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Abstract

There is a large literature evaluating forecasts by testing the rationality of forecasts and measuring the size of forecast errors, but we know little about the impact of forecast errors on economic outcomes. This paper constructs a measure of a forecast error shock for the Federal Reserve based on the assumption that the Fed follows a forward-looking Taylor rule. Given the effort the Fed puts towards producing forecasts that do not have an endogenous error component, this forecast error shock should be comparable to traditional monetary policy shocks and thus can be used to measure the impact of the Fed's forecast errors on the U.S. economy. We follow Romer and Romer (2004) and investigate the effect of the forecast error shock on output and price movements. Our results suggest that although the magnitude of the forecast error shock is large, the impact of our shock on the macroeconomy is quite small. The impact is somewhat larger when we take into consideration the Fed's inability to forecast recessions. The maximum impact across all potential models suggests a decline of approximately one percent of real GDP and two percent of GDP deflator in response to a one standard deviation contractionary forecast error shock.

[1] The views expressed in this paper are the authors' and should not be interpreted as CBO's. Corresponding author: Pao-Lin Tien: ptien@wesleyan.edu. The authors thank Olivier Coibion, Dean Croushore, Betty Daniels, Neil Ericsson, Masami Imai, Dennis Jansen, Fred Joutz, Ken Kuttner, Kajal Lahiri, William Larson, James Morley, Charles Nelson, Michael Owyang, Tatevik Sekhposyan, Jay Shambaugh, Herman Stekler, Simon van Norden, and Tony Yezer for helpful discussions. The authors also thank participants at the Southern Economic Association meetings, the Symposium for Nonlinear Dynamics and Econometrics, the International Association for Applied Econometrics conference, the George Washington University Seminar on Forecasting, the Eastern Economic Association conference, Texas A&M economics department seminar, the Pomona College Department of Economics Senior Colloquium Series, the Wesleyan University Division II Seminar series, the Joint Statistical Meetings, and the University at Albany Economics Seminar for useful comments. The authors gratefully acknowledge the support of the GW Institute for International Economic Policy for this project. All remaining errors are our own.

Do Fed Forecast Errors Matter?

I. Introduction

This paper presents an approach for measuring the potential economic impact of the forecast errors made by the Federal Reserve (Fed). We begin by assuming the Fed sets its federal funds interest rate target according to a forward-looking Taylor Rule (Clarida et al., 2000). The shock is then found to be a weighted sum of inflation and output growth forecast errors, following the approach of Sinclair et al. (2012). The Fed puts significant resources into producing accurate forecasts and is generally judged the best forecaster for the U.S. economy, particularly for output and inflation, which are the two series used in the Taylor Rule.[2] If the forecasts are rational and if the Fed's policy decisions can be well-approximated by a forward-looking Taylor Rule, as much research suggests (e.g. Orphanides 2001, Bernanke 2010), then we can interpret the impact of the Fed's forecast errors on the federal funds rate that the Fed targets as an exogenous shock which can then be used in the traditional ways to evaluate the impact of a monetary policy shock on the economy.[3] We document that this shock is large in absolute value, consistent with the findings of Sinclair et al. (2012), where the mean absolute error (MAE) of our forecast error shock is over 175 basis points as transformed into fed funds rate units.[4] Furthermore, these shocks are spread throughout the sample rather than concentrated in a few key time periods. Although the Fed is on target on average, the federal funds rate is far away

[2] See, for example, Romer and Romer (2000), Gamber and Smith (2009), and El-Shagi et al. (2014).
[3] One potential criticism of our assumption that the forecast errors are exogenous to other events in the economy is the research that suggests that forecast errors are worse around turning points (e.g. Sinclair et al., 2010). We address this in Section V.
[4] Based on our main four quarter ahead specification for the Taylor Rule for the sample period 1974Q2-2008Q2. Note that although the MAE is large, the forecasts appear unbiased, i.e. we cannot reject a zero mean, as reported in Table 1.

from the Fed's intended target most of the time. Thus these forecast errors could have large economic consequences.

Following Orphanides (2001) and Bernanke (2010), we assume the Fed follows a forward-looking Taylor rule using the staff's "Greenbook" forecasts as the input for GDP and inflation. These forecasts are prepared by the Federal Reserve staff before each Federal Open Market Committee (FOMC) meeting, and are shared with the FOMC members before each scheduled meeting. The FOMC members also make their own forecasts. Romer and Romer (2008) and Nunes (2013) found that the Greenbook forecasts are of higher quality than the FOMC forecasts.[5] One reason why the FOMC projections may be less accurate is that they are released immediately. Thus they may be used for communication purpose and/or may experience political pressures in a way that the Greenbook forecasts are not affected because they are released with a 5 year lag. Moreover, many research papers exploring monetary policy and forward-looking versions of the Taylor rule have assumed that the Greenbook forecasts are what are used for monetary policy decisions.[6] Furthermore, Ben Bernanke, in a speech in 2010 when he was Chairman of the Federal Reserve, presented an estimate of the Taylor rule based on Greenbook forecasts. He only used FOMC projections for the period when Greenbook forecasts were not yet publicly available (Bernanke 2010).

We use methods previously applied to measuring the impact of monetary policy on the economy in order to measure the impact of forecast errors. If the forecast errors are exogenous

[5] Romer and Romer (2008, page 234) argue that "Someone wishing to predict inflation and unemployment who had access to both the FOMC and staff forecasts would be well served by discarding the FOMC forecast and just using the staff predictions." Nunes (2013) finds that the FOMC forecasts put greater than optimal weight on public forecasts.

