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News, Real-time Forecasts, and the Price Puzzle

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Abstract

This paper revisits the effects of news shocks in the context of an otherwise standard New Keynesian dynamic general equilibrium (DSGE) model. We use the U.S. real-time forecasts from the Federal Reserve’s Green Book to model agents’ and the central bank’s expectations of future macroeconomic outcomes. We show that unlike with the ex post data where the identification of news shocks is driven by the modeling assumptions, the identification strategy that relies on the Greenbook forecasts ascribes a larger role to news shocks in explaining variation in the model’s endogenous variables. Furthermore, we demonstrate that the presence of sizable news shocks explains the emergence of the price puzzle in the structural vector autoregressive framework.

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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 methodology frequently models the economic agents' forward-looking behavior models via rational expectations whereby agents' use all of the currently available information to make forecasts of the future conditions. Recently, researchers' motivation for the source of business cycle fluctuations has shifted from models only driven by unexpected stochastic shocks (or surprises) to ones where exogenous drivers of macroeconomic fluctuations may be observed several periods in advance (news or anticipated shocks). This paper's contribution to this strand of the literature is two-fold. First, we examine the role of news shocks in an otherwise standard New Keynesian DSGE model using the real-time Greenbook forecasts produced by the Federal Reserve to identify these shocks. Second, we show that the presence of this type of shocks, particularly news about the evolution of future inflation, can lead to the emergence of a well-documented empirical phenomenon termed the 'price puzzle' whereby inflation produces a positive initial impulse response to a monetary contraction.

This paper follows the recent 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 Survey of Professional Forecasters data. In this paper, we consider two different datasets: ex post from the Federal Reserve Bank of St. Louis FRED2 database and the Federal Reserve Greenbook forecasts from the Federal Reserve Bank of Philadelphia. While the ex post data have been routinely used to estimate New Keynesian DSGE models, the use of the real-time data are new. Our motivation for choosing the Greenbook forecasts over other alternatives, such as the Survey of Professional Forecasters (SPF), is threefold. First, unlike the SPF, the Green Book contains real-time forecasts of the output gap, which is typically considered to be the explicitly modeled driver of inflation in the New Keynesian DSGE framework. Second, since we are interested in identifying the effect of the monetary policy shock,

the real-time information about the federal funds rate and its forward-looking projections, which are only available in the Green Book Financial Assumptions section, provide the closest fit for our purposes. Finally, there exists an extensive literature that demonstrates the forecasting superiority of the Greenbook forecasts relative to their private-sector counterparts.

Romer and Romer (2000) were among the first to have found that Greenbook forecasts outperform private sector forecasts. They 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. Furthermore, Romer and Romer (2000) found that the null hypothesis of rationality is not rejected at conventional significance levels. Gamber and Smith (2009) confirmed these findings using a longer data set that included a protracted period of inflation stability. Faust and Wright (2009) found that the Fed’s forecasts of inflation (albeit not output growth) were superior to a battery of univariate models. El-Shagi et al (2014) using also a longer data set provide evidence of the superiority of Greenbook forecasts, especially during the periods of economic uncertainty. Clements (2015), on the other hand, finds that the SPF forecasts largely fail to outperform projections of monotonic convergence towards long-run trends. 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; however, both the Fed and survey forecasts fail rationality tests. Responding to this result, Caunedo et al. (2016) find that the forecasts may be rationalizable under an asymmetric forecasting loss function. In sum, since identification of the future macroeconomic outcomes is critical to the central mechanisms in our model, using the Fed forecasts to characterize them makes practical sense.

We use Bayesian methods to estimate the baseline New Keynesian model with and without news shocks, using either the ex post data or employing the Greenbook forecasts to model expectations of future macroeconomic variables. We find that the specifications that feature news shocks have better fit than the ones that do not and that specifications that rely on the real-time forecasts to model future outcomes have better fit than the ones without them. These results suggest that news shocks are important in explaining dynamics in the context of the New Keynesian DSGE model and that the Greenbook forecasts capture meaningful information about future outcomes.

In the last section of this paper, we study the role of anticipated shocks in our model on the emergence of the so-called price puzzle in the atheoretical vector autoregressive (VAR) models. Sims (1980) seminal introduction of the VAR methodology has made it a popular tool for analyzing the transmission of monetary policy shocks. Sims (1992), however, noted that the response of inflation to a contractionary shock tended to be counterintuitively positive at short horizons, a phenomenon that Eichenbaum (1992) termed the ‘price puzzle’. Several explanations of its emergence have been advanced over the last two decades. Our contribution is to show how anticipated shocks that we identify with real-time data can give rise to the price puzzle in the VAR setting using data simulated from the preferred specification of our empirical DSGE model.

Theoretical explanations of the price puzzle have introduced a variety of mechanisms into the DSGE models. Ravenna and Walsh (2006) and Chowdhury et al. (2006) introduced the cost channel of transmission of monetary policy whereby higher interest rates generate increases in marginal costs for firms that have to borrow to finance their production. Their single-equation estimates of the Phillips curve in the U.S. and other countries pointed to a significant presence of the cost channel. Working with a fully specified DSGE model, however, Rabanal (2007) found the extent of the cost channel to be insufficient to generate the price puzzle. Furthermore, Kapinos (2011) showed that the positive cost channel estimates may arise spuriously if the estimated DSGE model ignores the presence of anticipated cost-push shocks and the conduct of monetary policy is forward-looking. Another theoretical mechanism that gives rise to the price puzzle is indeterminacy. Castelnuovo and Surico (2010) have shown that introducing indeterminacy whereby the central bank violates the so-called Taylor principle, i.e. reacts to higher inflation by raising interest rate less than proportionately, produces the price puzzle in simulated data. Similarly, Auray and Feve (2008) introduce indeterminacy into a model with flexible prices and monetary policy given by a money supply rule and also obtain the price puzzle in that setting. In contrast, the results in this paper show that the price puzzle may occur in settings without either the cost channel or indeterminacy.

Empirical explanations of the price puzzle have primarily focused on model misspecification that leads to poor identification of the monetary policy shocks. Sims’ (1991) original conjecture for explaining the price puzzle was that the central bank takes into account information about future inflation, responds to it preemptively, and thus produces outcomes consistent with the price puzzle. He pointed to commodity prices whose introduction into the vector autoregressive (VAR)

framework appeared to mitigate or eliminate it. However, Hanson (2004) found no relationship between different indicators' ability to forecast inflation and the reduction in the price puzzle's extent that their presence in the VAR would yield. Giordani (2004) showed that the price puzzle could be mitigated by replacing output with a measure of output gap in the standard three-variable SVAR model. However, his method does not resolve the price puzzle at the monthly frequency and is contingent on using a year-over-year, as opposed to, say quarter-over-quarter, measure of inflation. Romer and Romer (2004) argued that the identification of monetary shocks should take into account forward-looking information that the Federal Reserve may have in real time. They proposed a two-stage identification process, first regressing the policy interest rate on the Fed's forecasts of the future economic activity, and then using the single-equation autoregressive distributed lag (ARDL) models for output growth and inflation to obtain their impulse responses to residuals from the first stage.¹ Romer and Romer (2004) showed that the price puzzle largely disappeared once the monetary policy shocks were identified in the first stage, although it still took close to a year for the price impulse response to a contractionary monetary policy shock to become negative.

Our paper carries this insight into a standard New Keynesian DSGE model that uses the Fed's Greenbook forecasts as a descriptor of the anticipated future economic activity and the recent econometric advances for modeling news shocks. Our method offers several advantages over the Romer and Romer (2004) framework. First, it allows to estimate the model's structural parameters and thus take an explicit stance on important modeling choices, such as the presence of indeterminacy or the cost channel of transmission of monetary policy. Second, it allows to disentangle different sources of forward-looking information available to the Fed. The introduction of anticipated demand, supply, and monetary shocks allows us to pinpoint the type of forward-looking information that is important for the evolution of the model's endogenous variables. For instance, we find that even though the demand news shocks account for most of the forecast error variance decomposition of the nominal interest rate, it is the presence of the supply news shocks that is largely responsible for the emergence of the price puzzle. This result has a straightforward economic intuition: The central bank raises interest rates preemptively in anticipation of the future inflation, which induces a stronger positive comovement between observed inflation and nominal

¹Romer and Romer (2004) also conducted robustness checks forming a VAR model with log industrial production, log price level, and their measure of monetary policy shocks yielding similar results.

interest. Since the structural VAR cannot identify supply news precisely, the supply news enters the definition of residuals in both inflation and nominal interest equations in the VAR.² Third, our identification approach distinguishes between surprise and anticipated disturbances, including monetary shocks. As such, the effects of the surprise shocks affect real activity instantly whereas the effects of anticipated shocks may work more gradually. Anticipated monetary policy shocks have recently gained attention in the context of the literature on *forward guidance* offered by the Federal Reserve to the market participants.³ We find that the monetary news shocks have negligible contributions to the forecast error variance decompositions of output gap, inflation, and the nominal interest rate.⁴

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. We focus on the forward-looking conduct of monetary policy in the context of this model. Section 3 discusses the choice of priors and parametrization for the several theoretical exercises that establish the conditions for the likely emergence of the price puzzle. Section 4 describes the data and motivates the use of real-time forecasts for modeling forward-looking expectations in DSGE models. Section 5 lays out the Bayesian estimation strategy that we employ to estimate alternative specifications of our baseline model. Section 6 discusses estimation results. Section 7 studies the implications of alternative model specification for the emergence of the price puzzle in models with estimated, rather than calibrated, parameters. Finally, Section 8 concludes.

2 Model Summary

Our theoretical model is a variant of the standard New Keynesian model that, over the last two decades, has become the workhorse for the analysis of monetary policy. The model has three sectors whose behavior is characterized by corresponding structural equations that describe the evolution of the endogenous variable 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

²We show that this remains the case even when the VAR is augmented with a forward-looking measure of inflation and the statistical condition for identification of structural shocks via a VAR is met.

³See Milani and Treadwell (2012), Campbell et al. (2012), Del Negro et al. (2013), and Best and Kapinos (2016) for the discussion of the effect of anticipated monetary policy shocks.

⁴Importantly, our sample ends before the Great Recession due to the availability of the Greenbook data, hence our results have no bearing on the effectiveness of unconventional monetary policy during the crisis.

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 supply shock.

The central bank is assumed to set the nominal interest using the following version of the Taylor rule:

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

This equation reflects the possibility that, in practice, the Fed uses a specification closer to the one where the nominal interest rate responds to the future values of output gap and inflation at a particular horizon, as in assumed in Clarida et al (2000). Orphanides and Wieland (2008) who use the single-equation least squares approach to show that this assumption is supported by the U.S. data.

To model the possible availability of information about the future macroeconomic conditions to agents in the present, we assume that innovations in our three structural equations evolve according to the following processes:

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

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

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.

