

IS THE FED'S NEWS PERCEPTION DIFFERENT FROM THE PRIVATE SECTOR'S?

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Abstract

The recent literature on monetary policy has dedicated considerable attention to modeling agents' processing of information about the future in real time. This paper contributes to this growing strand by investigating the implied differences in the so-called *news shocks* estimated from the standard New Keynesian dynamic stochastic general equilibrium (DSGE) model using the real-time datasets from the Survey of Professional Forecasters (SPF) and the Federal Reserve's Greenbook (GB) forecasts. Alternative specifications with either the SPF or GB forecasts aim to delineate the differences in the private sector's and the Fed's expectations of future macroeconomic outcomes and identify the differences in their perception of news shocks. Our results indicate that while the demand news shocks have very similar distributions in the two datasets, the monetary and cost-push news shocks from the models estimated on the GB data tend to be larger than those from the SPF. These findings suggest that the Federal Reserve's forecasting methods allow for more variation in future outcomes than the SPF's. These findings mesh well with the extant literature on the superiority of the Fed's forecasts relative to the private sector's and provide a structural explanation for the source of this superiority.

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I INTRODUCTION

The most recent financial crisis has drawn renewed attention to exogenous variation in monetary policy and, in particular, the possibility that a central bank may exploit agents' forward-looking expectations to facilitate the escape from severely depressed macroeconomic conditions induced by the zero lower bound on the nominal interest rate, the standard tool for the conduct of conventional monetary policy. This approach to monetary policy has been termed 'forward guidance'; see Campbell et al (2012) for a detailed discussion.¹ It comprises of monetary policy announcements that future levels of the nominal interest rate will remain low even after the effect of adverse macroeconomic shocks has dissipated. Anticipation of these expansionary conditions stimulates the current state of the macroeconomy, as agents incorporate this future outcome into their forward-looking expectations. However, policy announcements by the Federal Open Market Committee (FOMC) had become an essential component of monetary policy-making in the United States even before the onset of the zero lower bound on the nominal interest rates. Farka (2011) provides a detailed discussion of the evolution of FOMC statements since 1994 where what she calls "forward-looking" statements appear. Since then the Fed has attempted to improve their communication strategy regarding their future economic outlook, intended path of policy, and had provided the rationale behind their policy decisions. It has been standard in the recent "news shocks" literature to model monetary policy announcements as anticipated deviations from an estimated policy reaction function.

Interest in the role of anticipated future exogenous shocks in general pre-dates the Great Recession; see Gilchrist and Leahy (2002) for a seminal contribution that is generally credited with launching the literature on the technological news shocks. The present paper builds on the recent literature that studies the effect of different types of news shocks by comparing the results from two different real-time forecast datasets: the real-time Survey of Professional Forecasters data and the Federal Reserve Greenbook forecasts, both from the Federal Reserve Bank of Philadelphia.² The

¹For a recent evaluation of the performance of forward guidance under the zero lower bound on the nominal interest rate, see Keen et al. (2017). Data limitations prevent our extending the empirical analysis below into the zero-lower-bound conditions.

²Brissimis and Magginas (2017) briefly discuss the role of alternative forecasts in a New Keynesian DSGE model similar to the one employed in this paper. However, the only focus on the role of difference in forecast estimates in the monetary policy reaction function, as opposed to how these differences affect all of the model's endogenous variables.

use of the real-time data in estimation of DSGE models is relatively new, with the majority of the empirical work in this vein carried out using *ex post* data. We find that the demand news shocks play roughly the same role in both datasets. However, the role of monetary and cost-push news appears to be considerably larger in the GB data than SPF, with the results being particularly strong for the former set of shocks. The Fed, therefore, appears to have better information about the future outcomes not driven by the currently observable surprise shocks, which have been the standard drivers of endogenous variables' movements in the New Keynesian DSGE models.

More specifically, we follow the work of Milani and Treadwell (2012) by introducing anticipated components to the model's stochastic shocks. Best and Kapinos (2016) build on that approach and show that the models with anticipated monetary news alone tend to fit the *ex post* data the best, suggesting the importance of forward guidance. Milani and Rajbhandari (2014) propose a way for identifying anticipated shocks by using real-time forecasts for several variables in the context of the Smets and Wouters (2007) model using the SPF data. Hirose and Kurozumi (2012) identify news shocks in a small scale New Keynesian model using also SPF data. Fuhrer (2017) finds that SPF data serve well as expectations proxies in the standard DSGE model, and that they aid with the identification of key parameters. We believe that our paper is the first attempt to evaluate the differences in the perceptions of the future macroeconomic conditions by the private sector and the Federal Reserve. In effect, we assume that both the private sector and the central bank assume that the structure of the economy is the same in terms of the underlying model, given by the workhorse New Keynesian model that has been extensively employed in the literature. They estimate it using different information sets, resulting in different parameter estimates and, more importantly for our purposes, different standard deviations of exogenous shocks, including news shocks about disturbances to the future values of endogenous variables not explicitly captured by the model. Therefore, differences in the estimation of the effect of news shocks on the economy capture the differences in how the private sector and the central bank *perceive* future events, or news, to affect the model's endogenous variables. The differences in perception result in different forecasts of future values for these variables.

Our main empirical finding adds to the extensive literature on the asymmetric information possessed by the Fed and the private sector. Faust and Wright (2009) and Gamber and Smith (2009) among others demonstrate the forecasting superiority of the Greenbook forecasts. For example,

Romer and Romer (2002) found that optimal forecasts would put no weight on commercial forecasts when provided with Fed's forecasts. The informational advantage comes from the additional resources that the Fed dedicates to forecasting, finding valuable information beyond what is included in commercial forecasts. The Fed's informational advantage also provides an explanation of why long-term interest rates rise in tandem with an exogenous shift to tighter policy rates. Tighter policy signals that the Fed has unfavorable information about inflation and market participants respond by revising their inflation expectations upward. Romer and Romer (2002) also perform rationality tests and find that the null hypothesis of rationality is never rejected at the conventional significance levels. Additionally, the Fed's forecasts appear to be more accurate than commercial forecasts due to their lower mean squared error. Using a larger data set, El-Shagi et al (2014) provide evidence supporting the Romers' results. In particular, the Fed made better inflation predictions than private forecasters when conditioning forecast performance on uncertainties in the economic environment. They attribute Greenbook forecasts superiority to the Fed's knowledge of the future path of interest rates. Rossi and Sekhposyan (2016) apply forecast rationality tests that are robust to instabilities to Greenbook and survey-based data and confirm that the Fed has additional information about the current and future states of the economy with respect to the private sector. Therefore, the superior properties of the Greenbook forecasts with respect to the private sector make them attractive for our purposes, since we are interested in identifying the sources of differences in the Fed's and private sector's perceptions of the future macroeconomic activity in real time. In effect, our results provide a DSGE explanation for the this strand of the forecasting literature: the Federal Reserve attributes larger variation in endogenous variables to the exogenous future information than the private sector.

This paper contribution to the extant literature is twofold. First, previous studies have documented the Fed's forecasting superiority mostly in the single-equation reduced-form type of approach. From a methodological perspective we aim to provide a structural explanation of the discrepancies in forecasts in the general equilibrium context. We are able to disentangle that the Fed's perceived contribution of monetary policy announcements as well as cost-push news play a larger role on macroeconomic conditions than what private agents perceive. This is important because the ability of policy announcements to affect the economy depend on their perceived private sector effectiveness. Second, we find large differences in the degree of perception of future macroeconomic

activity implied by the private sector and Fed forecasts. Our central finding that the cost-push and monetary news shocks play a more important role in the GB rather than SPF dataset suggests that the Fed’s forecasting superiority across all measures of macroeconomic activity largely stems from having a more nuanced and accurate understanding of the future disturbances to the trajectories of the measures of inflation and interest rates.

The rest of the paper is organized as follows. Section II summarizes a fairly standard New Keynesian model of monetary policy augmented with news shocks. Section III lays out the Bayesian estimation strategy that we employ to estimate alternative specifications of our baseline model and the priors for estimated parameters. Section IV discusses the data and motivates the use of real-time forecasts for modeling forward-looking expectations in DSGE models. Section V discusses estimation results. Finally, Section VI concludes.

II MODEL SUMMARY

In this section, we briefly outline the standard New Keynesian model augmented with news shocks previously used by Milani and Treadwell (2012) and Best and Kapinos (2016). The model has three sectors whose behavior is characterized by corresponding structural equations that describe the evolution of endogenous variables’ departures from the steady state. First, households maximize a discounted stream of utility from leisure and quasi-growth in consumption and are able to store wealth through bonds in the complete-markets setting. The first-order conditions for their optimization problem yield the so-called IS schedule:

$$y_t = \frac{b}{(1+b)}y_{t-1} + \frac{1}{(1+b)}E_t y_{t+1} - \frac{1-b}{\sigma(1+b)}(r_t - E_t \pi_{t+1}) + \epsilon_t^y, \quad (1)$$

where b is the degree of habit formation in consumption, which is used to reflect the observed persistence in real macroeconomic activity, σ is the inverse coefficient of relative risk aversion to changes in quasi-growth of consumption, y_t is output gap whose difference from consumption is swept into the exogenous demand shock ϵ_t^y , π_t is inflation, and r_t is the nominal interest rate.

As is standard in this strand of the literature, we assume monopolistically competitive firms whose decision to set optimal prices is subject to the Calvo (1983) pricing friction. The evolution

of inflation that can be derived in this setting is described by the so-called Phillips curve:

$$\pi_t = \frac{\omega_p}{1 + \beta\omega_p}\pi_{t-1} + \frac{\beta}{1 + \beta\omega_p}E_t\pi_{t+1} + \frac{\kappa_p}{1 + \beta\omega_p} \left[\eta y_t + \frac{\sigma}{1-b}(y_t - by_{t-1}) \right] + \epsilon_t^p \quad (2)$$

where β is the exogenous discount factor, ω_p reflects the share of firms who index prices to last period's inflation when they are not able to set them optimally, $\kappa_p = \frac{(1-\theta_p\beta)(1-\theta_p)}{\theta_p}$ and θ_p is the fraction of firms who are not able to set prices optimally in any given time period, η is the Frisch elasticity of labor supply, and ϵ_t^p is the exogenous cost-push shock.