[6] For example, see Nikolsko-Rzhevskyy (2011). Orphanides and Wieland (2008) compared FOMC projections in the Taylor rule with the currently available data referring to the same period. They found that the FOMC projections fit better. However, they did not make a similar comparison with the Greenbook forecasts that are only available with a five year lag.

to economic events then they should be a valid measure of a type of monetary policy shock. Research on measuring the impact of monetary policy shocks has attempted to separate the actual policy change from the policy change that was expected based on an information set dated prior to the policy change. These previous works capture *unexpected* monetary policy. We take the view that the Federal Reserve attempts to minimize monetary policy surprises.[7] Therefore, the unexpected component of monetary policy is likely to be small. Our shock thus captures a different dimension of surprise. If policy is based on forecasts, forecast errors will cause actual policy to deviate from intended. Thus our shock captures *unintended* as compared to *unanticipated* changes in the federal funds rate.

We examine the role of our forecast error shock using the same regression methodology as Romer and Romer (2004, henceforth R&R).[8] We compare the effect of our shock on output and prices against a variety of popular monetary policy shock measures, such as the R&R narrative shock, standard VAR monetary policy shock, and a hybrid R&R VAR shock.[9] In the baseline model, our results are consistent with the literature in that we find the R&R shock (or the hybrid VAR shock that embodies the R&R shock series) tends to produce the largest impact on output and prices regardless of the measure of output and price variables, while our forecast error shock produces the most moderate impact, with the VAR shocks in between.

Although our shock has very small impacts on average, we next go on to explore the possibility that there is asymmetry in terms of the impact of our shock (as well as the monetary

[7] This is especially true since the Fed moved toward greater policy transparency after 1994. Using federal funds futures data, Lange et al. (2003) found that prior to 1993, 60 percent of federal funds rate changes were surprises. After 1994 that percent fell to 24 percent.
[8] Other researchers have considered the economic costs of prediction errors in very different frameworks, see Clements (2004), Granger and Pesaran (2000a,b), and Pesaran and Skouras (2002).
[9] Using the terminology coined by Coibion (2012).

policy shocks we consider) on the macroeconomy during recessions as compared to expansions. This is an important point to consider since the Fed’s inability to predict recessions in advance (as documented in Sinclair et al. 2010) may affect the impact of our shock. Although contemporaneous recessions affect the results of other shock measures, we show that it is a forward-looking recession dummy that leads to our shock having a much larger effect on the economy, with maximum impact suggesting a decline of approximately one percent of real GDP and two percent of GDP deflator in response to a one standard deviation contractionary forecast error shock. Thus the Fed’s inability to predict recessions in advance may result in the largest impact of the Fed’s forecast errors on the economy.

Section II presents our methodology for constructing the shock. Section III presents a review of monetary policy shock measures that we use for comparison. Section IV describes the data, Section V details our empirical results, and Section VI presents various robustness checks of our analysis. We offer concluding remarks and discuss the implications of our results in Section VII.

II. Construction of the Forecast Error Shock

We assume that the Fed implicitly follows a forward-looking Taylor rule (Clarida et al., 2000) as their monetary policy rule. By “forward looking” we mean that the Fed sets the federal funds interest rate target based on forecasts of output growth and inflation. Our measure of the Fed’s forecast error shock is derived from the Taylor Rule as a weighted average of the forecast errors for inflation and output growth.

According to the forward-looking Taylor rule, the Fed, sets a target federal funds rate, i_t^{Tf} , based on equation (1) below, where the superscript "*f*" denotes that the target is based on forecasted variables.[10] The Fed's interest rate target (i_t^{Tf}) is written as:

$$(1) \qquad i_{t|t}^{Tf} = r^* + \pi_{t+h|t}^f + 0.5(\pi_{t+h|t}^f - \pi^*) + 0.5(y_{t+h|t}^f - y^*),$$

where r^* is the equilibrium real interest rate, π^* is the Fed's implicit inflation rate target, and y^* is the potential output growth rate.[11] The Fed forecasts both inflation, $\pi_{t+h|t}^f$, and output growth, $y_{t+h|t}^f$, *h* periods ahead.

The actual outcome in period *t+h*, however, likely differs from the Fed's forecasts. Therefore, if the members of the FOMC had known the actual values for π_{t+h} and y_{t+h} (i.e., if they had perfect forecasts or perfect foresight), they would have chosen a (potentially different) federal funds rate. Consequently, their interest rate target under perfect foresight $(i_{t|t+h}^T)$ would have been:

$$(2) \qquad i_{t|t+h}^T = r^* + \pi_{t+h} + 0.5(\pi_{t+h} - \pi^*) + 0.5(y_{t+h} - y^*),$$

[10] Following Orphanides (2001), we assume that the Fed uses the Greenbook forecasts in their decision rule, consistent with Bernanke (2010). The FOMC also makes their own forecasts. For an evaluation of those forecasts, see Romer and Romer (2008).