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 from the Federal Reserve's Green Book; see Milani and Rajbhandari (2012) and Hirose and Kurozumi (2012) who use the Survey of Professional Forecasters real-time data to identify news shocks in a similar model. This baseline specification allows us to study the effect of a relatively short run (up to 1 year) anticipation horizon of the shocks on the model's dynamics. 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 or the central bank's forward guidance.

3 Parameterization and Theoretical Motivation

In this section, we discuss three salient issues that need to be addressed prior to taking our model to the data. First, we summarize the baseline parameterization that will also serve as the basis for the choice of priors for our Bayesian estimation strategy and that are in line with the established consensus in the literature to date. Second, we address the possibility that the presence of news shocks may induce non-invertibility of the dynamic model, which leads to the inability of a VAR model to uncover structural shocks. We conduct sensitivity analysis with respect to key parameters that affect the dynamic propagation of shocks in the model and find that non-invertibility is neither a necessary nor a sufficient condition for the emergence of the price puzzle in the Cholesky SVAR model applied to the data simulated from our DSGE model. Finally, we use simulations of specific versions to our baseline model to highlight the settings where the price puzzle is likely to emerge.

3.1 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 0.2 following 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, among others, 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 and with standard deviations of 0.15. 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). 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.

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 in two important directions. First, we assign the priors for the standard deviations of the unanticipated and anticipated innovations to follow the 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 $q = [y, p, r]$, 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.

3.2 Additional Considerations

3.2.1 (Non)-invertibility

Much of the recent literature that explores identification of news shocks in empirical models has focused on the issue of invertibility that is key to the ability of VAR models to uncover structural

shocks.⁵ Fernandez-Villaverde et al. (2007) have provided a succinct yet general description of the problem. A log-linearized DSGE model yields a state-space representation of the following form:

$$s_t = As_{t-1} + B\epsilon_t, \quad (7)$$

$$x_t = Cs_{t-1} + D\epsilon_t, \quad (8)$$

where s_t is a $k \times 1$ vector of state variables, x_t is an $n \times 1$ vector of observed variables, and ϵ_t is an $m \times 1$ vector of structural shocks. Fernandez-Villaverde et al. (2007) derive the so-called “Poor Man’s Invertibility Condition” (PMIC) requiring the eigenvalues of $(A - BD^{-1}C)$ to be less than one in modulus. This is a sufficient condition for a VAR on observables to have innovations that map directly back into structural shocks in population. For D to be invertible, it has to be square and the number of observed variables has to equal to the number of shock processes, which, in the cases with news is always four: three concurrent shocks and one news, with varying anticipation lags, h . The three observed variables are y , π , r and the fourth one is the expected future variable of the same type as the news shock (e.g., interest when news is monetary) with the observation horizon set to match the anticipation horizon (e.g., $(E_t r_{t+h})$)⁶. The graphs describing the results of our simulation exercise will report e^* —the maximum absolute value of the eigenvalue associated with this test.

3.2.2 Price Stickiness

The parameter θ_p describes the degree of price stickiness in our model. A large body of recent literature has provided estimates of this parameter because it describes the key friction that provides a meaningful scope for the conduct of monetary policy. Woodford (2003) provides an authoritative theoretical motivation for the use of this modeling approach to nominal frictions and its implications for the conduct of monetary policy. Christiano et al. (2005), Rabanal and Rubio-Ramirez (2005), and Dennis (2007) among many others have provided its empirical estimates. Del Negro and Schorfheide (2008) discuss the role of prior selection in the Bayesian estimation of the standard

⁵Fernandez-Villaverde et al. (2007), Leeper et al. (2007), Sims (2012), and Blanchard et al. (2013) provide alternative approaches to this issue in the context of different types of news shocks.

⁶Experimenting with alternative setup for the lead structure of news shocks and observed expectations yielded qualitatively similar results

New Keynesian DSGE model and show that the posterior estimates may be heavily influenced by the prior chosen for θ_p .

To preview both our theoretical and empirical results, we do find that the value of this parameter is key to generating the price puzzle, since models with a high degree of price stickiness and a large role for news shocks provide the strongest set of conditions for the emergence of this phenomenon. To ensure that the relatively high mean estimate (over 0.9) that we obtain in the posterior distribution is driven by our choice of the prior, we set the mean of the latter at a relatively low value (0.5). Our simulation exercise below provides results for both values of this parameter.

3.2.3 Relative volatility of news shocks

The rest of the parameters are set to their prior values with the exception of the standard deviations of news shocks, which are set to either 0.05 (for the “low news” regime) or to 0.15 (for the “high news” regime). The results of simulations with alternative news shock regimes are compared to the standard setting where they are absent. These parameters capture the relative importance of news shocks compared with surprises.

3.3 Simulation of the Theoretical Model and the Price Puzzle

We set up our simulation exercise as follows. We use parameters that correspond to prior means described in Section 3.1 to produce 10,000 replications of model-consistent output y_t , inflation π_t , and nominal interest, r_t of length $T = 200$ discarding a 1000-period burn-in sample. We then estimate the standard VAR model:

$$\mathbf{y}_t = \alpha + \sum_{p=1}^P \mathbf{B}_p \mathbf{y}_{t-p} + \mathbf{u}_t, \quad (9)$$

where $\mathbf{y}_t = [y_t, \pi_t, r_t]'$ is the matrix of dependent variables, $\mathbf{B}_p$ are matrices of coefficients associated with different lags up to order P , and $\mathbf{u}_t$ are reduced-form residuals. We set $P = 2$ and use the Cholesky orthogonalization of the variance-covariance matrix of $\mathbf{u}_t$, $\mathbf{B}_0$ to identify ‘structural’ shocks that are clearly misspecified, given the presence of news shocks in the data-generating process. Our goal is to understand how the misspecification with regard to the structure of news shocks affects the emergence of the price puzzle in the Cholesky SVAR framework.

We first conduct this exercise in the setting without news shocks. Figure 1 presents the theoretical impulse responses of inflation to a one-standard deviation contractionary monetary policy shock along with the simulated mean impulse responses and 80% confidence intervals. The zero response of inflation on impact of the monetary policy shock is clearly at odds with the theoretical one, hence the imposition of Cholesky orthogonalization is not entirely costless even in the setting without news shocks, but at longer horizons the responses are quite similar. The top panel has the case where prices are relatively flexible ($\theta_p = 0.5$) and the bottom panel where they are relatively sticky ($\theta_p = 0.9$).⁷ The transmission of the monetary policy shock is stronger in the former case, both in the theoretical setting and the simulated one. However, the simulated averages are below zero in both cases, albeit insignificantly so in the latter case. Importantly, the maximum modulo of the PMIC test in both cases is zero and since it is less than one the model is invertible.

We next introduce news shocks into the model, limiting their type to just one, so as to investigate the relative importance of different news shocks for the emergence of the price puzzle. Figures 2 and 3 undertake the same exercise with respect to supply shocks. The maximum modulo of the PMIC test in all cases continues to be less than 1. In the case with $\theta_p = 0.5$, simulated IRFs are close to the theoretical ones after the obvious difference on impact motivated by the Choleski orthogonalization. Once θ_p increases to 0.9, however, simulated impulse responses become positive on average, their amplitude increases and confidence intervals tighten with higher standard deviation of news shocks. In fact, they become statistically significant for $h = 3$ or $h = 4$ when the standard deviation of supply news is twice the value of surprises. The intuition for this result is straightforward: the higher value of θ_p makes the Phillips Curve flatter in the output-gap/inflation plane. A given vertical shift of the Phillips Curve due to a supply shock, therefore, implies smaller ability for the central bank to stabilize against inflationary pressure for a given set of parameters governing the IS schedule together with the Taylor rule that jointly produce aggregate demand in this model. Since supply news shocks can be anticipated h periods ahead, the central bank starts raising the nominal interest rate sooner with stickier prices, which imparts a more inertial evolution of both inflation and nominal interest and produces a stronger correlations between them. Since the Cholesky SVAR framework cannot *fully* disentangle supply news and surprises even though the PMIC is met, thus

⁷The reason for this sensitivity check is that the prior mean for θ_p is 0.5 but the estimates reported in Section 6 are all in excess of 0.9.

partially loading supply news onto inflation and interest VAR shocks, this stronger comovement translates into the emergence of the price puzzle.

Figures 4 and 5 investigate the role of the demand news shocks in the emergence of the price puzzles, for $\theta_p = 0.5$ and $\theta_p = 0.9$, respectively, with anticipation horizons varying between $h = [1, \dots, 4]$. Again, the PMIC results suggest that non-invertibility is not an issue in this setting. The simulated impulse responses are negative at any anticipation horizon for $\theta_p = 0.5$ and news shock standard deviation at half the value of its surprise counterpart. For larger values of h with the news standard deviation set to twice the value of its surprise counterpart, the price puzzle begins to emerge, although the confidence intervals are very wide and the mean estimated IRF is positive but close to zero. The main effect of increasing θ_p to 0.9 is that all impulse responses lose amplitude and the confidence intervals are all virtually centered around zero. The reason why the demand shocks achieve this effect can also be gleaned from the textbook AS/AD model in the output-gap/inflation plane. Demand shocks shift the aggregate demand schedule horizontally (at a given level of inflation, they have a one-for-one effect on output gap as is evident from (1)). When the Phillips Curve is flat, they generate a relatively small change in inflation and hence moderate response in nominal interest rate. When the Phillips Curve is steep, on the other hand, the change in inflation rate is larger requiring a stronger response in the nominal interest rate and hence engineering a larger comovement between inflation and nominal interest.

Similar results obtain from Figures 6 and 7 that investigate the effect of monetary news shocks. The price puzzle is larger when the standard deviation of news shocks is larger and when prices are more flexible, all else equal.⁸ Interestingly, the PMIC fails to hold in several cases, indicating that the presence of monetary news shocks poses the strongest challenge to identifying monetary surprises in VARs. However, it is by no means a sufficient condition for generating the price puzzle, as average simulated IRFs remain negative in multiple cases where the maximum eigenvalue modulo is greater than 1.

In sum, the price puzzle is likely to emerge the strongest in settings where the supply news are strong, can be anticipated at relatively long horizons, and prices are relatively sticky. We next

⁸In AS/AD terms, the intuition for the effect of monetary shocks is similar to demand shocks. This follows from plugging (3) into (1) and solving for output gap. Monetary shocks will not have a one-for-one effect on output gap because they'll need to be adjusted by σ , the coefficient on the real interest rate in (1), and γ_y , the coefficient on output gap in (3), holding inflation constant.

explore how pronounced these effects are using estimated parameters in models where news shocks may be identified using real-time forecasts.