Finally, following the seminal work of Clarida et al (2000), the central bank is assumed to set the nominal interest using the following forward-looking version of the Taylor rule:

$$r_t = \rho r_{t-1} + (1 - \rho)(\gamma_p E_t \pi_{t+k} + \gamma_y E_t y_{t+k}) + \epsilon_t^r. \quad (3)$$

The Fed's response to macroeconomic variables led by several time period's highlights the forward-looking nature of monetary policy and emphasizes the importance of forecasting future macroeconomic conditions.³ To capture alternative assumptions on the inflation and output forecast horizons employed in the past literature, we consider two possibilities with respect to this timing and set $k = 1$ or $k = 4$ for robustness.

In addition to the relatively standard modeling the endogenous evolution of the agents' forward-looking behavior via the current expectations of future conditions described by the equations above, we augment the model with the exogenous disturbances that can be anticipated several time periods in advance. More specifically, we assume that innovations in our three structural equations evolve according to the following processes:

$$\epsilon_t^y = \rho_y \epsilon_{t-1}^y + v_t^y + \sum_{h=1}^H \nu_{t-h}^{y,h}, \quad (4)$$

$$\epsilon_t^p = \rho_p \epsilon_{t-1}^p + v_t^p + \sum_{h=1}^H \nu_{t-h}^{p,h}, \quad (5)$$

³See Orphanides (2001) for the seminal evaluation of the role of real-time forecasts in monetary policy rules. Best and Kapinos (2016) evaluate alternative modes of specifying forward-looking monetary policy rules and find that this functional form provides a good fit with the *ex post* data.

and

$$\epsilon_t^r = \rho_r \epsilon_{t-1}^r + v_t^r + \sum_{h=1}^H \nu_{t-h}^{r,h}, \quad (6)$$

where $v_t^y \sim iid(0, \sigma_y^2)$, $v_t^p \sim iid(0, \sigma_p^2)$, and $v_t^r \sim iid(0, \sigma_r^2)$ represent unanticipated innovations. Our specification allows structural shocks to be serially correlated with respective autocorrelation coefficients ρ_y , ρ_p , and ρ_r . The anticipated shock component of our model is given by $\nu_{t-h}^{y,h}$, $\nu_{t-h}^{p,h}$, and $\nu_{t-h}^{r,h}$, where h is the anticipation horizon. Insofar as the standard deviations of these news shocks are positive, they may provide additional sources of variation in the model's endogenous variables through the terms modeling agents' forward-looking behavior.

We consider a model with 1- to 4-quarter-ahead anticipated shocks to the Euler equation, the NKPC, and the Taylor Rule in the spirit of Schmitt-Grohe and Uribe (2012) and Milani and Treadwell (2012); the choice of anticipation horizon is motivated by the strategy of identifying news shocks with forecast data. We exploit real-time data sets on expectations from the Survey of Professional Forecasters and the Green Book, which correspond to forecasts for the four quarters after the current quarter at $t + h$, $h = [1, \dots, 4]$ of inflation, output growth, and the short term interest rate. This specification allows us to study the effect of a relatively short run (up to 1 year) anticipation horizon of the shocks on the dynamics of the model. The anticipated component of exogenous shocks may be interpreted as information about the future state of economy that is revealed to the agents ahead of time. Therefore, $\nu_{t-h}^{y,h}$ contain information about future realizations of IS determinants, such as shifts in fiscal policy; $\nu_{t-h}^{p,h}$ reveal news about the future evolution of firms' marginal cost; and $\nu_{t-h}^{r,h}$ may be interpreted as announcements regarding the future conduct of monetary policy. Milani and Rajbhandari (2014) were first to use the SPF real-time forecasts to identify news shocks in the context of a DSGE model. However, the present paper is first to evaluate their relative importance in alternative real-time datasets, comparing the their role for the private sector (SPF) and the Federal Reserve (Green Book).

III BAYESIAN ESTIMATION STRATEGY

This section outlines the mapping from the observed variables that included concurrent obser-

vations and forecasts of future macroeconomic conditions to the theoretical constructs described in the previous section. We first discuss the model's state-space representation and the estimation algorithm and then provide an overview of the literature that is relevant for motivating the choice of the priors for estimated parameters.

III.1 State-space Representation

The model can be written in state space form in the following way:

$$\Gamma_0 \alpha_t = \Gamma_1 \alpha_{t-1} + \Psi w_t + \Pi \Phi_t, \quad (7)$$

with $\alpha_t = [y_t, \pi_t, r_t, E_t y_{t+1}, \dots, E_t y_{t+4}, E_t \pi_{t+1}, \dots, E_t \pi_{t+4}, E_t r_{t+1}, \dots, E_t r_{t+4}, \epsilon_t^y, \epsilon_t^p, \epsilon_t^r, \nu_t^{r,h}, \nu_{t-1}^{r,h}, \dots, \nu_{t-h+1}^{r,h}, \nu_t^{y,h}, \nu_{t-1}^{y,h}, \dots, \nu_{t-h+1}^{y,h}, \nu_t^{p,h}, \nu_{t-1}^{p,h}, \dots, \nu_{t-h+1}^{p,h}]'$ is the state vector for horizons $h = [1, \dots, 4]$ in the Taylor rule, Euler Equation, and NKPC. The vector $w_t = [0, \dots, 0, v_t^r, v_t^y, v_t^p, \nu_t^{r,h}, \nu_t^{y,h}, \nu_t^{p,h}, \dots, 0]'$ collects all innovations. Lastly, the vector Φ_t includes all expectational errors i.e., $\Phi_t^p = \pi_t - E_{t-1} \pi_t$. Therefore, the state space representation has been expanded considerably because we are including the NKPC, Euler equation, and Taylor rule innovations containing news shocks with 1- to 4-quarter-ahead anticipation horizons. The set of model equations forming a linear rational expectations model was solved using the estimation procedure of Sims (2002). The observation equations that relate the model-implied variables to the observable variables are as follows:

$$\begin{bmatrix} \Delta y_t^{obs} \\ \pi_t^{obs} \\ r_t^{obs} \\ E_t \Delta y_{t+1}^{obs} \\ \dots \\ E_t \Delta y_{t+4}^{obs} \\ E_t \pi_{t+1}^{obs} \\ \dots \\ E_t \pi_{t+4}^{obs} \\ E_t r_{t+1}^{obs} \\ \dots \\ E_t r_{t+4}^{obs} \end{bmatrix} = \begin{bmatrix} \gamma \\ \bar{\pi} \\ \bar{r} \\ \gamma_1 \\ \dots \\ \gamma_4 \\ \bar{\pi}_1 \\ \dots \\ \bar{\pi}_4 \\ \bar{r}_1 \\ \dots \\ \bar{r}_4 \end{bmatrix} + H \begin{bmatrix} [y_t - y_{t-1}] \\ \pi_t \\ r_t \\ E_t [y_{t+1} - y_t] \\ \dots \\ E_t [y_{t+4} - y_{t+3}] \\ E_t \pi_{t+1} \\ \dots \\ E_t \pi_{t+4} \\ E_t r_{t+1} \\ \dots \\ E_t r_{t+4} \\ \tilde{\alpha} \end{bmatrix} + \Omega \begin{bmatrix} O_t^{\Delta y} \\ O_t^{E_t \Delta y_{t+1}} \\ O_t^{E_t \Delta y_{t+2}} \\ O_t^{E_t \Delta y_{t+3}} \\ O_t^{E_t \Delta y_{t+4}} \end{bmatrix}. \quad (8)$$

The previous observation equation can be summarized as:

$$\xi_t = \bar{\gamma} + H\alpha_t + \Omega_t. \quad (9)$$

The vectors ξ_t and $\bar{\gamma}$ contain the observable variables and their steady state values fixed to their sample means, respectively. The matrix H selects the observable variables from the state vector α and $\tilde{\alpha}$ gathers the remaining state variables. We include a measurement error for the output growth and expected output future growth variables to account for potential differences between these observables and their model definitions.

We estimate the set of structural parameters, autocorrelation coefficients, standard deviations of anticipated and unanticipated innovations, and measurement errors using likelihood-based Bayesian techniques; see An and Schorfheide (2007) for a comprehensive methodological overview. For our baseline specification, structural parameters represent a 29×1 vector Θ defined as:

$$\Theta = [b, \theta_p, \omega_p, \rho, \gamma_p, \gamma_y, \rho_r, \rho_y, \rho_p, \sigma_r, \sigma_y, \sigma_p, \sigma_{r1}, \sigma_{r2}, \sigma_{r3}, \sigma_{r4}, \sigma_{y1}, \sigma_{y2}, \sigma_{y3}, \sigma_{y4}, \dots, \sigma_{p1}, \sigma_{p2}, \sigma_{p3}, \sigma_{p4}, \sigma_{oy}, \sigma_{oy+1}, \sigma_{oy+2}, \sigma_{oy+3}, \sigma_{oy+4}]' \quad (10)$$

As is common in the literature, some parameters were fixed during the estimation strategy. Following Milani and Treadwell (2012), Castelnuovo (2012), Schmitt-Grohe and Uribe (2012), we set the household's discount factor β , to 0.99, the Frisch labor supply elasticity η to 2, and the intertemporal elasticity of substitution σ to 1. A prior distribution is assigned to the parameters of the model and is represented by $p(\Theta)$. The Kalman filter is used to evaluate the likelihood function given by $p(\xi^T|\Theta)$, where $\xi^T = [\xi_1, \dots, \xi_T]$. Lastly, the posterior distribution is obtained by updating prior beliefs through the Bayes' rule, taking into consideration the data reflected in the likelihood.

We generate draws from the posterior distribution through the Metropolis-Hastings algorithm.⁴ The specific simulation method that we use is random walk Metropolis Hastings for which we ran 500,000 iterations, discarding the initial 20% as burn-in. In addition, we ran several other chains with different initial values obtaining similar results.

⁴For details on the specification of the Metropolis-Hastings algorithm refer to Chib and Greenberg (1995).

