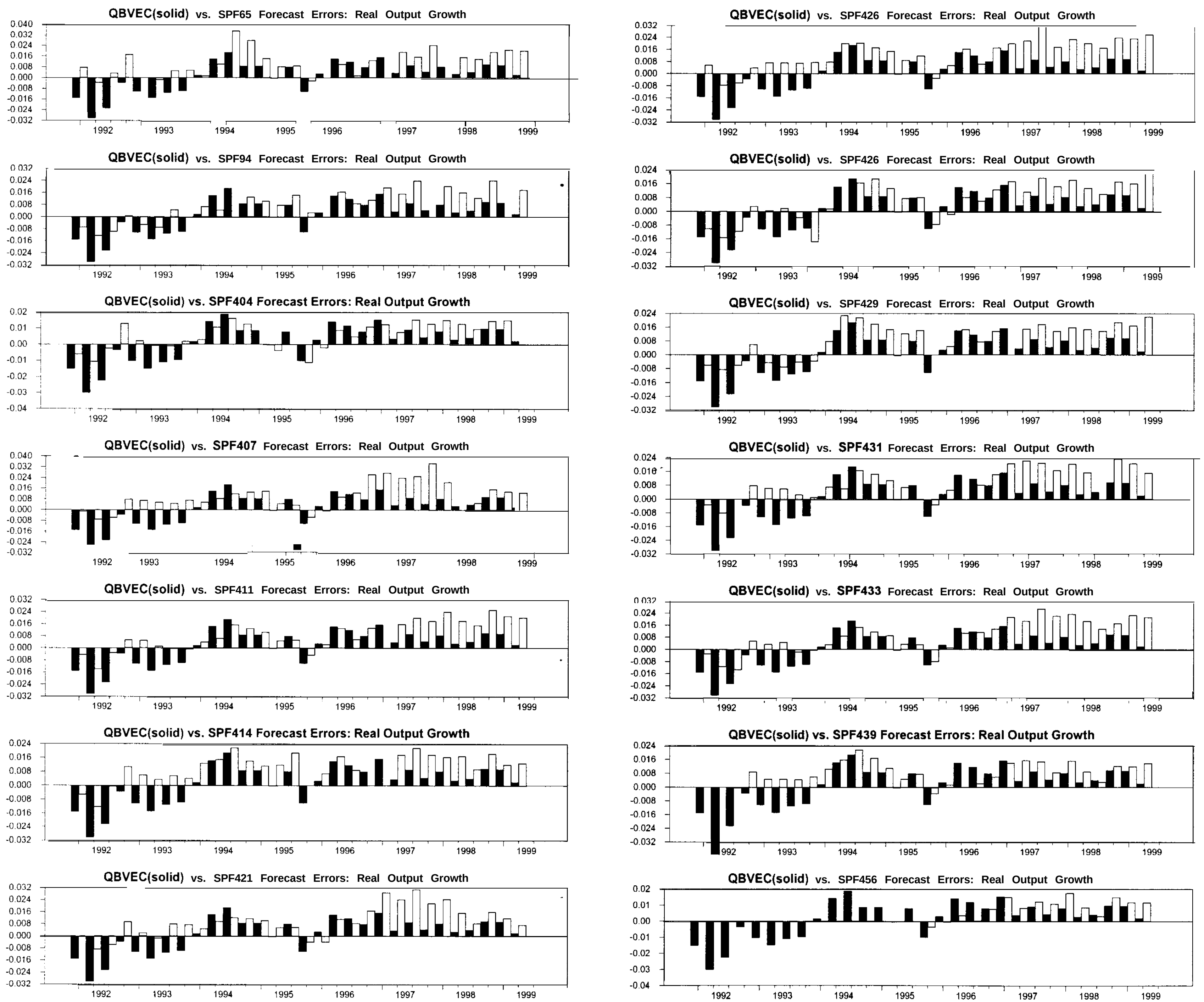

Figure 1
Forecast Errors For Four-Quarter-Average Real Output-Growth Forecasts

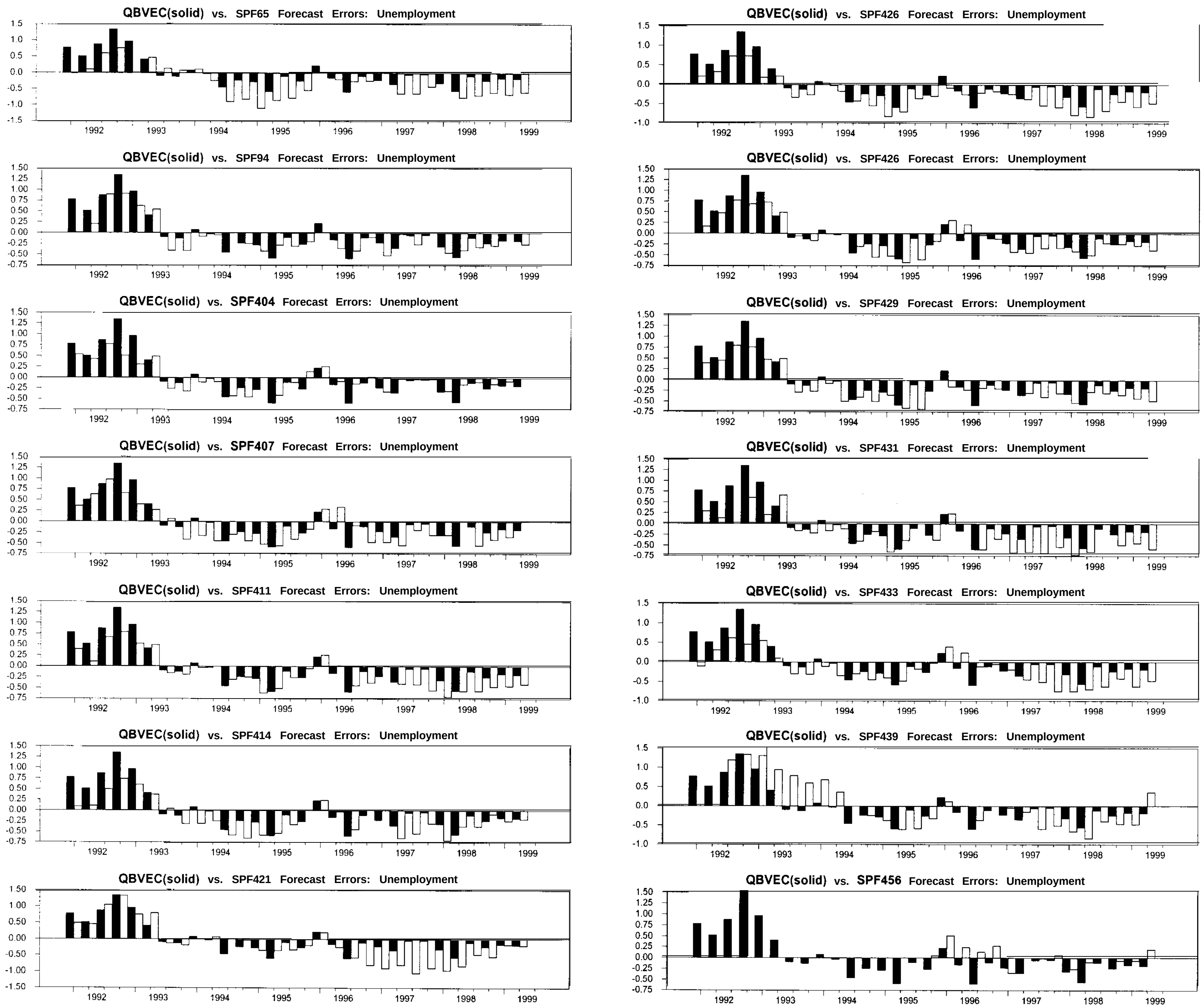

