A Comparison of Forecast Performance Between Federal Reserve Staff Forecasts, Simple Reduced-Form Models, and a DSGE Model

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Abstract

This paper considers the forecast performance of the Federal Reserve staff, five atheoretical reduced-form models, and an estimated dynamic stochastic general equilibrium (DSGE) model, focusing on the late 1990s through 2001. Our analysis finds that the DSGE model and atheoretical models forecast real GDP growth better than the Federal Reserve staff during this period by an economically significant margin; we find smaller differences across each method in the quality of inflation forecasts over this period. These results provide some support to the notion that richly specified DSGE models such the one used in this paper belong in the forecasting toolbox of a central bank.

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1 Introduction

This paper considers the forecast performance from the mid-1990s to 2001 of the Federal Reserve staff, three atheoretic reduced-form models, and an estimated dynamic stochastic general equilibrium (DSGE) model. Our goal is twofold. First, our inclusion of a DSGE model within the set of forecast models follows recent work (in particular by Smets and Wouters [2004]) suggesting that advances in Bayesian estimation methods have made DSGE models capable of providing informative forecasts. To date, this literature has compared forecasts from DSGE models with simple reduced-form forecasting techniques: Our comparison with Federal Reserve staff forecasts provides a potentially more stringent test, given that previous research has shown the staff forecast to be of high-quality relative to alternative methods (see, Romer and Romer [2000] and Sims [2003]).

In addition, our period of analysis focuses on a time during which the U.S. economy arguably underwent substantial swings in activity—that is, a rapid growth spurred by an acceleration of productivity in the late 1990s followed by the fall into recession in 2001. Moreover, this was a period for which the staff made relatively large errors in their forecast. Consequently, with the objective to improving future forecast performance, it is instructive to know whether the use of a DSGE model as a forecasting tool might have been able to improve forecast performance over the late 1990s to 2001 period. We also focus on this period because of data issues: Federal Reserve staff forecasts are publicly available only after a lag of five years. Therefore, a comparison of such staff forecasts, reduced-form models, and forecasts from our DSGE model can only be performed with the five-year lag.

Our analysis finds that the DSGE model and simple reduced-forms forecast real GDP growth better than the Federal Reserve staff during this period by an economically significant margin. We find smaller differences across each method in the quality of inflation forecasts over this period. Our findings with regard to the comparison of the Greenbook forecast and reduced-form alternatives accord with those of Tulip [2005], who documents the staff's large errors in the late 1990s through 2001—first on the low side during the late 1990s boom, and then on the high side as the economy fell into recession. Our results for the DSGE model provide some support to the notion that such models belong in the forecasting toolbox of a central bank. As emphasized in Edge, Kiley, and Laforte (2006a), this may be particularly valuable because such models also provide a coherent framework within which the economic factors driving the outlook can be decomposed. Such decompositions are absent from reduced-form forecasting equations, thereby limiting their usefulness and credibility in policy circles where articulating a "story" grounded in economic relationships is as important to a forecast as the numbers themselves.[1]

The DSGE model used in our forecasting exercise has been presented in previous work (see, Edge, Kiley, and Laforte, 2006a), in which we use the model to illustrate the nature of movements in potential output and the natural rate of interest in a DSGE framework and compare these movements to those from models with less direct "microfoundations," such as the Federal Reserve's FRB/US large-scale macroeconometric model. A documentation of the model that includes all of the model equations and parameter distributions along with a full set of variance decompositions, impulse response functions, and simulated observed and latent variable paths has also been prepared for this model (see Edge, Laforte, and Kiley, 2006b). We provide a brief summary of the structure of our DSGE model in the next section.

Section 3 then provides a discussion of the other projections against which we gauge the relative forecasting ability of our DSGE model. Specifically, we discuss the Federal Reserve Board's staff projections and the forecasts generated by three reduced-form forecasting equations. For our purposes, an accurate comparison of the performance of different forecasts necessitates the use of real-time data. The Federal Reserve's staff projections are already real-time forecasts. To obtain real-time forecasts for the DSGE model and reduced-form models we must estimate our models on real-time data and use the real-time values of the last historical quarters as the state variables off which to generate our forecast. The real-time databases upon which we estimate the DSGE model and reduced-form models are also discussed in Section 3. Section 4 presents the results from our forecast-generation exercises, while section 5 concludes and points to direction for future research.

2 A Two-Sector DSGE Model for Forecasting

We consider a dynamic, stochastic, general equilibrium model with a rich array of production, expenditure, factor market, and pricing decisions. Our framework builds upon recent work that has specified and estimated one-sector models with price and wage rigidities, and expands upon such specifications in order to better capture key cyclical and especially

[1]See Meyer, 1997, for a discussion of importance of storytelling in macroeconomic forecasting.

secular features of the US data.

In particular, our DSGE model is built around a two-sector growth model in which there exist two types of technological progress: sector-neutral technological change, which advances trend production equally in both sectors of the economy, and investment-specific technological change, which advances production in the investment goods sector only. This production setup allows the growth rates of output in different sectors of the economy to permanently diverge, which is an important feature of the US economy; relative prices for investment goods, especially high-tech investment goods, have fallen and real expenditure on (and production of) such goods has grown more rapidly than that for other goods and services.

Similarly, the demand side of our model has been expanded beyond the level typical of most recent treatments. We incorporate several expenditure categories. In the household sector, we disaggregate demand to a much greater degree than in standard treatments. Specifically, we distinguish among household expenditures on (i) consumer non-durable goods and non-housing services; (ii) consumer durable goods; and (iii) residential investment. On the business side of the model, non-residential investment is the only category of final demand. Our principal motivation for assuming this level of disaggregation stems from the differential cyclical properties of these expenditure categories, as well as policymakers' frequent interest in the behavior of detailed spending aggregates.[2]

Real effects of monetary policy with the DSGE model are generated through the assumption that adjustment costs to wage- and price-setting lead to sticky prices and wages. Since our economy possesses two separate production sectors, it has direct implications for relative prices for the economy's two goods, which can be compared to the data. Other features, such as habit persistence in consumption and adjustment costs in the economy's multiple capital stocks, are added to the model to allow for greater empirical validation of short-run dynamics.

In specifying and estimating our DSGE model, we match, as closely as possible, the concepts underlying our model variables with those in the National Income and Product Accounts and the BLS Productivity and Costs data. From the point of view of any model used to inform forecasting and policymaking discussion this is clearly important since the

[2]A more thorough discussion of the motivation for modeling choice can be found in Edge, Kiley, and Laforte (2006a).

model's output must be comparable to the data series focussed on by staff who are not themselves directly involved in using the model. The forecast generated by the DSGE model can therefore easily be compared with the Federal Reserve staff's forecast.

The remainder of this section summarizes briefly key aspects of the DSGE model. Details can be found in Edge, Kiley, and Laforte (2006a, 2006b).