III.2 Priors

Priors for the estimated parameters are summarized in Table 1. Their values for the degree of price inflation indexation, interest smoothing parameter, and Calvo price stickiness follow a Beta distribution with means of 0.7, 0.7, and 0.5, respectively, and standard deviation of 0.17, 0.17, and 0.16 similar to Milani and Treadwell (2012). The prior for the degree of habit persistence has a mean of 0.5 and a standard deviation of 0.16. Although slightly lower than the value used in other studies, this prior mean is consistent with previously estimated posterior means for this parameter, as in, Smets and Wouters (2007). Importantly, this shape of the prior distribution prevents posterior peaks from being trapped at the upper corner of the respective estimation intervals set between 0 and 1. The autoregressive coefficients in consumption Euler equation, the NKPC, and the Taylor rule take Normal distributions centered at 0.5. The magnitude for the response to inflation and the output gap in the Taylor rule also take Normal distributions centered at 1.5, and 0.5, with the latter value slightly higher than in Milani and Treadwell (2012) and Castelnuovo (2012).

We follow Schmitt-Grohe and Uribe (2012) and Milani and Rajbhandari (2012) in our treatment of the priors for the standard deviations of anticipated and unanticipated shocks, and measurement error. The priors for the standard deviations of the unanticipated and anticipated innovations follow a Gamma distribution. Although the inverse Gamma distributions are commonly used as priors for standard deviations, as is well known, their use may push the estimates of shocks' standard deviations away from zero. Our use of the Gamma distribution, on the other hand, assigns a positive probability that the standard deviations of anticipated innovations could take a value of zero, thus capturing the possibility that news shocks play an insignificant role in the dynamics of the model. Second, we assume that 75% of the variance of observed disturbances is driven by the unanticipated component. More specifically, if σ_q is the standard deviation of the observed shock ϵ^q where $q = [y, p, z]$, the variance of its concurrent component $\sigma_{c,q}$ is given by:

$$\sigma_{c,q}^2 = w\sigma_q^2$$

and its news components by:

$$\sigma_{n,q}^2 = (1 - w)\sigma_q^2,$$

where the weight of the unanticipated component is set to $w = 0.75$. Variances of individual news shocks at different horizons h can be constructed using:

$$\sigma_{h,q}^2 = \frac{1}{N} \sigma_{n,q}^2,$$

where N is the number of news shocks at different horizons. These assumptions on the priors give limited scope to the anticipated shocks. Hence our priors need to be overwhelmed by the data to find a significant role for them.

IV DATA

We estimate the model described in the previous section using the real-time vintages—as opposed to the final revisions used in the standard *ex post* estimation—of real output growth, inflation (measured as the percentage change in the output deflator), and the short-term nominal interest rate. The two datasets for current expectations of future variables; the sources of the latter are the the Federal Reserve’s Green Book and the mean estimates from the Survey of Professional Forecasters to proxy the private sector’s expectations. Our sample is limited by the availability of the Greenbook data, hence in all of our estimation the sample period is 1987Q3 through 2007Q4. We use the Real Time Data Set for Macroeconomists (RTDSM) available from Federal Reserve Bank of Philadelphia to construct the concurrent values of the model’s observables.⁵ The real-time data correspond to the first available vintage for each observation seasonally adjusted. The output growth series (Δy_t^{obs}) was calculated taking the log first difference of the first vintage of real GDP using the series with acronym ROUTPUT.⁶ Inflation (π_t^{obs}) was calculated using the log first difference of the Price Index for GNP/GDP with acronym P. In this case, the short-term nominal interest rate (r_t^{obs}) used as observable is the 3-Month Treasury Bill Rate, percentage points, not seasonally adjusted, quarterly average from the Survey of Professional Forecasters (SPF). It corresponds to the series with the acronym TBILL2 which represent the forecast for the current

⁵The SPF forecasts are currently provided by the Philadelphia Fed and were previously collected by the American Statistical Association (ASA) and the National Bureau of Economic Research (NBER). The GB and RTDSM data are also available from the Philadelphia Fed website.

⁶In the collection of the Real Time Data Set for Macroeconomics, the output variable changes in 1992 from GNP to GDP. Therefore, we are using for our estimation the GDP growth rate before 1992 and the GDP growth rate thereafter.

quarter, defined as the quarter in which the survey is conducted.⁷ The concurrent real time data set remains the same across both specifications (SPF and GB), making the forecasts the only source of difference due to our focus on the identification of news shocks.

In addition to the observable *concurrent* variables, we use data on expectations of future macroeconomic outcomes of the private sector and the Federal Reserve for two reasons: first, to identify the policymakers' response to explicit forecasts of inflation and output in a monetary policy feedback rule; and second, to help in the identification of the news shocks to monetary policy, the IS equation, and the Phillips curve. The first estimation resorts to the following expectations series (the mean response across forecasters) obtained from the SPF: The forecasts for real GDP growth, $E_t \Delta y_{t+h}^{obs}$, for $h = [1, \dots, 4]$ were obtained using the forecasts for the Real GDP series with acronyms RGDP3-RGDP6. The forecasts for inflation, $E_t \pi_{t+h}^{obs}$ for $h = [1, \dots, 4]$ were computed from the forecasts for the Price index for the GDP series with acronyms PGDP3-PGDP6. While the forecasts for the short-term interest rate $E_t r_{t+h}^{obs}$ for $h = [1, \dots, 4]$ correspond to the 3-Month Treasury Bill Rate with acronyms TBILL3-TBILL6. The second estimation uses data from the Greenbook forecasts and financial assumptions produced by the Federal Reserve Board of Governors for the Federal Open Market Committee (FOMC) meetings and maintained by the Federal Reserve Bank of Philadelphia for inflation $E_t \pi_{t+h}^{obs}$, the output growth $E_t \Delta y_{t+h}^{obs}$, and the federal funds rate $E_t r_{t+h}^{obs}$. The series used were quarter-over-quarter growth in real GDP (acronym gRGDP) and the price index for GDP (acronym gPGDP), both series transformed to quarterly rates for quarters $t + h$, $h = [1, \dots, 4]$. The real-time Federal Funds Rate projections used come from the Greenbook Financial Assumptions that are estimates used by the Board of Governors of the Fed used in the construction of Greenbook forecasts.

The forecast of inflation, output growth, and interest rates using the SPF and GB forecasts follow similar but by no means identical patterns.⁸ Inflation forecasts, represented in Figure 1, were persistently overestimated during the late 1980s and 1990s. In fact, Romer and Romer (1989) provide narrative evidence that suggests the Fed took preemptive measures to control inflation during this time, probably as a results of its overestimation of inflation at all horizons. This pattern changed in the late 1990s to early 2000s when the forecast errors became persistently

⁷See Milani and Rajbhandari (2014) for the details of merging the RTDSM and SPF datasets and related timing assumptions.

⁸Similar discussion of the differences between the two datasets in terms of forecast errors is available upon request.

negative. Inflation forecasts appear less overestimated in the GB data in the 1980s and 1990s but were more evident in the late 1990s and 2000s, highlighting tangible differences with the SPF data.

Output growth forecasts at different horizons are plotted in Figure 2. While the forecast bias becomes more evident at longer horizons here as well, their dynamic evolution is quite different. Output growth forecasts are underestimated in the late 1980s and 1990s, except for a short spell in the early 1990, which was probably due to forecasters inability to predict turning points in macroeconomic variable dynamics. In fact, Sinclair et al (2010) conclude that although the Fed misses downturns and upward movements, when the economy changes direction, the Fed incorporates this new information quickly and revises its forecasts in the right direction. In the 2000s, we observe a consistent overestimation of output growth forecasts. In the former period, forecast errors follow a similar pattern using GB and SPF data, however, in the latter period, the Fed seems more optimistic producing larger forecasts errors indicating a larger overestimate of future output growth at every horizon.

Finally, interest rate forecasts are displayed in Figure 3.⁹ We note that during the recessions of the early 1990s and 2000s, and during the Great Recession, forecasts of short term interest rates exceeded their ex post realizations, while we observe their underestimation during expansions. These differences highlight the variation in the perception of the Fed's forward guidance discussed in Section V.

In all cases, as the horizon increases, forecasts become more diffuse, as their precision decreases and errors increase. We believe that this property is important and provides motivation on why news at different anticipation horizons can have various magnitudes and have different effects in the relevant macroeconomic variables. In addition, we observe consistent biases in inflation and output growth forecasts that differ depending on the source of the forecasts. We next turn to investigating these differences in the context of the DSGE model described in Section II.

V RESULTS

Our main task is to disentangle the relative importance of the different types of anticipated news shocks for the model's agents and the Fed. We first discuss the differences in parameter estimates

⁹Since the ex post values of the federal funds rate and the 3-month T-bill rate are virtually identical, we only use the latter in these graphs for visual clarity.

obtained from the SPF and GB datasets, paying particularly close attention to the distributions of estimated standard deviations of these shocks. We then focus on the differences in transmission of these shocks across the two datasets using forecast error variance decompositions.

V.1 Parameter Estimates

Table 2 presents the parameter estimates for the case of $k = 1$ whereas Table 3 does the same for $k = 4$. The estimates of the standard deviations of different types of news shocks suggest that they are important sources of exogenous variation in endogenous variables. In all cases, their magnitudes are comparable to those of the standard deviations of surprise shocks and in some cases are larger. The data fit the model best when the Taylor rule is explicitly responding to 4-quarter-ahead forecasts of inflation and output growth than to only 1-quarter-ahead forecasts. The marginal likelihood is higher when $k = 4$ in the Taylor rule for the model with SPF data, however we perceive the opposite in the Greenbook model meaning that the model with $k = 1$ in the Taylor better fits the data. Our estimates also suggest that the Fed is forward-looking and its mean policy response to one year ahead inflation is slightly higher than its 1-period-ahead response ($\gamma_p = 2.231$ for $k = 4$ vs. $\gamma_p = 1.906$). It is possible that one indication of the Fed's improved inflation-stabilizing credibility is that agents perceptions about the Fed's policy responses follow the same pattern; $\gamma_p = 2.388$ at $k = 4$ while $\gamma_p = 1.862$ at $k = 1$. In fact, agents perceive the highest monetary policy response to inflation at $k = 4$ across all specifications. Moreover, there is some indication that agents perceive a higher mean response to output growth response than the Fed.

