A Dynamic Multivariate Model for Use in Formulating Policy

TAO ZHA

The author is an economist in the macropolicy section of the Atlanta Fed's research department.
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On March 25, 1997, the Federal Open Market Committee (FOMC) raised its key short-term interest rate target—the federal funds rate—by 25 basis points. The *Wall Street Journal* called the move Chairman Alan Greenspan's "preemptive strike against inflation" (Wessel 1997). According to Greenspan, the FOMC "believes it is crucial to keep inflation contained in the near term and ultimately to move toward price stability" (1997a, 1). The FOMC described this increase "as a prudent step that affords greater assurance of prolonging the current economic expansion by sustaining the existing low inflation environment through the rest of this year and next" (Wessel 1997).

The notion of "preemptive strike" or "prudent step" connotes the most important part of policy making: the process of looking forward. Because the Federal Reserve's monetary policy has effects on the overall economy only through long and variable delays, policymakers must look forward to forecast, to the best of their abilities, how today's policy actions will affect economic conditions such as inflation in the future. This process of anticipating the future is indispensable in formulating sound monetary policy (see, for example, Cecchetti 1995, King 1997, and Blinder 1997).

The Humprey-Hawkins Act has set out multiple objectives for the Federal Reserve, including balanced growth and stable prices (Board of Governors 1994). A policy action by the Fed consists of using any one of various instruments, such as the federal funds rate and different measures of money, to pursue its multiple objectives. However, to provide clearer analysis this article characterizes monetary policy actions more narrowly as changes in the federal funds rate and the discussion concentrates on only one of the Federal Reserve's objectives—keeping inflation, as measured by the consumer price index (CPI), low and stable. In such a framework, one aspect of effectively advising policymakers is to provide a forecast of how inflation outlook changes if the Federal Reserve adopts different paths of the federal funds rate over the next two or three years. By consulting a menu of such projected outcomes, called policy projections, policymakers can decide which particular policy actions are most likely to keep inflation around the level commensurate with their objective.

Policy projections are essential in helping policymakers decide on policy actions. Unfortunately, obtaining an accurate estimation of such projections is a daunting task. Because the projections are based on various forecasts under different scenarios—here, alternative federal funds rate paths—the first and critical step is to develop good forecasting models (Sims 1980). It is therefore the purpose of this article to present a forecasting model that seems to overcome conceptual and empirical difficulties encountered in other models and promises to provide policymakers with a more useful tool for anticipating effects of policy.

The model, one of a class of models called dynamic multivariate models, introduces new techniques that offer two distinctive advantages. One is the ability to forecast the values of key macroeconomic variables such as inflation and output beyond a period over which these values are known, on the assumption that the trends followed within the period continue beyond it. These extrapolated forecasts are known in technical jargon as out-of-sample forecasts. The model's other advantage is its explicit structure that allows empirically coherent ways to assess the uncertainty of forecasts through error bands. These error bands are constructed so that there is a two-thirds probability that actual outcome is contained within the band.

The article first discusses dynamic multivariate modeling in general and reviews other approaches to forecasting. The discussion then turns to the model itself. After describing the specifics of the model, the article presents the model's point forecasts through the 1980s and 1990s. These forecasts represent the scenarios most likely to develop. Finally, the article shows how to use probability distributions to gauge forecast errors.

Dynamic Multivariate Modeling

The term *dynamic* means that economic variables influence one another through variable lags over time. For example, today's change in the federal funds rate will have consequences on the path of inflation in a year or two. The term *multivariate* implies that a set of multiple variables are examined together, not separately, in one framework. By *dynamic multivariate models* this article means a class of models that are designed to capture, in a single framework, joint movements and dynamic patterns in an array of multiple key macroeconomic variables over a particular period of time. (Technical details are discussed in Box 1 in relation to the specific model presented here.)

The dynamic multivariate model presented in this article provides a useful tool for gauging future uncertainty and an empirically consistent way to update forecasts.

Other Approaches. Before explaining the key aspects of dynamic multivariate modeling, it is perhaps useful to review briefly two other approaches to forecasting and policy analysis. One approach is to use rules of thumb. Rules of thumb are often used in actual policy discussions because they may be based on theoretical work and thus can provide compelling stories to policymakers. Unfortunately, they are generally insufficient for characterizing the actual economy, and therefore forecasts derived from these rules are likely to be quantitatively unreliable. For example, one rule of thumb often referred to in the popular press is the Phillips curve relationship, which implies that whenever the unemployment rate is low (high), inflation will soon rise (fall).[1] Chart 1 displays annual inflation and the annual unemployment rate from 1960 to 1996. As the chart shows, there were times when inflation and unemployment tended to move in the same direction, not in opposite directions. For instance, from the early to mid-1970s, rising unemployment was coupled with rising inflation; from 1982 to 1986 both inflation and the unemployment rate fell. During other times inflation and unemployment moved in quite different fashions. Consider 1992–96, for example. During this period, the unemployment rate fell steadily but inflation stayed almost flat. If one used the negative relationship between inflation and unemployment in the 1987–91 period to predict inflation, the result would be to overpredict inflation for 1992–96.[2]

Another example of rules of thumb is the bivariate relationship between inflation and the growth rate of money. A number of economists (for example, Friedman 1992) have argued that the M2 growth rate in particular appears to have a stable relationship to inflation. Chart 2 displays time-series patterns of inflation and the M2

1. *A.W. Phillips first noted such a relationship in 1958. His original study examined a temporary trade-off between changes in nominal wages and the unemployment rate in the United Kingdom over a period from 1861 to 1957.*
2. *The literature presents several versions of the bivariate relationship between unemployment and inflation. For critical discussions consult, for example, Chang (1997), Espinosa and Russell (1997), and Staiger, Stock, and Watson (1997).*

Details of the Model

This box, heavily drawn from Sims and Zha (1998), describes the important features of the model that is used to produce the results presented in Charts 6–10. The dynamic multivariate model takes the following simultaneous equations form:

$$y(t)A(L) = \boldsymbol{\varepsilon}(t), t = 1,...,T, \tag{1}$$

where *A(L)* is an $m \times m$ matrix polynomial of parameters in lag operator L, *y(t)* is a $1 \times m$ vector of observations of m variables at time t, and $\boldsymbol{\varepsilon}(t)$ is a $1 \times m$ vector of independently, identically distributed (i.i.d.) structural shocks so that

$$E\boldsymbol{\varepsilon}(t) = 0, E\boldsymbol{\varepsilon}(t)'\boldsymbol{\varepsilon}(t) = \underset{m\times m}{I}. \tag{2}$$

Note that T is the sample size. To estimate system (1), the likelihood function is multiplied by a probability density function. This probability density, formally a Bayesian prior distribution, aims at eliminating the undesirable problems associated with the estimation. These problems are discussed in detail below.