2.1 The Production Technology

Our model economy produces two final goods and services: slow-growing "consumption" goods and services X_t^{cbi} and fast-growing "capital" goods X_t^{kb}. These final goods are produced by aggregating—according to a Dixit-Stiglitz technology—an infinite number of differentiated inputs.

$$X_t^s = \left(\int_0^1 X_t^s(j)^{\frac{\Theta_t^{x,s}-1}{\Theta_t^{x,s}}} dj \right)^{\frac{\Theta_t^{x,s}}{\Theta_t^{x,s}-1}}, \qquad s = cbi, kb, \tag{1}$$

The jth differentiated intermediate good in sector s (which is used as an input in equation 1) is produced by combining each variety of the economy's differentiated labor inputs $\{L_t^s(i,j)\}_{i=0}^1$ with the sector's specific *utilized* non-residential capital stock $K_t^{u,nr,s}(j)$. (Utilized non-residential capital, $K_t^{u,nr,s}(j)$, is equal to the product of *physical* non-residential capital, $K_t^{nr,s}(j)$, and the utilization rate, $U_t^{nr,s}(j)$). A Dixit-Stiglitz aggregator characterizes the way in which differentiated labor inputs are combined to yield a composite bundle of labor, denoted $L_t^s(j)$. A Cobb-Douglas production function then characterizes how this composite bundle of labor is used with capital to produce—given the current level of multifactor productivity MFP_t^s in the sector s—the intermediate good $X_t^s(j)$. The production of intermediate good j is represented by the function:

$$X_t^{m,s}(j) = (K_t^{u,nr,s}(j))^{\alpha} \left(\underbrace{Z_t^m Z_t^s}_{MFP_t^s} L_t^{x,s}(j) \right)^{1-\alpha} \text{ where } L_t^{x,s}(j) = \left(\int_0^1 L_t^{x,s}(i,j)^{\frac{\Theta_t^l-1}{\Theta_t^l}} di \right)^{\frac{\Theta_t^l}{\Theta_t^l-1}} s = cbi, kb \tag{2}$$

and where we assume $Z_t^{cbi} \equiv 1$. The parameter α in equation (2) is the elasticity of output with respect to capital while Θ_t^l denotes the stochastic elasticity of substitution between the differentiated labor inputs.

The level of productivity in the capital goods producing sector has two components. The Z_t^m component represents an economy-wide productivity shock, while the Z_t^{kb} term represents a productivity shock that is specific to the capital goods sectors. The level of productivity in the consumption goods producing sector has only the one economy-wide component, Z_t^m. The exogenous productivity terms contain a unit root, that is, they exhibit permanent movements in their levels. We assume that the stochastic process Z_t^s evolves according to

$$\ln Z_t^s - \ln Z_{t-1}^s = \ln \Gamma_t^{z,s} = \ln\left(\Gamma_*^{z,s} \cdot \exp[\gamma_t^{z,s}]\right) = \ln \Gamma_*^{z,s} + \gamma_t^{z,s},\ s = kb, m \tag{3}$$

where $\Gamma_*^{z,s}$ and $\gamma_t^{z,s}$ are the steady-state and stochastic components of $\Gamma_t^{z,s}$. The stochastic component $\gamma_t^{z,s}$ is assumed to evolve according to

$$\gamma_t^{z,s} = \rho^{z,s}\gamma_{t-1}^{z,s} + \epsilon_t^{z,s}. \tag{4}$$

where $\epsilon_t^{z,s}$ is an i.i.d shock process, and $\rho^{z,s}$ represents the persistence of $\gamma_t^{z,s}$ to a shock. In line with historical experience, we assume a more rapid rate of technological progress in capital goods production by calibrating $\Gamma_*^{z,k} > 1$, where an asterisk on a variable denotes its steady-state value.

2.2 Capital Stock Evolution

As already noted, there are three types of *physical* capital stocks in our model economy: non-residential capital, K_t^{nr}, residential capital, K_t^r, and consumer durables capital K_t^{cd}.

Purchases of the economy's fast-growing "capital" good can be transformed into either non-residential capital, K_{t+1}^{nr}, (that can then be used in the production of either the slow-growing "consumption" good or the fast-growing "capital" good) or into the economy's consumer-durable capital stock, K_{t+1}^{cd}, (from which households derive utility). Purchases of the economy's slow-growing "consumption" good can be transformed into residential capital.

The evolution of the economy's three capital stocks are given below. We assume that there is some stochastic element affecting the efficiency of investment—reflected in the term A_t^s, for $s = nr$, cd, and r—in the capital accumulation process. These shocks are uncorrelated from each other and exhibit only transitory movements from their steady-state unit mean. Letting $a_t^s \equiv \ln A_t^s$ denote the log-deviation of A_t^s from its steady-state value of unity, we assume that:

$$a_t^s = \rho^{a,s}a_{t-1}^s + \epsilon_t^{a,s},\ s = nr, cd, r. \tag{5}$$

We also asssume that not all investment expenditure results in productive capital, since some fraction is absorbed by adjustment costs in the process of installation:

$$
\begin{aligned}
K_{t+1}^{nr}(k) =& (1-\delta^{nr})K_t^{nr}(k) + A_t^{nr}E_t^{nr}(k) \\
&- \frac{100\cdot\chi^{nr}}{2}\left(\frac{E_t^{nr}(k) - \eta^{nr}E_{t-1}^{nr}(k)\Gamma_t^{x,kb} - (1-\eta^{nr})\widetilde{E}_*^{nr}Z_t^m Z_t^{kb}}{K_t^{nr}}\right)^2 K_t^{nr} \qquad (6)\\
K_{t+1}^{cd}(k) =& (1-\delta^{cd})K_t^{cd}(k) + A_t^{cd}E_t^{cd}(k) \\
&- \frac{100\cdot\chi^{cd}}{2}\left(\frac{E_t^{cd}(k) - \eta^{cd}E_{t-1}^{cd}(k)\Gamma_t^{x,kb} - (1-\eta^{cd})\widetilde{E}_*^{cd}Z_t^m Z_t^{kb}}{K_t^{cd}}\right)^2 K_t^{cd} \qquad (7)\\
K_{t+1}^{r}(k) =& (1-\delta^{r})K_t^{r}(k) + A_t^{r}E_t^{r}(k) \\
&- \frac{100\cdot\chi^{r}}{2}\left(\frac{E_t^{r}(k) - \eta^{r}E_{t-1}^{r}(k)\Gamma_t^{x,cbi} - (1-\eta^{r})\widetilde{E}_*^{r}Z_t^m (Z_t^{kb})^{\alpha}(Z_t^{cbi})^{1-\alpha}}{K_t^{r}}\right)^2 K_t^{r}. \qquad (8)
\end{aligned}
$$

