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. These specifications with the SPF and GB forecasts aim to model the private sector's and the Fed's expectations of future macroeconomic outcomes and aid with the identification of news shocks. Our results indicate that while the demand news shocks have very similar distributions in the two datasets, the monetary and supply 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. **JEL Classification:** E31; E32; E52.

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1 Introduction

Over the last few decades, New Keynesian dynamic stochastic general equilibrium (DSGE) models have been widely used to analyze business cycle fluctuations and, in particular, the conduct of monetary policy as a means of mitigating business cycle fluctuations. The New Keynesian DSGE framework combined the microfoundations and methodological rigor of neoclassical macroeconomic models developed in response to the seminal Lucas (1976) critique with nominal and real rigidities that motivated a meaningful policy conduct. Central to these frameworks is the economic agents' forward-looking behavior modeled via rational expectations whereby agents' use all of the currently available information to make forecasts of the future conditions. One implication of the Lucas critique was that the exploitation of the inflation-unemployment tradeoff would break down, as agents revised their expectations of future inflation, thereby offsetting the policy's desired effect. In large part due this argument, much of the early theoretical New Keynesian literature focused on the design of optimal monetary policy to stabilize the economy against fluctuations induced by exogenous stochastic shocks; see Clarida et al (1999) for a comprehensive summary. Recent advances in theoretical models and econometric estimation techniques, however, have allowed merging policy announcements with forward-looking expectation in the context of New Keynesian DSGE models. Moreover, it may be possible that policy announcements are more important in managing business cycle fluctuations than contemporaneous policy actions.

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-

[1] For 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.

looking expectations. While the recent literature has paid considerable attention to the effect of forward guidance on the macroeconomy implications of a potential gap between the central bank's forward-looking intentions and their perception by the private sector, in the DSGE context, has not been explored.[2]

To fill this gap, the present paper estimates the same New Keynesian DSGE model with news shocks using the Federal Reserve's Greenbook (GB) and private sector's Survey of Professional Forecasters' (SPF) forecasts to identify these shocks. More specifically, we follow the work of Milani and Treadwell (2012) by introducing anticipated components to the model's stochastic shocks. Best and Kapinos (2015) 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.[3] Below, we employ two different datasets: the real-time Survey of Professional Forecasters data and the Federal Reserve Greenbook forecasts, both from the Federal Reserve Bank of Philadelphia. The 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 supply 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.

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

[2]Brissimis 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.

[3]Hirose and Kurozumi (2012) identify news shocks in a small scare 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.

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. They found a spike in the explanatory power of Greenbook forecasts between 1995 and 2001, however, the Fed's informational improvement weakens after 2003. They focus on testing forecast unbiasedness, efficiency, and rationality and their results show that both the Fed and survey forecasts fail rationality tests. However, Caunedo et al. (2016) follow up on Rossi and Sekhposyan (2016) analysis of Greenbook forecasts by estimating an asymmetric loss function that accounts for possible interactions between variables. They conclude that inflation forecast are rationalizable but asymmetric—due to Volcker's disinflation episode—while unemployment and output growth forecasts are symmetric and symmetric prior to Volckers' appointment, respectively. Sinclair et al (2015) perform a multivariate analysis of the bias of the forecasts and find evidence that the Greenbook nowcasts and one-quarter ahead forecasts deliver an overall view of the economy that is accurate and consistent with the BEA's estimates that are released at least 30 days later. 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.

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 supply 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 supply 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 2 summarizes a fairly standard New Keynesian model of monetary policy augmented with news shocks. Section 3 lays out the Bayesian estimation strategy that we employ to estimate alternative specifications of our baseline model and the priors for estimated parameters. Section 4 discusses the data and motivates the use of real-time forecasts for modeling forward-looking expectations in DSGE models. Section 5 discusses estimation results. Finally, Section 6 concludes.

2 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 the 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:

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

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:

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

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 supply 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:

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

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.[4] 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-

[4]See 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.

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:

$$\epsilon_t^y = \rho_y \epsilon_{t-1}^y + \upsilon_t^y + \sum_{h=1}^{H} \nu_{t-h}^{y,h}, \tag{4}$$

$$\epsilon_t^p = \rho_p \epsilon_{t-1}^p + \upsilon_t^p + \sum_{h=1}^{H} \nu_{t-h}^{p,h}, \tag{5}$$

and

$$\epsilon_t^r = \rho_r \epsilon_{t-1}^r + \upsilon_t^r + \sum_{h=1}^{H} \nu_{t-h}^{r,h}, \tag{6}$$

where $\upsilon_t^y \sim iid(0, \sigma_y^2)$, $\upsilon_t^p \sim iid(0, \sigma_p^2)$, and $\upsilon_t^r \sim iid(0, \sigma_r^2)$ 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 $t + h,\ h = [1, \ldots, 4]$ 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).

3 Bayesian Estimation Strategy

This section outlines the mapping from the observed variables that included concurrent observations 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.

3.1 State-space Representation

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

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

with α_t=$[y_t, \pi_t, r_t, E_t y_{t+1}, ..., E_t y_{t+4}, E_t \pi_{t+1}, ..., E_t \pi_{t+4}, E_t r_{t+1}, ..., E_t r_{t+4}, \epsilon_t^y, \epsilon_t^p, \epsilon_t^r, \nu_t^{r,h}, \nu_{t-1}^{r,h}, ...$ $\nu_{t-h+1}^{r,h}, \nu_t^{y,h}, \nu_{t-1}^{y,h}, ..., \nu_{t-h+1}^{y,h}, \nu_t^{p,h}, \nu_{t-1}^{p,h}, ..., \nu_{t-h+1}^{p,h}]'$ is the state vector for horizons $h = [1, \ldots, 4]$ in the Taylor rule, Euler Equation, and NKPC. The vector $w_t = [0, ..., 0, v_t^r, v_t^y, v_t^p, \nu_t^{r,h}, \nu_t^{y,h}, \nu_t^{p,h}, ..., 0]'$ 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:

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

The previous observation equation can be summarized as:

$$\xi_t = \bar{\gamma} + H\alpha_t + \Omega o_t. \tag{9}$$

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:

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

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 $\xi^T = [\xi_1, ..., \xi_T]$. 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.[5] 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.