The number of parameters in $A(L)$ grows with the square of the number of variables in system (1). Given the short period of macroeconomic data after World War II, traditional, ordinary least squares (OLS) estimation of a large model (for example, the eighteen-variable model studied by Leeper, Sims, and Zha 1996) becomes imprecise because of relatively low degrees of freedom and a large number of parameters. Thus, models used in macroeconomics are often of small size (say, six variables). For small models like the six-variable model presented in this article, error bands on the OLS estimates of parameters are usually tight, and thus quantitative analysis from these models can be informative. Nonetheless, when a model is used for out-of-sample forecasting, one can no longer take comfort in "good" in-sample properties of the OLS estimates. Three major problems prevent reasonable out-of-sample forecasting, especially over long horizons (such as two or three years out).

The first problem is a familiar one: overfitting. Because of a large number of parameters, the model tends to fit the sample unrealistically well but fails badly for out-of-sample forecasting.[1] To see how unbelievable the overfitting problem could become, Chart A displays actual values and in-sample (*not* out-of-sample) forecasts of the stock of M1 from January 1960 to March 1996. These in-sample forecasts, drawn directly from Sims and Zha (1998), are made as of 1959:12 from the estimated model (using the data from 1959:7 to 1996:3) without any prior distribution (that is, with OLS estimates). As shown in Chart A, one could, in 1959, predict with almost perfect precision the level of M1 stock in 1996—an incredible outcome.

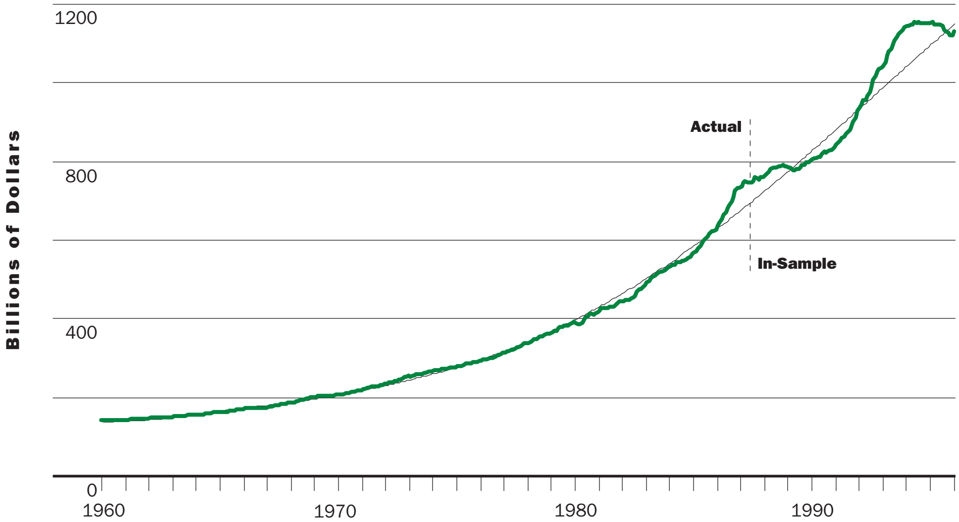
Another aspect of overfitting, which has not been addressed in the textbooks, is an unreasonable extraction of business cycles into deterministic components (see Sims and Zha 1998 for technical details). This undesirable feature may have contributed to findings about substantial differences in OLS estimates across different subsamples. It may distort long-run relationships among variables in the model as well. To deal with these overfitting problems, the model used here, following Sims and Zha (1998), uses priors that favor unit roots and cointegration.[2] At the same time, the model avoids imposing exact, but likely spurious, unit roots and cointegrated relationships with a probability of one.

The third problem relates to low degrees of freedom in most macroeconomic models. Typically, OLS estimates tend to produce large coefficients on distant lags and erratic sampling errors. One of the prior distributions used in the model here is to downweight the influence of distant lags or the unreasonable degree of explosiveness. This prior distribution is essential for ensuring reasonable small-sample properties of the model, especially when degrees of freedom are relatively low.

The prior distributions used here do not intend to encompass all briefs that are likely to improve out-of-sample forecasts. Rather, they reflect some widely held briefs that are likely to be uncontroversial. In this sense, the prior distributions are of a reference nature, and such an approach closely follows the likelihood principle.

1. *Dynamic multivariate models are not the only types that produce overfitting. This problem is common across many empirical models (see Diebold 1998b).*
2. *From a different perspective, Christofferson and Diebold (1997) discuss why cointegrated relationships are important for short-term forecasts.*

CHART A
Actual and Forecast M1 Monthly Series
(1960:1–1996:3)



Source: Sims and Zha 1996.

growth rate from 1960 to 1996. The M2 growth rate reached a peak three times—in 1972, 1976, and 1983. But the path of inflation after each peak was quite different. Clearly, past M2 growth rates predict future inflation through variable lags, and there are no regular patterns.

Another approach to forecasting is to link forecasts of macroeconomic variables to a large array of other variables through econometric techniques. This approach usually involves many strong assumptions or judgmental adjustments. Large-scale structural econometric models are examples of this approach. The goal of these models is to not only provide forecasts of key macroeconomic variables but also examine in detail many different sectors of the economy (Diebold 1998a). Because of their detailed, intricate nature, however, these models are often difficult to produce and evaluate independently. Furthermore, strong assumptions contained in these kinds of models, such as the Phillips curve relationship, may be at odds with the data. Judgmental adjustments consequently play roles in the model's outcomes from period to period. Such periodical adjustments make it difficult to gauge the quality of the model itself.