Figure 2

Forecast Errors For Four-Quarter-Average Unemployment-Rate Forecasts

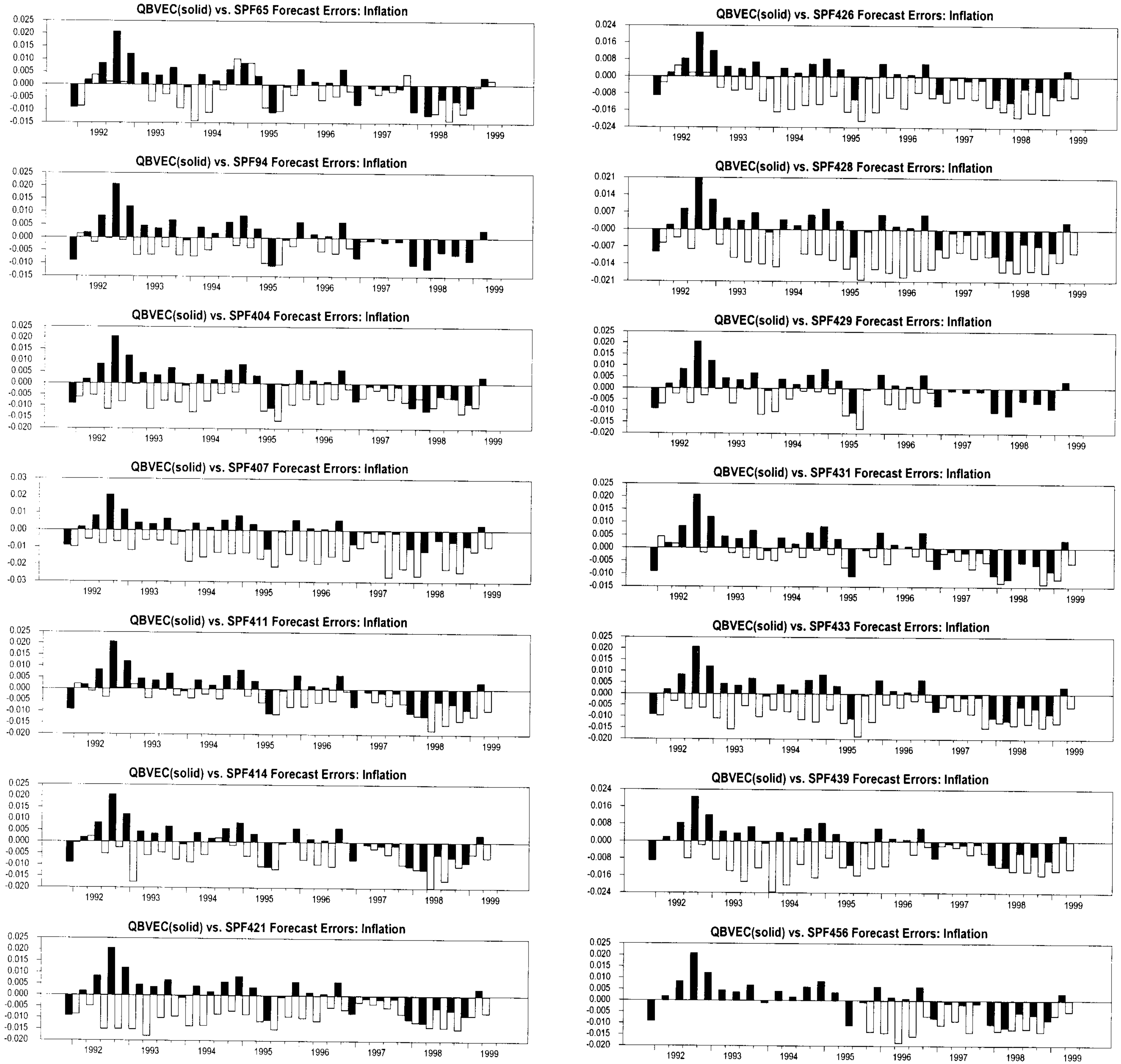

Figure 3

Forecast Errors For Four-Quarter-Average Inflation Forecasts