[11] While the output gap is typically used in the Taylor rule, the growth rate is typically used in forecast evaluation. The growth rate of the actuals is approximately $\ln(Y_t) - \ln(Y_{t-1})$, whereas the growth rate of the forecasts is approximately $\ln(Y^f_t) - \ln(Y_{t-1})$. Thus, when we subtract one from the other for the policy forecast error, we have $\ln(Y_t)$- $\ln(Y^f_t)$. Approximating the output gaps in the same manner, we have $\ln(Y_t) - \ln(Y^*)$ and $\ln(Y^f_t) - \ln(Y^*)$, so again we have $\ln(Y_t)$- $\ln(Y^f_t)$. It is this result that permits us to use the growth rate in order to construct the shocks. This analysis does assume, however, that potential output, Y^*, is known rather than a forecast. This assumption is based on the lack of forecasts for this variable in the Greenbook. For a discussion of the role of real time output gap estimates and the Taylor rule, see Orphanides (2001).

where π_{t+h} and y_{t+h} represent the actual realizations of inflation and real output growth *h* periods ahead. The difference between $i^{T}_{t|t+h}$ and $i^{Tf}_{t|t}$ measures the difference in the Fed funds rate that occurs because of inaccurate forecasts of output growth and inflation and thus represents the forecast error shock:

$$(3) \qquad shock_t = i^{T}_{t|t+h} - i^{Tf}_{t|t} = 1.5\left(\pi_{t+h} - \pi^{f}_{t+h|t}\right) + 0.5\left(y_{t+h} - y^{f}_{t+h|t}\right).$$

The differences, $\left(\pi_{t+h} - \pi^{f}_{t+h|t}\right)$ and $\left(y_{t+h} - y^{f}_{t+h|t}\right)$, are the Fed's forecast errors for the inflation rate and real output growth respectively. In equation (3) we define the shock as perfect foresight minus forecast, following the traditional forecast evaluation literature. In our analysis below, however, we make use of the inverse of the shock to be directly comparable with the monetary policy shock measures.[12] Throughout the results section we will be focusing on a contractionary shock.

III. A Brief Review of Monetary Policy Shock Measures

The standard method for constructing monetary policy shocks is as follows:

$$(4) \qquad r_t = r_{t|t-i} + shock_t,$$

[12] A negative innovation in our forecast error shock means that the Fed set the fed funds rate in period *t* higher than what they would have set it at, had they had full knowledge of the realized values of output and inflation in period *t+h*. Thus, a negative innovation in our shock series should be comparable to a contractionary monetary policy shock (which is a positive innovation in commonly used measures of monetary policy shocks).

where r_t is the policy instrument, $r_{t|t-i} = E[r_t \mid \Omega_{t-i}]$ is the expectation of the policy instrument based on information set Ω_{t-i}, i = 1, 2, 3,…. The difference between the expectation and the actual values of the instrument, $shock_t$ measures the unanticipated movement in policy.

In the VAR approach to measuring monetary policy shocks Ω_{t-i} contains the past values of policy as well as past values of the other variables in the VAR. Christiano et al. (1999) provides a detailed discussion of these monetary VAR models. Of course, there is nothing barring researchers from including in Ω_{t-i} forecasts of macroeconomic variables. In Romer and Romer (2004) and Thapar (2008), for example, Ω_{t-i} contains the Federal Reserve's Greenbook forecasts.

The measure of monetary policy shocks described by equation (4) is clearly sensitive to the researcher's choice of information set. There are two dimensions to this choice: a cross-sectional dimension and a time-series dimension. The cross-sectional dimension is the choice about what variables to include in the information set. The evolution of the VAR literature on measuring monetary policy shocks, particularly in dealing with the "price puzzle" evident in much of the earlier literature, illustrates the importance of this choice. Sims (1992) identified a price puzzle where the price level increases in response to a monetary tightening. He reasoned that the Fed likely conditions its policy on indicators of future inflation (such as commodity prices). In a VAR that does not include these indicators, the price level is actually responding to a combination of the inflation that is in the pipeline and the monetary tightening. Therefore, omitting indicators of future inflation will lead to an increase in the price level in response to a monetary tightening. Sims resolved this issue by adding commodity prices to Ω_{t-i}.

It is obviously not possible for a VAR to include all of the varied and detailed information that the Federal Reserve incorporates into their monetary policy decisions.[13] The validity of the VAR methodology rests on whether the small number of variables included in the VAR is a reasonable approximation to that varied and detailed information. Romer and Romer (2004) and Thapar (2008) take the view that variables included in Ω_{t-i} by VAR researchers do not closely approximate the information set used by the Federal Reserve. They therefore replace VAR generated forecasts with the Fed's own Greenbook forecasts which presumably include varied and detailed information about the economy.

The second dimension to the choice of what to include in the information set is the temporal dimension. If a researcher is using quarterly data (Thapar, 2008, for example) and information that might influence the Fed's policy choice becomes available at a higher frequency, the measured shock will be mis-identified because it will actually include systematic changes in the Fed's policy instrument.

Kuttner (2001), Poole and Rasche (2003), Lange et al. (2003), Swanson (2006), and Barakchian and Crowe (2013) attempt to measure monetary policy shocks using high-frequency data on federal funds futures in order to minimize the misspecification described above. These authors define monetary policy surprises as the difference between the federal funds rate expected by the futures market and the actual realized federal funds rate target. These measures show a large decline in the proportion of federal funds interest rate targets that is due to monetary surprises after 1994.

Overall in this literature there remains substantial debate as to the best way to identify a monetary policy shock as well as the size of the impact of the resulting shocks. The main

[13] There have been attempts to incorporate large information sets in a VAR setting. For example, Faust and Rogers (2003) has a 14 variable VAR identified with sign restrictions, and Bernanke, Boivin, and Eliasz (2005) adopts the FAVAR (factor-augmented VAR) approach that incorporates a balanced panel of 120 macroeconomic time series.

question is whether the identified shocks are truly exogenous, or if they are impacted in some way by anticipatory movements or other factors such that they do not accurately measure the impact of monetary policy on the economy. Thus we will compare our forecast error shock with a range of monetary policy shocks from the literature.