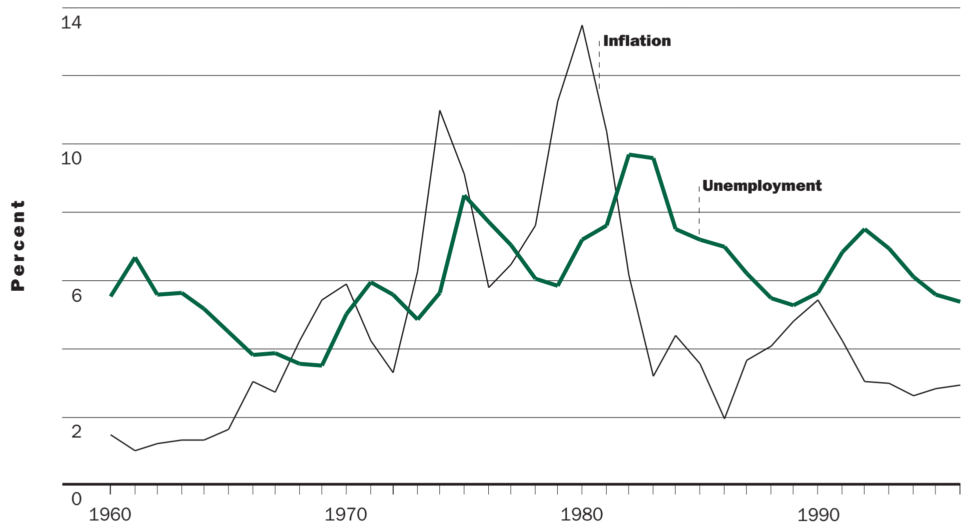
Distinctive Aspects of Dynamic Multivariate Modeling. Dynamic multivariate modeling offers a different approach. It is not designed to study every detail of the economy. Rather, it is designed to capture only essential elements so that the model can be readily understood and reproduced. It is closely connected to modern economic theory and usually involves only six to eight variables.[3] After the model—the array of variables, the lag length, and other assumptions—is set up, forecasts from the model will not be altered from period to period on the basis of judgments or assumptions outside the model itself. Thus, the model can be evaluated objectively.

At the same time, dynamic multivariate modeling has complex structures in the sense that it allows both contemporaneous and dynamic interactions among the macroeconomic variables. In relation to rules of thumb, dynamic multivariate models capture the relationships implied by these rules if such relationships exist in the data. In contrast to large-scale models, dynamic multivariate modeling avoids imposing strong assumptions that may be at odds with the data. Consequently, both the Federal Reserve's complex behavior and the public's expectations about future policy actions are implicitly embedded in dynamic multivariate models.

More important, dynamic multivariate modeling provides empirically coherent ways to assess the uncertainty about forecasts (Sims and Zha 1998). All forecasts have errors. The errors usually come from two sources—uncertainty about model parameters and uncertainty emanating from exogenous shocks (that is, those that cannot be predicted by the model). Dynamic multivariate

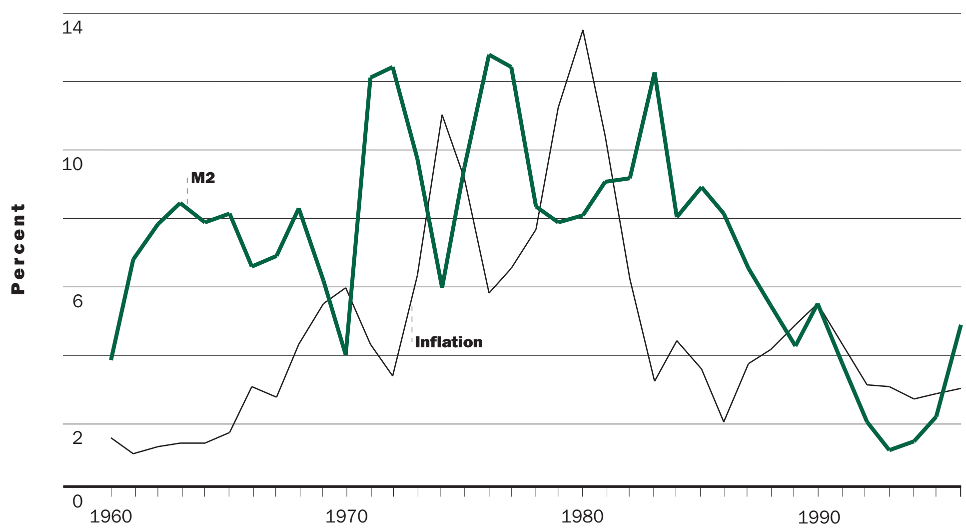
3. See, for example, Diebold (1998a) and Sims and Zha (1996) for detailed discussions.

CHART 1 Annual Inflation and Unemployment Rates, 1960–96



Source: See Box 2.

CHART 2 Annual Inflation and M2 Growth Rates, 1960–96



Source: See Box 2.

modeling lays out a probabilistic structure that takes both types of uncertainties into account explicitly. When probability distributions or error bands are attached to point forecasts, policymakers will be well informed of the likelihood of future inflation.

The Model

The dynamic multivariate model used in this article employs monthly data with the six key macroeconomic variables often used in the literature: the federal funds rate, the stock of M2, the consumer price index, real (inflation-adjusted) gross domestic product, the unemployment rate, and an index of commodity prices (see Box 2 for a precise description of the data set). The data begin at 1959:1 and end at the time when the forecast is made. The model allows these variables to interact with one another both simultaneously and through lags.[4] The lag length is thirteen months, meaning that variables in the past thirteen months are allowed to affect those in the current month.

BOX 2

Data Description

The model uses monthly data from 1959:1 to 1997:9 for six macroeconomic variables:

CPI. Consumer price index for urban consumers (CPI-U), seasonally adjusted. Source: Bureau of Economic Analysis, the Department of Commerce (BEA).

Commodity Prices. International Monetary Fund's index of world commodity prices. Source: International Financial Statistics.

Federal Funds Rate. Effective rate, monthly average. Source: Board of Governors of the Federal Reserve System.

GDP. Real GDP, seasonally adjusted, billions of chain 1992 dollars. Monthly real GDP is interpolated using the procedure described in Leeper, Sims, and Zha (1996). Source: BEA.

M2. M2 money stock, seasonally adjusted, billions of dollars. Source: Bureau of Labor Statistics (BLS).

Unemployment. Civilian unemployment rate (ages sixteen and over), seasonally adjusted. Source: BLS.

Because the model does not allow for judgmental adjustments periodically, it aims at strong performance of out-of-sample forecasting by the model itself (see Box 1 for details). When decision making is guided by forecasts extrapolated from the model, actual data for the future period are of course not available to policymakers. Therefore, out-of-sample forecasts, with probability distributions or error bands attached, can be invaluable. The error bands of forecasts give policymakers an indication of the range of the future data. Before the discussion turns to greater detail about the use of probability distributions of forecasts, the next three sections discuss out-of-sample point forecasts produced from the specific dynamic multivariate model presented here.