The parameter δ^s denotes the depreciation rate for either the non-residential ($s = nr$), consumer durables ($s = cd$), or residential ($s = r$) capital stocks. The term $\widetilde{E}_*^s$ denotes the value of steady-state non-residential ($s = nr$), consumer durables ($s = cd$), or residential ($s = r$) investment spending normalized by the level of productivity so as to be constant in the steady state. Note that investment adjustment costs are zero for non-residential capital when $\frac{E_t^{nr}}{Z_t^m Z_t^{kb}} = \frac{E_{t-1}^{nr}}{Z_{t-1}^m Z_{t-1}^{kb}} = \widetilde{E}_*^{nr}$ but rise to above zero, at an increasing rate, as non-residential investment growth moves further away from this. The costs for altering non-residential investment depend on both the level of (growth-adjusted) investment spending from the preceding period as well as the steady-state level of investment spending. The parameter χ^{nr} governs how quickly these costs increase away from the steady-state. The relative values of $\frac{E_t^{cd}}{Z_t^m Z_t^{kb}}$, $\frac{E_{t-1}^{cd}}{Z_{t-1}^m Z_{t-1}^{kb}}$, and $\widetilde{E}_*^{cd}$ have similar implications for the adjustment costs entailed in the accumulation of consumer durables capital, as do the relative values of $\frac{E_t^{r}}{Z_t^m (Z_t^{kb})^{\alpha}(Z_t^{cbi})^{1-\alpha}}$, $\frac{E_{t-1}^{r}}{Z_{t-1}^m (Z_{t-1}^{kb})^{\alpha}(Z_{t-1}^{cbi})^{1-\alpha}}$, and $\widetilde{E}_*^{r}$ for the accumulation of residential capital. Similarly, the values of the parameter χ^{cd} and χ^r govern how quickly these costs increase away from the steady-state. Adjustment costs are quite important in models such as ours in ensuring gradual responses of investment to shocks.

2.3 Preferences

The ith household derives utility from four sources: its purchases of the consumer non-durable goods and non-housing services, $E_t^{cnn}(i)$, the flow of services from its rental of consumer-durable capital, $K_t^{cd}(i)$, the flow of services from its rental of residential capital

$K_t^r(i)$, and its leisure time, which is equal to what remains of its time endowment after $L_t^{cbi}(i)+L_t^{kb}(i)$ hours are spent working. The preferences of household i are separable over all of the arguments of its utility function. The utility that the household derives from the three components of its goods and services consumption is influenced by its habit stock for each of these consumption components, a feature that has been shown to be important for consumption dynamics in similar models. Household i's habit stock for its consumption of non-durable goods and non-housing services, is equal to a factor h^{cnn} multiplied by its consumption last period $E_{t-1}^{cnn}(i)$). The household's habit stock for its other components of consumption is defined similarly. In summary, the preferences of household i are represented by the utility function:

$$\mathcal{E}_0\sum_{t=0}^{\infty}\beta^t\Big\{\varsigma^{cnn}\Xi_t^{cnn}\ln(E_t^{cnn}(i)-h^{cnn}E_{t-1}^{cnn}(i))+\varsigma^{cd}\Xi_t^{cd}\ln(K_t^{cd}(i)-h^{cd}K_{t-1}^{cd}(i))$$
$$+\varsigma^{r}\Xi_t^{r}\ln(K_t^{r}(i)-h^{r}K_{t-1}^{r}(i))-\varsigma^{l}\Xi_t^{l}\frac{(L_t^{cbi}(i)+L_t^{kb}(i))^{1+\nu}}{1+\nu}\Big\}. \tag{9}$$

The parameter β is the household's discount factor, ν denotes its inverse labor supply elasticity, while ς^{cnn}, ς^{cd}, ς^{r}, and ς^{l} are scale parameter that tie down the ratios between the household's consumption components. The stationary, unit-mean, stochastic variables Ξ_t^{cnn}, Ξ_t^{cd}, Ξ_t^{r}, and Ξ_t^{l} represent aggregate shocks to the household's utility of its consumption components and its disutility of labor. Letting $\xi_t^x \equiv \ln\Xi_t^x - \ln\Xi_*^x$ denote the log-deviation of Ξ_t^x from its steady-state value of Ξ_*^x, we assume that

$$\xi_t^x = \rho^{\xi,x}\xi_{t-1}^x + \epsilon_t^{\xi,x}, \qquad x = cnn, cd, r, l. \tag{10}$$

The variable $\epsilon_t^{\xi,x}$ is an i.i.d. shock process, and $\rho^{\xi,x}$ represents the persistence of Ξ_t^x away from steady-state following a shock to equation (10).

2.4 Price and Wage Setting

Intermediate producers in both the consumption and capital goods sectors of the economy have monopolistically competitive price setting power over their differentiated output and consequently set their prices subject to the demand curve that they face—that is, $X_t^s(j)=(P_t^s(j)/P_t^s)^{-\Theta_t^{x,s}}X_t^s$, for $s=c,k$—from the final goods producing firm. In addition intermediate goods producing firms face costs in adjusting their prices which we assume depends on the lagged and steady-state inflation rate, scaled by some parameter

χ^p. Specifically, adjustment costs take the following form:

$$\text{Price setting adjustment costs} = \frac{100 \cdot \chi^p}{2} \left(\frac{P_t^s(j)}{P_{t-1}^s(j)} - \eta^p \Pi_{t-1}^{p,s} - (1-\eta^p) \Pi_*^{p,s} \right)^2 P_t^s X_t^s.$$

When the firm solves its price-setting profit maximization problem, these costs are subtracted from the profits that it earns as a result of its monopolistically-competititve power.

Households, similarly, have monopolistically competitive wage setting power over their differentiated labor supplies and consequently set their wages subject to the demand curve that they face—that is, $L_t^s(i) = (W_t^s(i)/W_t^s)^{-\Theta_t^{l,s}} L_t^s$, for $s = c, k$—from the intermediate goods producing firms. Like intermediate goods producing firms, households face costs in adjusting their wages that depend on the lagged and steady-state rates of wage inflation; specifically,

$$\text{Wage setting adjustment costs} = \frac{100 \cdot \chi^w}{2} \left(\frac{W_t^s(j)}{W_{t-1}^s(j)} - \eta^w \Pi_{t-1}^{w,s} - (1-\eta^w) \Pi_*^{w,s} \right)^2 W_t^s L_t^s.$$

These costs are subtracted from the household's budget constraint, against which households solve their utility maximization problem.

2.5 Monetary Authority

The central bank sets monetary policy in accordance with an Taylor-type interest-rate feedback rule. Policymakers smoothly adjust the actual interest rate R_t to its target level $\bar{R}_t$

$$R_t = (R_{t-1})^{\phi^r} \left(\bar{R}_t\right)^{1-\phi^r} \exp\left[\epsilon_t^r\right], \tag{11}$$

where the parameter ϕ^r reflects the degree of interest rate smoothing, while ϵ_t^r represents a monetary policy shock. The central bank's target nominal interest rate $\bar{R}_t$ is given by:

$$\bar{R}_t = \left(\Pi_t^{p,gdp} / \Pi_*^{p,gdp}\right)^{\phi^{\pi,gdp}} \left(\Delta\Pi_t^{p,gdp}\right)^{\phi^{\Delta\pi,gdp}} \left(H_t^{gdp} / H_*^{gdp}\right)^{\phi^{h,gdp}} \left(\Delta H_t^{gdp}\right)^{\phi^{\Delta h,gdp}} R_*. \tag{12}$$

where R_* denotes the economy's steady-state nominal interest rate and $\phi^{\pi,gdp}$, $\phi^{\Delta\pi,gdp}$, $\phi^{h,gdp}$, and $\phi^{\Delta h,gdp}$ denote the weights in the feedback rule. GDP growth is denoted by H_t^{gdp}.