3.2 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

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

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:

$$\sigma^2_{c,q} = w\sigma^2_q$$

and its news components by:

$$\sigma^2_{n,q} = (1 - w)\sigma^2_q,$$

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:

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

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.

4 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.[6] 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.[7] 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 quarter, defined as the quarter in which the survey is conducted.[8] 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 $h = [1, \ldots, 4]$ 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 $h = [1, \ldots, 4]$ 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 $h = [1, \ldots, 4]$ 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

[6]The 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.

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

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

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 $t+h,\ h=[1,\ldots,4]$. 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 errors of inflation, output growth, and interest rates using the SPF and GB forecasts follow similar but by no means identical patterns.[9] 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 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.

Forecast errors of output growth at different horizons are plotted in Figure 2, as expected the forecast bias becomes more evident at longer horizons. The opposite pattern to inflation forecast errors is observed regarding output growth. 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, forecast errors for interest rates are plotted in Figure 3. We note that during the recessions of the early 1990s and 2000s, and during the Great Recession, forecast errors of short term interest rates were negative and consistent with forecast overestimates; while during expansions, we observe underestimation of the forecast of short term interest rates. These differences highlight the variation in the perception of the Fed's forward guidance discussed in Section 1.

[9]Forecast errors are there to magnify or clarify the differences between the two datasets

In all cases, as the horizon increases, forecast 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 2.

5 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 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.

5.1 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 likelihoods are across the board higher when $k = 4$ in the Taylor rule. 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 ($\gamma_p = 2.188$ for $k = 4$ vs. $\gamma_p = 1.978$). 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; $\gamma_p = 2.47$ at $k = 4$ while $\gamma_p = 1.819$ 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 supply news shocks. Figures 4 through 6 present priors and posterior distributions for the monetary policy, demand, and supply 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 supply news, identification of news using SPF data are perceived to have a considerably stronger standard deviation at $h = 3$, than supply 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.

5.2 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 supply 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 supply ($> 20\%$) 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.

6 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 supply 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 supply 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 supply 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 supply 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 supply 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	SPF		Greenbook	
	Mean	Pos. Prob. Int.	Mean	Pos. Prob. Int.
b	0.989	[0.987, 0.992]	0.989	[0.986, 0.991]
θ_p	0.853	[0.852, 0.854]	0.854	[0.851, 0.856]
ω_p	0.020	[0.006, 0.043]	0.016	[0.005, 0.033]
ρ	0.918	[0.904, 0.930]	0.840	[0.812, 0.862]
γ_p	1.819	[1.562, 2.007]	1.978	[1.77, 2.157]
γ_y	0.486	[0.341, 0.633]	0.260	[0.041, 0.482]
ρ_r	0.336	[0.258, 0.419]	0.562	[0.497, 0.622]
ρ_y	0.009	[0.001, 0.026]	0.009	[0.001, 0.025]
ρ_p	0.999	[0.998, 0.999]	0.999	[0.998, 0.999]
σ_r	0.098	[0.084, 0.114]	0.066	[0.057, 0.077]
σ_y	0.058	[0.043, 0.076]	0.065	[0.049, 0.082]
σ_p	0.015	[0.001, 0.041]	0.031	[0.001, 0.077]
σ_{r1}	0.056	[0.048, 0.067]	0.054	[0.047, 0.063]
σ_{r2}	0.025	[0.021, 0.029]	0.041	[0.035, 0.048]
σ_{r3}	0.022	[0.018, 0.026]	0.039	[0.033, 0.046]
σ_{r4}	0.018	[0.015, 0.022]	0.033	[0.028, 0.039]
σ_{y1}	0.032	[0.023, 0.042]	0.020	[0.014, 0.026]
σ_{y2}	0.022	[0.017, 0.029]	0.017	[0.013, 0.022]
σ_{y3}	0.015	[0.008, 0.022]	0.012	[0.008, 0.017]
σ_{y4}	0.008	[0.004, 0.013]	0.006	[0.002, 0.010]
σ_{p1}	0.016	[0.001, 0.042]	0.044	[0.003, 0.082]
σ_{p2}	0.021	[0.001, 0.056]	0.052	[0.021, 0.074]
σ_{p3}	0.064	[0.038, 0.095]	0.023	[0.004, 0.051]
σ_{p4}	0.070	[0.047, 0.098]	0.072	[0.057, 0.089]
σ_{oy}	0.407	[0.344, 0.453]	0.449	[0.381, 0.534]
σ_{oy+1}	0.177	[0.150, 0.210]	0.270	[0.233, 0.316]
σ_{oy+2}	0.142	[0.121, 0.169]	0.227	[0.193, 0.268]
σ_{oy+3}	0.131	[0.113, 0.151]	0.208	[0.177, 0.246]
σ_{oy+4}	0.137	[0.118, 0.161]	0.186	[0.160, 0.217]
Marginal L	824.10		681.21	

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

Parameters	SPF		Greenbook	
	Mean	Pos. Prob. Int.	Mean	Pos. Prob. Int.
b	0.984	[0.978, 0.988]	0.988	[0.986, 0.991]
θ_p	0.813	[0.790, 0.833]	0.855	[0.853, 0.857]
ω_p	0.017	[0.005, 0.036]	0.014	[0.004, 0.031]
ρ	0.764	[0.741, 0.794]	0.748	[0.718, 0.790]
γ_p	2.474	[2.265, 2.699]	2.188	[1.945, 2.424]
γ_y	0.502	[0.320, 0.698]	0.384	[0.143, 0.616]
ρ_r	0.637	[0.576, 0.694]	0.622	[0.562, 0.672]
ρ_y	0.009	[0.001, 0.025]	0.008	[0.001, 0.022]
ρ_p	0.999	[0.998, 0.999]	0.999	[0.998, 0.999]
σ_r	0.102	[0.086, 0.120]	0.080	[0.068, 0.095]
σ_y	0.051	[0.040, 0.064]	0.066	[0.050, 0.083]
σ_p	0.022	[0.001, 0.059]	0.023	[0.001, 0.063]
σ_{r1}	0.063	[0.054, 0.075]	0.051	[0.044, 0.060]
σ_{r2}	0.025	[0.021, 0.029]	0.036	[0.031, 0.042]
σ_{r3}	0.016	[0.014, 0.019]	0.033	[0.028, 0.039]
σ_{r4}	0.013	[0.011, 0.015]	0.032	[0.027, 0.037]
σ_{y1}	0.029	[0.022, 0.038]	0.021	[0.015, 0.027]
σ_{y2}	0.022	[0.016, 0.029]	0.019	[0.014, 0.024]
σ_{y3}	0.016	[0.010, 0.020]	0.014	[0.009, 0.018]
σ_{y4}	0.008	[0.005, 0.012]	0.003	[0.000, 0.007]
σ_{p1}	0.021	[0.001, 0.058]	0.029	[0.002, 0.061]
σ_{p2}	0.024	[0.001, 0.060]	0.041	[0.017, 0.064]
σ_{p3}	0.060	[0.032, 0.089]	0.020	[0.001, 0.043]
σ_{p4}	0.071	[0.050, 0.096]	0.069	[0.054, 0.088]
σ_{oy}	0.415	[0.353, 0.477]	0.440	[0.376, 0.543]
σ_{oy+1}	0.175	[0.150, 0.204]	0.270	[0.231, 0.316]
σ_{oy+2}	0.145	[0.123, 0.166]	0.228	[0.200, 0.265]
σ_{oy+3}	0.133	[0.115, 0.155]	0.210	[0.179, 0.245]
σ_{oy+4}	0.139	[0.119, 0.163]	0.187	[0.161, 0.218]
Marginal L	862.79		692.19	