4 Data

One contribution of this paper is to compare structural coefficient estimates obtained using a final vintage, ex post dataset and a real-time dataset. Our ex post series are from the Federal Reserve Economic Data (FRED) website maintained by the Federal Reserve Bank of St. Louis. Inflation is given by the first difference of the log implicit GDP price deflator. Output gap is the log difference between the real GDP and potential GDP estimated by the Congressional Budget Office. The nominal interest rate is given by the federal funds rate (FFR) transformed into quarterly rates to be consistent with the model.

The real-time data set comes 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. The projections are typically made with long lags that vary by the specific series. For instance, as of the writing of this draft, data for the projections of the federal funds rate are available only through 2008Q3, which does not allow us to incorporate the effects of the Great Recession. To keep our data consistent with the ‘normal’ macroeconomic environment, we end our sample in 2007Q4. Availability of the output gap projections motivates the beginning of our sample, which is 1987Q3. Similar to the ex post dataset, the third variable is inflation given by the projections for the implicit GDP price deflator.

To provide a sense of the relationship between the two datasets, we summarize the evolution of the three endogenous variables and, in the Greenbook case, their forecasts over time. Figure 8 displays the evolution of inflation and its forecasts. The Federal Reserve tended to overpredict inflation in the mid-1990s and underpredict it in the early 2000s, with the size of the forecast error, given by the vertical difference between the two series, typically increasing with the forecast horizon. Figure 9 describes similar results for output gap. Federal Reserve was somewhat optimistic about the state of the economy through the 1990s but otherwise the Greenbook forecasts match up with the ex post outcomes quite well, without exhibiting an increase in the forecast error at longer forecast horizons. Finally, Figure 10 shows the evolution of the FFR and its Greenbook projections.

While very accurate at short horizons, the latter appear to stretch too far into the future, which may be indicative of the Fed being late to recognize the turning points in the business cycles as has been documented by Sinclair (2010). As with inflation, the size of the FFR forecast errors tends to increase with the forecast horizon.

We introduce these real-time forecasts into the model by assuming that they represent a rational expectation of the future outcome for a particular variable. For instance, the forecast of inflation is modeled as $E_t \pi_{t+h}^{obs}$, where $h = [1, \dots, 4]$. Similar logic applies to the output gap and FFR series.

5 Bayesian Estimation Strategy

We estimate the set of structural parameters, autocorrelation coefficients, and standard deviations of anticipated and unanticipated innovations using likelihood-based Bayesian techniques; see An and Schorfheide (2007) for a comprehensive methodological overview. For our baseline specification, structural parameters represent a 26×1 vector Θ defined as:

$$\Theta = [b, \theta_p, \omega_p, \rho_r, \gamma_\pi, \gamma_y, \rho_p, \rho_r, \rho_y, \xi, \alpha\sigma^p, \sigma^z, \sigma^y, \sigma_1^p, \sigma_2^p, \sigma_3^p, \sigma_4^p, \sigma_1^r, \sigma_2^r, \sigma_3^r, \sigma_4^r, \sigma_1^y, \sigma_2^y, \sigma_3^y, \sigma_4^y]' \quad (10)$$

As it is customary in the NK-DSGE literature parameters β , η , and σ were fixed to values previously obtained in the literature and described in Section 3.1. The vector of observed variables consists of the output gap, the inflation rate, and the federal funds rate $Y_t = [y_t, \pi_t, r_t]$. 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 $p(Y^T|\Theta)$, where $Y^T = [Y_1, \dots, Y_T]$. Lastly, the posterior distribution is obtained by updating prior beliefs through the Bayes' rule, taking into consideration the data reflected in the likelihood.

The model's state space representation including news shocks follows Schmitt-Grohe and Uribe (2012) and Milani and Treadwell (2012) can be written in the following form:

$$\Gamma_0 \alpha_t = \Gamma_1 \alpha_{t-1} + \Psi w_t + \Pi \Phi_t, \quad (11)$$

where $\alpha_t = [\pi_t, y_t, r_t, E_t \pi_{t+1}, E_t y_{t+1}, E_t r_{t+1}, \epsilon_t^p, \epsilon_t^y, \epsilon_t^z, \nu_t^{p,h}, \nu_{t-1}^{p,h}, \dots, \nu_{t-h+1}^{p,h}, \nu_t^{y,h}, \nu_{t-1}^{y,h}, \dots, \nu_{t-h+1}^{y,h}, \nu_t^{r,h}, \nu_{t-1}^{r,h}, \dots, \nu_{t-h+1}^{r,h}]'$ is the state vector for horizons $h = [1, \dots, 4]$ in the Phillips Curve,

Euler Equation, and Taylor rule. The vector $w_t = [0, \dots, 0, v_t^p, v_t^y, v_t^r, \nu_t^{p,h}, \nu_t^{y,h}, \nu_t^{r,h}, \dots, 0]'$ collects all innovations. Lastly, the vector $\Phi_t = [0, \dots, 0, \Phi_t^p, \Phi_t^y, \Phi_t^r, 0 \dots 0]$ includes all expectational errors i.e., $\Phi_t^p = \pi_t - E_{t-1}\pi_t$. Thus, innovations included in each of the three structural equations, which contain news with 1- to 4-quarter-ahead anticipation horizons, expands the state considerably. The set of model equations forming a linear rational expectations model was solved using the estimation procedure of Sims (2002).

We generate draws from the posterior distribution through the Metropolis-Hastings algorithm.⁹ 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.

6 Results

Our main task in the estimation exercise is to disentangle the relative importance of the different types of anticipated shocks and to contrast the results from the ex post and real-time datasets. Tables 2 and 3 present the parameter estimates for the cases of $k = 1$ and for $k = 4$ in (3), respectively. Importantly, all specifications have estimates of θ_p in excess of 0.9, which, if news shocks play an important role, allows for the emergence of the price puzzle. Ex post specifications with news shocks have lower likelihood than without; the real-time specification with news has the highest likelihood. The estimated standard deviations of news shocks are higher in the Greenbook specifications. Supply news shocks have the largest standard deviation at the forecast horizon of 1 for $k = 1$ and at $h = 4$ for $k = 4$, which suggest that the price puzzle may be easier to generate in the latter case. Finally, the $k = 4$ specifications have lower likelihoods than their $k = 1$ counterparts.

These estimation results allows us to evaluate the relative importance of different shocks in explaining the forecast error variance decomposition (FEVD) of the model's endogenous variables. (For brevity, we omit the results for the ex post specifications with news and compare ex post without news to Greenbook with news.) Figure 11 shows that in the absence of news shocks, own surprises are most important to the evolution of output gap and inflation. Demand shocks take the largest share of the FFR FEVD after a horizons of about 5 quarters, with a roughly even split

⁹For details on the specification of the Metropolis-Hastings algorithm refer to Chib and Greenberg (1995).

between the three shocks on impact.

This pattern changes significantly with the introduction of news shocks in the Greenbook specifications displayed in Figures 12 through 14. Monetary news shocks play by far the smallest role and their impact dissipates quickly. For all variables and across all specifications, the combined effect of these shocks across all four horizons does not exceed 6% and is negligible for explaining the FFR FEVD, especially at longer horizons. Contributions of surprise shocks drop off rapidly in all cases. Demand news appear to be the most important for explaining the output gap and FFR FEVDs, whereas supply news appear to be the most important for explaining the evolution of inflation.

7 News and the Price Puzzle

In this section, we study the role of anticipated shocks about the future macroeconomic conditions in generating a positive response of prices to a contractionary monetary shock or the price puzzle in the standard Cholesky 3-variables SVAR. Again, we generate 10,000 replications, in each case dropping the initial 1,000 observations and keeping the subsequent 200 for output gap, inflation, and the nominal interest rate using the parameter estimates in Tables 2 and 3. The top row of Figure 15 produces the impulse responses of inflation to a monetary contractionary shock using the ex post specification without news: the price puzzle clearly does not emerge and the estimated impulse response is close to the theoretical one. The middle row of Figure 15 repeats this exercise for the ex post specification with news that assigns a relatively small role to news shocks. The confidence intervals widen appreciably but the price puzzle does not materialize and the impulse response remains close to the theoretical one. Finally, the bottom row of Figure 15 uses the Greenbook specification that assigns a relatively large role to news shocks. In this case, the price puzzle clearly emerges, as the estimated mean impulse response remains positive for the entire twenty-quarter horizon. While a large fraction of impulse responses continue to be negative, their mass clearly shifts in the positive direction with the top 10th percentile showing a peak response of 0.07 percentage points to a 1 standard deviation shock to the nominal interest rate. These results are consistent with the intuition discussed in Section 3.3.

8 Conclusion

In this paper, we augmented the basic New Keynesian DSGE model with news shocks and modeled future outcomes using the real-time forecasts from the Fed’s Green Book. We began by examining the potential role of alternative news shocks in the emergence of the price puzzle and established that supply news shocks combined with relatively sticky prices provide the data-generating setting where the price puzzle is most likely to emerge. We attribute the higher comovement between inflation and nominal interest necessary for the emergence of the price puzzle to the Cholesky SVAR inability to disentangle the effect of supply news from supply and monetary surprises, even in the presence of forward-looking inflation measures and when the so-called Poor Man’s Invertibility Condition for structural shock identification is met. We then estimated several specifications of the New Keynesian DSGE model, with and without news shocks, and demonstrated that using the real-time forecasts to identify expected future outcomes of macroeconomic variables results in a significantly larger role for news shocks. We re-examine the possibility of the price puzzle emerging using estimated, rather than calibrated, parameter values and show that it is far more likely to emerge in the estimated model with news shocks that employs real-time forecasts. Finally, we find that the specifications with news shocks and real-time forecasts fit the data the best.

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A Tables

Table 1: Parameter Description and Priors

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
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

Note: Asterisk (*) refers to the structure of news shocks with $h = 4, 8$, and 12 . The symbols for the prior distributions stand for B =Beta, N =Normal, and Γ =Gamma distributions.