IV. Data

The forecasts used to construct our forecast error shock are from the Federal Reserve's Greenbook from the middle of each quarter from 1965Q4 through 2008Q4 (the Greenbook forecasts are only released after a five year delay) available from the Federal Reserve Bank of Philadelphia. The projections used in this analysis are the growth rate of real output (Gross National Product or GNP from 1965 to 1991 and Gross Domestic Product or GDP from 1992 on)[14] and the inflation rate (based on the implicit price deflator through the first quarter of 1996, then the chain-weighted PCE price index from 1996Q2 on). Our main results are based on the 4 quarter-ahead forecasts of real output growth and inflation (following Orphanides 2001). The actual figures were the data published approximately 90 days after the end of the quarter to which they refer. Use of the real time data avoids definitional and classification changes of the output and price variables.

In addition to the forecast error shock, we also consider a range of alternative measures of monetary policy shocks to compare against. Similar to Coibion (2012), we look at:

- R&R narrative monetary policy shock[15]

[14] The last forecast in the fourth quarter of 1991 was the first forecast of GDP.

[15] We use the expanded R&R shock constructed by Barakchian and Crowe (2013) in order to allow for as long of a sample period as possible for comparison purposes. The monthly shock series is summed to produce its quarterly equivalent.

- Monetary policy shock extracted from a standard 3 variable (output, price, fed funds rate) VAR identified using short-run Cholesky decomposition.[16] This is a variation of the VAR examined by Christiano et al. (1999), and also used by Romer and Romer (2008), and more recently by Barakchian and Crowe (2013).
- Hybrid monetary policy shock extracted from the same standard 3 variable VAR as specified above but with the cumulated R&R shock replacing the fed funds rate.

Furthermore, we include the change in the actual fed funds rate as a naïve shock specification.

Before assessing the impact of the shocks on the macroeconomy, it is important to first examine the scale and historical pattern seen in our shock as compared to the others in the literature. This is shown in Figure 1. All the shocks are normalized following the standard in the literature where a positive shock is capturing a contractionary movement in policy.

The first noticeable difference between the policy forecasting shock and the others is that it has a much larger magnitude.[17] The only one that comes close is the early part of the sample of the change in federal funds rate. Forecast errors are frequent and large as compared to other shocks that have been previously used to identify exogenous changes in monetary policy.

The other interesting pattern obvious in these comparisons is at the end of the sample: all the shocks other than the forecast error shock suggest that there were expansionary shocks in 2007 and 2008 (the beginning of the Great Recession), but our forecast error shock suggests that as the Fed was overestimating output and inflation in this period it resulted in a large *contractionary* shock.

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[16] Both the VAR and Hybrid VAR are estimated with 12 lags. We also tried estimating the VARs with 4 lags, the results are qualitatively similar, hence only the VAR shocks estimated with 12 lags are reported.

[17] One reason our shock is so large is because we did not allow for smoothing in the Taylor rule. As discussed in Sinclair et al. (2012), smoothing monotonically decreases the magnitude of the shock. Thus our results provide an upper bound for the size of the shock. Given that our results suggest that the impact of even the large shock is small, we report only this upper bound.

V. Results

We employ the regression framework in R&R to analyze the effect of our forecast error shock on output and prices. Specifically, we use real GDP (seasonally adjusted) as our output measure and the GNP/GDP deflator price index (seasonally adjusted, 2009 = 100) as our price measure.[18] The sample period we consider goes from 1974Q2 to 2008Q2. The basic specification is set up as follows:

(5) $$x_t = a_0 + \sum_{i=1}^{L_x} b_i x_{t-i} + \sum_{j=1}^{L_S} c_j S_{t-j} + e_t,$$

where x indicates the macroeconomic variable under investigation (growth rate of output or price measures) and S indicates the shock series. Lagged values in both the macroeconomic variable and shock series are allowed for to accommodate the dynamic movements of the variable and possible delayed effect of shocks, where L_x is the maximum number of lags included of the dependent variable and L_S is the maximum number of lags included of the shock. Following R&R, for both output growth and inflation we allow for a maximum of eight quarters of lags of the dependent variable. As for the shocks, twelve lags are used for the output growth estimation, and sixteen lags are used for the inflation estimation. The longer set of lags of the shock for inflation is to accommodate the argument that monetary policy shocks have longer lasting effects on prices (R&R).

[18] Alternative measures of output and prices are considered in Section VI.

To summarize the results, we examine the impulse response of the macroeconomic variable to a one-time realization of the forecast error shock of 100 basis points. The impulse responses are cumulated to show the effect of the shock on the levels of the macroeconomic variables rather than their growth rates.

a. The Impact of Forecast Error Shocks on Output

Figure 2 illustrates the impact of the forecast error shock on output. The left side of panel 1 shows the impulse response of GDP to a 100 basis point innovation in the shock series. The impulse response function (IRF) is surrounded by 1-standard error bands.[19] Not surprisingly, a contractionary innovation in our shock series leads to a decline in output peaking at quarter 4 but eventually reverting back to zero by quarter 8. The maximum decline in output is about 0.19%, and this number is statistically significant with two standard error confidence interval. To put this result in context, the left plot in panel 2 illustrates the IRFs of GDP to a 100 basis point innovation in our shock series along with 100 basis point innovations in the other monetary policy shocks we consider. Overall we can see that the estimated impact of our shock is quite muted as compared to the other shocks used in the literature, with the R&R narrative shock having the largest impact (almost 1.6% decline at the peak), and the VAR shocks in between. All the shocks generate similar dynamics on output where the declines in output eventually dissipates. The only exception is the naïve specification of change in actual fed funds rate, whose impact on output appears to be more persistent.