B Figures

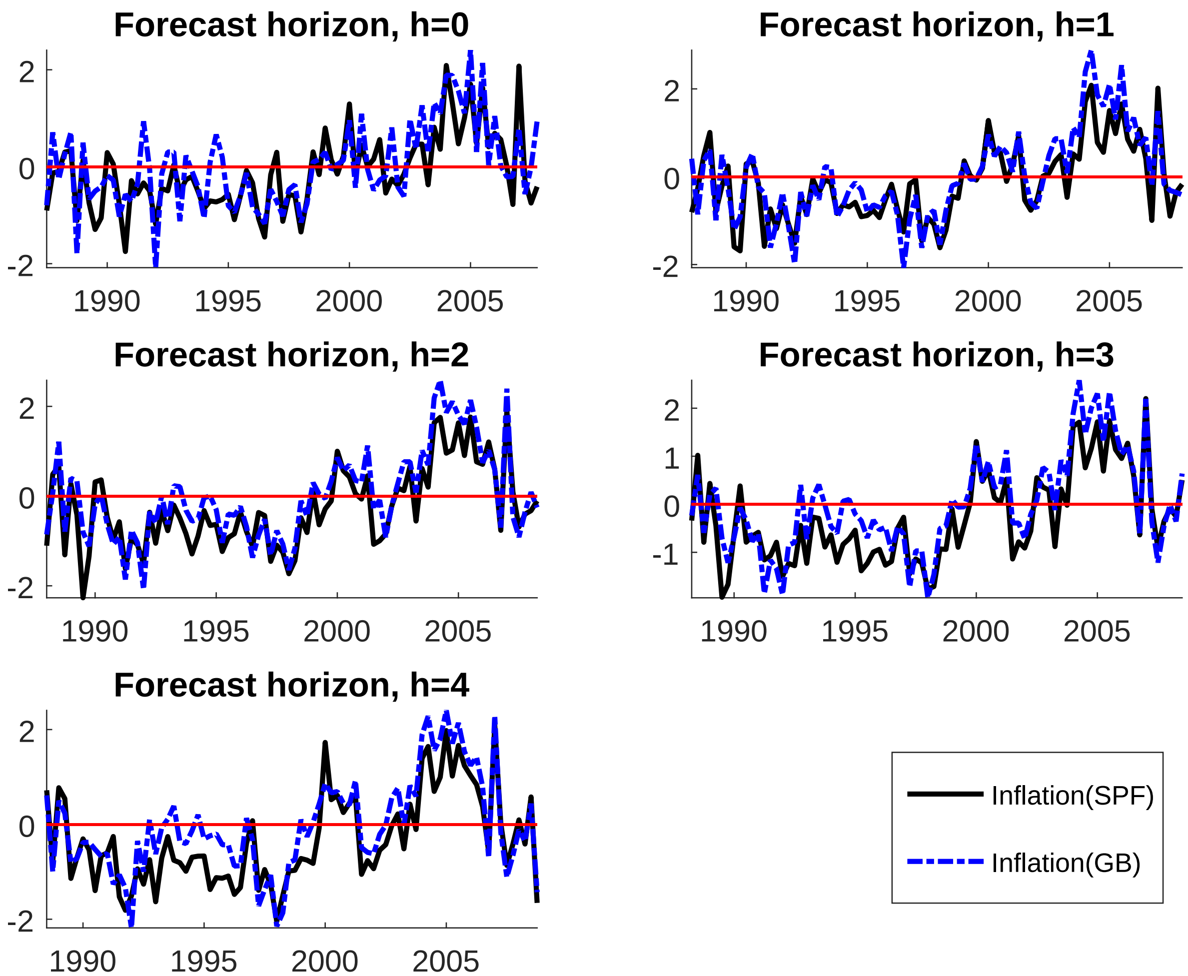

Figure 1: Forecast error of inflation at horizons h=[0,. . . ,4]. Survey of professional forecasts in black solid line and Greenbook forecasts in blue dash dotted line.