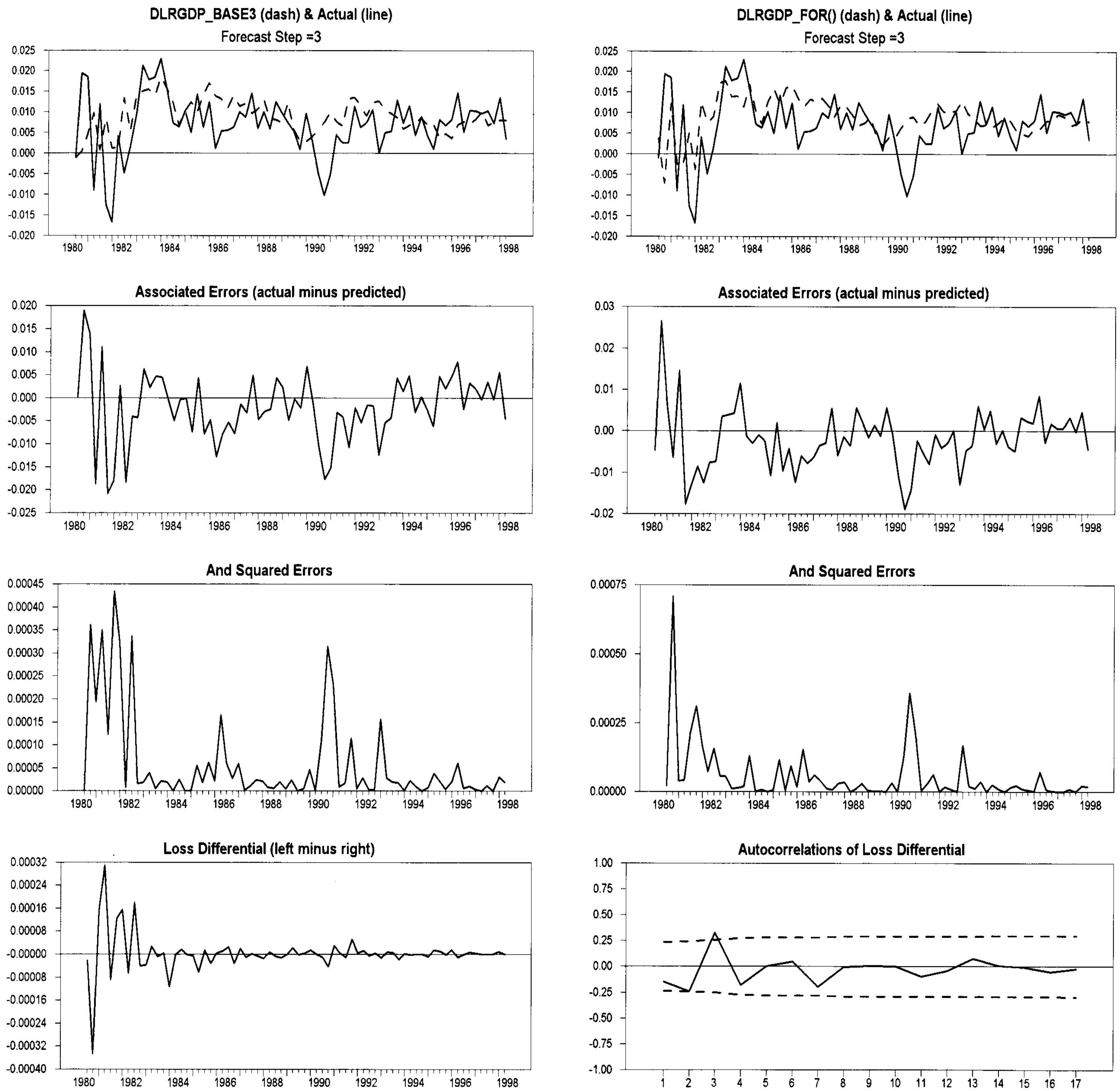

Figure 4
Comparison of Three-Quarter-Ahead Quarterly Real GDP Growth Forecasts:
Baseline vs. Case 1.2