There is a clear pattern that emerges when considering monetary policy, demand, and cost-push news shocks. Figures 4 through 6 present priors and posterior distributions for the monetary policy, demand, and cost-push news shocks that are identified using explicit expectations data from the GB and from the SPF. At $h = 1$, the posteriors overlap for news identified with both data sets on expectations, however this is not the case as the anticipation horizon increases. We have seen that the forecast biases increase with the anticipation horizon in the GB and SPF datasets. Furthermore, we find that the posterior probability interval for demand news shocks have considerable overlap illustrated in Figure 4. However, the GB monetary news have indisputably higher standard deviations with posterior probability intervals that do not overlap, as depicted in Figure 5. Thus,

the Fed estimates the standard deviations of monetary news shocks that the recent literature has ascribed to forward guidance are stronger than what private sector agents perceive. With regard to cost-push news, identification of news using SPF data are perceived to have a considerably stronger standard deviation at $h = 3$, than cost-push news estimated using the GB data, as in Figure 6. Hence the role of anticipated news shocks, as measured by their estimated standard deviations, seems to vary substantially with the real-time dataset. We next investigate differences in the shock transmission process to endogenous variables.

V.2 Variance Decomposition

Figures 7 through 9 present the variance decomposition of interest rates, inflation, and the output gap by surprise and news shocks using the SPF and GB estimates for $k = 1$ and $k = 4$ in the policy rule. We find that the news shocks play a predominant role at explaining the three variables, as roughly 80% of the variance can be attributed to them after 20 periods. Therefore, including the expectations data from the SPF and GB not only helps with the identification of the news shocks, but it also it alters the contribution of news shocks at explaining the aforementioned variables. Moreover, it suggest that the mix of monetary, demand, and cost-push news shocks differs between estimates obtained with agents' and Fed's expectations. Figure 7, shows the contribution of the surprise and news shocks to output growth. In this graph, demand news shocks play a predominant role at explaining the variance of output growth for private agents while this role is much lower for the Fed. Figure 8 illustrates that the monetary policy news shocks, or policy announcements, play a larger role at explaining the variance of interest rates under the GB estimates compared to the SPF estimates. This could be interpreted as the Fed's belief that forward guidance has a stronger effect on interest rates than what private agents think. It also shows that inflationary news shocks are more important contributors to the interest rates for the Fed than for the private agents while the latter perceives that the contribution of demand shocks is more important than the former. Finally, Figure 9 presents the involvement of the news and surprise shocks in the variance of inflation. It appears that cost-push ($> 20\%$) and monetary shocks (15% for $k = 1$) contribute more to the variance of inflation for the Fed than for the private sector ($< 10\%$ and $< 10\%$, respectively).

We can conclude that for the estimates that arise from using Greenbook data, the perceived contribution of monetary policy news or forward guidance to the variance of inflation, the output

growth, and the interest rate is higher than under the estimates using SPF. This finding reiterates the information asymmetry between the Fed and the private sector. Furthermore, it suggests that the ability of policy announcements to affect the economy depend on their perceived effectiveness by the private sector, which may be smaller than the Fed's. These results suggest that the Fed might be more optimistic than the private sector regarding their usefulness of policy announcements to stabilize the economy against fluctuations.

VI CONCLUSION

In this paper, we have provided a structural explanation for the superiority of the Federal Reserve forecasts of inflation and real activity that has been well-documented in the literature on forecasting these variables using reduced-form methods. We find that the estimates of the standard New Keynesian DSGE model augmented with news shocks attribute a stronger role to these disturbances, particularly to the cost-push and monetary news. These finding suggests that the Fed's understanding of the future path of inflation and interest rates is likely responsible for its forecasting superiority over the private sector. In particular, monetary policy announcements play a larger role at the determination of the future path of inflation and interest rates by the Fed compared to the private sector.

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A Tables

Table 1: Parameter Description and Priors—Gamma for Errors and Medium Exogenous Persistence

Parameters	Description	Dist.	Mean	SD
b	Degree of habit persistence	B	0.50	0.16
θ_p	Calvo probability of price stickiness	B	0.50	0.16
ω_p	Degree of price indexation	B	0.70	0.17
ρ	Interest-smoothing parameter	B	0.70	0.17
γ_p	Magnitude of response to inflation target	N	1.50	0.25
γ_y	Magnitude of response to output gap target	N	0.50	0.12
ρ_y	Exogenous persistence of demand shock	N	0.50	0.23
ρ_r	Exogenous persistence of monetary shock	N	0.50	0.15
ρ_p	Exogenous persistence of cost-push shock	N	0.50	0.15
ξ	Degree of forward-looking monetary policy (Calvo T.R.)	B	0.60	0.12
α	Degree of forward-looking monetary policy	U	0.20	0.29
σ_y	Standard deviation of demand shock, concurrent only	Γ	0.34	0.30
σ_r	Standard deviation of monetary shock, concurrent only	Γ	0.34	0.30
σ_p	Standard deviation of cost-push shock, concurrent only	Γ	0.34	0.30
σ_y	Standard deviation of demand shock, concurrent, with news	Γ	0.30	0.30
σ_r	Standard deviation of monetary shock, concurrent, with news	Γ	0.30	0.30
σ_p	Standard deviation of cost-push shock, concurrent, with news	Γ	0.30	0.30
$\sigma_{y,n}$	Standard deviation of demand shock, news only*	Γ	0.10	0.15
$\sigma_{r,n}$	Standard deviation of monetary shock, news only*	Γ	0.10	0.15
$\sigma_{p,n}$	Standard deviation of cost-push shock, news only*	Γ	0.10	0.15
$\sigma_{oy(+h)}$	Measurement error for output growth and its forecasts	IG	0.25	0.10

Note: Asterisk (*) refers to the structure of news shocks with $h = 1 - 4$. The symbols for the prior distributions stand for B =Beta, N =Normal, Γ =Gamma, and IG =Inverse Gamma distributions.

Table 2: Parameter Estimate Posteriors Benchmark model, $k = 1$

Parameters	Greenbook		SPF	
	Mean	Pos. Prob. Int.	Mean	Pos. Prob. Int.
b	0.988	[0.986, 0.991]	0.989	[0.987, 0.992]
θ_p	0.854	[0.853, 0.856]	0.854	[0.853, 0.855]
ω_p	0.015	[0.004, 0.031]	0.018	[0.005, 0.041]
ρ	0.840	[0.812, 0.864]	0.919	[0.905, 0.931]
γ_p	1.906	[1.731, 2.103]	1.862	[1.707, 2.036]
γ_y	0.286	[0.098, 0.436]	0.504	[0.322, 0.690]
ρ_r	0.563	[0.499, 0.624]	0.334	[0.255, 0.416]
ρ_y	0.009	[0.001, 0.024]	0.009	[0.001, 0.026]
ρ_p	0.999	[0.998, 0.999]	0.999	[0.998, 0.999]
σ_r	0.066	[0.057, 0.077]	0.098	[0.084, 0.114]
σ_y	0.066	[0.051, 0.084]	0.059	[0.044, 0.075]
σ_p	0.026	[0.001, 0.073]	0.015	[0.001, 0.041]
σ_{r1}	0.054	[0.047, 0.064]	0.056	[0.048, 0.067]
σ_{r2}	0.041	[0.035, 0.048]	0.025	[0.021, 0.029]
σ_{r3}	0.039	[0.033, 0.046]	0.022	[0.018, 0.026]
σ_{r4}	0.033	[0.028, 0.039]	0.018	[0.015, 0.022]
σ_{y1}	0.021	[0.015, 0.028]	0.033	[0.023, 0.045]
σ_{y2}	0.018	[0.013, 0.023]	0.024	[0.016, 0.031]
σ_{y3}	0.014	[0.010, 0.019]	0.016	[0.009, 0.023]
σ_{y4}	0.006	[0.001, 0.010]	0.009	[0.005, 0.013]
σ_{p1}	0.035	[0.002, 0.072]	0.015	[0.001, 0.040]
σ_{p2}	0.046	[0.020, 0.069]	0.019	[0.001, 0.051]
σ_{p3}	0.020	[0.001, 0.045]	0.062	[0.039, 0.090]
σ_{p4}	0.071	[0.054, 0.090]	0.068	[0.047, 0.095]
σ_{oy}	0.422	[0.367, 0.483]	0.404	[0.355, 0.449]
σ_{oy+1}	0.272	[0.231, 0.318]	0.176	[0.150, 0.205]
σ_{oy+2}	0.232	[0.198, 0.277]	0.143	[0.121, 0.170]
σ_{oy+3}	0.211	[0.177, 0.247]	0.130	[0.112, 0.152]
σ_{oy+4}	0.186	[0.160, 0.216]	0.138	[0.118, 0.162]
Marginal L		697.67		819.66

Table 3: Parameter Estimate Posteriors Benchmark model, $k = 4$

Parameters	Greenbook		SPF	
	Mean	Pos. Prob. Int.	Mean	Pos. Prob. Int.
b	0.993	[0.989, 0.994]	0.983	[0.979, 0.988]
θ_p	0.887	[0.865, 0.904]	0.813	[0.795, 0.831]
ω_p	0.014	[0.004, 0.028]	0.015	[0.004, 0.033]
ρ	0.770	[0.718, 0.823]	0.762	[0.739, 0.793]
γ_p	2.231	[2.014, 2.395]	2.388	[2.114, 2.674]
γ_y	0.418	[0.241, 0.660]	0.437	[0.221, 0.684]
ρ_r	0.642	[0.572, 0.707]	0.635	[0.5672, 0.692]
ρ_y	0.008	[0.000, 0.023]	0.010	[0.001, 0.033]
ρ_p	0.999	[0.998, 0.999]	0.999	[0.998, 0.999]
σ_r	0.078	[0.066, 0.092]	0.101	[0.086, 0.119]
σ_y	0.072	[0.054, 0.091]	0.052	[0.039, 0.073]
σ_p	0.016	[0.001, 0.045]	0.023	[0.001, 0.053]
σ_{r1}	0.051	[0.043, 0.060]	0.063	[0.053, 0.075]
σ_{r2}	0.036	[0.031, 0.042]	0.024	[0.021, 0.029]
σ_{r3}	0.034	[0.029, 0.039]	0.016	[0.013, 0.018]
σ_{r4}	0.032	[0.027, 0.037]	0.012	[0.011, 0.015]
σ_{y1}	0.024	[0.0163, 0.031]	0.028	[0.020, 0.039]
σ_{y2}	0.020	[0.014, 0.026]	0.021	[0.014, 0.030]
σ_{y3}	0.013	[0.006, 0.018]	0.014	[0.007, 0.022]
σ_{y4}	0.003	[0.001, 0.006]	0.008	[0.005, 0.012]
σ_{p1}	0.018	[0.001, 0.048]	0.021	[0.001, 0.054]
σ_{p2}	0.032	[0.001, 0.056]	0.027	[0.001, 0.069]
σ_{p3}	0.018	[0.001, 0.044]	0.061	[0.031, 0.091]
σ_{p4}	0.068	[0.052, 0.086]	0.071	[0.049, 0.101]
σ_{oy}	0.437	[0.384, 0.501]	0.415	[0.358, 0.486]
σ_{oy+1}	0.271	[0.232, 0.313]	0.175	[0.152, 0.206]
σ_{oy+2}	0.230	[0.196, 0.259]	0.144	[0.123, 0.173]
σ_{oy+3}	0.214	[0.186, 0.246]	0.133	[0.114, 0.157]
σ_{oy+4}	0.187	[0.161, 0.217]	0.139	[0.119, 0.162]
Marginal L	693.98		848.47	

B Figures

Figure 1:

Forecasts of inflation at horizons $h=[0, \dots, 4]$ vs actual inflation. Survey of professional forecasts in black solid line; Greenbook forecasts in red dashed line; ex post realization in thick blue line.