Out-of-Sample Point Forecasts

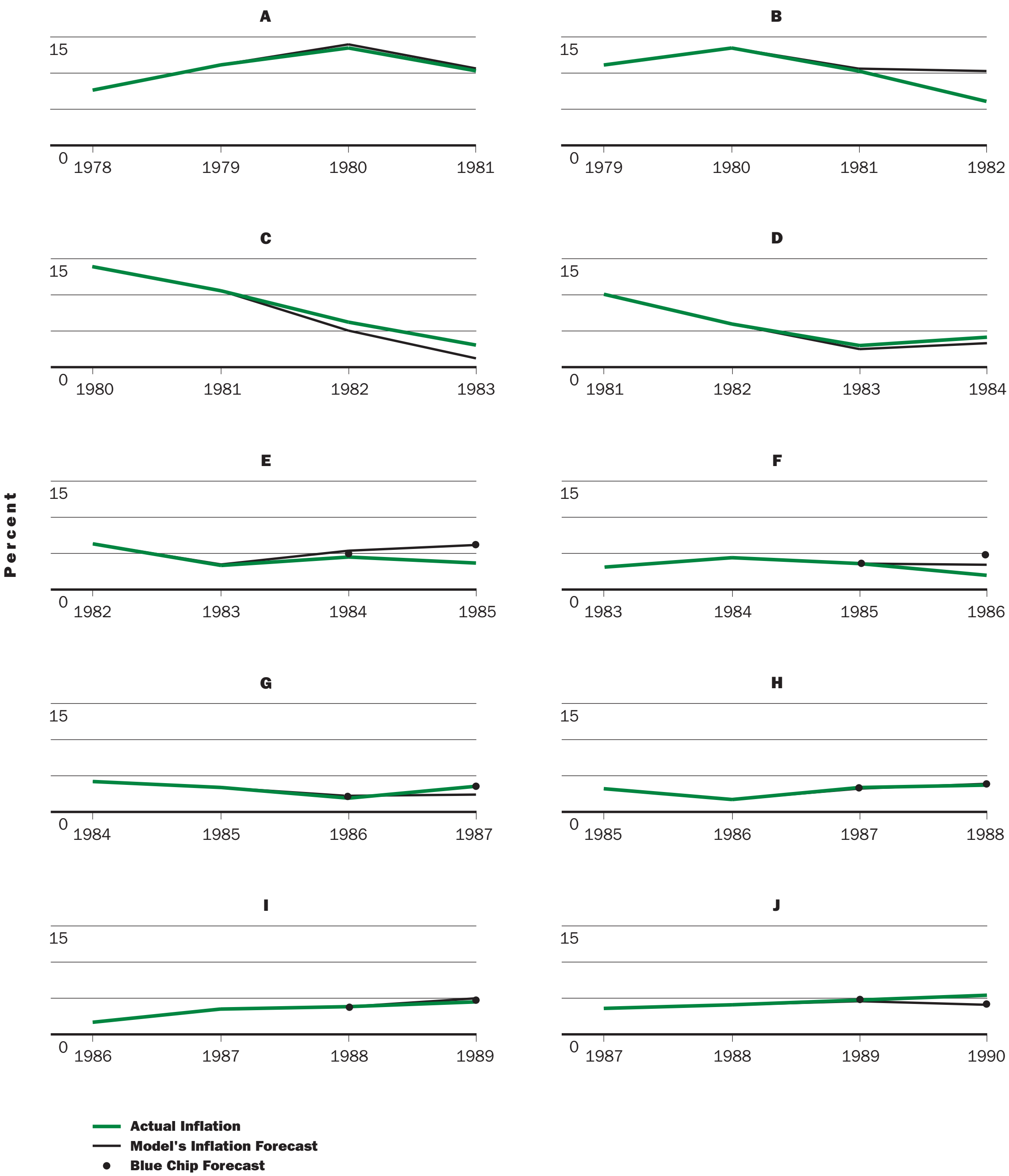
The 1980s. In the late 1970s inflation was accelerating to rates unprecedented in the period since 1960. Then in the 1980s inflation slowed down more quickly than the public thought possible. Thus, 1980s inflation is difficult to forecast. Chart 3 displays the model's forecasts of annual inflation through the 1980s. In each panel of Chart 3, the thick line represents actual outcomes of inflation, the thin line represents the model's forecasts for the next two years, and the dots are the Blue Chip forecasts for the next two years.[5] Note that the Blue Chip forecasts at the beginnings of 1980, 1981, 1982, and 1983 are not displayed here because the new methodology introduced to compute the CPI has significantly changed figures for actual inflation before 1984. New definitions or revisions of the data always affect the accuracy of evaluating the forecasts that were made using old data at the time. Inflation figures after 1983, however, have not been altered much by subsequent data revisions. In Panel E, for instance, the Blue Chip forecasts were made at the beginning of 1984. To be comparable, the model's forecasts are also made at the beginning of 1984. In addition, Panel E displays the actual data in the two years (1982 and 1983) prior to the forecast year. Similarly, in all other panels, the forecasts for the next two years are displayed along with the actual data in the two years prior to the forecast year. For example, in Panel F, inflation forecasts in 1985 and 1986 (the thin line and dots) are made at the beginning of 1985 along with actual inflation in 1983 and 1984.

As Chart 3 shows, without periodic judgmental adjustments the dynamic multivariate model here produces quite reasonable results that are as least as accurate as the Blue Chip forecasts. In particular, the model forecasts the slowdown of inflation in the 1980s fairly well. Because the model is dynamic, it adjusts its forecasts accordingly by systematically incorporating the most recent data. For example, at the beginning of 1981 the model tends to predict that the trend of inflation will be higher than that of actual outcome (Panel B); by the time 1981 is over, the model is able to predict the downturn of future inflation (Panel C).

How do the new data in 1981 help ameliorate the forecasting performance? Remember that the model is not only dynamic but also multivariate. The new data

4. *The mathematical structure is similar to Sims and Zha (1998). See Box 1 for details.*
5. Blue Chip Forecasts *is a monthly publication based on a survey of a number of forecasters from different industries. The Blue Chip forecasts displayed in this article are the consensus forecasts.*

CHART 3 Point Forecasts of Annual Inflation Rate, 1980s



Source: See Box 2; *Blue Chip Forecasts.*

include prices as well as the model's other macroeconomic variables, such as output, the interest rate, and the unemployment rate. The model systematically explores the dynamic relationships among these other variables and the CPI, complex though they might be. It is therefore unsurprising that inflation forecasting can be further improved by the model's ability to capture multivariate relationships in new data.