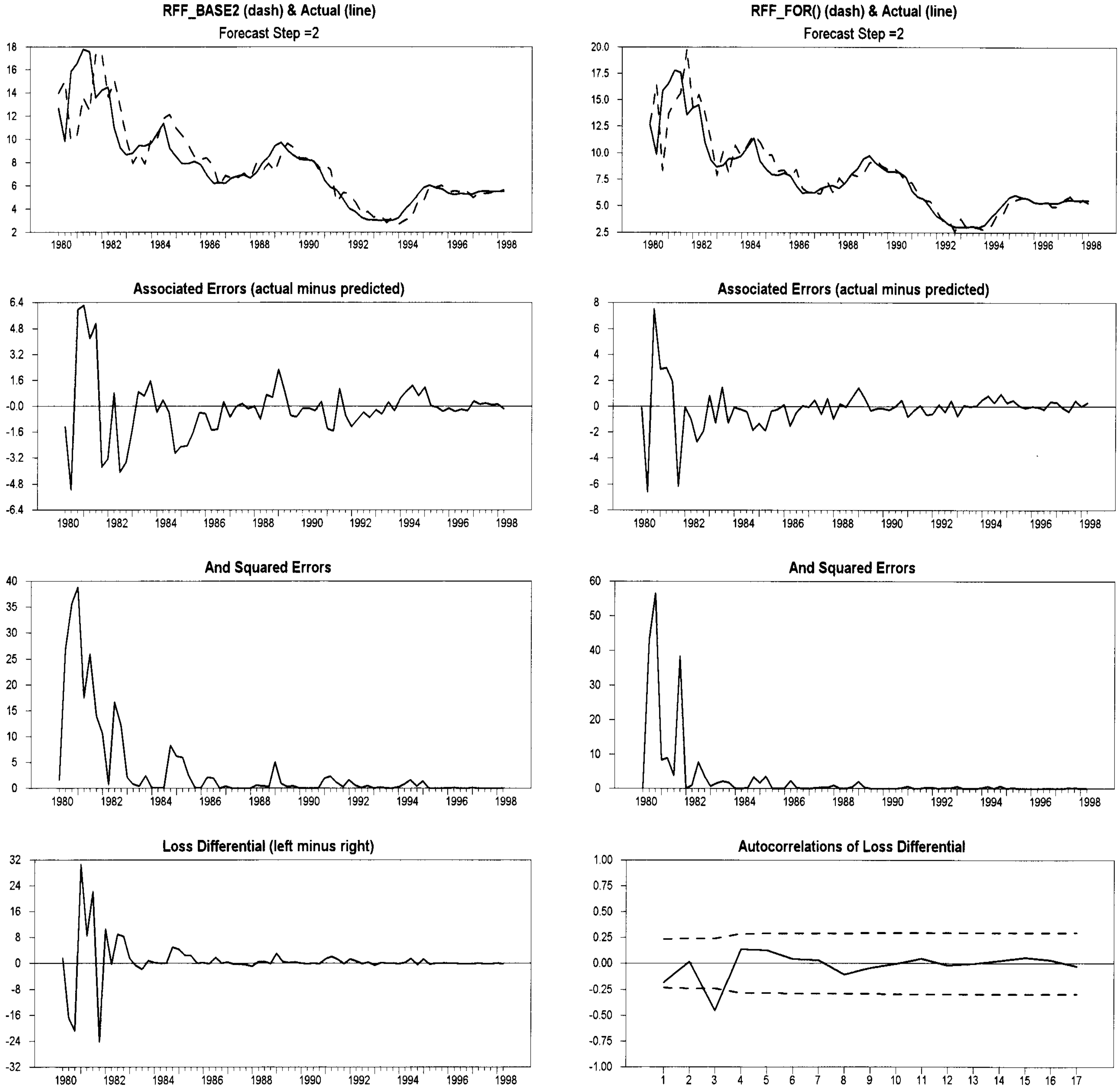

Figure 5
Comparison of Two-Quarter-Ahead Federal Funds Rate Forecasts:
Baseline vs. Case 1.2