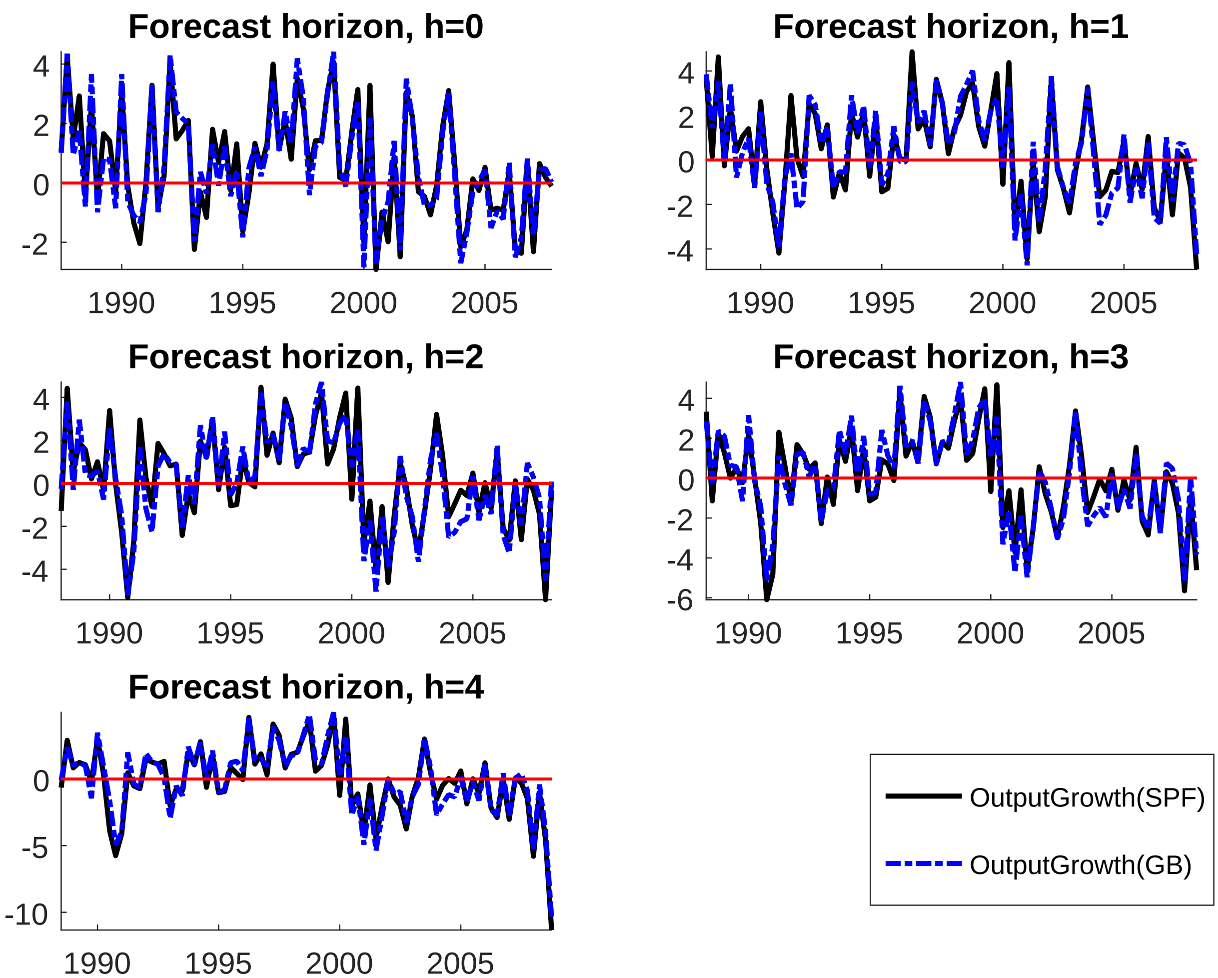

Figure 2: Forecast of error output growth at horizons h=[0,. . . ,4]. Survey of professional forecasts in black solid line and Greenbook forecasts in blue dash dotted line.

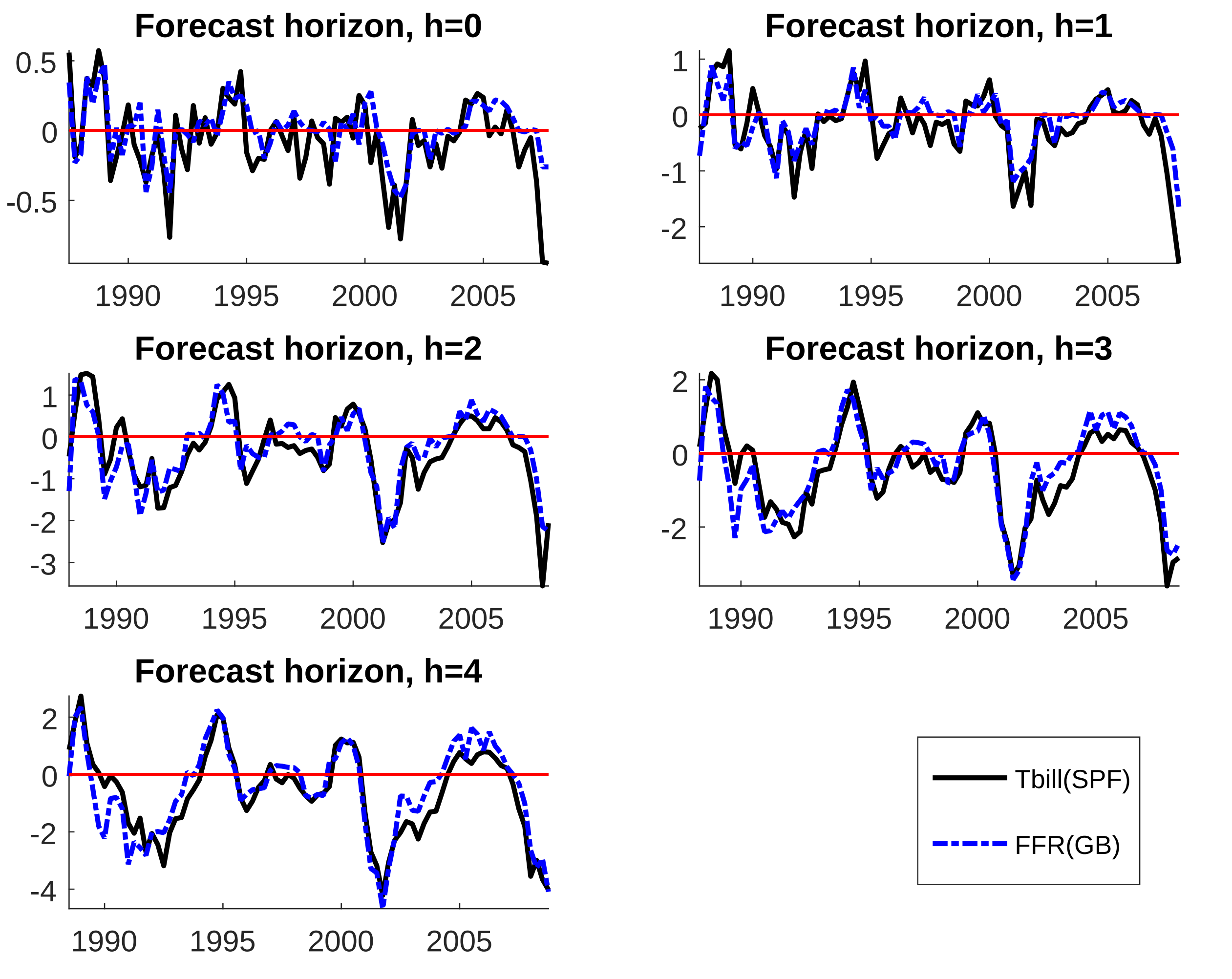

Figure 3: Forecast error of short-term interest rate at horizons h=[0,...,4]. Survey of professional forecasts in black solid line and Greenbook forecasts in blue dash dotted line.