The 1990s. 1990 was a turning point for inflation. Since then, inflation has declined steadily, from 5.4 percent in 1990 to 2.9 percent in 1996. Such a favorable environment has, to a large extent, surprised the public and professional forecasters as well. Indeed, many forecasting firms have overpredicted inflation for this period. The 1990s is thus considered another very difficult inflation period to forecast. Nonetheless, the model's forecasts for this period, as shown in Chart 4, look reasonable in capturing the steadily declining pattern of inflation.

From Chart 4 one can see that since 1991, Blue Chip forecasts have been consistently higher than actual outcomes. The overprediction of inflation in the 1990s is consistent with simple rules of thumb such as the Phillips curve trade-off, given the declining unemployment rate after 1992. In contrast, the model's dynamic forecasts are more optimistic about the downward trend in inflation and closer to actual outcomes.

Regime Shifts. There is a common view that monetary policy follows simple rules and that these rules change from time to time in an exogenous fashion. For example, the 1979–82 period is often regarded as one in which the policy "rule" was completely changed because the Federal Reserve adopted new operating procedures to target nonborrowed reserves rather than the federal funds rate. After 1982 the Federal Reserve returned to targeting the federal funds rate. By this argument, the period after 1982 has been under a different regime than the 1979–82 period, and some empirical modelers use a sample period that begins only after 1982 as if the data before 1983 were irrelevant.

To examine this idea, the model here is reestimated using the data starting in 1983. Chart 5 reports inflation forecasts out of sample (indicated by the dots). Evidently, throwing away the data before 1983 does not improve out-of-sample forecasting in general and worsens it considerably in some cases (Panels D, E, and F).[6] One interpretation of these findings is that the Federal Reserve's behavior is complicated and cannot be characterized by discontinuous or abrupt changes in simple rules. Even among economists there is no agreement on whether the Federal Reserve's behavior during the 1979–82 period was actually different (Cook 1989). For example, Goodfriend (1993, 4) argues that "it is more accurate to refer to the period from October 1979 to October 1982 as one of aggressive federal funds rate targeting than one of nonborrowed reserve targeting." From a forecasting point of view, Charts 3 and 4 show that including data in this period helps forecast inflation in the 1980s and 1990s; Chart 5 suggests that in dismissing the data simply by a priori reasoning valuable information may be lost.

In a nutshell, the dynamic multivariate model that generates results in Charts 3–5 aims at accounting for both short-run dynamics and long-run relationships among the six key macroeconomic variables. Such a modeling strategy may explain the model's reasonable performance in forecasting inflation. Model-based forecasts provide benchmarks by which policymakers can decide on the best policy action given all current information. Furthermore, explicit modeling makes it easy to document the model's forecasting performance (as in Charts 3–5) and to continue improving the model or replace it by a better model when available.

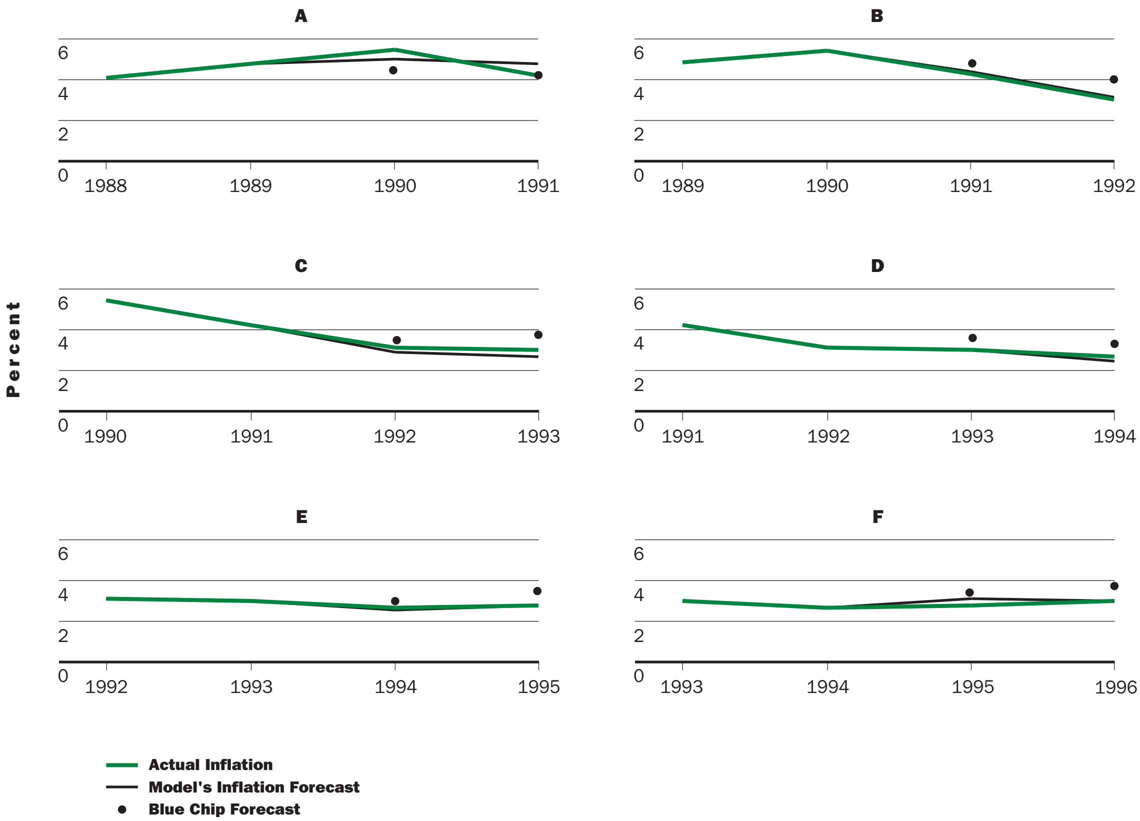
All models at best only approximate the actual economy. No model can forecast economic conditions with perfect accuracy. Thus, policymakers must use point forecasts cautiously and carefully.

The Distributions of Forecasts

All models at best only approximate the actual economy. No model can forecast economic conditions with perfect accuracy. Thus, policymakers must use point forecasts cautiously and carefully. When a model is used to advise policymakers, it is desirable that an explicit measure of uncertainty about the model's forecasts be provided. One effective way to measure uncertainty is to provide probability distributions of particular forecasts. With such a distribution, one is able to construct an error band on the forecast or to infer how likely the forecast is to be above or below a certain number. Error bands provide a sense of the uncertainty of economic conditions in the future and where the distribution of, say, inflation lies. Producing realistic error bands on forecasts has been a difficult technical problem. In a

6. *Technically, these two sets of forecasts may not be statistically different when error bands are considered. Small samples such as the data after 1982 tend to give unreliable results due to erratic sampling errors, as found in, say, Cecchetti (1995). The fact that the model with only the post-1982 data delivers reasonable results may be due to recent developments in Bayesian methods that deal with problems associated with low degrees of freedom (see Sims and Zha 1998 and also Box 1). This feature is still largely unexplored and deserves further research.*

CHART 4 Point Forecasts of Annual Inflation Rate, 1990s



Source: See Box 2; *Blue Chip Forecasts.*

recent paper Sims and Zha (1998) provide ways to compute probability distributions of forecasts from dynamic multivariate models (see also Box 1).