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

Parameters	Ex post, no news			Ex post, news			Greenbook, news		
	Mean	Pos.	Prob. Int.	Mean	Pos.	Prob. Int.	Mean	Pos.	Prob. Int.
b	0.602	[0.450, 0.762]		0.481	[0.272, 0.700]		0.270	[0.211, 0.328]	
θ_p	0.912	[0.908, 0.918]		0.921	[0.894, 0.943]		0.932	[0.902, 0.959]	
ω_p	0.391	[0.076, 0.801]		0.170	[0.048, 0.337]		0.942	[0.791, 0.997]	
ρ	0.821	[0.753, 0.876]		0.810	[0.733, 0.869]		0.874	[0.844, 0.901]	
γ_p	1.636	[1.198, 2.082]		1.663	[1.189, 2.131]		1.677	[1.359, 1.942]	
γ_y	0.546	[0.371, 0.742]		0.544	[0.378, 0.726]		0.431	[0.291, 0.597]	
ρ_r	0.671	[0.549, 0.773]		0.734	[0.593, 0.844]		0.653	[0.535, 0.771]	
ρ_y	0.743	[0.599, 0.843]		0.551	[0.120, 0.816]		0.902	[0.879, 0.922]	
ρ_p	0.292	[0.017, 0.599]		0.212	[0.077, 0.398]		0.009	[0.001, 0.028]	
σ^r	0.097	[0.080, 0.118]		0.061	[0.014, 0.096]		0.066	[0.056, 0.078]	
σ^y	0.148	[0.110, 0.196]		0.131	[0.038, 0.211]		0.190	[0.163, 0.224]	
σ^p	0.122	[0.082, 0.160]		0.117	[0.088, 0.147]		0.162	[0.139, 0.192]	
σ^{r1}				0.022	[0.001, 0.056]		0.047	[0.040, 0.054]	
σ^{r2}				0.022	[0.001, 0.057]		0.042	[0.035, 0.050]	
σ^{r3}				0.017	[0.001, 0.048]		0.039	[0.033, 0.045]	
σ^{r4}				0.018	[0.001, 0.050]		0.041	[0.034, 0.050]	
σ^{y1}				0.032	[0.001, 0.092]		0.219	[0.192, 0.255]	
σ^{y2}				0.083	[0.003, 0.210]		0.153	[0.132, 0.180]	
σ^{y3}				0.060	[0.002, 0.169]		0.152	[0.128, 0.178]	
σ^{y4}				0.155	[0.013, 0.308]		0.149	[0.123, 0.180]	
σ^{p1}				0.016	[0.001, 0.047]		0.120	[0.103, 0.139]	
σ^{p2}				0.018	[0.001, 0.051]		0.051	[0.043, 0.059]	
σ^{p3}				0.026	[0.001, 0.076]		0.052	[0.042, 0.066]	
σ^{p4}				0.051	[0.007, 0.097]		0.060	[0.044, 0.084]	
Marginal L		-1.224			-13.670			745.507	

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

Parameters	Ex post, no news			Ex post, news			Greenbook, news		
	Mean	Pos.	Prob. Int.	Mean	Pos.	Prob. Int.	Mean	Pos.	Prob. Int.
b	0.704	[0.418, 0.912]		0.616	[0.307, 0.888]		0.255	[0.197, 0.314]	
θ_p	0.914	[0.908, 0.921]		0.941	[0.924, 0.957]		0.930	[0.902, 0.958]	
ω_p	0.180	[0.045, 0.449]		0.178	[0.049, 0.456]		0.057	[0.020, 0.098]	
ρ	0.739	[0.638, 0.825]		0.808	[0.725, 0.874]		0.889	[0.861, 0.914]	
γ_p	1.649	[1.161, 2.147]		1.538	[1.064, 2.009]		1.268	[0.989, 1.546]	
γ_y	0.641	[0.446, 0.846]		0.629	[0.441, 0.833]		0.640	[0.493, 0.793]	
ρ_r	0.688	[0.569, 0.792]		0.713	[0.563, 0.831]		0.551	[0.464, 0.637]	
ρ_y	0.570	[0.172, 0.868]		0.575	[0.086, 0.897]		0.938	[0.913, 0.964]	
ρ_p	0.536	[0.182, 0.751]		0.215	[0.076, 0.442]		0.100	[0.066, 0.118]	
σ^r	0.117	[0.093, 0.150]		0.076	[0.046, 0.105]		0.080	[0.066, 0.096]	
σ^y	0.169	[0.085, 0.291]		0.129	[0.026, 0.237]		0.191	[0.164, 0.223]	
σ^p	0.099	[0.054, 0.169]		0.117	[0.084, 0.153]		0.179	[0.154, 0.210]	
σ^{r1}				0.014	[0.001, 0.042]		0.051	[0.044, 0.061]	
σ^{r2}				0.015	[0.001, 0.041]		0.038	[0.033, 0.045]	
σ^{r3}				0.014	[0.001, 0.041]		0.036	[0.031, 0.042]	
σ^{r4}				0.016	[0.001, 0.043]		0.036	[0.031, 0.043]	
σ^{y1}				0.028	[0.001, 0.081]		0.226	[0.194, 0.258]	
σ^{y2}				0.042	[0.001, 0.118]		0.158	[0.136, 0.184]	
σ^{y3}				0.039	[0.001, 0.103]		0.145	[0.122, 0.174]	
σ^{y4}				0.072	[0.006, 0.140]		0.136	[0.114, 0.163]	
σ^{p1}				0.023	[0.001, 0.062]		0.096	[0.082, 0.112]	
σ^{p2}				0.016	[0.001, 0.049]		0.048	[0.041, 0.056]	
σ^{p3}				0.019	[0.001, 0.054]		0.185	[0.142, 0.245]	
σ^{p4}				0.039	[0.003, 0.078]		0.212	[0.155, 0.282]	
Marginal L		-13.312			-24.802			706.609	

B Figures

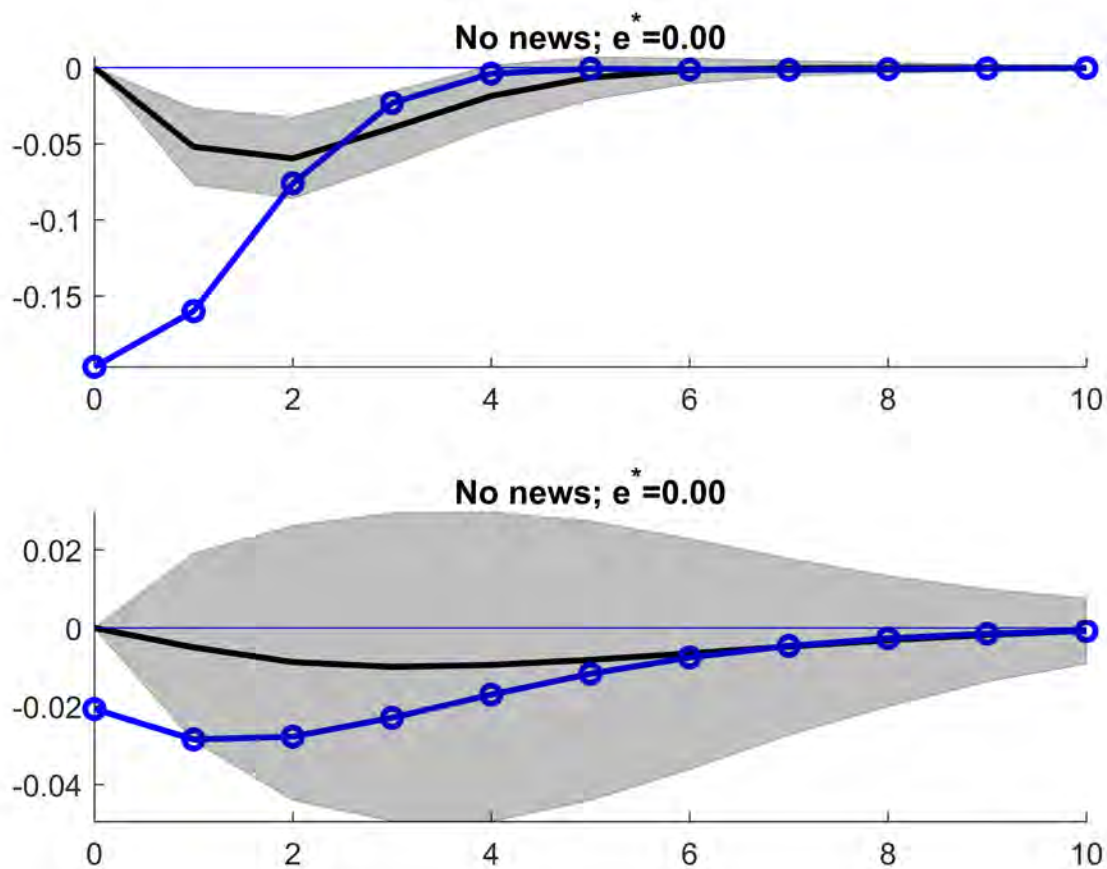


Figure 1: Theoretical impulse response of inflation to monetary contraction—blue line with circles; Estimated Choleski SVAR response of inflation to monetary contraction (average of 10,000 simulations)—solid black line. Here and below, e^* is the maximum eigenvalue in modulo for the PMIC. Top panel— $\theta_p = 0.5$; bottom panel— $\theta_p = 0.9$.

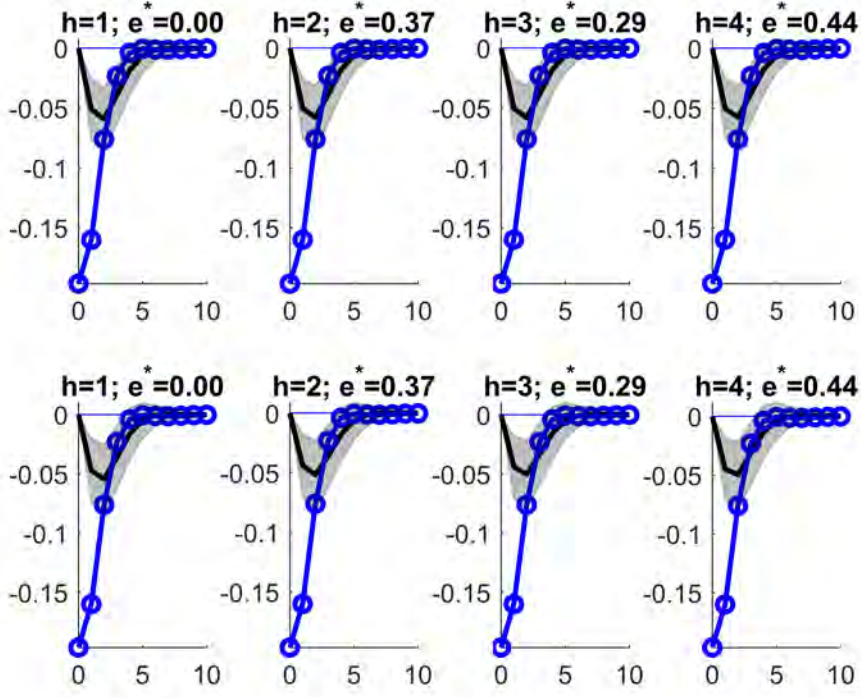


Figure 2: Simulated impulse responses to supply news shocks with $\theta_p = 0.5$: blue line with circles—theoretical response of inflation to monetary surprise; top row: black solid line with 80% confidence interval—Cholesky SVAR simulation where news shock standard deviation is one half of the surprise standard deviation; bottom row: Cholesky SVAR simulation where news shock standard deviation is twice the surprise.