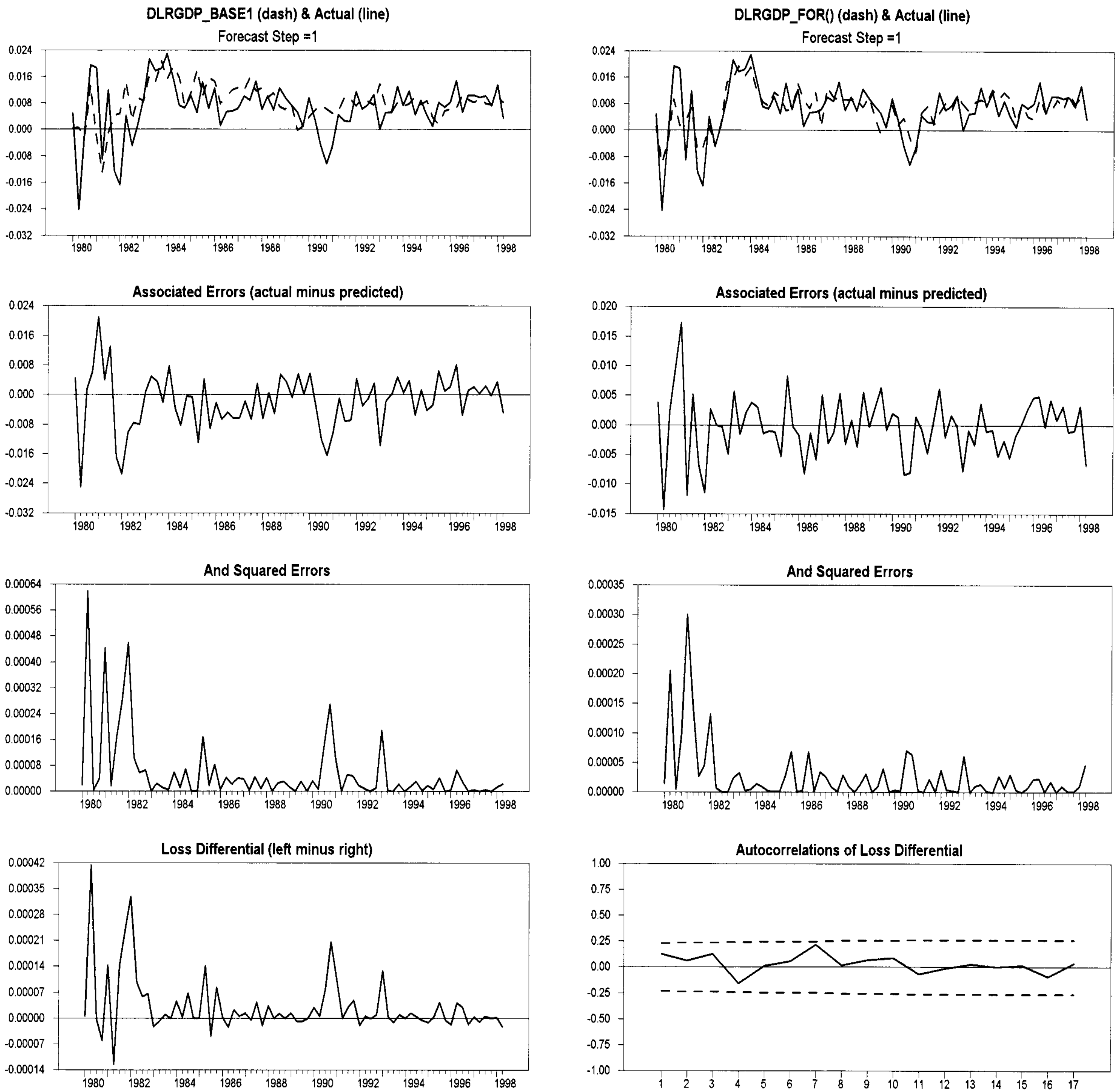

Figure 6.A
Comparison of One-Quarter-Ahead Quarterly Real GDP Growth Forecasts:
Baseline vs. Case 1.2

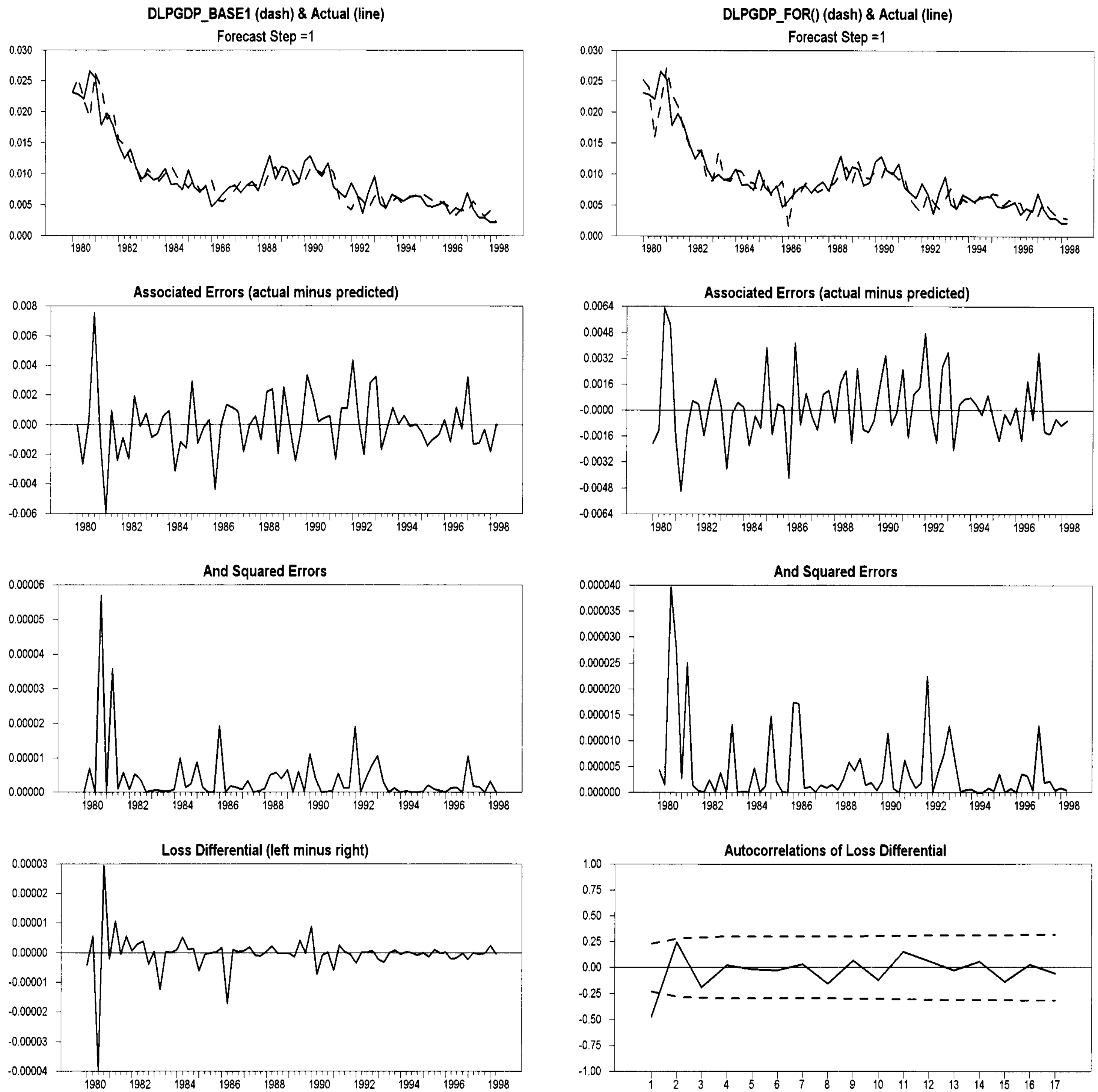

Figure 6.B
Comparison of One-Quarter-Ahead Quarterly Inflation Forecasts:
Baseline vs. Case 1.2