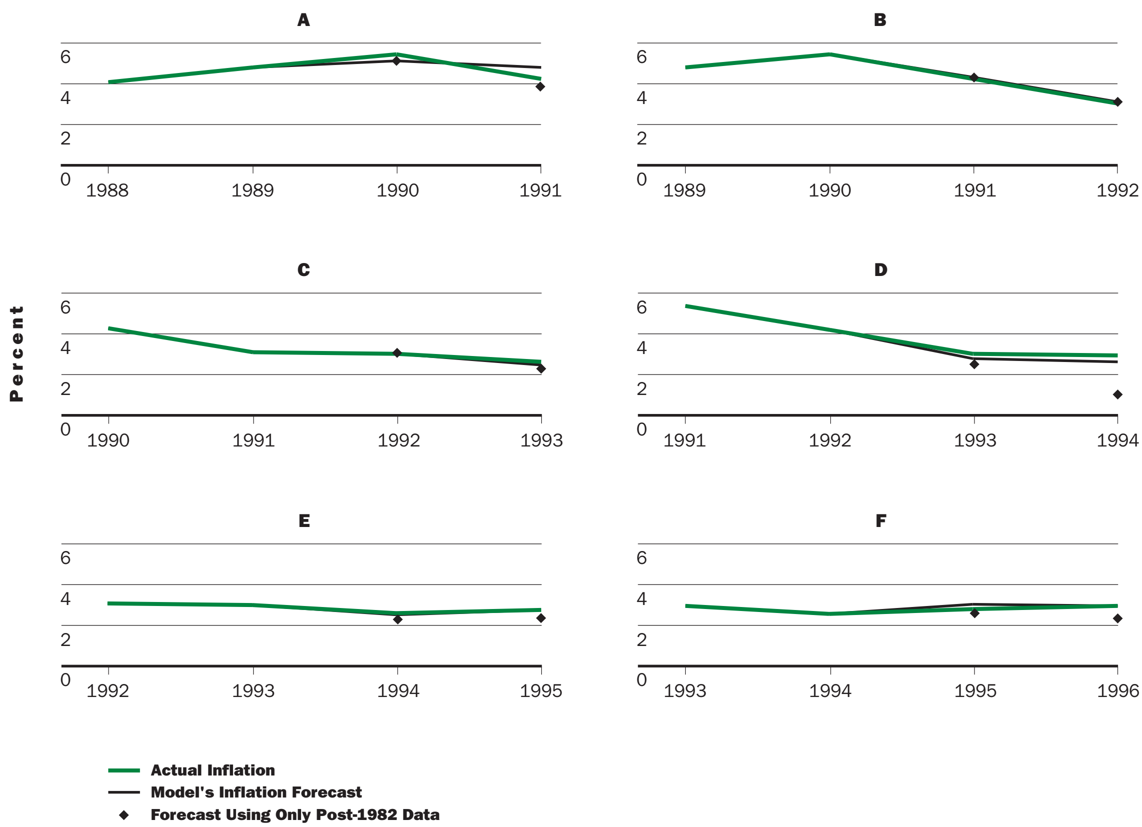
Given probability distributions of forecasts, error bands can be constructed for any desired probability. The purpose of constructing such a band is to demarcate reasonably high and low probability regions usable for policy deliberations. The error bands used in this article are constructed so that there is a two-thirds probability that the realized value is contained within the band. With this demarcation, events outside the band are given low probability and thus should be given less weight in decision making. One should bear in mind that low probability events do occur at times but less frequently.

As an example, Chart 6 presents the same forecasts as in Panel B of Chart 3 but with error bands attached. Whereas actual inflation for 1981 falls within the error band, actual 1982 inflation lies outside the error band. The error band at the two-year forecast horizon (that is, 1982) suggests that it is unlikely that 1982 inflation would return to the 1980 level, which indeed did not occur. At the same time, the model gives low probability to values far below 7.9 percent (the lower bound of the 1982 error band). But actual inflation in 1982 did occur at the level of 6.2 percent.

Most of the time, however, actual outcomes of inflation fall within error bands. This evidence is clear from Charts 3 and 4, in which point forecasts are often close to actual values of inflation. In addition to assessing quantitatively the uncertainty of forecasts, error bands provide ways of evaluating forecasts from other sources.[7] To show an example, Chart 7 displays the model's forecasts for the real GDP growth rate in 1995 and 1996 with error bands and Blue Chip predictions.[8] Actual GDP growth is inside the error bands, but the Blue Chip 1995 forecast of GDP growth at about 3.2 percent is far outside the error band. The model suggests that such a high growth rate is unlikely for 1995.

Although the error bands considered here are sufficient for most purposes, it is sometimes useful to know the entire distribution or likelihood that a particular forecast is going to be realized. Charts 8 and 9 provide two examples. Corresponding to Chart 6, Chart 8 presents the distribution of the inflation forecast for 1982. The two dashed vertical lines mark the band that contains two-thirds probability, and the solid vertical line marks the actual out-

CHART 5 Point Forecasts of Annual Inflation Rate, 1990s (Using post-1982 data)



Source: See Box 2.

come of inflation in 1982. The dispersed distribution in Chart 8 reflects a great uncertainty about inflation shortly after the high volatility of inflation during the late 1970s and early 1980s. Note that although actual inflation is outside the band, it is close to the lower bound of the band (that is, far away from the tail of the distribution).

Chart 9, corresponding to Chart 7, displays the distribution of the forecast of the real GDP growth rate in 1995. Again, the two dashed vertical lines mark the two-thirds probability band, the solid vertical line at 2 marks actual output growth in 1995, and the outer vertical line indicates the Blue Chip forecast. As can be seen in Chart 9, the Blue Chip forecast is near the tail of the distribution, implying that by the model's criterion such a forecast is very unlikely to be realized.