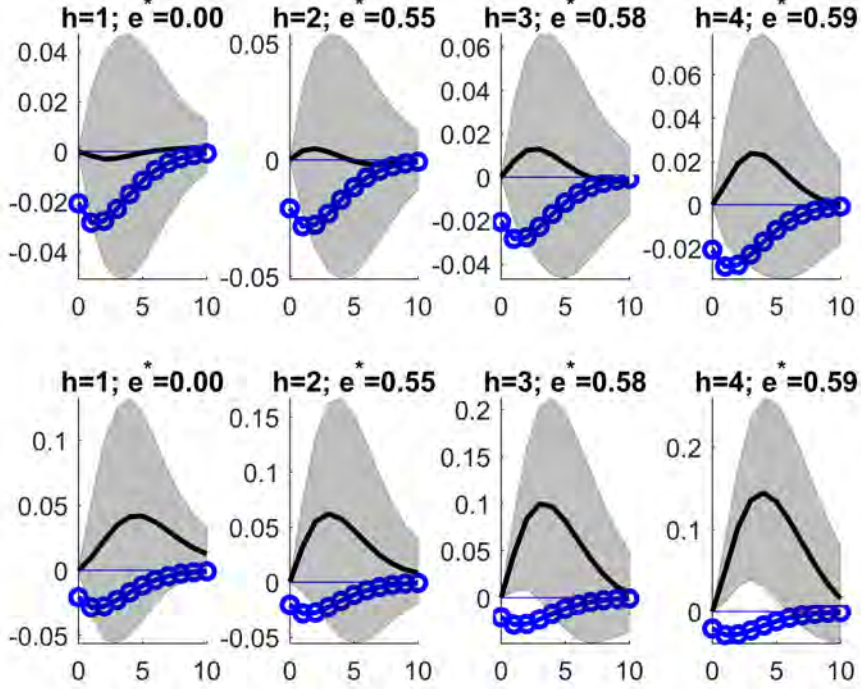


Figure 3: Simulated impulse responses to supply news shocks with $\theta_p = 0.9$: blue line with circles—theoretical response of inflation to monetary surprise; top row: black solid line with 80% confidence interval—Cholesky SVAR simulation where demand news shock standard deviation is one half of the surprise standard deviation; bottom row: Cholesky SVAR simulation where news shock standard deviation is twice the surprise.

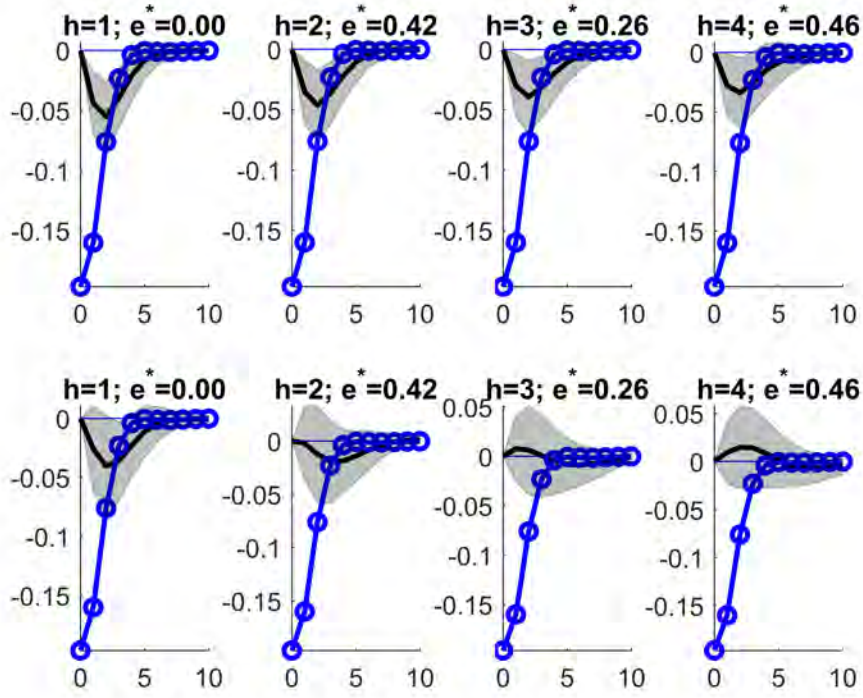


Figure 4: Simulated impulse responses to demand news shocks with $\theta_p = 0.5$: blue line with circles—theoretical response of inflation to monetary surprise; top row: black solid line with 80% confidence interval—Cholesky SVAR simulation where news shock standard deviation is one half of the surprise standard deviation; bottom row: Cholesky SVAR simulation where news shock standard deviation is twice the surprise.

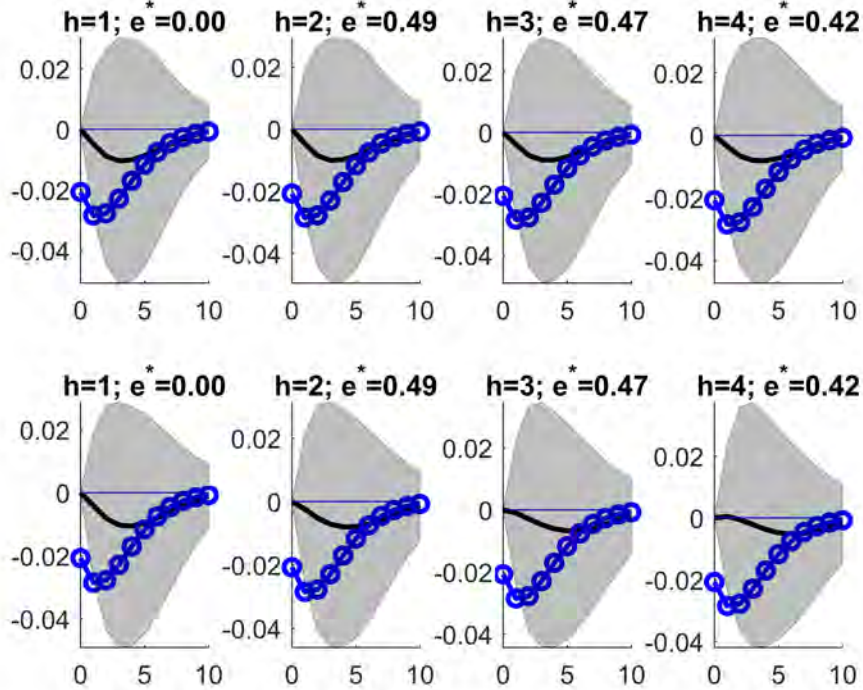


Figure 5: Simulated impulse responses to demand news shocks with $\theta_p = 0.9$: blue line with circles—theoretical response of inflation to monetary surprise; top row: black solid line with 80% confidence interval—Cholesky SVAR simulation where demand news shock standard deviation is one half of the surprise standard deviation; bottom row: Cholesky SVAR simulation where news shock standard deviation is twice the surprise.

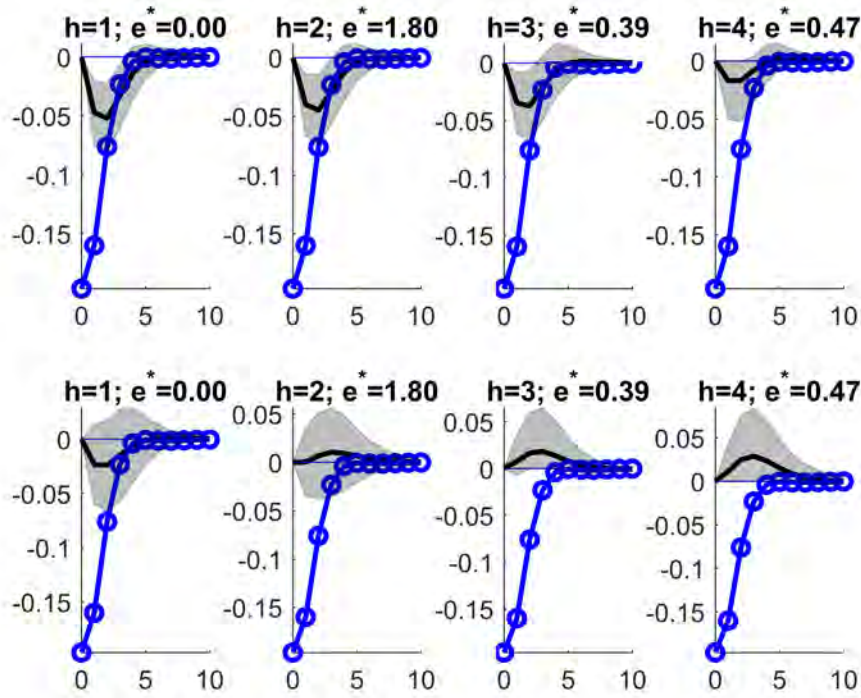


Figure 6: Simulated impulse responses to monetary news shocks with $\theta_p = 0.5$: blue line with circles—theoretical response of inflation to monetary surprise; top row: black solid line with 80% confidence interval—Cholesky SVAR simulation where news shock standard deviation is one half of the surprise standard deviation; bottom row: Cholesky SVAR simulation where news shock standard deviation is twice the surprise.

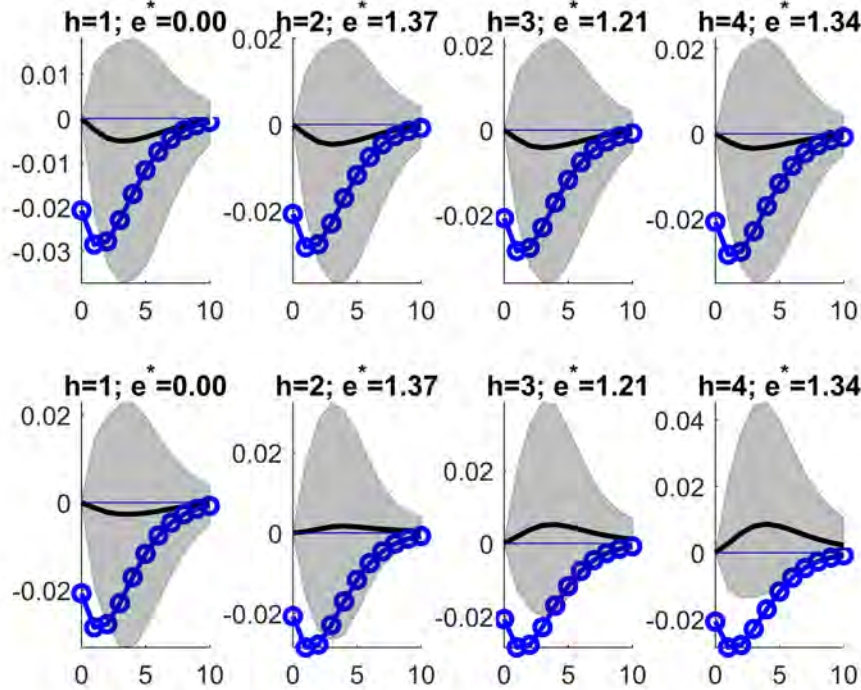


Figure 7: Simulated impulse responses to monetary news shocks with $\theta_p = 0.9$: blue line with circles—theoretical response of inflation to monetary surprise; top row: black solid line with 80% confidence interval—Cholesky SVAR simulation where demand news shock standard deviation is one half of the surprise standard deviation; bottom row: Cholesky SVAR simulation where news shock standard deviation is twice the surprise. ²⁸