2.6 Summary of Key Properties

Our presentation of the model has purposefully been quite terse, and a companion piece (Edge, Laforte, and Kiley, 2006b) provides details of the equations that define equilibrium in the model. Our presentation here highlights several important points. First, our model, while considering production and expenditures decisions in a bit more detail, is very similar to many others in the literature. In addition, our economy is subject to a rich set of productivity, preference, and markup shocks. Finally, our model includes a large number of adjustment costs in order to slow the response of endogenous variables to fundamentals.

As emphasized below, we estimate this model using real-time data to generate a forecast record. Rather than discuss the estimates of key parameters at different points in time, we focus here on a few key properties of the model estimated over the full 1984 to 2004 sample period. Turning first to preference and adjustment cost parameters related to household decisions, the set of parameters related to habit persistence (the h parameters for each type of consumption in our utility function) are uniformly large. For nondurables and services excluding housing, the habit parameter (at the posterior mode) is about 0.8 – close to the value in Fuhrer [2000] and other DSGE models of the United States. For durables expenditure, the habit parameter takes on a somewhat smaller value (at the posterior mode). Most DSGE models do not consider durables expenditure, and hence it is not immediately obvious that this value lies near any sort of consensus; however, we view this parameter as quite plausible within the context of our model, as habit persistence for the stock of durable goods will make utility from this flow (partially) dependent on the level of durable investment, thereby smoothing the growth rate in this series relative to the negative autocorrelation implied by the model absent habits (e.g., Mankiw [1982]). The habit parameter is not quite as large for housing (at about 1/2 at the posterior mode). However, investment adjustment costs are estimated to be very significant for residential investment and of modest importance for consumer durables, and both these factors contribute to "hump-shaped" responses of these series to monetary policy shocks. (In fact, it appears from simulations of the posterior distribution of parameters that habit persistence and adjustment costs for consumer durables are closely related). The adjustment cost parameters are a bit hard to interpret. It is perhaps easier to think of the implications of these parameters for the elasticity of investment with respect to the capital-stock specific measure of marginal q; this elasticity is about one for consumer durables and about 1/7 for residential investment.

With regard to other preference parameters, the estimate of the inverse of the labor supply elasticity, at a bit over one at the posterior mode, is a bit higher than suggested by the balance of microeconomic evidence (Abowd and Card [1989]) and results from earlier

DSGE models with sticky wages. The sticky wage assumption is important in this regard, as it allows households to be "off" their labor supply schedule in the short-run; in flexible wage models, the labor supply elasticity typically must be much larger to generate the required volatility in hours.

With regard to other adjustment cost parameters, we estimate significant costs to the change in investment flows for business investment (as well as the investment in household stocks noted above), a standard result; these costs imply an elasticity of investment to marginal q of about 1/3. We also find an important role for the sectoral adjustment costs to labor: In our multisector setup, shocks to productivity or preferences in one sector of the economy will result in a strong shift of labor towards that sector—an undesirable implication given the high sectoral comovement in the data. The adjustment costs to the sectoral mix of labor input ameliorate this potential problem, as in Boldrin *et al.* [2001].

Finally, adjustment costs to prices and wages are both estimated to be important, although prices appear "stickier" than wages. Our quadratic costs of price and wage adjustment can be translated into frequencies of adjustment consistent with the Calvo model; these are about six quarters for prices and about one quarter for wages. However, these estimates are very sensitive to the specifics of our model. Incorporating additional features, such as a "kinked" demand curve or firm-specific factors would alter the mapping from our parameter estimates to measures of the frequency of price adjustment. With regard to the importance of indexation, we find only a modest role for lagged inflation in our adjustment cost specification (around 1/3), equivalent to modest indexation to lagged inflation in other sticky-price specifications. This differs from some other estimates, perhaps because of the focus on a more recent post-1983 sample (similar to results in Kiley [2005] and Laforte [2005]).

3 Alternative Forecasts

We compare the forecasts from our DSGE model with six alternatives: The Federal Reserve Board's Greenbook projection and three atheoretic reduced form models. In this section these alternative forecasts.

3.1 The Greenbook Forecast

The first set of forecasts that we compare our DSGE model projection against are those produced by the staff at the Federal Reserve Board. The Federal Open Market Committee (FOMC) meets eight times a year at slightly irregularly spaced intervals. In the lead up to each of these meetings, the staff at the Board of Governors put together a detailed forecast of the economic outlook that is published (usually three or four business days before the FOMC meeting) in a document unofficially known as the Greenbook. The Greenbook forecast, which are most readily available on the web-site of the Federal Reserve Bank of Philadelphia, reflect the views of the staff and not the Committee members.

The projection horizon for the Greenbook forecast vintages that we consider in this paper vary from six to ten quarters. In September of each year, the staff extend the forecast to include the year following the next in the projection period. Since the third quarter is not yet finished at the time of the September forecast, that quarter is included in the Greenbook projection horizon, generating a maximum horizon of ten quarters. The end point of the projection horizon remains fixed for subsequent forecasts as the starting point moves forward. As a result, by the July/August forecast round of the following year the projection period extends out only six quarters. The first column of tables 1 to 3 lists the Greenbook forecasts that we consider in this paper while the second column lists the dates on which they we finalized and archived. The last column of these tables lists the horizon over which the forecast in each Greenbook was made.

3.2 Forecasts Generated by Atheoretic Reduced-form Models

We consider the forecasts generated by three atheoretic reduced-form models: The first "model" is a set of random walk univariate time-series equations for the key macro variables of real GDP growth (H_t^{gdp}), GDP price inflation (Π_t^{gdp}), real non-durables and services PCE growth ($H^{cnn} = \widetilde{E}_t^{cnn}/\widetilde{E}_{t-1}^{cnn}$), and non-durables and services PCE price inflation ($\Pi_t^{x,cbi}$); specifically, $V_t = V_{t-1} + \epsilon_t$ for $V \in \{H_t^{gdp}, \Pi_t^{gdp}, H^{cnn}, \Pi_t^{x,cbi}\}$. This choice of model is motivated by the work of Atkenson and Ohanian [2001], who demonstrate that, at least for certain periods, a simple extrapolative forecast for GDP inflation performs as well as a "Phillips Curve" relation linking inflation and unemployment.