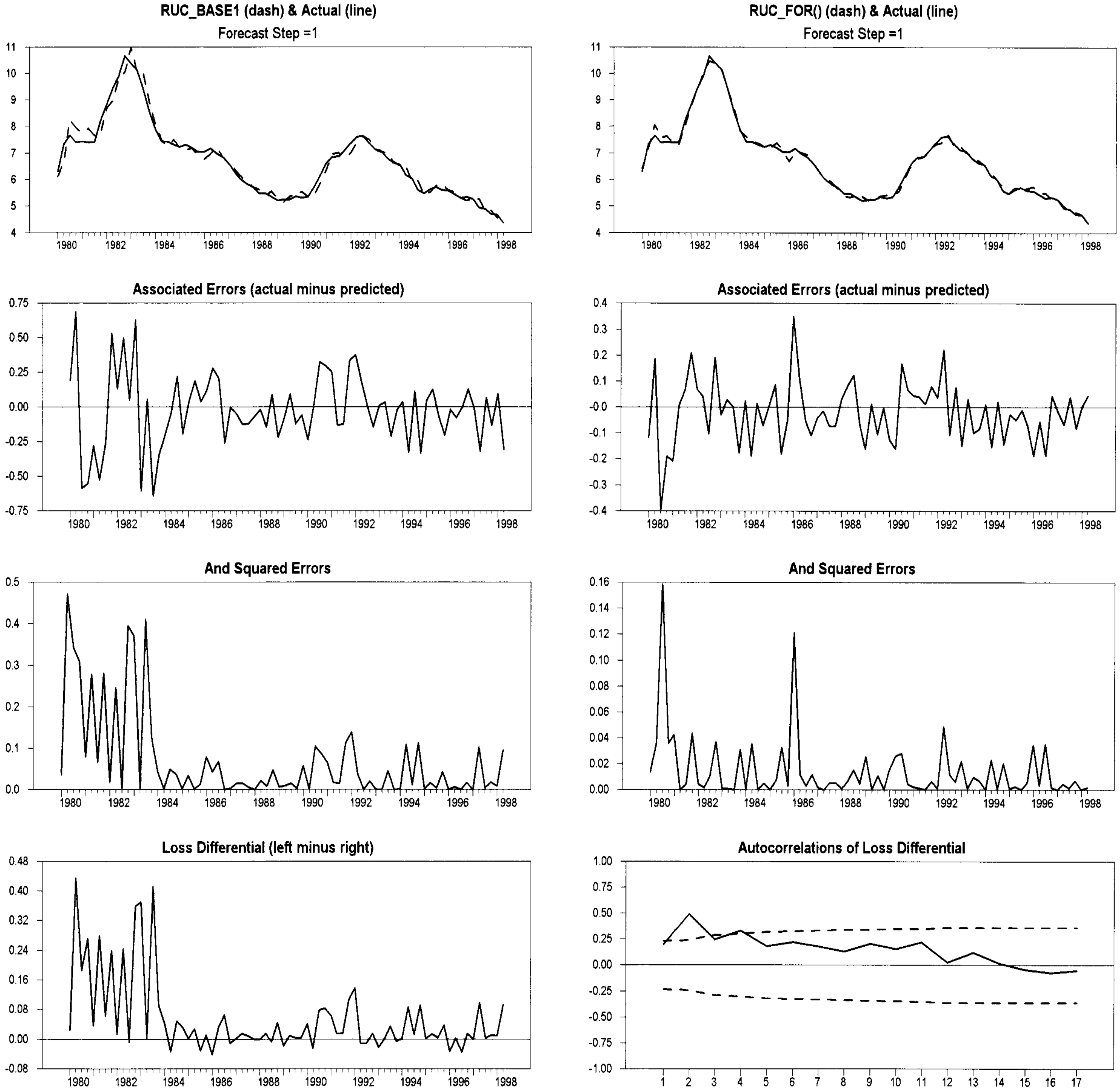

Figure 6.C
Comparison of One-Quarter-Ahead Unemployment-Rate Forecasts:
Baseline vs. Case 1.2