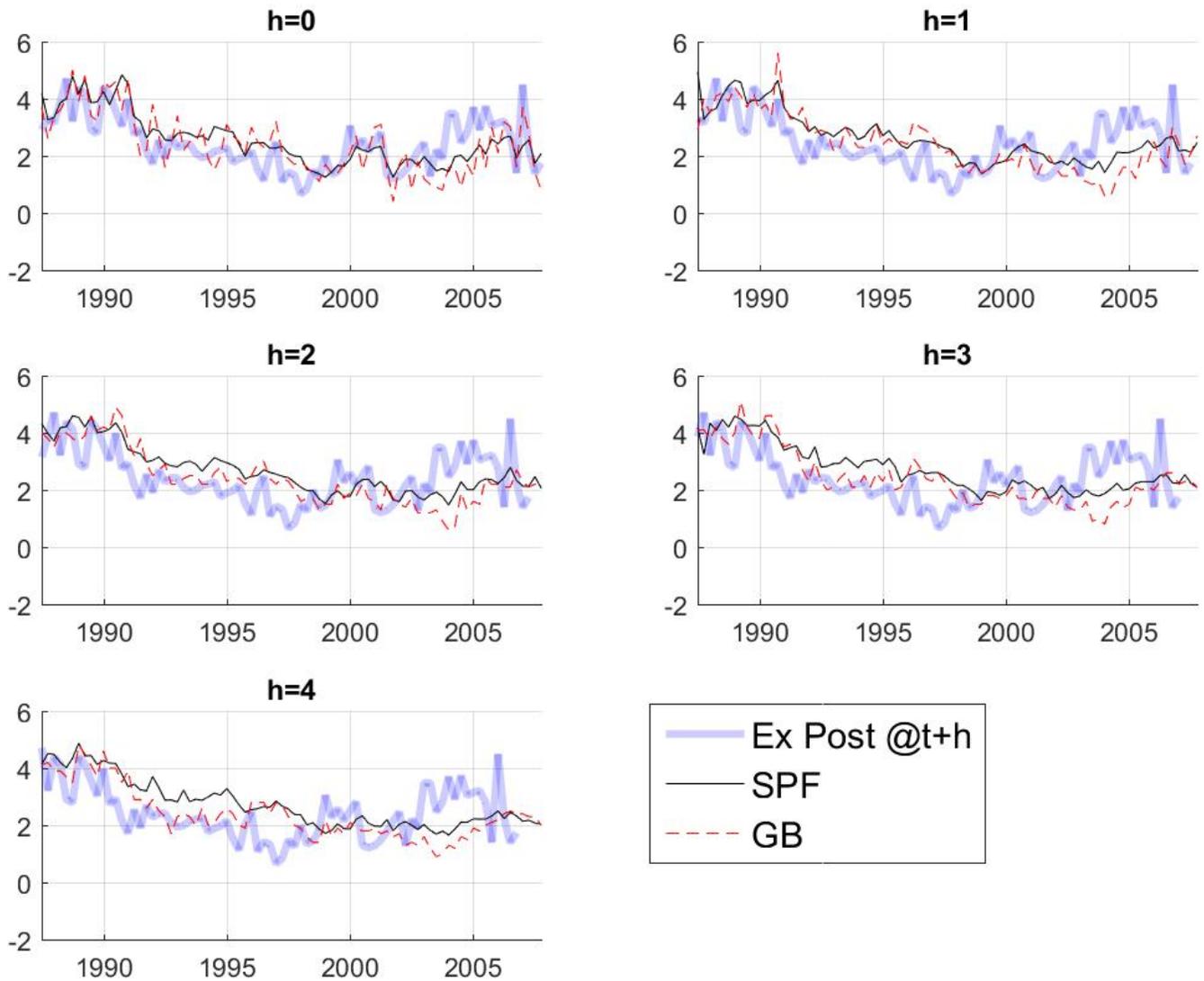


Figure 2:

Forecasts of output growth at horizons $h=[0, \dots, 4]$ vs actual output growth. Survey of professional forecasts in black solid line; Greenbook forecasts in red dashed line; ex post realization in thick blue line.

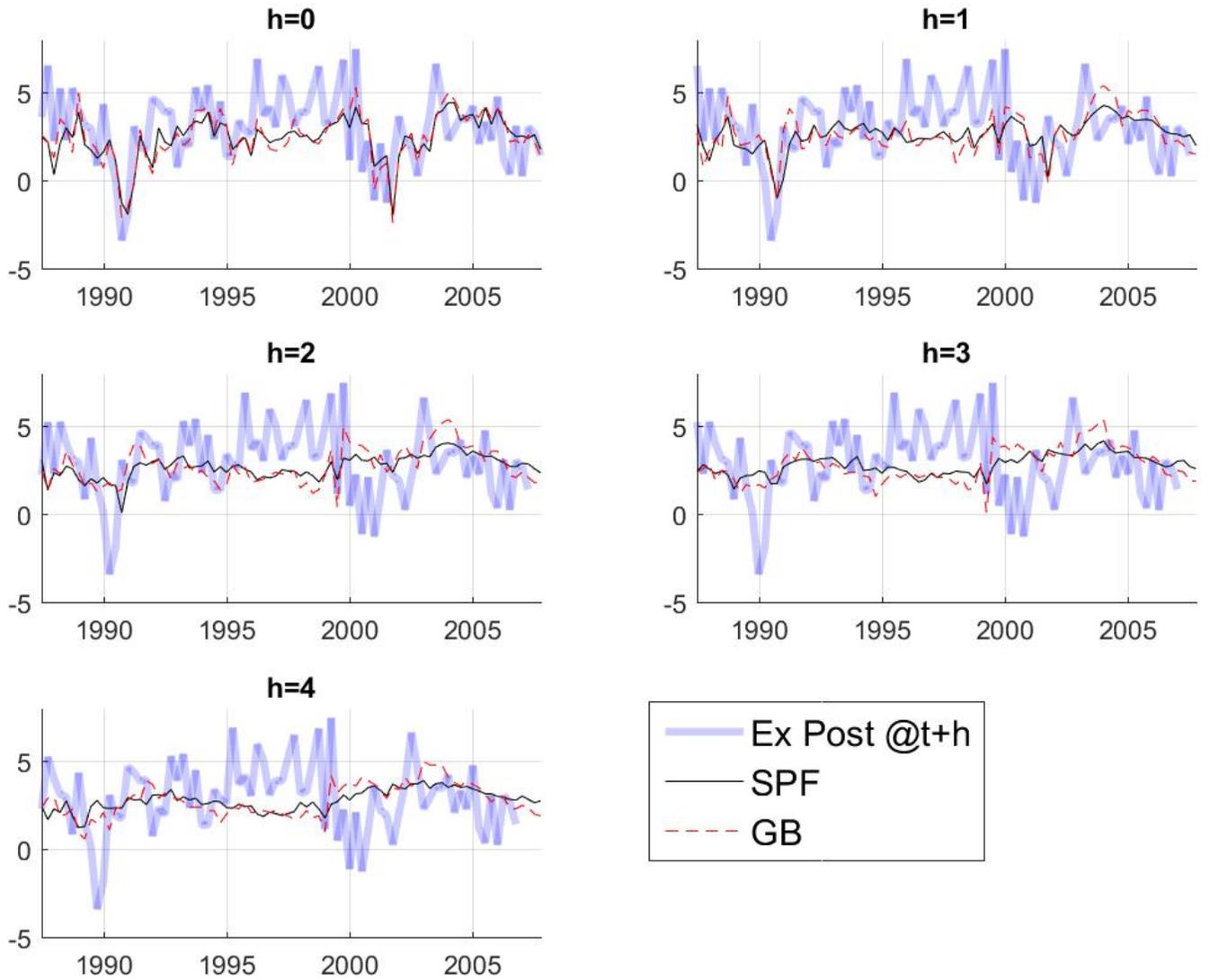


Figure 3:

Forecasts of the short-term interest rate at horizons $h=[0, \dots, 4]$ vs actual rates. Survey of professional forecasts in black solid line; Greenbook forecasts in red dashed line; ex post realization in thick blue line.