The discussion so far has been concerned exclusively with probability distributions or error bands around individual forecasts. While this focus is sufficient and effective for most policy analyses, it is important to bear in mind that individual forecasts are not independent of one another. Indeed, because of the multivariate nature of the model, forecasts of a set of variables of interest have a joint distribution. Such a distribution can be used to construct an error region that describes how likely forecasts of, say, both high output growth and low inflation are. Chart 10, for example, displays the error region that contains both real GDP growth and inflation for 1998 with a two-thirds probability.[9] The square represents the model's point forecast. The scattered circles are forecasts of real GDP growth and inflation for 1998 from fifty-five different

7. *These sources can be various commercial firms, particular economic theories, institutional knowledge, or even ad hoc views.*
8. *All forecasts are made at the beginning of 1995. Although this article concentrates on inflation for simplicity of the analysis, forecasts of other macroeconomic variables such as output and unemployment are equally important for monetary policy. In particular, a number of economists believe that there is a short-term trade-off between inflation and output, especially when unexpected large shocks hit the economy (King 1997).*
9. *Similar to error bands of individual forecasts, error regions of joint forecasts can be constructed for any desired probability. Again, the discussion here focuses on two-thirds probability.*

CHART 6 Inflation Forecasts with Error Bands for 1981 and 1982

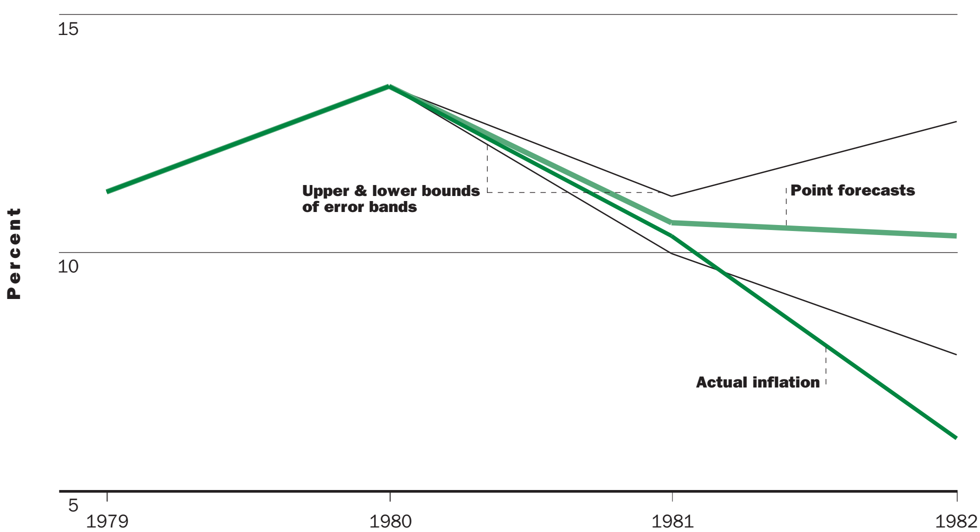
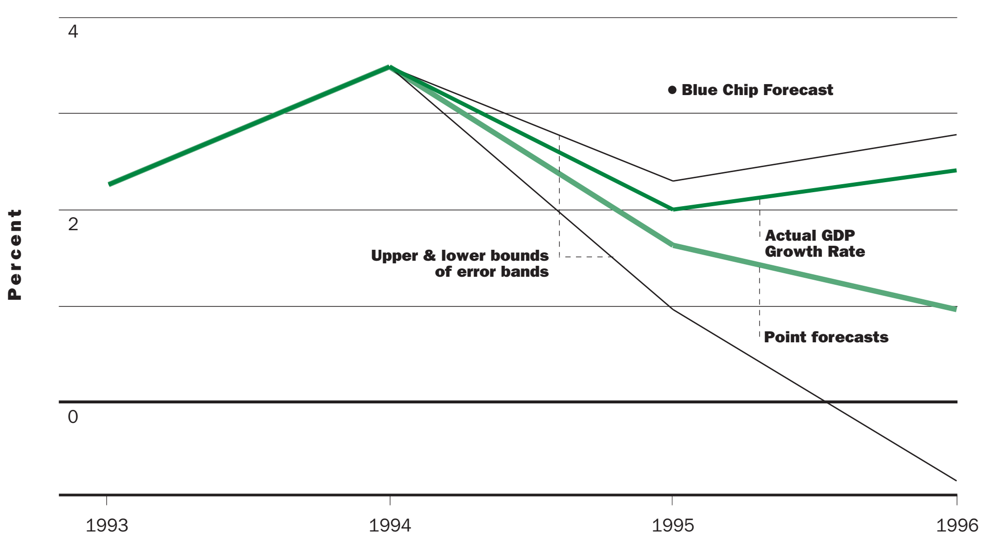


CHART 7 Real GDP Forecasts with Error Bands for 1995 and 1996



firms, published by the *Wall Street Journal* on January 2, 1998. Because these forecasts were submitted by December 18, 1997, the model's 1998 forecasts and error region in Chart 10 were made as of December 1997 to be as compatible with the *Wall Street Journal* forecasts as possible.[10] According to the error region, the model gives as much probability to the scenario of high GDP growth (3.5–5.5 percent) and low inflation (around 2 percent) as to that of medium GDP growth (2–3.5 percent) and low inflation (around 2 percent). But the model gives low probability to the scenario of low GDP growth (under 2 percent). The *Wall Street Journal* forecasts are unequally dispersed. At least one-fifth of the firms produced forecasts outside the model's error region. None of the firms produced forecasts that fall within the top half of the error region implied by the model.

Conclusion

The real world of monetary policy is complex. Because of long and variable lags in the effects of policy actions, the Federal Reserve faces a difficult task in trying to achieve its multiple objectives. The