[19] Following R&R, error bands are constructed using Monte Carlo methods where we repeatedly draw coefficients from a multivariate normal distribution with mean and variance-covariance matrix given by the point estimates and variance-covariance matrix of the regression coefficients. The standard errors are the standard deviations over each forecast horizon across the different 1000 draws that we conduct.

The small impact that the forecast error shock exhibits here relative to the other shocks might be due to the fact that a 100 basis point shock is a rather small forecast error. Given that our shock is much larger in magnitude than the others,[20] a one standard deviation shock comparison may be more appropriate. The right side of the panels in Figure 2 illustrate the impact of a 1 standard deviation forecast error shock on output and its impact relative to other shocks. The normalization more than doubles the peak effect our forecast error shock has on GDP, and appears to dampen the impact of the monetary policy shocks (particularly the R&R narrative shock). However, the magnitude of the impact remains small for the forecast error shock, generating a decrease of just below 0.5% at the maximum.

b. The Impact of Forecast Error Shocks on Prices

Figure 3 illustrates the impulse responses of prices as measured by the GNP/GDP deflator price index to a 100 basis point increase in the forecast error shock variable. Similar to what we presented for output, we include in Figure 3 the IRFs for the commonly used monetary policy shocks both on a common 100 basis point scale and on a 1 standard deviation scale. From both of these it is clear that even though a contractionary innovation in our shock series generates a persistent decline in the price level as expected, the magnitude of the impact on prices is small relative to the other shocks. The largest effect is only about a 0.7% decline in price (16^{th} quarter, 1 standard deviation shock). The R&R narrative shock still posts a strong influence over prices, though the VAR shock appears to generate the largest decline in prices here (about 1.6% in quarter 16) when we compare shocks on the standard deviation scale.

c. Controlling for Recessions

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[20] The mean of the absolute value of our shock series is about 177 basis points, whereas the means of the absolute values of the other shocks consider are all no larger than 100 basis points.

Economists have often argued that monetary policy may have asymmetric effects on the real economy, and there is a growing body of empirical work on that topic.[21] Most of the research looks at the asymmetry in output response to an expansionary versus a contractionary monetary policy shock (for example, Cover 1992, or more recently, Lo and Piger 2005, and Hayford 2006), but some do pay attention to a different aspect of asymmetry, that of the effect of shocks during boom times versus recession periods (e.g. Garcia and Schaller 2002, Höppner et al. 2008, Tenreyro and Thwaites 2013). Given that the forecast evaluation literature (e.g. Sinclair et al. 2010 and Joutz and Stekler 2000) has documented that the Fed is unable to predict recessions in advance and hence make more severe forecasting mistakes around turning points, we are interested in investigating whether our forecast error shock exhibits the second type of asymmetry mentioned above. Thus, in this section, we consider the possibility that either a recession occurring at the time of the shock (our contemporaneous recession dummy) or a recession affecting the period the Fed is focused on in their forward-looking Taylor rule (our forward-looking recession dummy) might affect our results.[22] We augment equation (5) to include a recession dummy and interaction terms between the shock variable and the recession dummy:

$$(6) \qquad x_t = a_0 + \sum_{i=1}^{L_x} b_i x_{t-i} + \sum_{j=1}^{L_S} c_j S_{t-j} + recession_t + \sum_{j=1}^{L_S} d_j S_{t-j} recession_{t-j} + e_t$$

[21] See, for example, Cover (1992), DeLong and Summers (1988), Donayre (2014), Garcia and Schaller (2002), Hayford (2006), Höppner et al. (2008), Karras (1996), Karras and Stokes (1999), Kasuya (2005), Kaufmann (2002), Lo and Piger (2005), Morgan (1993), Parker and Rothman (2004), Peersman and Smets (2002), Rhee and Rich (1995), Tenreyro and Thwaites (2013), and Weise (1999).

[22] For example, for the 2001Q1 to 2001Q4 recession, the contemporaneous dummy will take on the value 1 for 2001Q1 through 2001Q4, while the forward looking dummy will take on the value 1 for 2000Q1 to 2000Q4. We use the NBER business cycle dates to construct the dummies.

The cumulative IRFs generated from estimating equation (6) for both output and prices are presented in Figures 4 and 5. For output (Figure 4), the magnitude of the decline with the contemporaneous recession dummy is similar to that reported in Figure 2, but if we consider the forward-looking recession dummy, the impact of the forecast error shock is much stronger. The maximal decline in output is about 0.4% when we focus on the 100 basis point shock, and about 1% when we look at the standard deviation shock, both of these numbers are about twice as large as the maximal decline without the recession dummy. A similar pattern emerges when we look at the price variable (Figure 5). The maximal decline in price with the forward looking recession dummy in response to a 100 basis point shock (-0.83%) is more than twice as large as the maximal decline reported in Figure 3 without the dummy. The same thing applies when we look at the response of prices to a 1 standard deviation shock.

So it would appear that we find asymmetry in the impact of our shock on output and prices. Specifically, the effect of the forecast error shock on the macroeconomy is much stronger when the forecasted time period in the forward-looking Taylor rule turns out to be a recession date. This result is consistent with the majority of the literature on monetary policy asymmetry that report stronger effects of policy during recessions.[23]

One thing to note here is that by including a forward looking recession dummy, the magnitude of the macroeconomic effect of our forecast error shock becomes quite comparable with the monetary policy shocks we consider. Figure 6 illustrates that comparison. Included in the figure are the IRFs of all the shocks taking into account a contemporaneous recession dummy. We also superimpose the IRF generated using our forecast error shock and the forward

[23] Most of the relevant papers we cited earlier report stronger effect of monetary policy on output during recessions, but that does not necessarily apply to the price response. Contrary to those results, Hayford (2006) finds that monetary policy is equally effective during booms or recessions, while Tenreyro and Thwaites (2013) find stronger effect during booms using the R&R narrative shock.

looking recession dummy onto the graphs.[24] As can be seen from Figure 6, under a 100 basis point innovation comparison, the forecast error shock does not generate the largest declines in output and price. However, once we consider the more appropriate 1 standard deviation innovation comparison, the forecast error shock with the forward looking recession dummy taken into account ends up having a larger effect than all the other monetary policy shocks. This is true for our output as well as price measures.