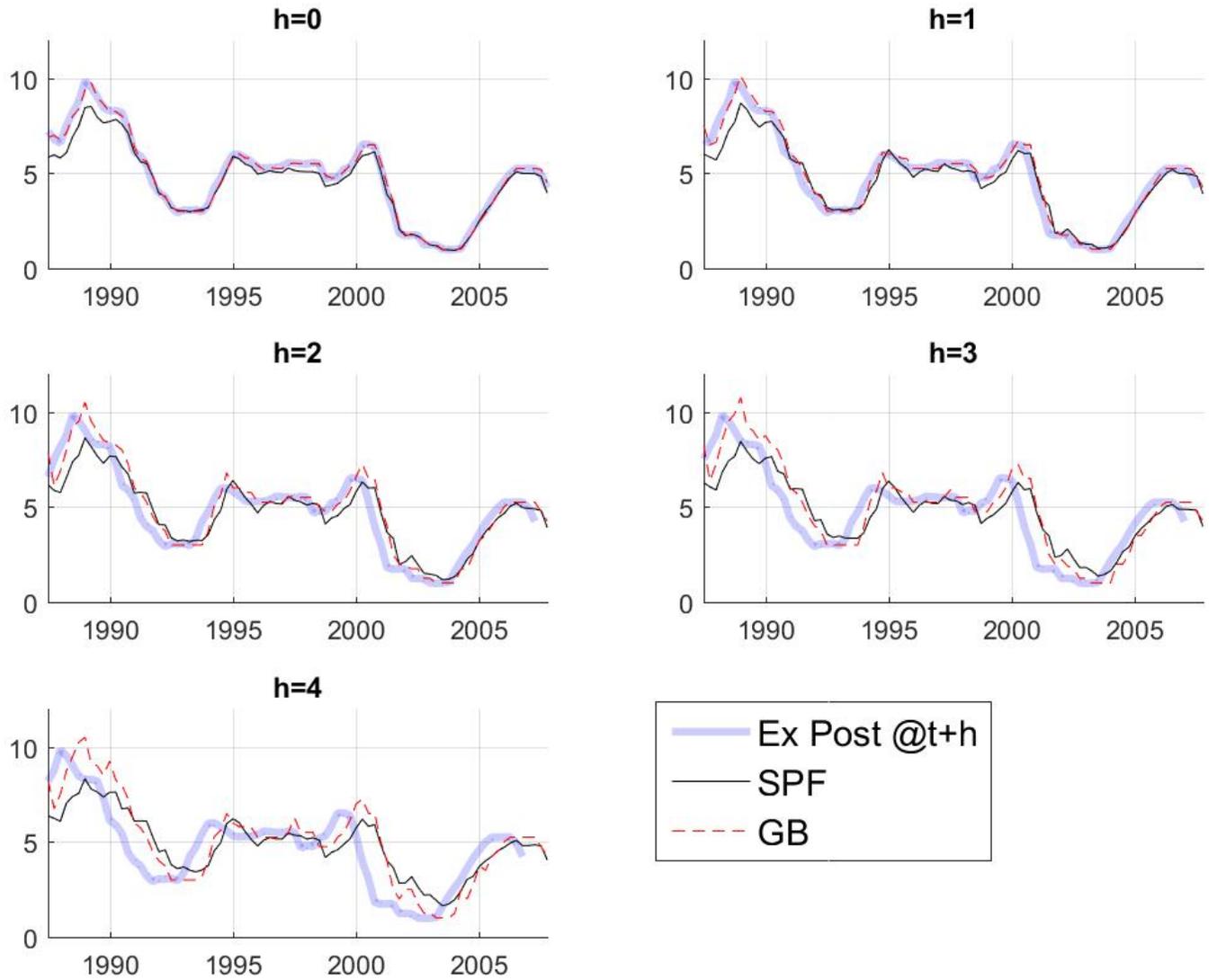


Figure 4: Distributions of estimated standard deviations of demand news shocks: Grey dashed line—prior; blue solid line—Greenbook; red punctuated line—SPF

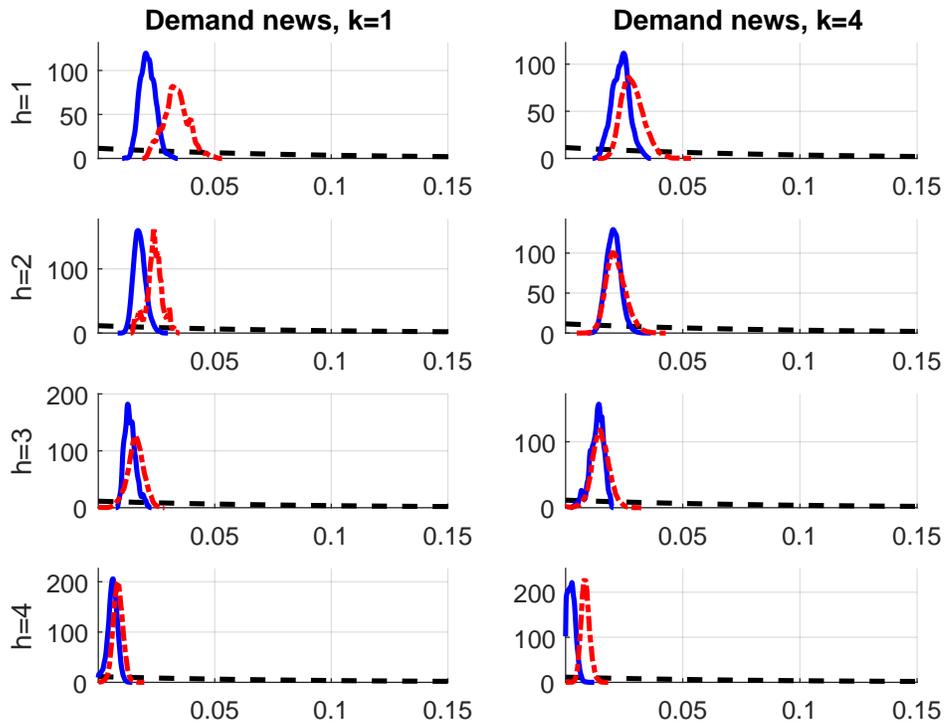


Figure 5: Distributions of estimated standard deviations of monetary news shocks: Grey dashed line—prior; blue solid line—Greenbook; red punctuated line—SPF

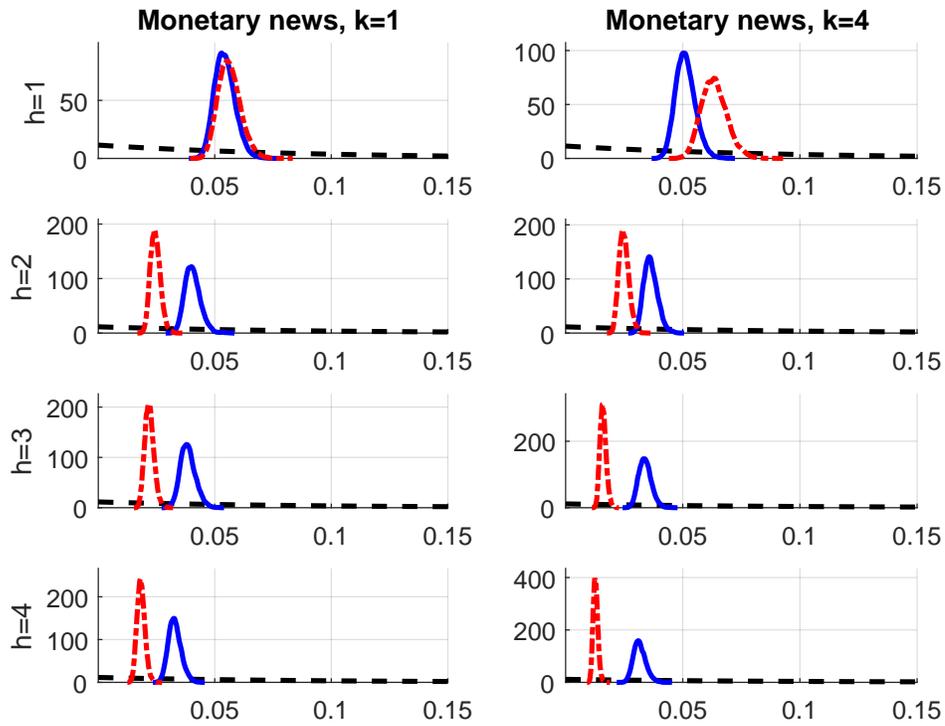


Figure 6: Distributions of estimated standard deviations of cost-push news shocks: Grey dashed line—prior; blue solid line—Greenbook; red punctuated line—SPF

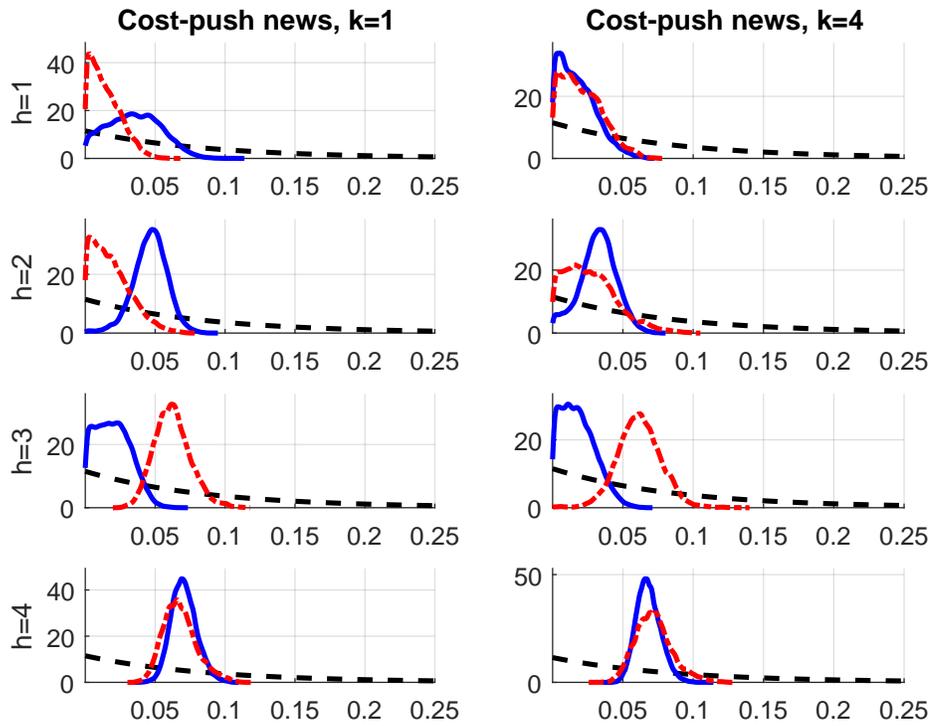


Figure 7:

Forecast error variance decomposition of output growth: GB vs SPF data. Surprises: blue shade—cost-push shocks; cross-hatched—demand shocks; red shade—monetary shocks. News: darkest shade— $h = 1$; lightest shade— $h = 4$.