The other two models we consider are four-lag VAR systems consisting of real GDP growth (H_t^{gdp}), GDP price inflation (Π_t^{gdp}), real non-durables and services PCE growth

($H^{cnn} = \widetilde{E}_t^{cnn}/\widetilde{E}_{t-1}^{cnn}$), non-durables and services PCE price inflation ($\Pi_t^{x,cbi}$), and the nominal interest rate (R_t). Specifically,

$$\underbrace{[V_t]}_{5\times 1} = \underbrace{[B_0]}_{5\times 1} + \sum_{s=1}^{4} \underbrace{[B_s]}_{5\times 5} \cdot \underbrace{[V_{t-s}]}_{5\times 1} + \underbrace{[\epsilon_t]}_{5\times 1} \text{ where } V = [H_t^{gdp}, \Pi_t^{gdp}, H^{cnn}, \Pi_t^{x,cbi}, R_t].$$

The first of our two multivariate models is an unrestricted VAR. The second is a Bayesian VAR that introduces onto the coeffients a modified version of the Litterman [1980] prior. The values of the hyperparameters are the following: the overall tightness is 0.2; the cross-equation tightness is 0.5; and, finally, the harmonic lag decay is set to 0.5. The prior distributions of the "constant" parameters are normal densities centered at zero with a standard deviation of one. Since the Litterman prior was originally proposed for variables in levels while the Bayesian VAR model's variables are specified either in first-differences or stationary are in levels, we replace the unit root prior on the dynamic coefficient of a variable on its own first lag with a lower value of 0.7. The posterior distribution is sampled using Gibbs-Sampling methods as explained in Kadiyala and Karlsson [1997].

3.3 Generating Real Time Forecasts

An accurate comparison of the performance of different forecasts requires the use of real-time data. The Federal Reserve Board's Greenbook projections are already real-time forecasts as they are untouched since they were archived on the dates shown in tables 1 to 3. Real-time forecasts for our DSGE models and reduced-form models can only be obtained by estimating our models on real-time data and using the real-time values for the lags of state variables in generating the forecast.

Since March 1996 the staff have stored the Greenbook projection from each FOMC forecasting round in readable electronic databases that contain a reasonable level of detail.[3] Importantly, for the purposes of this paper these databases also include historical data for the data series the staff forecast that extend back to about 1975. Because these databases were archived at the time that each particular Greenbook forecast was closed, the historical data from these databases represent the realtime data available to the staff at the time that they were preparing their forecast. Consequently, if we estimate our DSGE and atheoretic time-series models with historical data from the past Greenbook databases we are implicitly assuming the same information set with which the Greenbook forecast was actually made.

[3] Prior to March 1996 only paper copies of the forecast are available.

Constructing real-time datasets on which to estimate our DSGE and atheoretic models simply involves pulling the relevant series from the Greenbook database listed in tables 1 to 3. For our atheoretic models we pull the following series from each database:

1. Real gross domestic product;
2. GDP price inflation;
3. Real consumption of non-durables and services;
4. Inflation for consumer nondurables and services; and,
5. The federal funds rate (which is never revised).

The atheoretic models are then estimated for each Greenbook database over the sample 1985:Q1 to the last historical quarter, which is given in the second to last column in tables 1 to 3.[4] For our DSGE model the (eleven) series that we pull from each Greenbook database are:

1. Nominal gross domestic product;
2. Nominal consumption expenditure on nondurables and services;
3. Nominal consumption expenditure on durables;
4. Nominal residential investment expenditure;
5. Nominal business investment expenditure, which equals nominal gross private domestic investment minus nominal residential investment;
6. GDP price inflation;
7. Inflation for consumer nondurables and services;
8. Inflation for consumer durables;
9. Hours, which equals hours of all persons in the non-farm business sector scaled up by the ratio of nominal spending in our model to nominal non-farm business sector output in order to model a level of hours more appropriate for the total economy;
10. Wage inflation, which equals compensation per hour in the non-farm business sector; and,
11. The federal funds rate.

[4] In general, the staff's estimate of the last quarter of history is only exactly equal to the BEA's estimate after the final release of the NIPA and perhaps for a couple days after the advance and preliminary NIPA releases. A lot of NIPA source data comes out after the advance release based on which the staff adjust their estimate of the last quarter of history.

In principle, the construction of real-time forecasts from the DSGE model presents no additional difficulties. In practice, however, some issues arise. The DSGE model involves modeling the joint stochastic process followed by a large number of variables, which may improve the estimates of underlying structural parameters and hence forecast accuracy. In addition, the solution and estimation of the DSGE model is somewhat more involved than that associated with simple time series regressions (which can be estimated almost instantly in virtually any software package, including even simple spreadsheets). As a result estimation in the DSGE model is performed using the real-time datasets once per year, specifically in the July/August round in which an annual rebenchmarking of the the NIPA takes place.[5] Parameter estimates are then held constant for the forecasts generated in subsequent rounds until the following July/August, at which point the model is re-estimated using the four additional quarters of data. Note that it is only the data used to estimate the model that remains constant across the forecasts for the year. The "jumping-off" period that is used for each forecast generated by the DSGE model is the staff's estimate of the last quarter of history taken from the corresponding Greenbook database.

As is the standard practice, we estimate a log-linearized approximation to our model, which we cast in its state space representation for the set of (in our case 11) observable variables listed above. We then use the Kalman filter to evaluate the likelihood of the observed variables, and form the posterior distribution of the parameters of interest by combining the likelihood function with a joint density characterizing some prior beliefs over parameters. Since we do not have a closed-form solution of the posterior, we rely on Markov-Chain Monte Carlo (MCMC) methods.[6] We also add measurement errors processes, denoted η_t, for all of the observed series used in estimation except the nominal interest rate and the aggregate hours series. In all cases, the measurement errors explain less than 5 percent of the observed series.

[5] Were we to move our DSGE model into production we would in all likelihood reestimate the model every forecast round, since estimating such a model would not be onerous if it was to be performed only every six week. It is just for this present exercise in which we would have to obtain 36 different estimated models where the task becomes more tedious.

[6] We also make one simplification to the model that we estimate, which is that we set the parameter $\eta^{nr} = \eta^{r} = \eta^{cd} = 0$. This is just to maintain comparability with standard investment adjustment cost specifications.

4 Results

Our key results are summarized in figures 1 to 3, and table 4. Each figure and table presents measures of forecast accuracy (either Mean Absolute Errors, MAE, Root Mean Square Errors, RMSEs, or estimates of the bias from a particular forecasting technique) at various horizons for our main variables of interest—real GDP, real personal consumption expenditures (PCE), GDP prices, and PCE prices. Our discussion is organized by variable, with a summary of key implications in the last subsection.

4.1 Real GDP

The mid-1990s to early 2001 were a period of rapid growth in real US GDP. Moreover, the pace of growth over this period was widely unanticipated. In fact, observers were fairly pessimistic regarding real growth prospects for the second half of the 1990s; for example, the Congressional Budget Office projected that real GDP growth was likely to average less than [$2\frac{1}{2}$ percent] per year over this period in early 1996, reflecting an expectation that productivity growth would repeat the lackluster performance of the previous two decades while labor force growth slowed with the maturation of the baby boom generation.