Figure 7 shows that even when we compare the IRFs for the monetary policy shocks without recession dummies (reported earlier in Figures 2 and 3, these exhibit slightly stronger effects on output and price) against IRF generated by our forecast error shock with forward looking recession dummy, the forecast error shock still ends up with the largest impact on both output and price.

VI. Robustness Checks

a. Alternative Measures of Output and Inflation

There are many other measures of output and prices that researchers use to gauge the state of the economy, hence we want to make sure the results reported earlier are robust to alternative measures of output growth and inflation. For output we consider another commonly adopted measure, the Industrial Production (IP, seasonally adjusted, average of monthly data). For price we consider the Personal Consumption Expenditures chained type price index (PCE, seasonally adjusted, 2009 = 100) that the Fed currently focuses on as their preferred price measure.

[24] Forward looking recession dummy only makes sense for our particular shock as we specifically include 4 quarter ahead forecasts in the construction of the forecast error shock. Hence this dummy is not used to estimate equation (6) for the monetary policy shocks considered.

The results are presented in Figures 8 and 9. Our results for IP are very similar to the results reported for GDP, except the scales are larger. IP appears to react more strongly than GDP to all shocks. For PCE, the results are again similar to our benchmark price variable the GDP deflator. The magnitudes of the IRFs do not differ much from that reported in Figure 3 for the deflator, and that is true not just for our forecast error shock, but across all shocks.

b. Limiting the Sample Size

Many researchers have argued that monetary policy has become more forward looking since the 1980s (see Barakchian and Crowe 2013, henceforth B&C). All of the monetary policy shocks we consider in this paper for comparison against our forecast error shock either omit forward looking information in the construction of the shock, or do not change the relative weight on those forward looking elements as time goes on. B&C argues that if we restrict the sample period to that post 1980, many of these shocks just described will end up generating puzzling behaviors in output and prices (i.e. increases in output and prices in response to a contractionary shock). Therefore, we would like to consider a shorter sample period from 1988Q4 to 2008Q2 (matching up with the sample used in B&C) to see how our forecast error shock would perform against the other monetary policy shocks. Note that our forecast error shock specifically takes into account the forward looking behavior of policymakers. Hence we expect that a contractionary innovation in our shock series would generate IRFs that show declines in output and prices.

To conduct our analysis, we simply took the shocks constructed for the full sample (1974Q2 to 2008Q2) and removed the data prior to 1988Q4 to re-estimate equation (5) for the shorter sample.[25] Figure 10 presents the short sample results for GDP and Figure 11 presents the results for GDP deflator. Note that we include an additional monetary policy shock constructed by B&C here for comparison.[26]

Panel 1 in both Figures 10 and 11 shows that a contractionary innovation in our shock series generates the expected declines in output and price. The magnitude of the decline in GDP is similar to using full sample (for example, maximal decline in GDP is about 0.2% for the full sample versus 0.26% for the subsample for a 100 basis point shock), while the magnitude of the decline in GDP deflator is much smaller when we restrict the sample to post 1988 (for example, maximal decline in deflator is 0.32% for the full sample but only about 0.17% for the subsample for a 100 basis point shock). Panel 2 in Figures 10 and 11 shows some interesting comparisons of our shock against the other monetary policy shocks. Similar to what is reported in B&C, many of the popular monetary policy shocks exhibit an increase in output in response to a contractionary impulse in the shock series. The exceptions are the VAR shock and the B&C shock. As for the price variable, the hybrid VAR shock and the R&R narrative shock generate the expected decline in price, but the B&C shock ends up with a price puzzle.

Our results here illustrate the importance of taking into account the role of forecasts in the identification of monetary policy shocks. Although the results of the other shocks we use for comparison are affected by the change in sample period, the results of our forecast error shock are remarkably consistent but remain economically small.

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[25] The other option is to re-construct the shocks specifically for the sample period 1988Q4 to 2008Q2, as well as changing the weights in the Taylor rule as suggested by Clarida et al. (2000) for the forecast error shock. We choose the simpler route for now and leave this alternative option for further research.

[26] The B&C shock makes use of Fed Funds futures data and factor model to extract new information related to monetary policy announcements that cause changes in expected policy rates. This they interpret to be their measure of monetary policy shock which incorporates forward looking information. Hence, this shock should not suffer from the same mis-specification of the other monetary policy shocks under consideration here post 1988.

c. The Role of Forecast Horizon

There has been much debate in the Taylor rule literature about the length of the forecasting horizon that the Fed uses in the Taylor rule. To obtain a proper estimate of the forecast error shock, it is important for us to employ the appropriate forecast horizon used by the Fed.[27] We considered here an alternative forecast horizon, the current quarter forecast (nowcast). The results of replacing the 4 quarter ahead forecasts with nowcasts of GDP and GDP deflator is presented in Figure 12 for GDP and the GDP deflator. Panel 1 of Figure 12 shows a very different impact for GDP than our previous results – we get a *positive* output response to a contractionary innovation in our shock series. For the deflator (Figure 12 panel 2), even though we still get the expected decline in price in response to the contractionary shock, the IRF dynamic shows a less persistent price decline. Because of the counterintuitive output result, we interpret this as suggesting that the Fed is indeed using a forward looking Taylor rule.