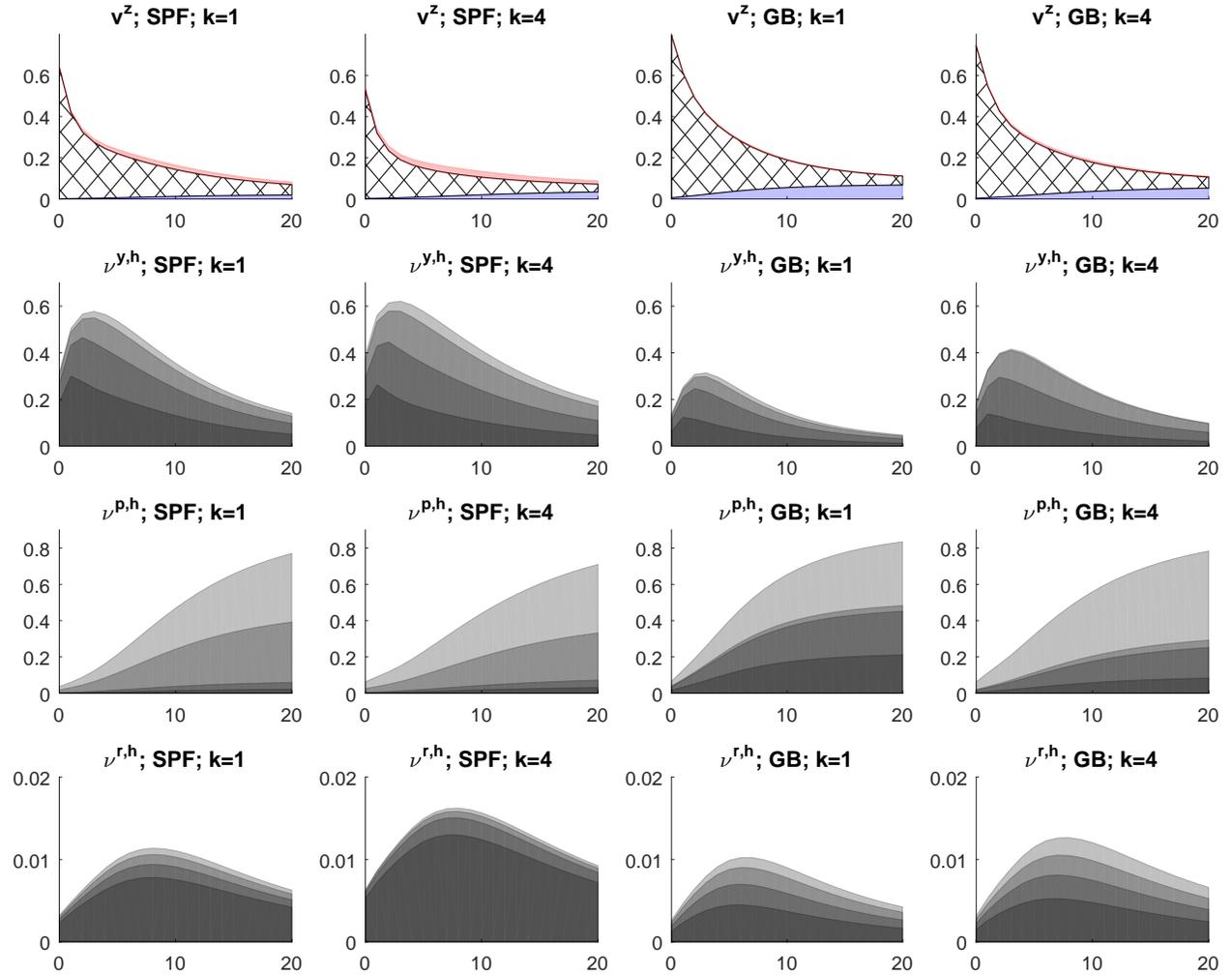


Figure 8:

Forecast error variance decomposition of the nominal interest rate: GB vs SPF data. Surprises: blue shade—cost-push shocks; cross-hatched—demand shocks; red shade—monetary shocks. News: darkest shade— $h = 1$; lightest shade— $h = 4$.

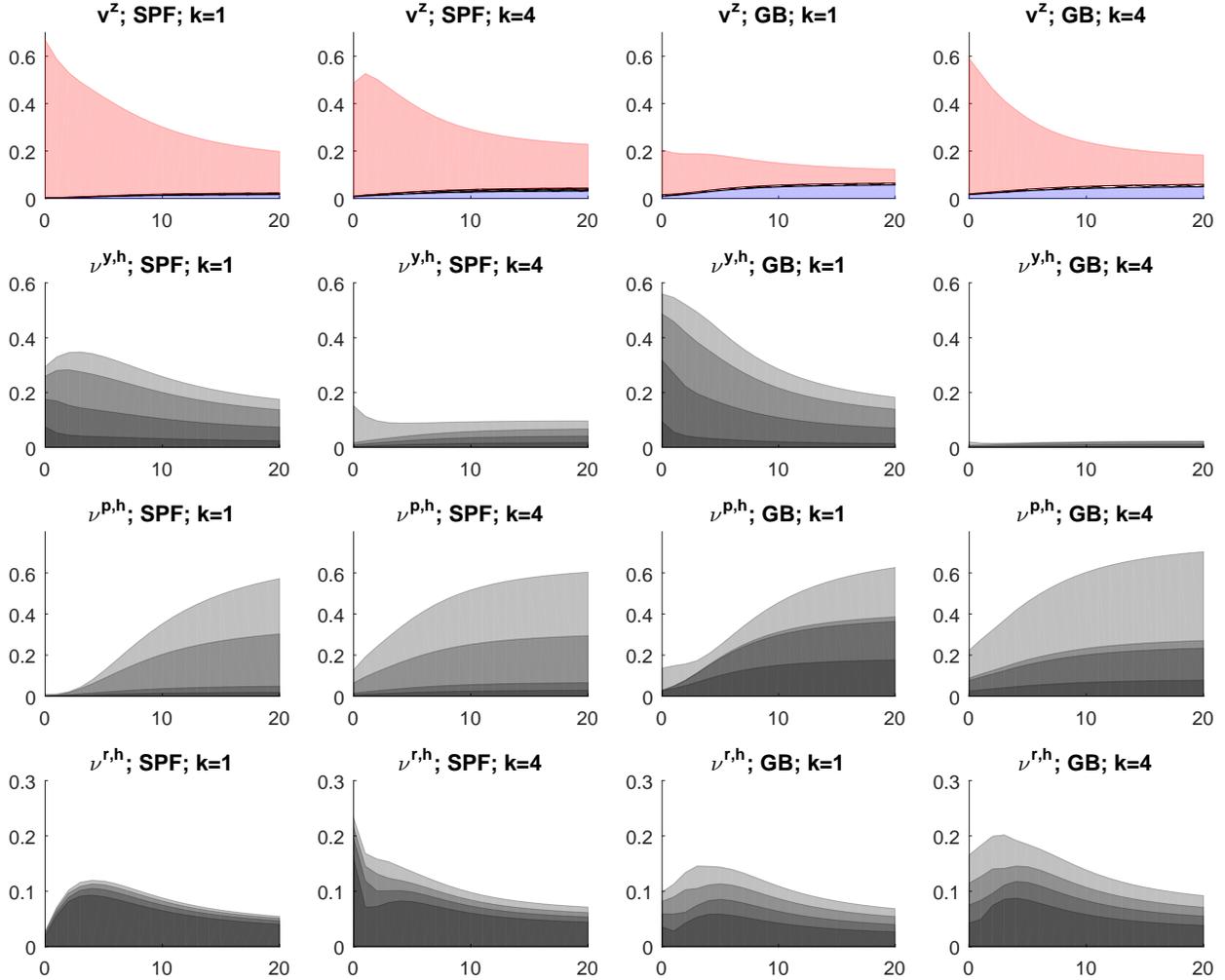
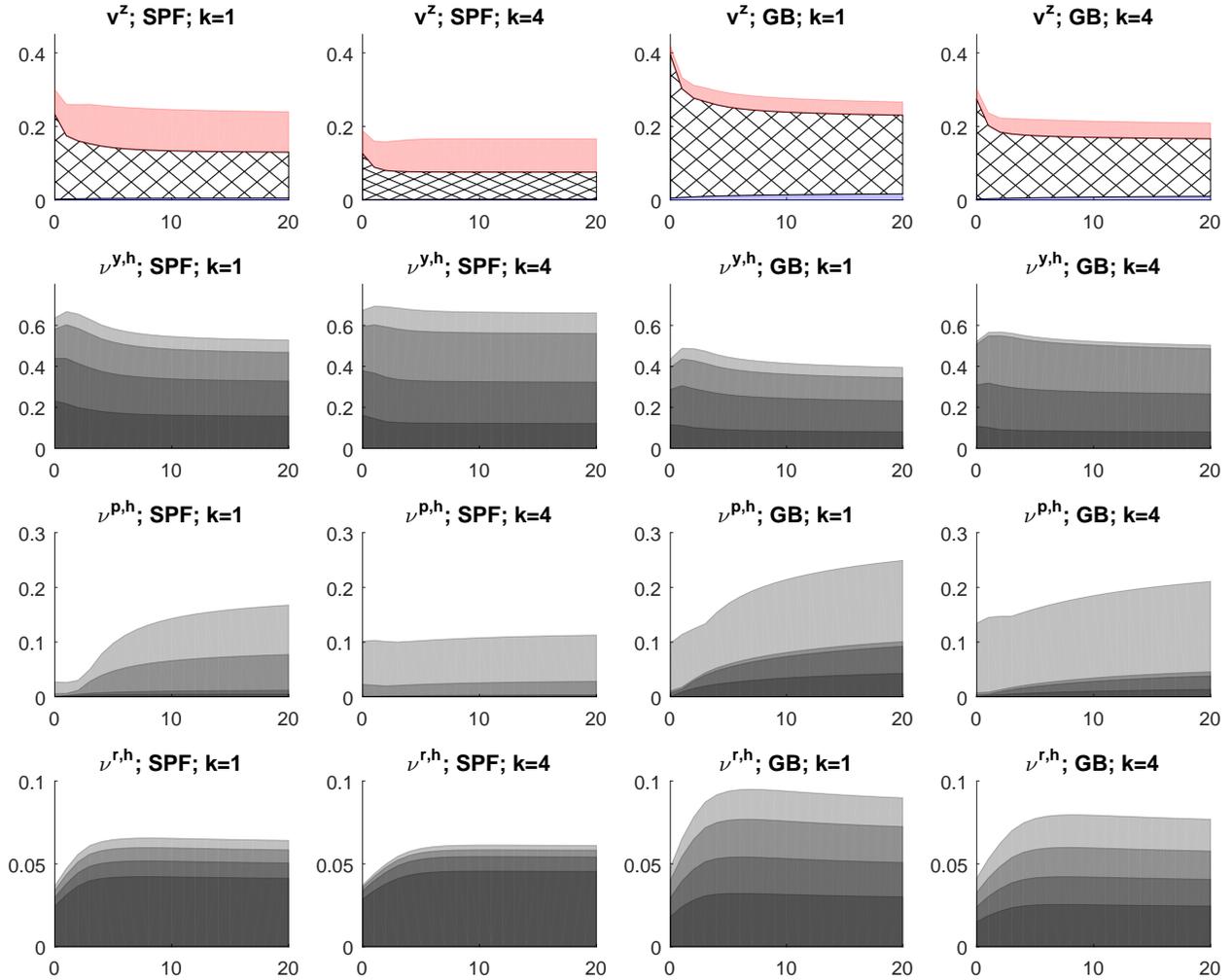