In the event, real GDP growth was much stronger than anticipated. And this error was shared by the staff at the Federal Reserve—as has been documented previously by Tulip [2005]. As reported in table 4 and shown in the upper left panels of figures 1 and 2, the RSMA or MAE of the Greenbook forecast for GDP growth at various horizons was moderately worse than that from a random walk forecast. These forecast errors were larger than those that would have been associated with real-time forecasts from our suite of simple time-series models; the VAR and BVAR RMSEs are lower than those from the Greenbook or random walk models by modest margins.

With regard to our DSGE model, its forecast performance along the real GDP dimension appear comparable to the time series alternatives over this period, suggesting that the structure imposed by the model does not impinge upon its ability to summarize the time series properties of economic growth. This is a partial victory in itself: As we have emphasized in previous work (Edge, Kiley, and Laforte (2006a)), the ability of a structural model like our DSGE model to tell economically meaningful stories can make such models more attractive in a policy context than time-series alternatives, and the additional result that forecast performance may be acceptable as well adds further support to the consideration of such tools.

Finally, in unreported results it appears that the DSGE model performs particularly poorly during the recession—the last year of our evaluation period, which includes forecasts presented to the FOMC in March 2000 and hence includes early staff forecasts for 2001. An investigation of the ability of different forecasting techniques to adopt to an emerging recession may prove illuminating.

4.2 Real PCE

Looking underneath aggregate GDP growth provides further insight into the forecast performance of the Federal Reserve staff and the potential for structural DSGE models. As illustrated in the upper right panels of figures 1 and 2 and in table 4, the RMSE of the Federal Reserve staff forecast for real (nondurables and services) personal consumption expenditures is lower than that of our DSGE model, about the same as the random walk model, and higher than the two VAR models. The Greenbook forecast implies a lower RMSE than the DSGE model for real (NDS) PCE despite the fact that this component of spending is more than one half of GDP and the RMSEs by the staff were higher for real GDP.

The economic story here is quite clear, investment spending surged in the United States over the second half of the 1990s, and this acceleration was unanticipated. While the relative success of the time-series models for GDP is something of a black-box result, the DSGE story here is economically compelling: our two-sector model provides reasonably good forecasts for aggregate GDP growth over the late 1990s because it interprets incoming data as consistent with an pickup in technological growth and efficiency, particularly for business investment. Of course, the success during this period does raise the question of whether the particular structure of our DSGE model would prove as successful at other times, when relative strength in business investment is not so important for the aggregate growth outlook.

The differences between the relative RMSEs of real GDP and real personal consumption expenditures indicate that developments to the consumption side of the model will like prove the most fruitful in terms of forecast performance.

4.3 GDP and PCE prices

Our final set of results refer to forecasts for GDP and consumer prices (summarized in the bottom two panels of figures 1 and 2 and table 4). On balance, the Greenbook forecast performs slightly better than the time-series alternatives for GDP price inflation, while the DSGE-model forecast performs noticably worse than them all. For consumer prices the DSGE model has a similar forecast performance to the time-series alternative, while the staff forecast performs noticably better.

4.4 Summary of Empirical Results

Overall, we have found that our DSGE model provides forecasts for activity and inflation that are competitive with those from time-series models or the staff of the Federal Reserve Board. The relative success of our DSGE model at forecasting provides support to the use of such models in a policy context.

Despite these positive findings, our results are perhaps less supportive of the relative performance of DSGE models than other recent work that has pursued a different empirical strategy. For example, much of the emphasis in Smets and Wouters [2004] and subsequent research has evaluated relative performance via posterior odds. As has been emphasized by Sims (2003), posterior odds can in some cases appear surprisingly decisive, and our results suggest that the support for DSGE models using such metrics may be a case in point. Future research on alternative methods for evaluation of DSGE models will help clarify these issues.

5 Conclusions

Our goal has been to provide a comparison between forecasts from a richly-specified DSGE model with those from simple time-series alternatives and the staff forecasts of the Federal Reserve. Overall, our results are mixed. For certain series, our DSGE model dominates other forecasting alternatives; in other cases, our DSGE model is strongly dominated.

We take several lessons from these findings both for policy-related analyses and future research. Most importantly, the finding that a complex DSGE model is competitive with reasonable forecast alternatives provides support for the use of such models in forecasting and other policy-relevant work. However, our findings point to a more nuanced assessment of the strengths of such models. For example, much research on evaluation of DSGE models for policy work has focused on a a few properties (e.g., matching certain impulse response functions as in Christiano *et al.* [2005]) or on summary measures of fit such as the marginal likelihood or posterior odds ratio of a model. The former focus may be too narrow, and the latter too broad: To the extent policymakers are interested in a model with good forecasting properties for certain key series (e.g., consumer price inflation) and strong general equilibirum foundations, our findings of mixed results for forecasts of certain series suggests that evaluation of DSGE models must take care to focus on statistics of relevance to key decisionmakers.

We also find the results comparing forecast performance for real GDP and its price level compared with those for consumption and its price level very interesting. We hope to investigate further the reasons why our DSGE model performs well for GDP aggregates but less well for consumption aggregates. Such work may also have broader macroeconomic implications, as basic macroeconomic theory often is sued to suggest that real consumption should be more difficult to forecast than GDP.

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Table 1: Greenbook and National Accounts Release Dates (Sep. 96 to Jan. 98).

GB Name	Date GB Closed	Date(s) of FOMC Meeting	Estim. Period, DSGE Model	Last Qtr. of History	GB Forecast Horizon
Sep. 96	Sep. 18, 96	Sep. 24, 96	85:Q1-96:Q2	96:Q2	96:Q3-98:Q4
Interim NIPA releases: 96:Q2 Final (9/27/96), 96:Q3 Advan. (10/30/96)					
Nov. 96	Nov. 6, 96	Nov. 13, 96	85:Q1-96:Q2	96:Q3	96:Q4-98:Q4
Interim NIPA releases: 96:Q3 Prelim. (11/27/96)					
Dec. 96	Dec. 12, 96	Dec. 17, 96	85:Q1-96:Q2	96:Q3	96:Q4-98:Q4
Interim NIPA releases: 96:Q3 Final (12/20/96)					
Jan. 97	Jan. 29, 97	Feb. 4 & 5, 97	85:Q1-96:Q2	96:Q4	97:Q1-98:Q4
Interim NIPA releases: 96:Q4 Advan. (1/31/97), 96:Q4 Prelim. (2/28/97)					
Mar. 97	Mar. 19, 97	Mar. 25, 97	85:Q1-96:Q2	96:Q4	97:Q1-98:Q4
Interim NIPA releases: 96:Q4 Final (3/28/97), 97:Q1 Advan. (4/30/97)					
May 97	May 15, 97	May 20, 97	85:Q1-96:Q2	97:Q1	97:Q2-98:Q4
Interim NIPA releases: 97:Q1 Prelim. (5/30/97)					
Jun. 97	Jun. 25, 97	Jul. 1 & 2, 97	85:Q1-96:Q2	97:Q1	97:Q2-98:Q4
Interim NIPA releases: 97:Q1 Final (6/27/97), 97:Q2 Advan. & 94-96 Annual Revision (7/31/97)					
Aug. 97	Aug. 14, 97	Aug. 19, 97	85:Q1-97:Q2	97:Q2	97:Q3-98:Q4
Interim NIPA releases: 97:Q2 Prelim. (8/28/97)					
Sep. 97	Sep. 24, 97	Sep. 30, 97	85:Q1-97:Q2	97:Q2	97:Q3-99:Q4
Interim NIPA releases: 97:Q2 Final (9/26/97), 97:Q3 Advan. (10/31/97)					
Nov. 97	Nov. 6, 97	Nov. 12, 97	85:Q1-97:Q2	97:Q3	97:Q4-99:Q4
Interim NIPA releases: 97:Q3 Prelim. (11/26/97)					
Dec. 97	Dec. 11, 97	Dec. 16, 97	85:Q1-97:Q2	97:Q3	97:Q4-99:Q4
Interim NIPA releases: 97:Q3 Final (12/23/97)					
Jan. 98	Jan. 28, 98	Feb. 3 & 4, 98	85:Q1-97:Q2	97:Q4	98:Q1-99:Q4
Interim NIPA releases: 97:Q4 Advan. (1/30/98), 97:Q4 Prelim. (2/27/98)					