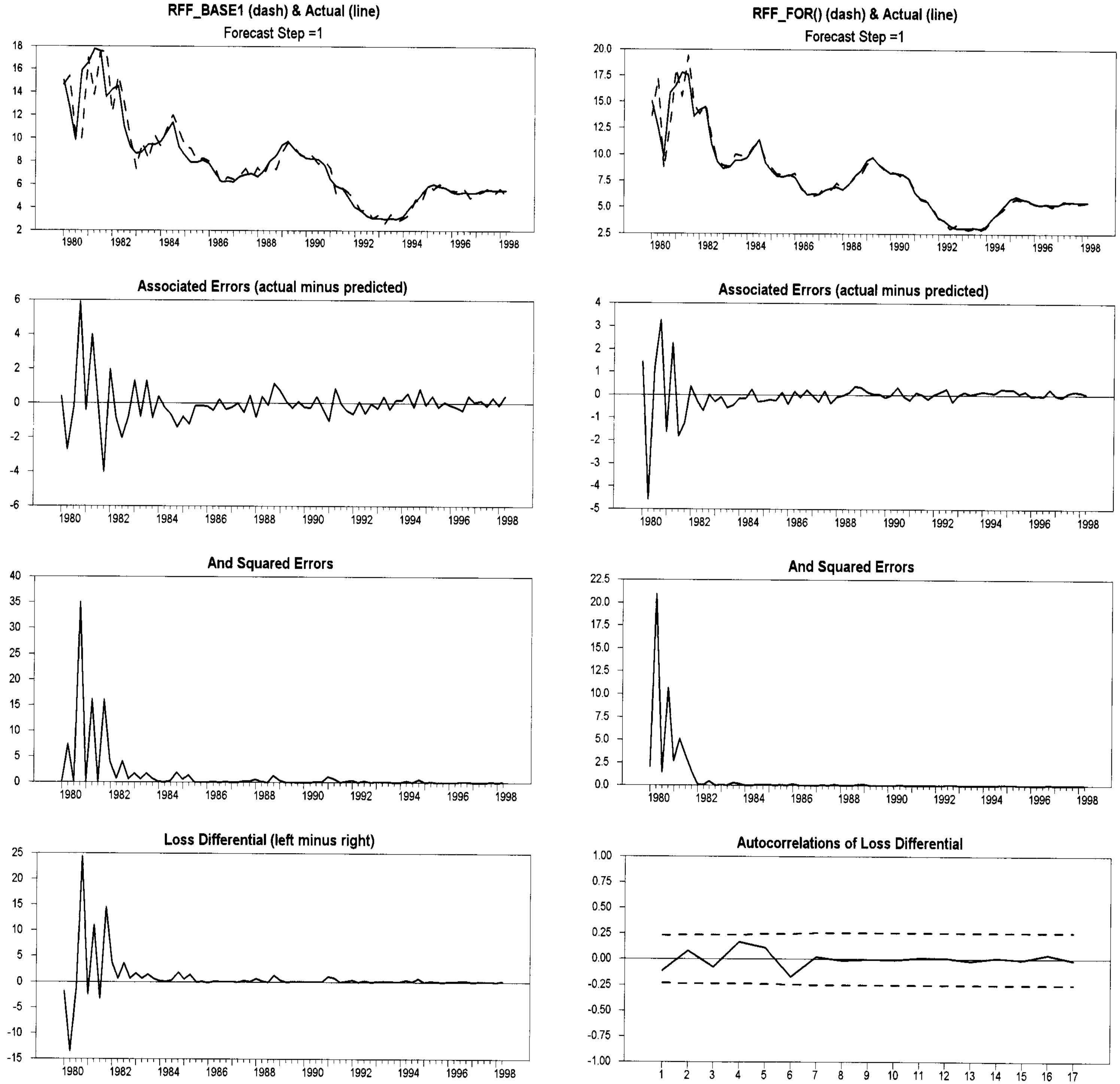

Figure 6.D
Comparison of One-Quarter-Ahead Federal Funds Rate Forecasts:
Baseline vs. Case 1.2