Figure 9:

Forecast error variance decomposition of inflation: GB vs SPF data. Surprises: blue shade—cost-push shocks; cross-hatched—demand shocks; red shade—monetary shocks. News: darkest shade— $h = 1$; lightest shade— $h = 4$.



C SPF and Greenbook Expectations Specification

In the previous sections we used real-time data series from the Philadelphia Fed Real-Time Data set to match current observations; however in one case, all expectations are matched to the SPF, and in the other case, all expectations are matched to the Greenbook forecasts. An obvious extension should be to use SPF expectations to match expectations included in the Euler Equation and the New Keynesian Phillips Curve (NKPC)—as those represent expectations of households and firms—and Greenbook expectations for the terms in the Taylor rule—as those represent central bank’s forecasts. Therefore, the two forecasts should be mixed in the same model and this is the approach that we take in the current section.

The model is encompassed by equations (1)-(6). The expectations included in equations (1) and (2) that are our IS schedule and NKPC are pinned down by expectational data from the SPF. In an attempt to capture the central bank’s behavior, equation (3) is identified using data that is generated by the Federal Reserve. In particular the expectational terms in the Taylor rule $E_t \pi_{t+k}^{GB}$ and $E_t \Delta y_{t+k}^{GB}$ for $k = 1$ are identified by using one quarter ahead Greenbook forecasts for inflation and output growth, while the current interest rate used is the Effective Federal Funds Rate obtained from the FRED that is the economic database from the Federal Reserve Bank of St. Louis.¹⁰

In addition, the anticipated shock component of our model is given by $\nu_{t-h}^{y,h}$, $\nu_{t-h}^{p,h}$, and $\nu_{t-h}^{r,h}$, where h is the anticipation horizon. We consider 1- to 4 quarter-ahead anticipated shocks to the Euler equation ($\nu_{t-h}^{y,h}$), and the NKPC ($\nu_{t-h}^{p,h}$), that are identified using expectations data from the Survey of Professional Forecasters as described in Section 4. However, the monetary policy anticipated shocks ($\nu_{t-h}^{r,h}$) resorts to Federal Funds Rate projections from the Greenbook Financial Assumptions that are used in the construction of Greenbook forecasts. Therefore, we are adding four additional variables to the space vector (α_t) that are the forecast of inflation $E_t \pi_{t+k}^{GB}$ and output gap $E_t \delta y_{t+k}^{GB}$ —which enter the monetary policy reaction function—and their corresponding expectational error terms $\nu_t^{p,1}$, and $\nu_t^{y,1}$ with standard deviations σ_{p1}^{GB} and σ_{y1}^{GB} . In addition, the observation equation (8) was modified to include the two new observable variables—GB forecasts of inflation and output growth—and a measurement error ($\epsilon_t^{E_t \Delta y_{t+1}^{GB}}$) (with standard deviation σ_{oy+1}^{GB}) for the expected future output growth to account for potential discrepancies between this observable and the model’s definition.

Table 4 presents the posterior parameter estimate results. The main differences with our main specification in Tables 2 and 3 is that the degree of price stickiness, θ , increases almost up to its theoretical limit of 1 and the degree of persistence drops considerably, which suggests that all shocks directly affecting the

¹⁰We also estimated a model where the central bank is responding to 4 quarters ahead Greenbook forecasts of inflation and output growth ($k = 4$) in the Taylor rule, however this estimation becomes problematic because dimension of the matrix in the state space representation increases considerably, and multiple determinacy arise. Therefore, we stick to the ($k = 1$) estimation which yields manageable matrices and no determinacy issues.

Phillips curve, both surprises and news, will have marked differently transmission mechanisms in this model. This intuition is confirmed in the forecast error variance decompositions of Figure 11. It demonstrates that all variables respond primarily to their own surprises and news, a feature that is likely driven by the fact that instead of all forecasts being driven by mutually consistent models, this specification mixes forecasted variables that were obtained using different methodologies. In terms of the monetary policy parameter estimates and news shocks, we observe that the response to inflation in the Taylor rule in this specification where the Greenbook forecasts are only used in the identification of monetary policy aspects of the model, is lower ($\gamma_p = 1.317$), which may suggest that the Fed's response to inflation forecast is smaller than what is perceived by the private agents. In addition, we find evidence supporting our previous results that monetary policy news shocks identified using GB are across the board higher than SPF estimates, consistent with the forward guidance strategy followed by the Fed in recent years. Lastly, the supply shocks, identified with SPF data only, have higher standard deviation at all horizons; unfortunately, the implications of this last finding is dubious given the transmission mechanism results in the FEVD.

Table 4: Parameter Estimate Posteriors Combined Expectations model, $k = 1$

Parameters	Greenbook and SPF	
	Mean	Pos. Prob. Int.
b	0.988	[0.986, 0.991]
θ_p	0.998	[0.996, 0.999]
ω_p	0.072	[0.021, 0.158]
ρ	0.948	[0.930, 0.963]
γ_p	1.317	[1.022, 1.722]
γ_y	0.411	[0.185, 0.644]
ρ_r	0.516	[0.435, 0.595]
ρ_y	0.129	[0.044, 0.222]
ρ_p	0.065	[0.021, 0.130]
σ_r	0.066	[0.057, 0.077]
σ_y	0.120	[0.093, 0.149]
σ_p	0.233	[0.200, 0.272]
σ_{r1}	0.053	[0.046, 0.062]
σ_{r2}	0.038	[0.033, 0.045]
σ_{r3}	0.035	[0.030, 0.041]
σ_{r4}	0.034	[0.029, 0.041]
σ_{y1}	0.031	[0.002, 0.057]
σ_{y2}	0.032	[0.007, 0.049]
σ_{y3}	0.012	[0.001, 0.030]
σ_{y4}	0.026	[0.018, 0.034]
σ_{p1}	0.104	[0.088, 0.123]
σ_{p2}	0.096	[0.081, 0.112]
σ_{p3}	0.180	[0.147, 0.217]
σ_{p4}	0.173	[0.141, 0.208]
σ_{oy}	1.891	[1.685, 2.093]
σ_{oy+1}	0.113	[0.089, 0.143]
σ_{oy+2}	0.080	[0.062, 0.101]
σ_{oy+3}	0.090	[0.073, 0.111]
σ_{oy+4}	0.119	[0.101, 0.141]
σ_{y1}^{GB}	0.086	[0.002, 0.324]
σ_{p1}^{GB}	0.052	[0.001, 0.178]
σ_{oy+1}^{GB}	0.184	[0.153, 0.220]
Marginal L	298.32	

Figure 10: Distributions of estimated standard deviations of cost-push news shocks: Grey dashed line—prior; blue solid line—Greenbook; red punctuated line—SPF; green dotted line—combined

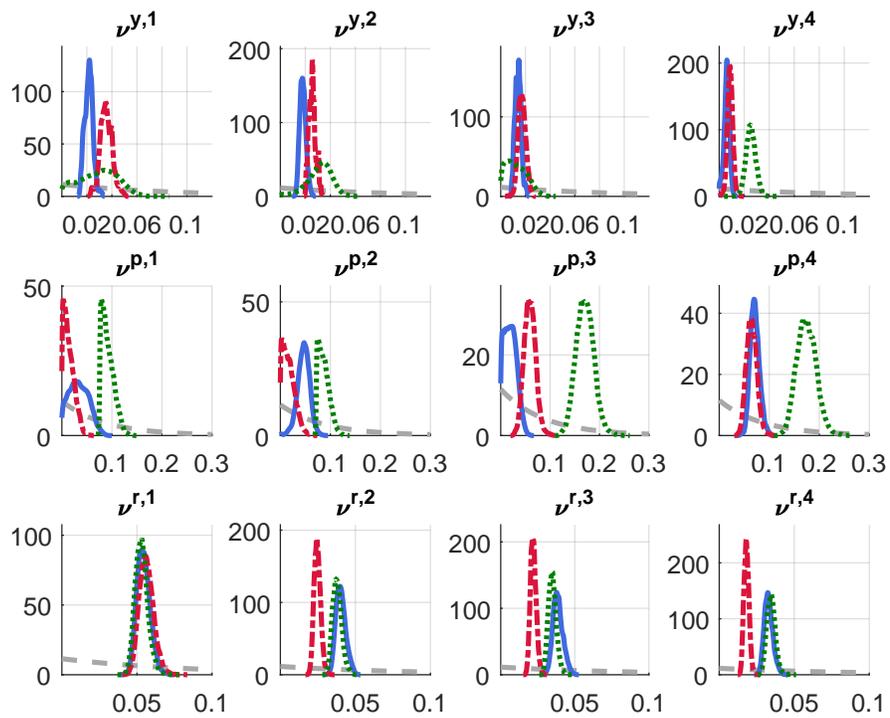


Figure 11: Forecast error variance decompositions: combined GB vs SPF data. Surprises: blue shade—cost-push shocks; cross-hatched—demand shocks; red shade—monetary shocks. News: darkest shade— $h = 1$; lightest shade— $h = 4$.