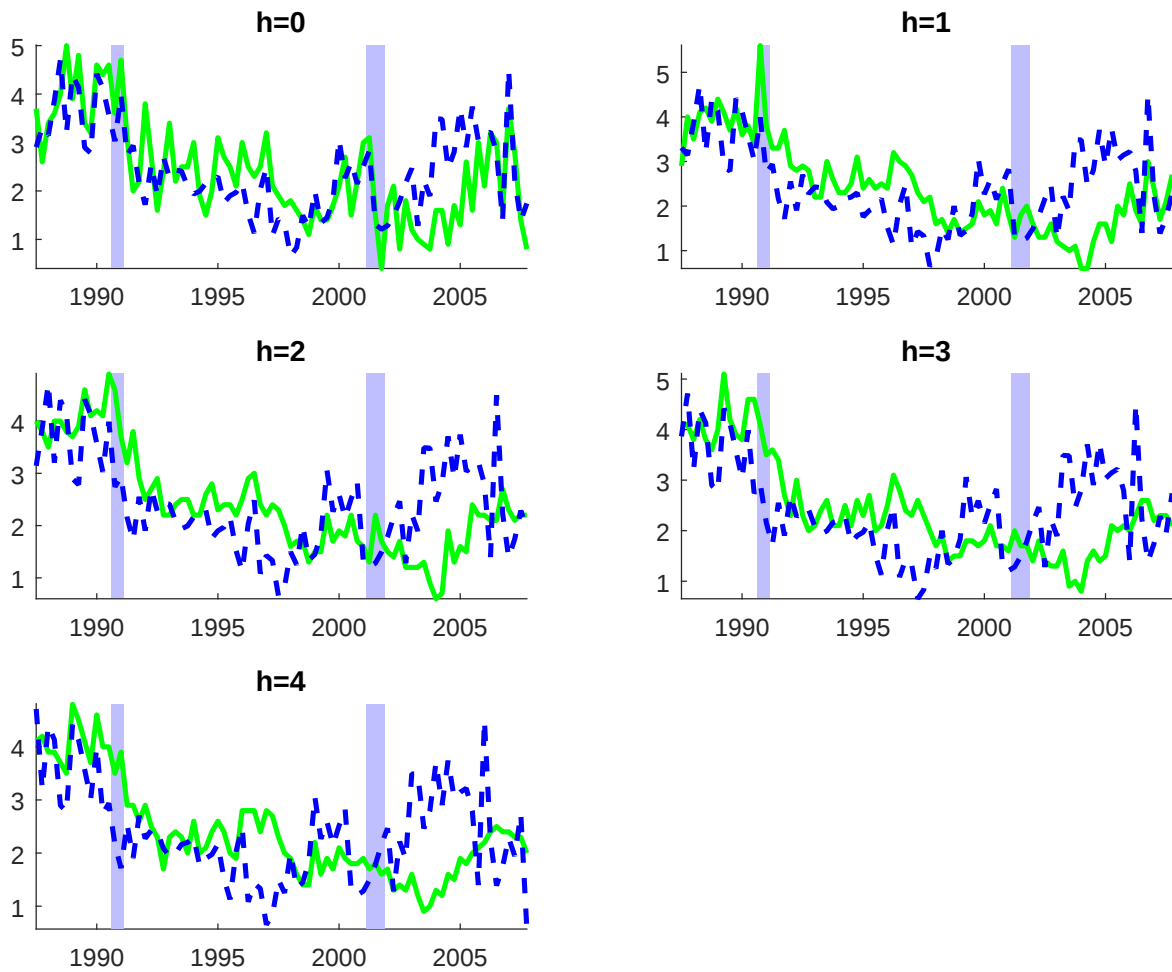


Figure 8: Each subplot is an h -quarter-ahead Greenbook forecast of inflation at t (green solid line) matched with ex post inflation at $t + h$ (dashed blue line).

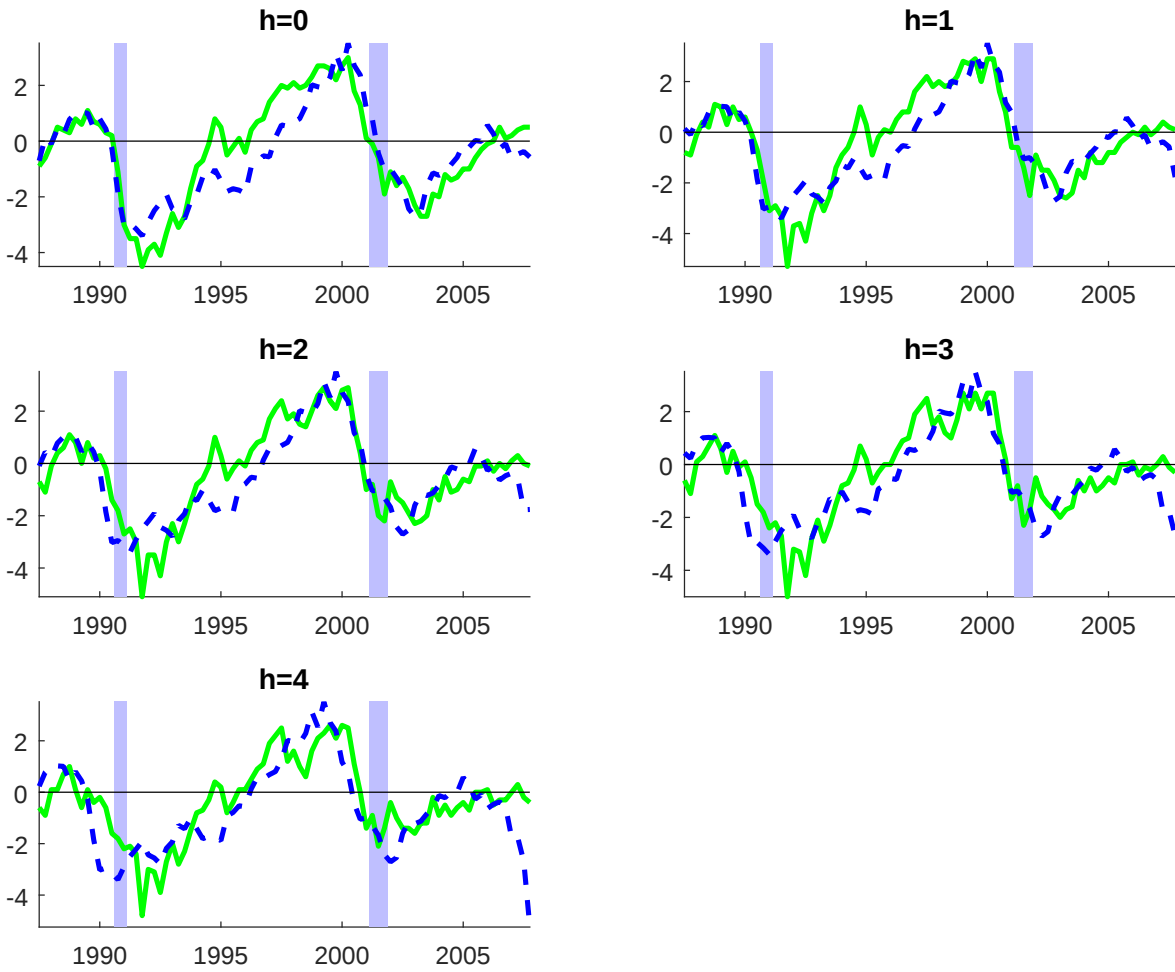


Figure 9: Each subplot is an h -quarter-ahead Greenbook forecast of output gap at t (green solid line) matched with ex post output gap at $t+h$ (dashed blue line).

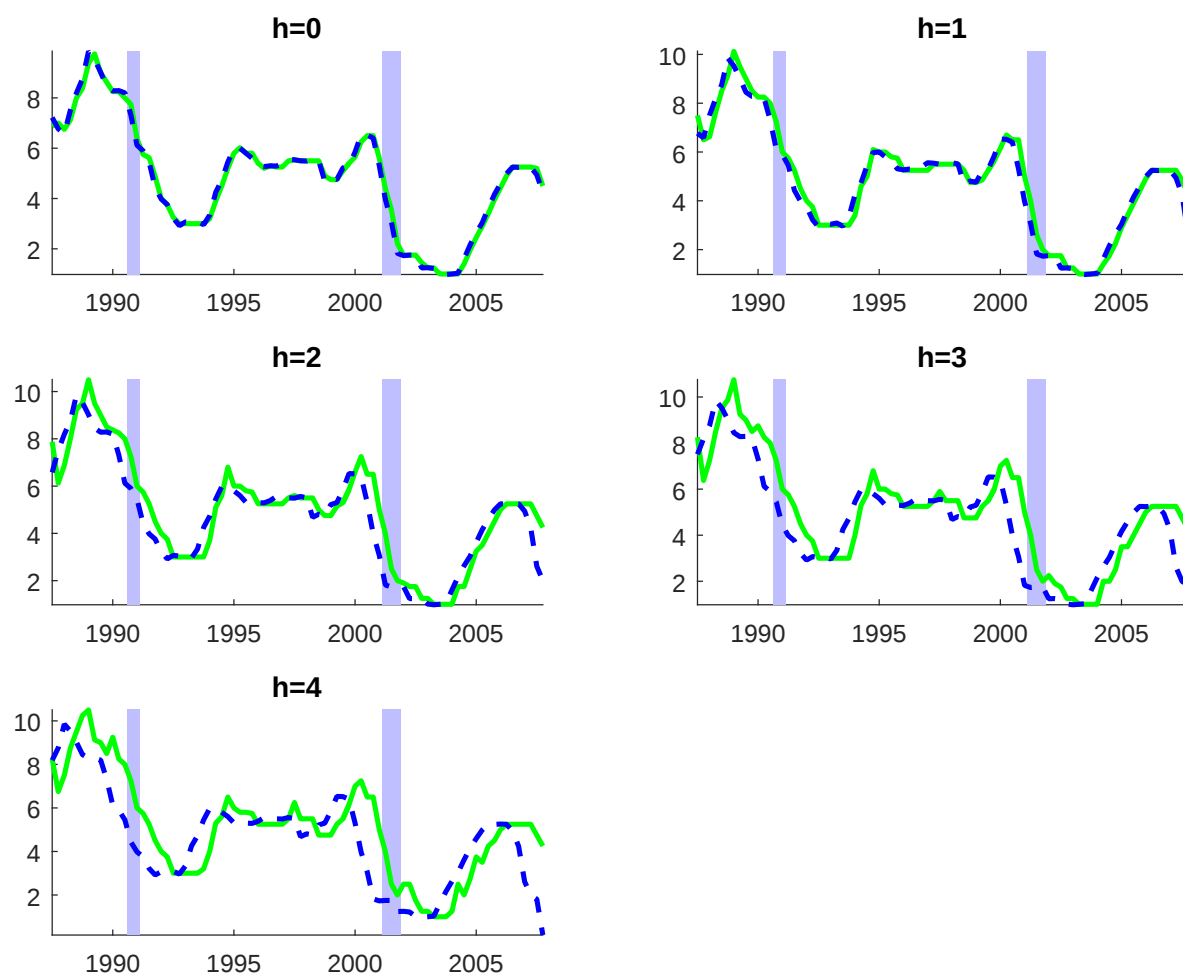


Figure 10: Each subplot is an h -quarter-ahead Greenbook forecast of the nominal interest rate at t (green solid line) matched with ex post nominal interest at $t + h$ (dashed blue line).