Table 2: Greenbook and National Accounts Release Dates (Mar. 98 to Aug. 99).

GB Name	Date GB Closed	Date(s) of FOMC Meeting	Estim. Period, DSGE Models	Last Qtr. of History	GB Forecast Horizon
Mar. 98	Mar. 19, 98	Mar. 25, 98	85:Q1-97:Q2	97:Q4	98:Q1-99:Q4
Interim NIPA releases: 97:Q4 Final (3/26/98), 98:Q1 Advan. (4/30/98)					
May 98	May 14, 98	May 19, 98	85:Q1-97:Q2	98:Q1	98:Q2-99:Q4
Interim NIPA releases: 97:Q1 Prelim. (5/28/98)					
Jun. 98	Jun. 24, 98	Jun. 30 & Jul. 1, 98	85:Q1-97:Q2	98:Q1	98:Q2-99:Q4
Interim NIPA releases: 97:Q1 Final (6/25/98), 98:Q2 Advan. & 95-97 Annual Revision (7/31/98)					
Aug. 98	Aug. 13, 98	Aug. 18, 98	85:Q1-98:Q2	98:Q2	98:Q3-99:Q4
Interim NIPA releases: 98:Q2 Prelim. (8/27/98)					
Sep. 98	Sep. 23, 98	Sep. 29, 98	85:Q1-98:Q2	98:Q2	98:Q3-00:Q4
Interim NIPA releases: 98:Q2 Final (9/24/98), 98:Q3 Advan. (10/30/98)					
Nov. 98	Nov. 13, 98	Nov. 17, 98	85:Q1-98:Q2	98:Q3	98:Q4-00:Q4
Interim NIPA releases: 98:Q3 Prelim. (11/24/98)					
Dec. 98	Dec. 16, 98	Dec. 22, 98	85:Q1-98:Q2	96:Q3	98:Q4-00:Q4
Interim NIPA releases: 98:Q3 Final (12/23/98)					
Jan. 99	Jan. 28, 99	Feb. 2 & 3, 99	85:Q1-98:Q2	98:Q4	99:Q1-00:Q4
Interim NIPA releases: 98:Q4 Advan. (1/29/99), 98:Q4 Prelim. (2/26/99)					
Mar. 99	Mar. 24, 99	Mar. 30, 99	85:Q1-98:Q2	98:Q4	99:Q1-00:Q4
Interim NIPA releases: 98:Q4 Final (3/31/99), 98:Q1 Advan. (4/30/99)					
May 99	May 13, 99	May 18, 99	85:Q1-98:Q2	99:Q1	99:Q2-00:Q4
Interim NIPA releases: 99:Q1 Prelim. (5/27/99)					
Jun. 99	Jun. 23, 99	Jun. 29 & 30, 99	85:Q1-98:Q2	99:Q1	99:Q2-00:Q4
Interim NIPA releases: 99:Q1 Final (6/25/99), 99:Q2 Advan. (7/29/99)					
Aug. 99	Aug. 18, 99	Aug. 24, 99	85:Q1-99:Q2	99:Q2	99:Q3-00:Q4
Interim NIPA releases: 99:Q2 Prelim. (8/26/99)					

Table 3: Greenbook and National Accounts Release Dates (Sep. 99 to Mar. 01).

GB Name	Date GB Closed	Date(s) of FOMC Meeting	Estim. Period, DSGE Models	Last Qtr. of History	GB Forecast Horizon
Sep. 99	Sep. 29, 99	Oct. 5, 99	85:Q1-99:Q2	99:Q2	99:Q3-01:Q4
Interim NIPA releases: 99:Q2 Final (9/30/99), 99:Q3 Advan. & Comprehensive Revision (10/28/99)					
Nov. 99	Nov. 10, 99	Nov. 16, 99	85:Q1-99:Q3	96:Q3	99:Q4-01:Q4
Interim NIPA releases: 99:Q3 Prelim. (11/24/99)					
Dec. 99	Dec. 15, 99	Dec. 21, 99	85:Q1-99:Q3	99:Q3	99:Q4-01:Q4
Interim NIPA releases: 99:Q3 Final (12/22/99)					
Jan. 00	Jan. 27, 00	Feb. 1 & 2, 00	85:Q1-99:Q3	99:Q4	00:Q1-01:Q4
Interim NIPA releases: 99:Q4 Advan. (1/28/00), 99:Q4 Prelim. (2/25/00)					
Mar. 00	Mar. 15, 00	Mar. 21, 00	85:Q1-99:Q3	99:Q4	00:Q1-01:Q4
Interim NIPA releases: 99:Q4 Final (3/30/00), 99:Q1 Advan. (4/27/00)					
May 00	May 11, 00	May 16, 00	85:Q1-99:Q3	00:Q1	00:Q2-01:Q4
Interim NIPA releases: 00:Q1 Prelim. (5/25/00)					
Jun. 00	Jun. 21, 00	Jun. 27 & 28, 00	85:Q1-99:Q3	00:Q1	00:Q2-01:Q4
Interim NIPA releases: 00:Q1 Final (6/27/00), 00:Q2 Advan. & 97-99 Annual Revision (7/28/00)					
Aug. 00	Aug. 16, 00	Aug. 22, 00	85:Q1-00:Q2	00:Q2	00:Q3-01:Q4
Interim NIPA releases: 00:Q2 Prelim. (8/25/00)					
Sep. 00	Sep. 27, 00	Oct. 3, 00	85:Q1-00:Q2	00:Q2	00:Q3-02:Q4
Interim NIPA releases: 00:Q2 Final (9/28/00), 00:Q3 Advan. (10/27/00)					
Nov. 00	Nov. 8, 00	Nov. 15, 00	85:Q1-00:Q2	00:Q3	00:Q4-02:Q4
Interim NIPA releases: 00:Q3 Prelim. (11/29/00)					
Dec. 00	Dec. 13, 00	Dec. 19, 00	85:Q1-00:Q2	00:Q3	00:Q4-02:Q4
Interim NIPA releases: 00:Q3 Final (12/21/00)					
Jan. 01	Jan. 25, 01	Jan. 30 & 31, 01	85:Q1-00:Q2	00:Q4	01:Q1-02:Q4