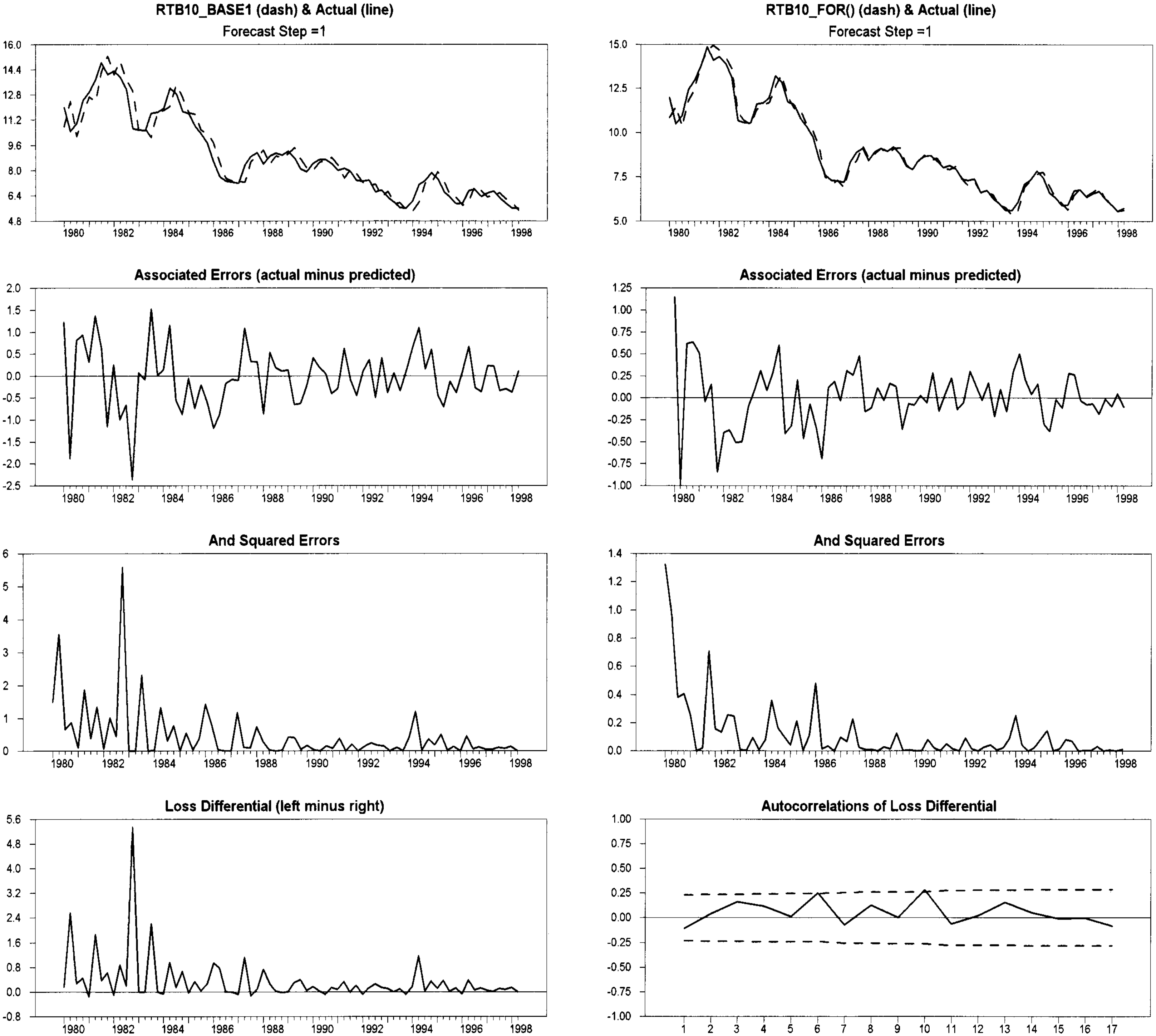

Figure 6.E
Comparison of One-Quarter-Ahead 10-Year Treasury-Rate Forecasts:
Baseline vs. Case 1.2

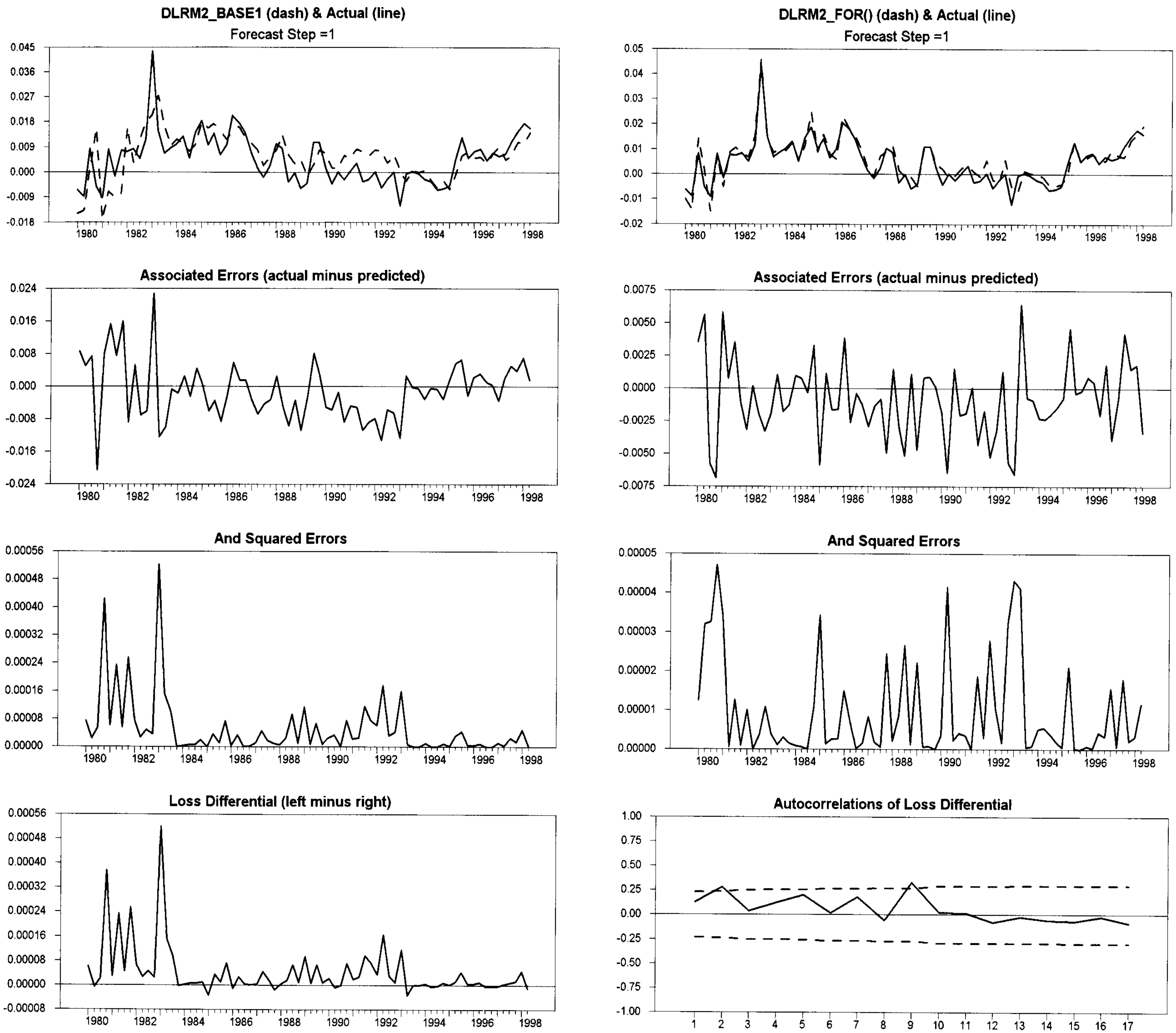

Figure 6.F
Comparison of One-Quarter-Ahead Quarterly Real M2 Growth Forecasts:
Baseline vs. Case 1.2