d. Reducing the Number of Lags for the Shocks

It is possible that using the forward-looking Taylor rule to construct our forecast error shock may induce correlation between our shock and lags of our dependent variable. In order to address this concern, we also estimate a model with only one quarterly lag (rather than 12 or 16 quarterly lags) for the shock series (i.e. we estimate equation 5 with $L_S = 1$ for both output and price) which should not be correlated with our forecast error shock that looks 4 quarters ahead. The estimated cumulative IRFs are shown in Figure 13. For both GDP and GDP deflator, the results are qualitatively similar to those using 12 (for output) or 16 (for price) lags. Both output

[27] For example, Sinclair et al. (2012) focus on short horizons to avoid being affected by the Fed's future path for monetary policy. If that is not actually the horizon used by the Fed in the Taylor rule, however, then it would be an inappropriate measure for the forecast error shock.

and price decline in response to a contractionary forecast error shock, and the economic significance of the impact remains small.

VII. Conclusions and Implications of Results

This paper constructs a measure of unintended changes in the federal funds rate based on forecast errors in the Taylor rule. Forecast error shocks are defined as the difference between the target federal funds rate that would have been set using the Taylor rule with perfect foresight and the federal funds rate target that would have been set using a forward-looking Taylor rule based on forecasted output growth and inflation.

Given that the forecast errors are supposed to be orthogonal to all known variables in the economy in order for the Fed to be producing rational forecasts, it seems that our forecast error measure should be a high quality measure of exogenous variation in monetary policy. Our results suggest that the forecast error shock has the expected direction of impact on real output and prices, but that the impact is much smaller than that identified from monetary policy shock measures from the literature. In some ways that is reassuring, we would hope that forecast errors would not have a large impact on the economy, particularly given their size and prevalence as documented in the forecast evaluation literature and confirmed for our measure and sample. However, once we take into consideration the possibility that the Fed's forecasts may be of lower quality in recessions, we find a more significant effect of the Fed's forecast errors on the economy. This suggests that there should be more emphasis in improving the Fed's ability to forecast recessions.

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TABLE 1

RATIONALITY TEST RESULTS FOR FORECAST ERROR SHOCK

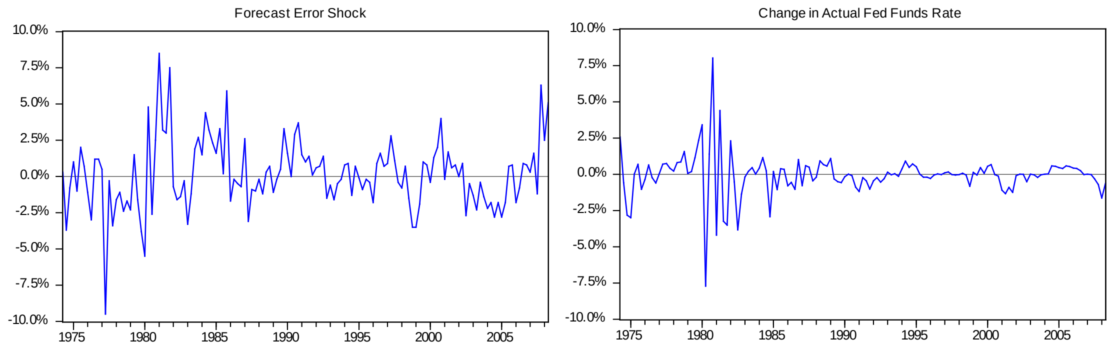
Dependent Variable	Constant	AR(1)	AR(2)
Forecast error shock	-0.137226 (0.205085)		
Forecast error shock	-0.225745 (0.356776)	0.231489** (0.085040)	0.224262** (0.085365)

Note: Sample period 1974Q2 to 2008Q2. Numbers in brackets indicate standard errors. ** indicates the estimated coefficient is statistically significant at the 1% level.