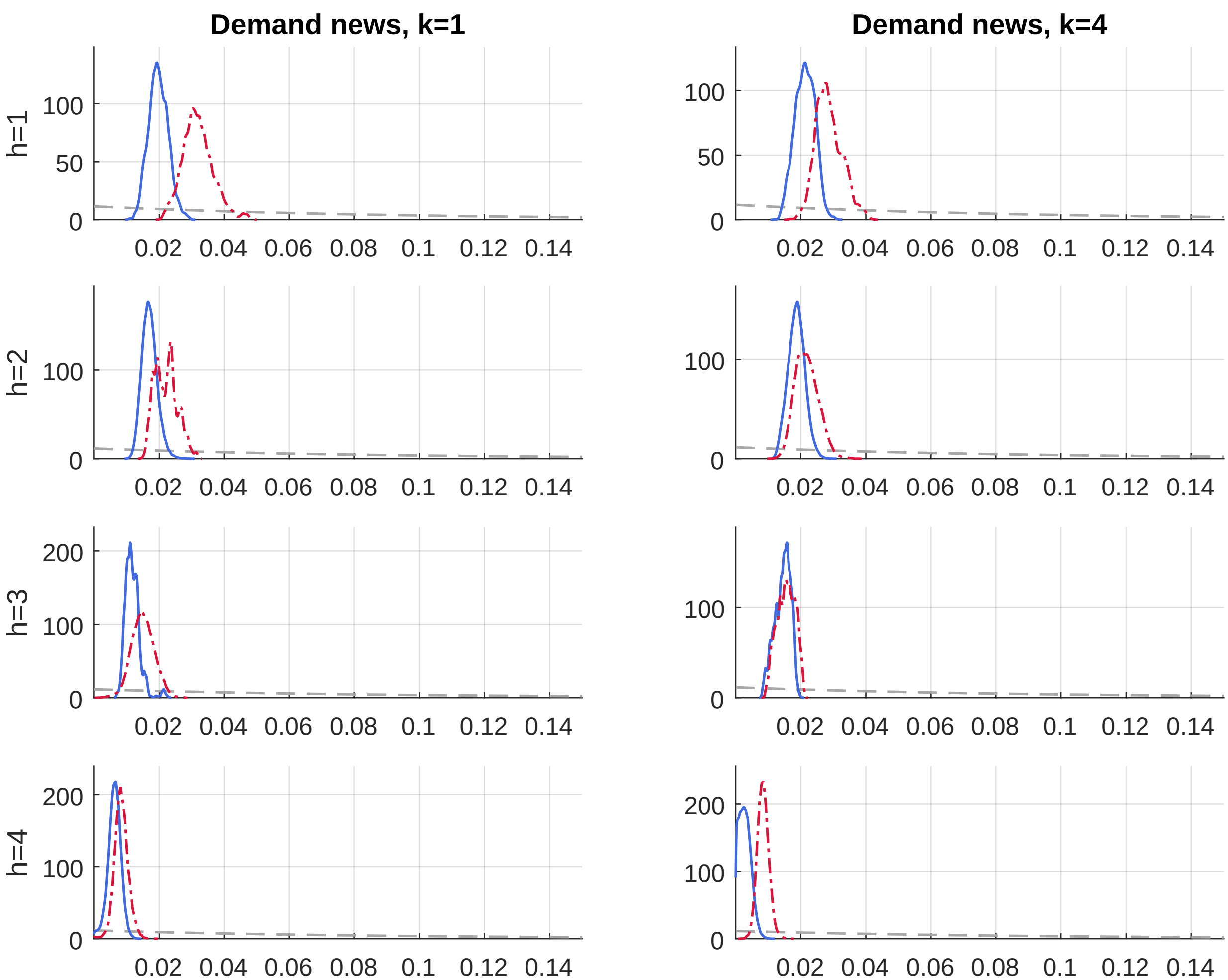

Figure 4: Distributions of estimated standard deviations of demand news shocks: Grey dashed line—prior; blue solid line—Greenbook; red punctuated line—SPF