Table 4: Mean Absolute Errors of Models (Relative to Random Walk Forecast)

Model	1Q	4Q	6Q	8Q
	Real GDP Growth			
DSGE	1.109	0.832	0.844	0.985
Greenbook	1.000	1.532	1.443	1.356
VAR(4)	1.168	0.868	0.787	0.991
BVAR(4)	0.831	0.950	0.897	0.922
	Real Consumption Growth			
DSGE	1.387	1.967	1.533	1.425
Greenbook	0.957	1.036	1.076	1.103
VAR(4)	0.945	0.789	0.636	0.603
BVAR(4)	0.877	0.913	0.875	0.863
	GDP Inflation			
DSGE	1.086	1.775	1.553	1.800
Greenbook	0.886	0.948	0.954	0.941
VAR(4)	1.158	1.197	1.162	1.202
BVAR(4)	1.002	1.157	1.157	1.163
	PCE Inflation			
DSGE	1.355	1.078	0.973	0.924
Greenbook	1.021	0.854	0.875	0.645
VAR(4)	1.349	1.288	1.176	1.013
BVAR(4)	1.174	1.157	1.122	0.902

Figure 1: RMSEs of Different Models and Greenbook (August 1996 - March 2000)

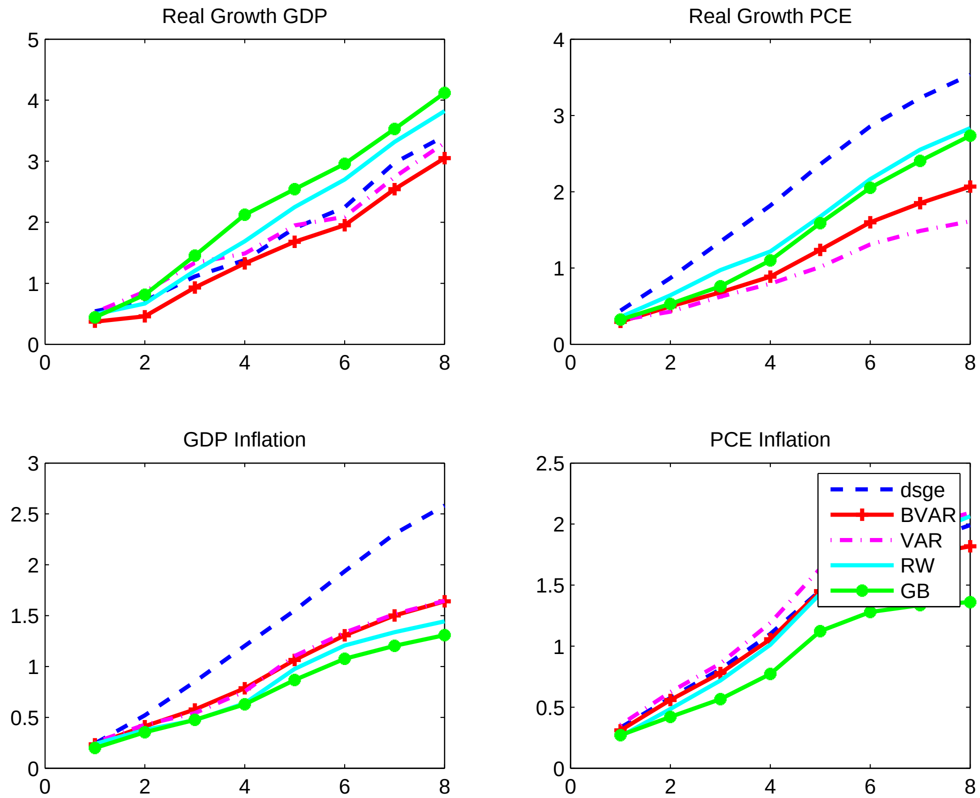

Figure 2: MAEs of Different Models and Greenbook (August 1996 - March 2000)

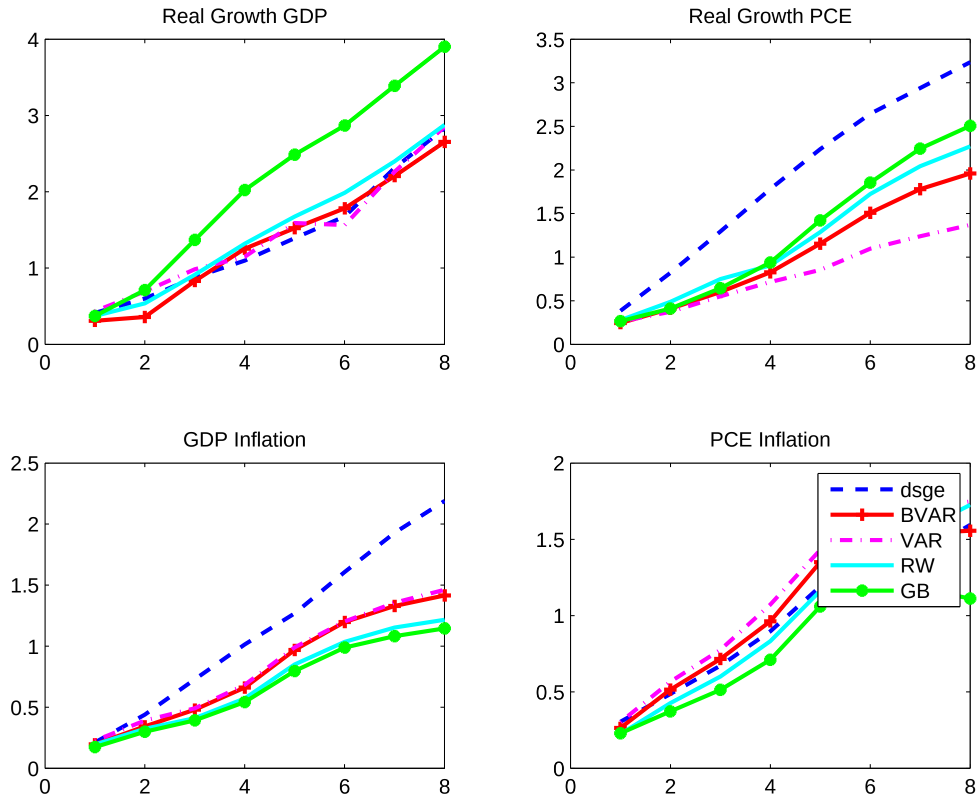

Figure 3: Forecast Bias of Different Models and Greenbook (August 1996 - March 2000)
(Figure displays the fraction of periods for which the model's forecast is greater than zero)