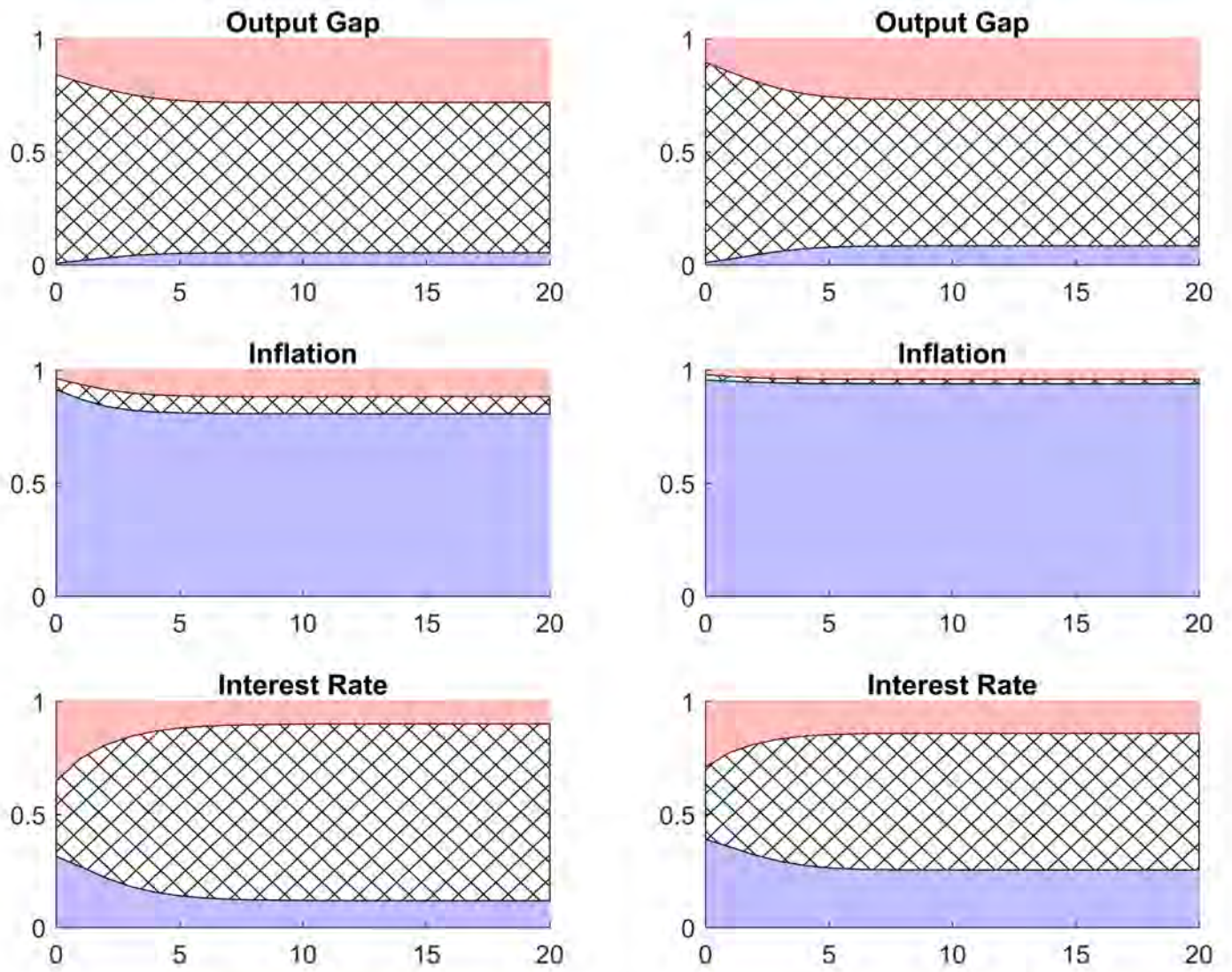


Figure 11: Forecast error variance decomposition due to surprise shocks; ex post data, model without news shocks. Blue shade—supply shocks; cross-hatched—demand shocks; red shade—monetary shocks. Left column— $k = 1$, right column— $k = 4$.

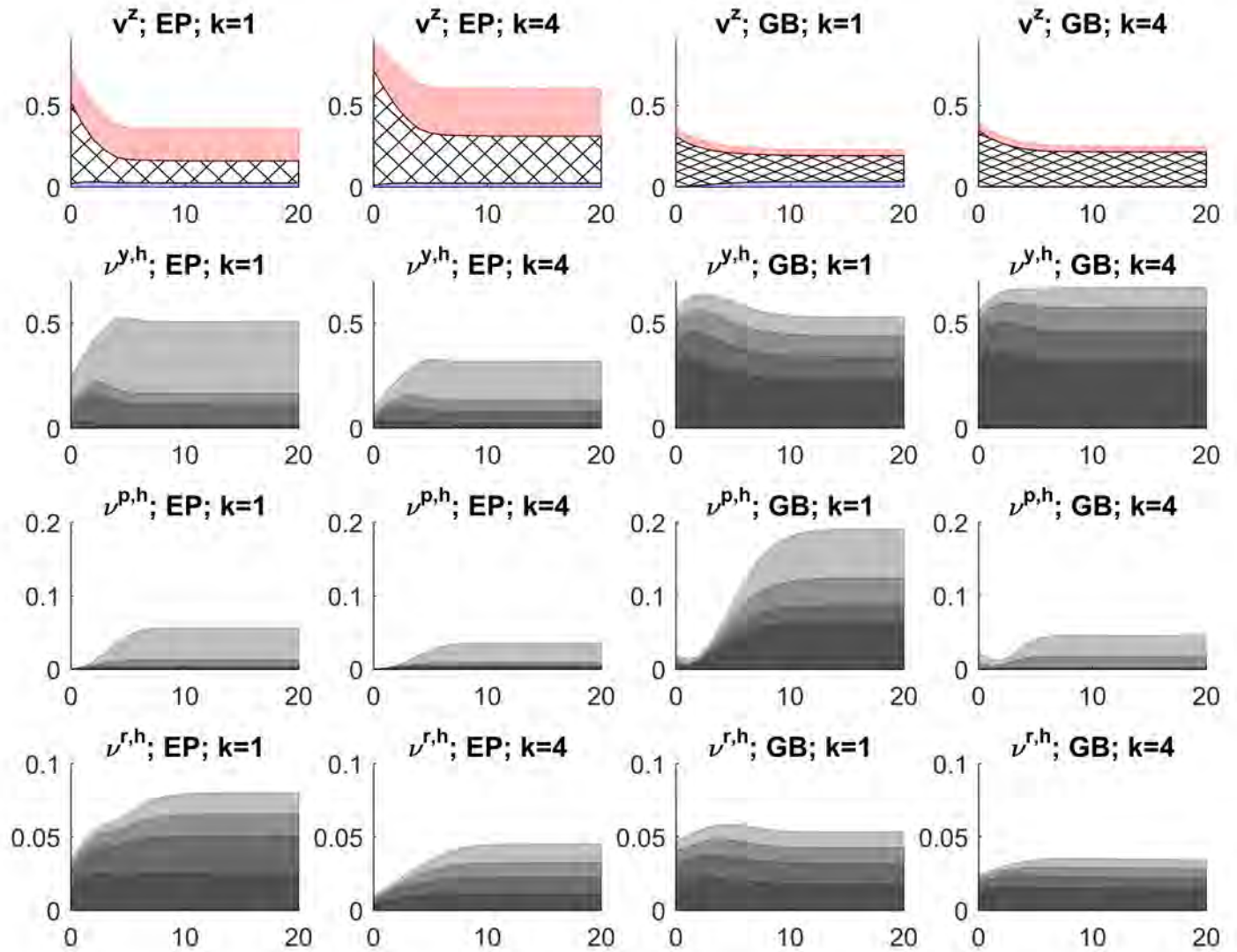


Figure 12: Forecast error variance decomposition of output gap: Ex Post (EP) vs Greenbook (GB) data. Surprises: blue shade—supply shocks; cross-hatched—demand shocks; red shade—monetary shocks. News: darkest shade— $h = 1$; lightest shade— $h = 4$.