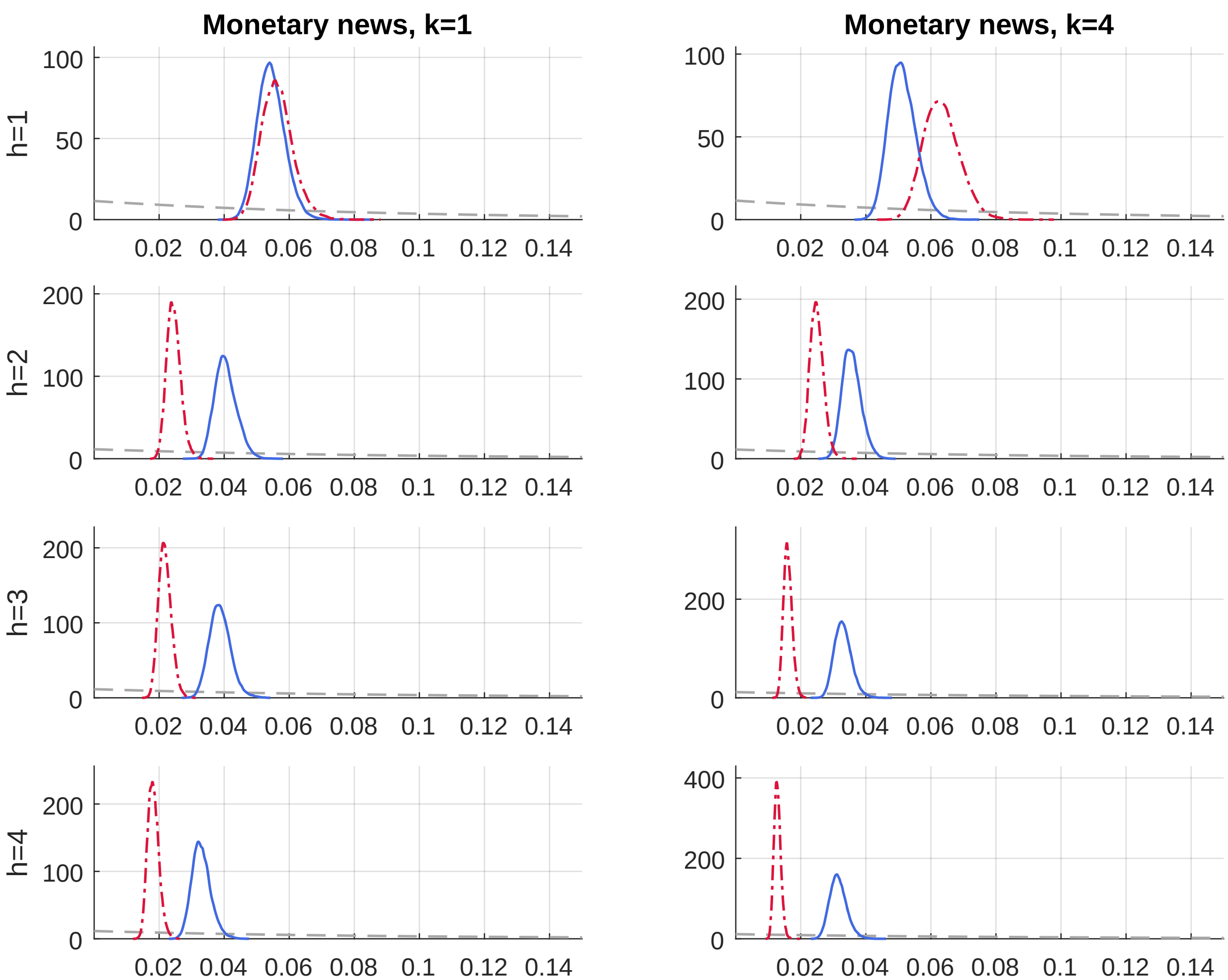

Figure 5: Distributions of estimated standard deviations of monetary news shocks: Grey dashed line—prior; blue solid line—Greenbook; red punctuated line—SPF

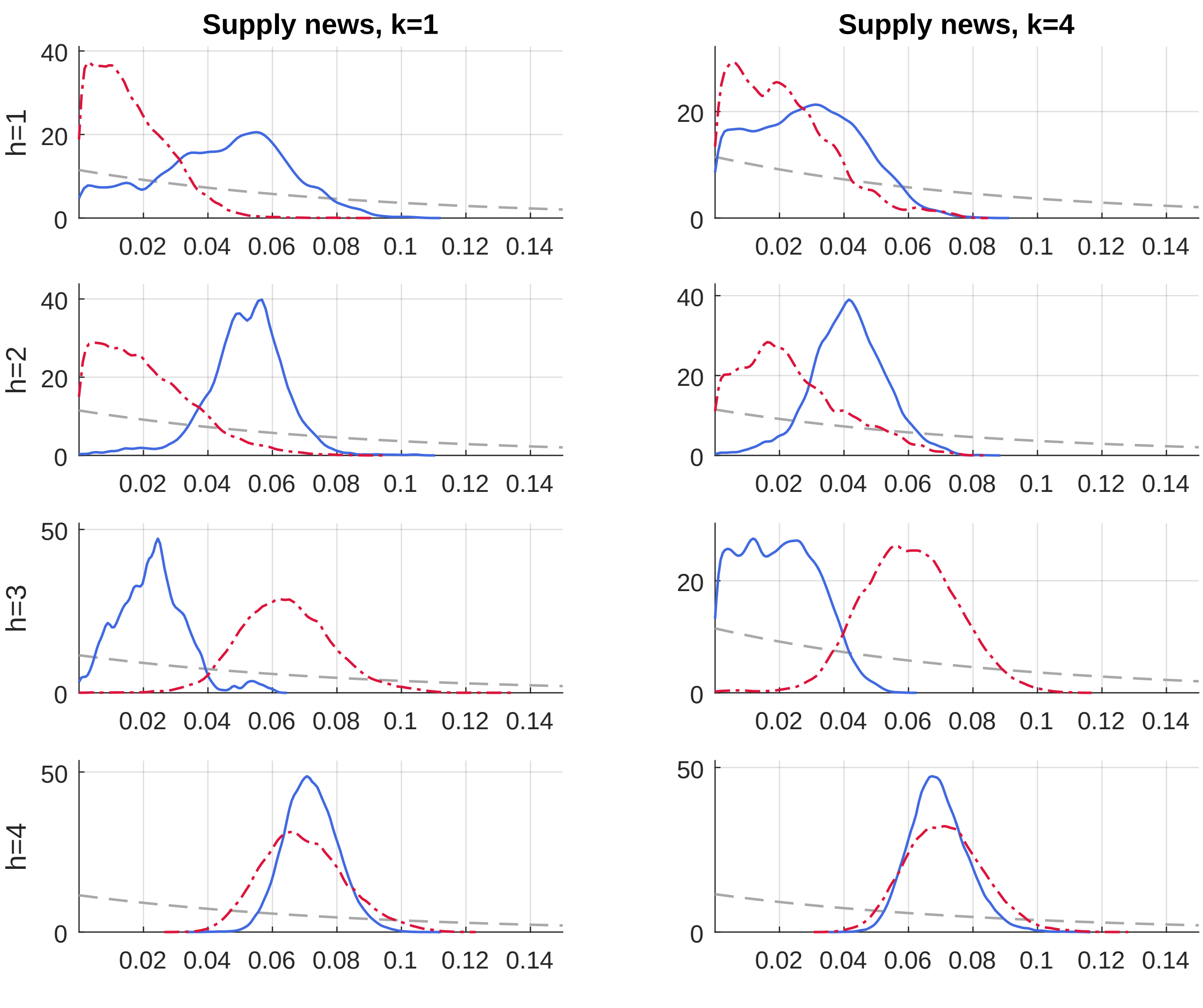

Figure 6: Distributions of estimated standard deviations of supply news shocks: Grey dashed line—prior; blue solid line—Greenbook; red punctuated line—SPF