CHART 8 Distribution of Inflation Rate Forecast for 1982

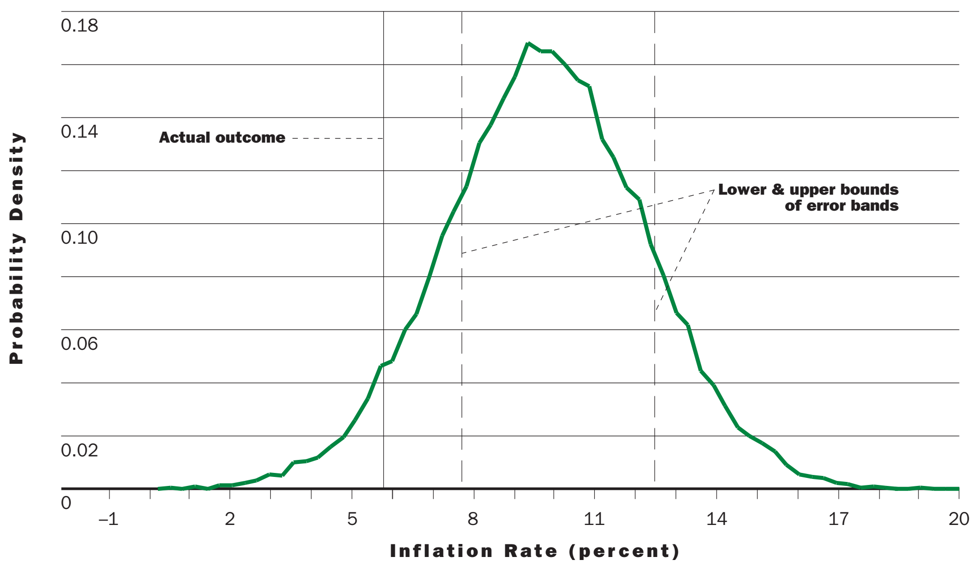
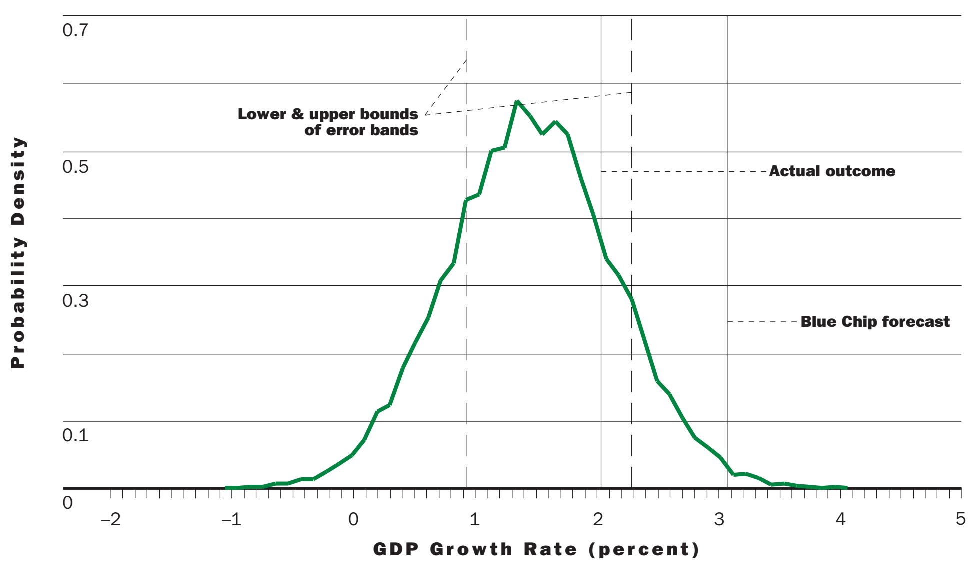


CHART 9 Forecast Distribution of GDP Growth Rate for 1995

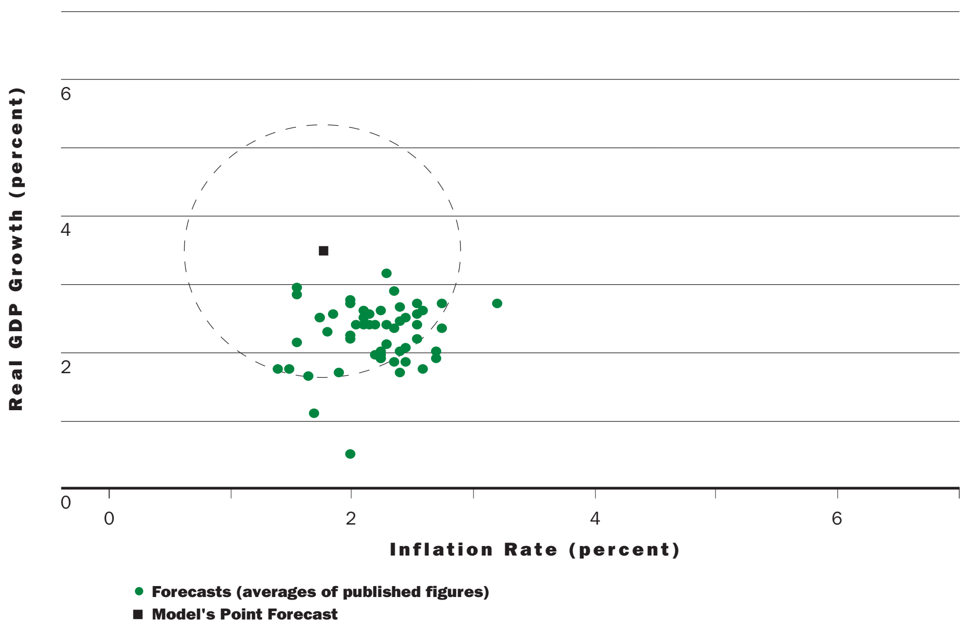


foregoing discussion concentrates on only one of these objectives—to keep the path of inflation low and stable. Given this objective, policy projections under different paths of a policy instrument (for example, the federal funds rate) are an integrated part of forward-looking policy formation. And reliable forecasts of the path of inflation are the first step in this process (Bernanke and Mishkin 1997).

The dynamic multivariate model discussed here is transparent enough to be reproduced and improved. At the same time, it is sufficiently complex to capture dynamic interplay between policymakers and the private sector. Consequently, it shows reasonable performance in forecasting as compared with other forecasts. More important, this approach provides empirically coherent ways to assess the uncertainty inherent in forecasts. Error

10. The forecasts displayed in Chart 10 are the 1998 averages of published figures in the Wall Street Journal.

CHART 10 Error Region for Forecasts of Real GDP Growth and Inflation Rates for 1998



Source: *Wall Street Journal,* January 2, 1998.

bands or distributions of forecasts are essential for gauging this uncertainty in at least two aspects. First, they offer an assessment of how likely or realistic other forecasts are. Second, error bands inform policymakers of the uncertainty they face, reminding them of the "need to be flexible in revising forecasts and the policy stance in response to new information contradicting their previous predictions" (Kohn 1995, 233).

As Chairman Greenspan has observed, "Operating on uncertain forecasts, of course, is not unusual. . . . [I]n conducting monetary policy the Federal Reserve needs constantly to look down the road to gauge the future risks to the economy and act accordingly" (1997b, 17). The dynamic multivariate model presented in this article provides a useful tool for gauging future uncertainty and an empirically consistent way to update forecasts. It is hoped that future research will apply such a model to tasks of policy projections.

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