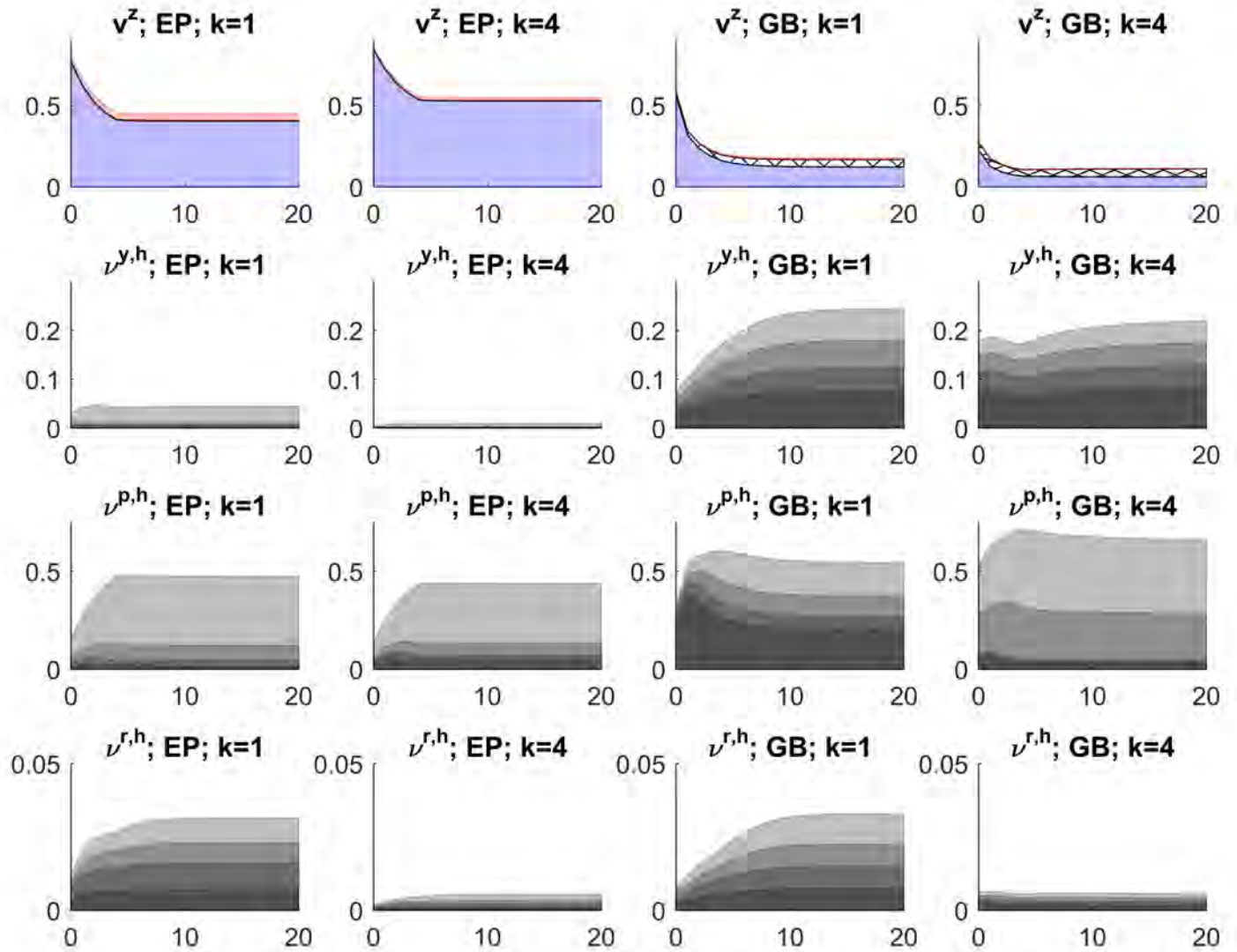


Figure 13: Forecast error variance decomposition of inflation: Ex Post (EP) vs Greenbook (GB) data. Surprises: blue shade—supply shocks; cross-hatched—demand shocks; red shade—monetary shocks. News: darkest shade— $h = 1$; lightest shade— $h = 4$.

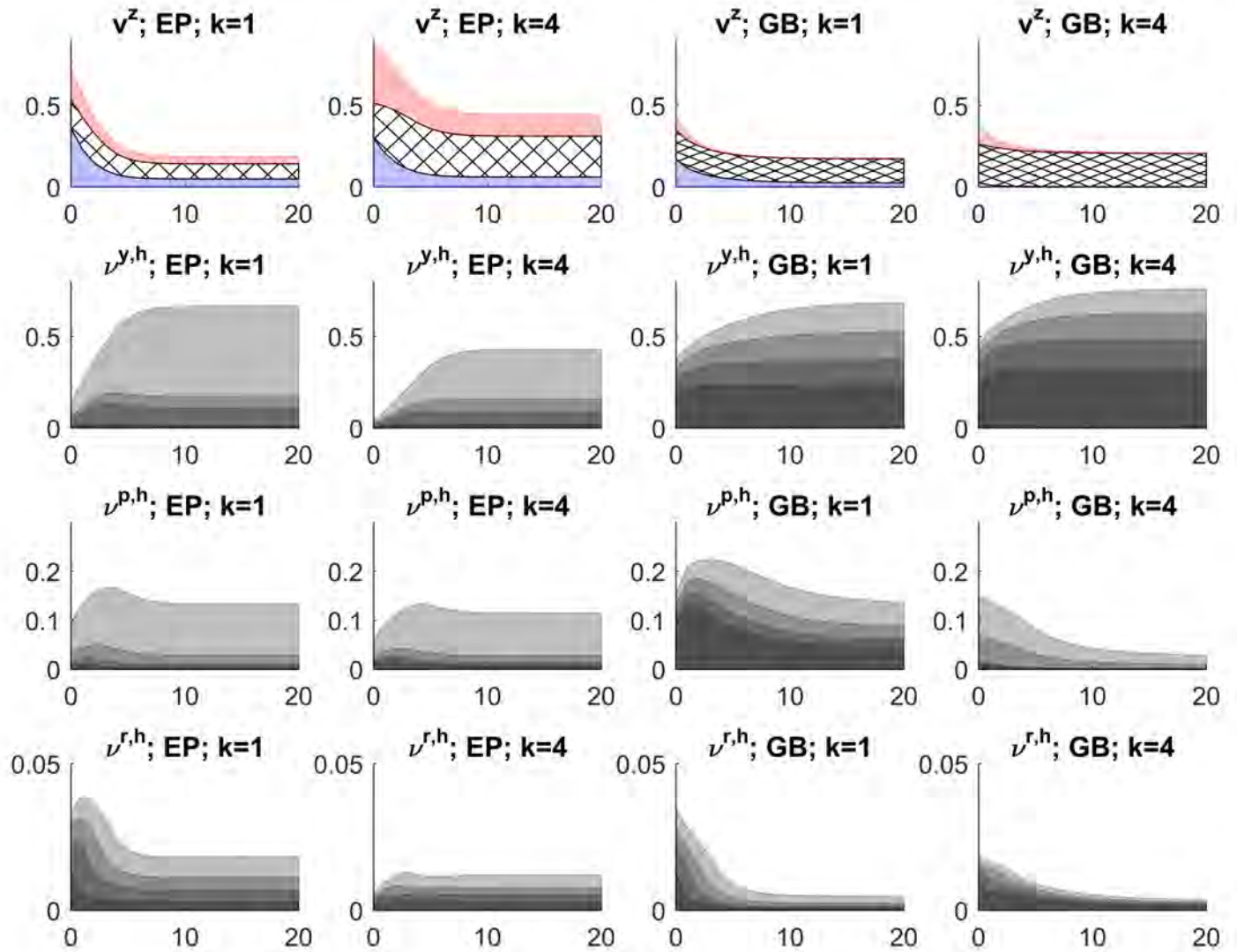


Figure 14: Forecast error variance decomposition of interest rate: Ex Post (EP) vs Greenbook (GB) data. Surprises: blue shade—supply shocks; cross-hatched—demand shocks; red shade—monetary shocks. News: darkest shade— $h = 1$; lightest shade— $h = 4$.

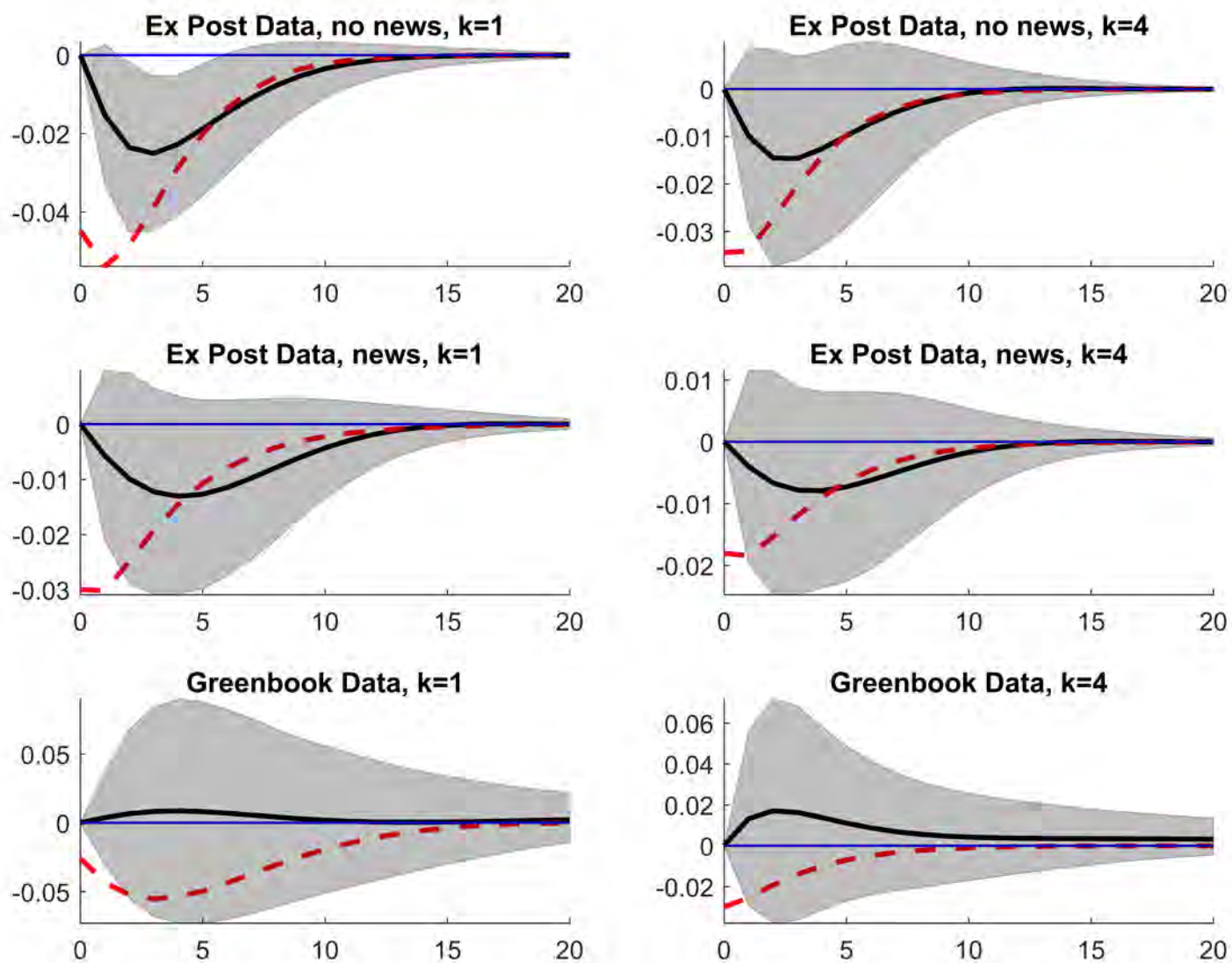


Figure 15: Theoretical (red, dashed) and simulated IRFs (black, solid) with 80% confidence intervals for the following models: top row—ex post, no news; middle row—ex post, with news; bottom row—Greenbook, with news; left column— $k = 1$; right column— $k = 4$.