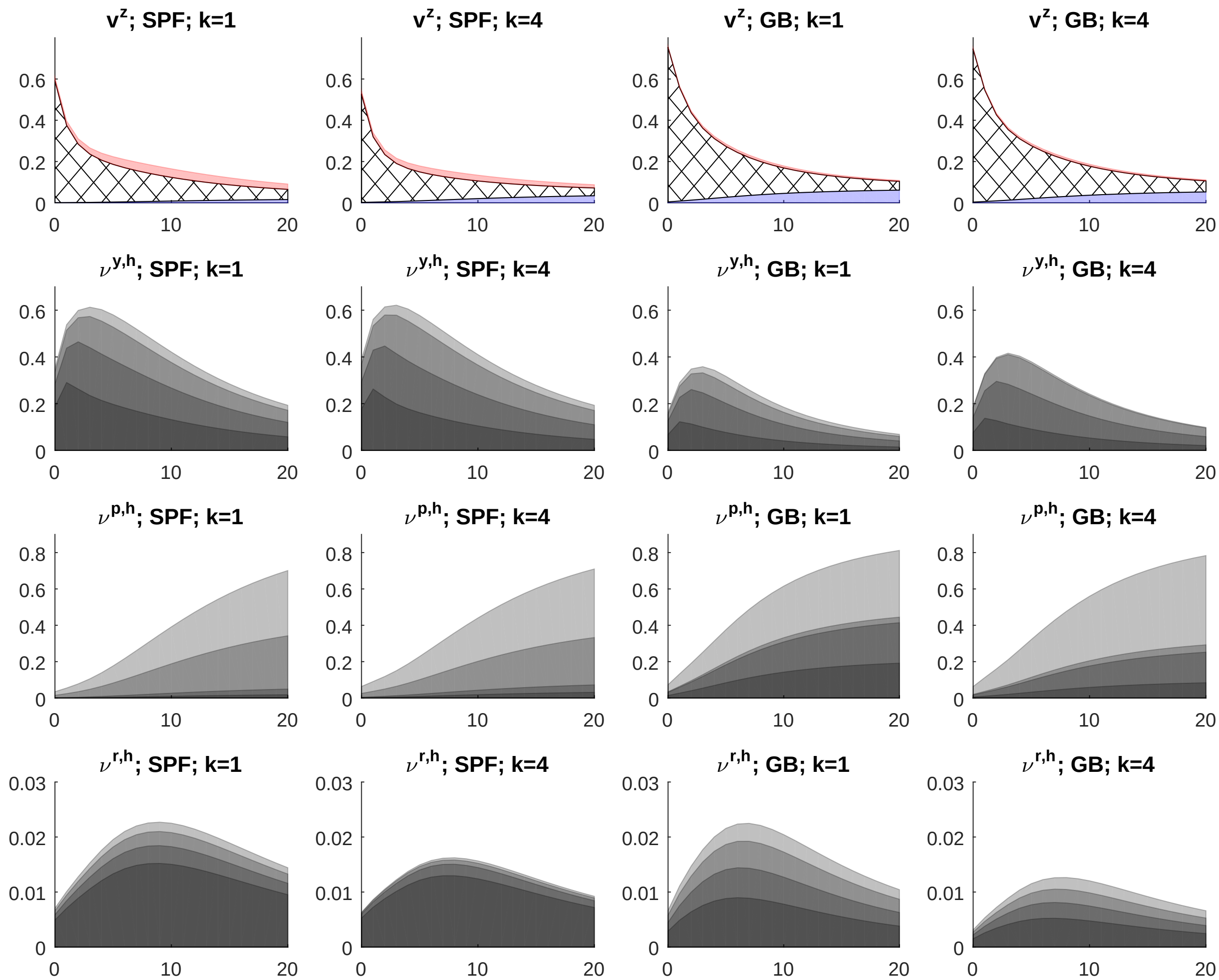

Figure 7: Forecast error variance decomposition of output gap: GB vs SPF data. Surprises: blue shade—supply shocks; cross-hatched—demand shocks; red shade—monetary shocks. News: darkest shade—$h = 1$; lightest shade—$h = 4$.

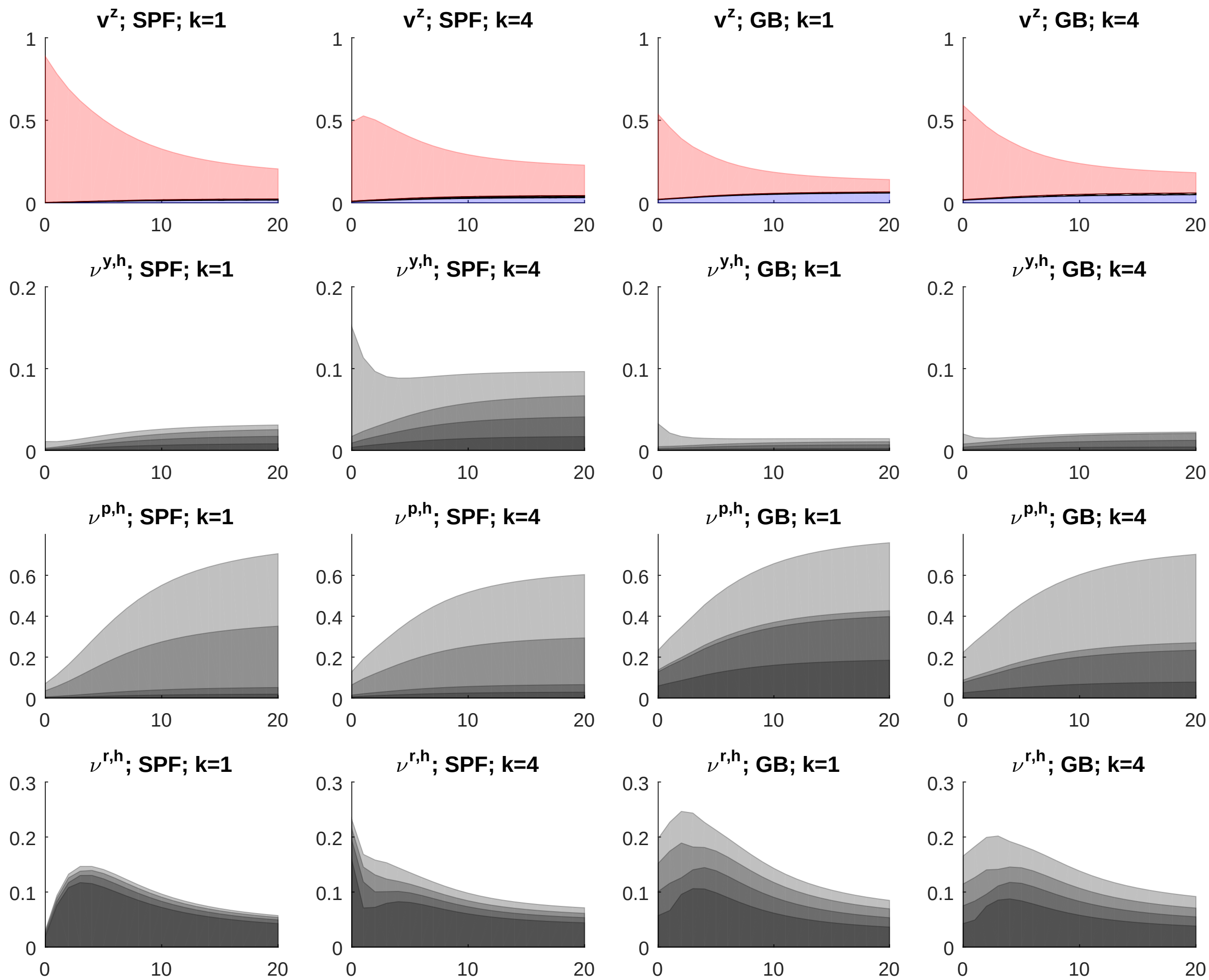

Figure 8: Forecast error variance decomposition of the nominal interest rate: GB vs SPF data. Surprises: blue shade—supply shocks; cross-hatched—demand shocks; red shade—monetary shocks. News: darkest shade—$h = 1$; lightest shade—$h = 4$.

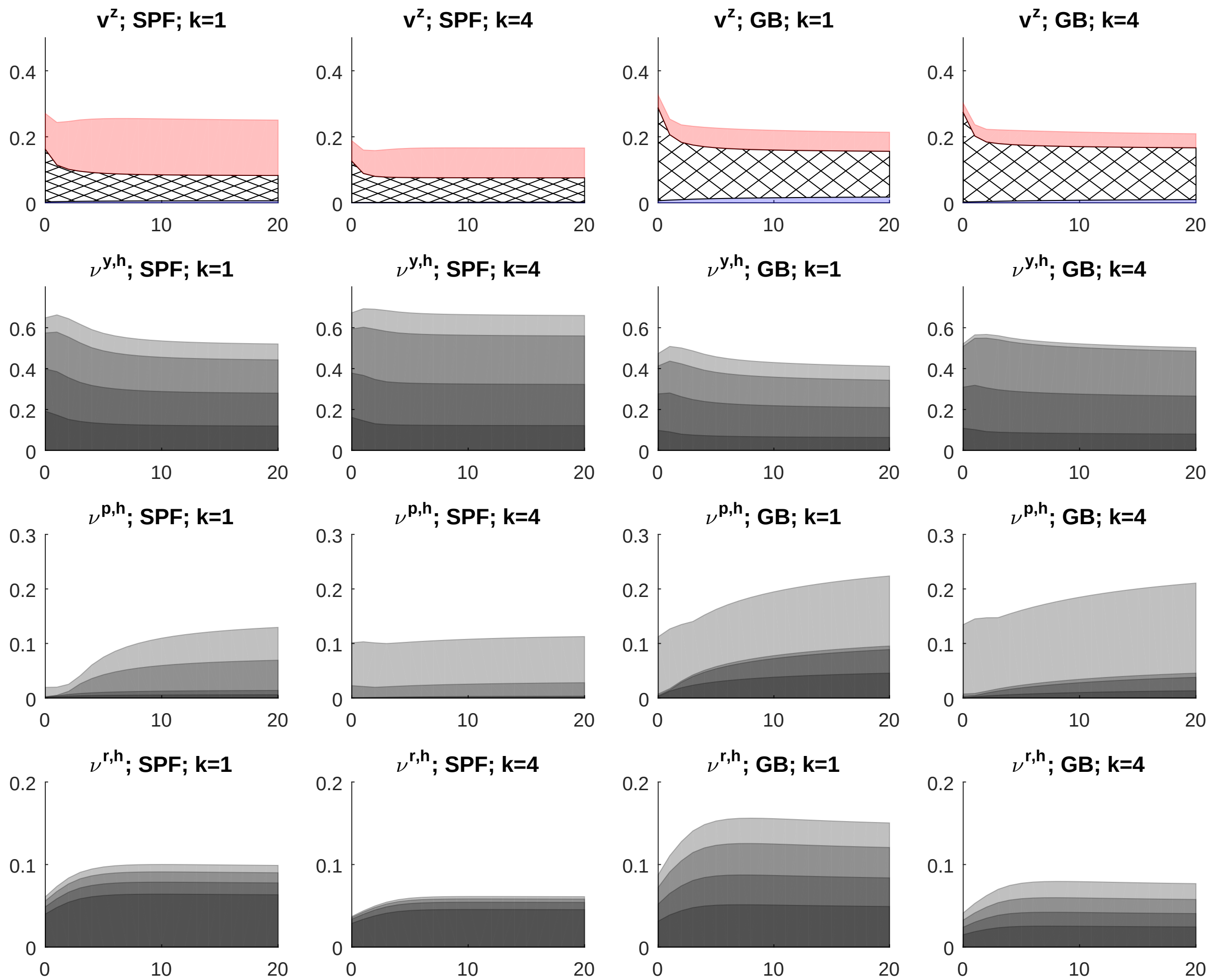

Figure 9: Forecast error variance decomposition of inflation: GB vs SPF data. Surprises: blue shade—supply shocks; cross-hatched—demand shocks; red shade—monetary shocks. News: darkest shade—$h = 1$; lightest shade—$h = 4$.