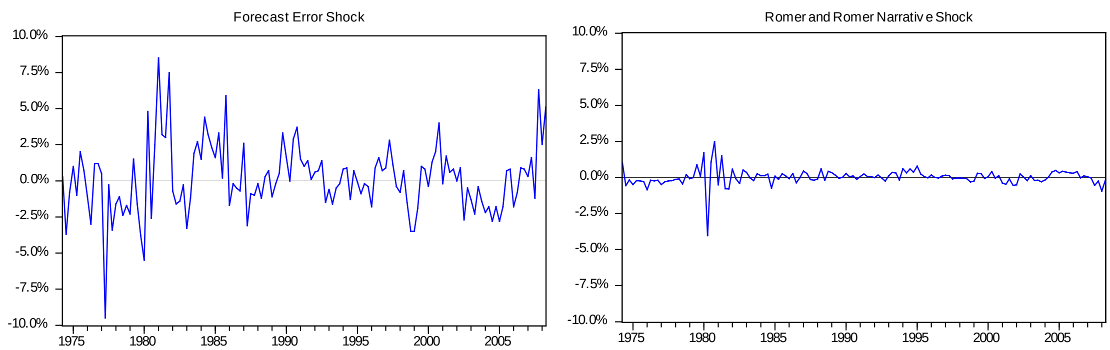
FIGURE 1

MEASURES OF MONETARY POLICY SHOCKS VERSUS FORECAST ERROR SHOCK

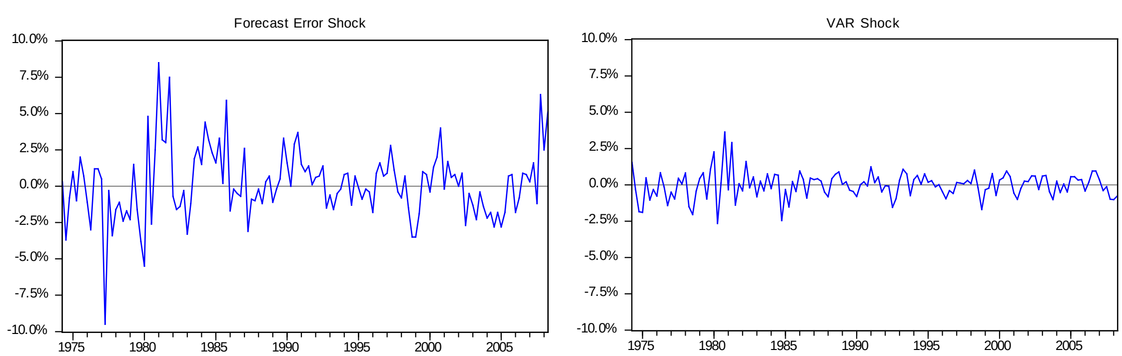
Panel 1



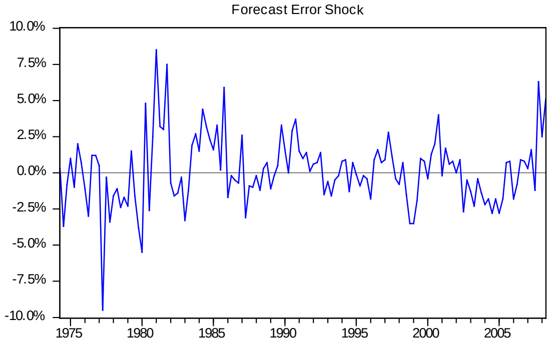
Panel 2



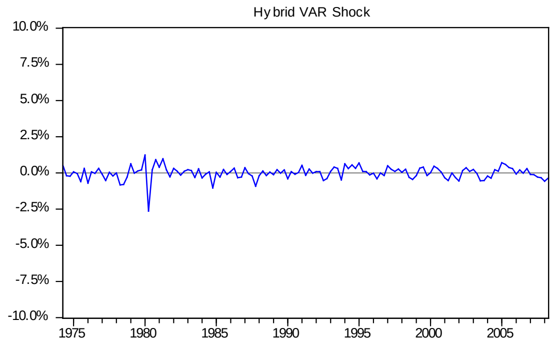
Panel 3



Panel 4



Forecast Error Shock
10.0%
7.5%
5.0%
2.5%
0.0%
-2.5%
-5.0%
-7.5%
-10.0%
1975
1980
1985
1990
1995
2000
2005

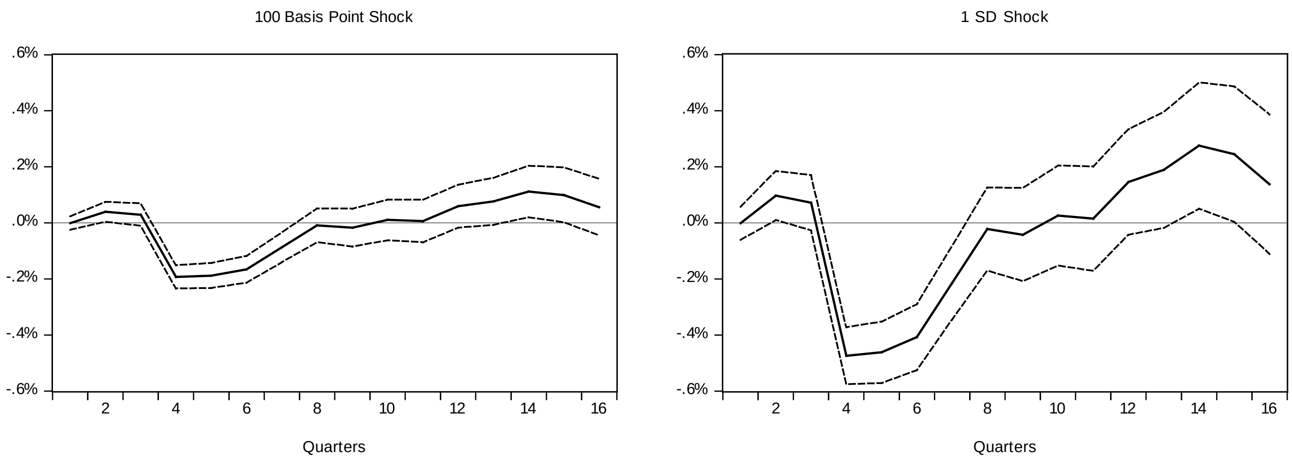


Hybrid VAR Shock
10.0%
7.5%
5.0%
2.5%
0.0%
-2.5%
-5.0%
-7.5%
-10.0%
1975
1980
1985
1990
1995
2000
2005

FIGURE 2

EFFECT OF SHOCKS ON GROSS DOMESTIC PRODUCT (GDP)

Panel 1: Impact of Forecast Error Shock on GDP



Note: Solid lines display the cumulative effect of the shock on the macroeconomic variable up to 16 quarters. Dashed lines are 1 standard error bands computed using Monte Carlo methods drawing from a multivariate normal distribution.

Panel 2: Impact of All Shocks on GDP

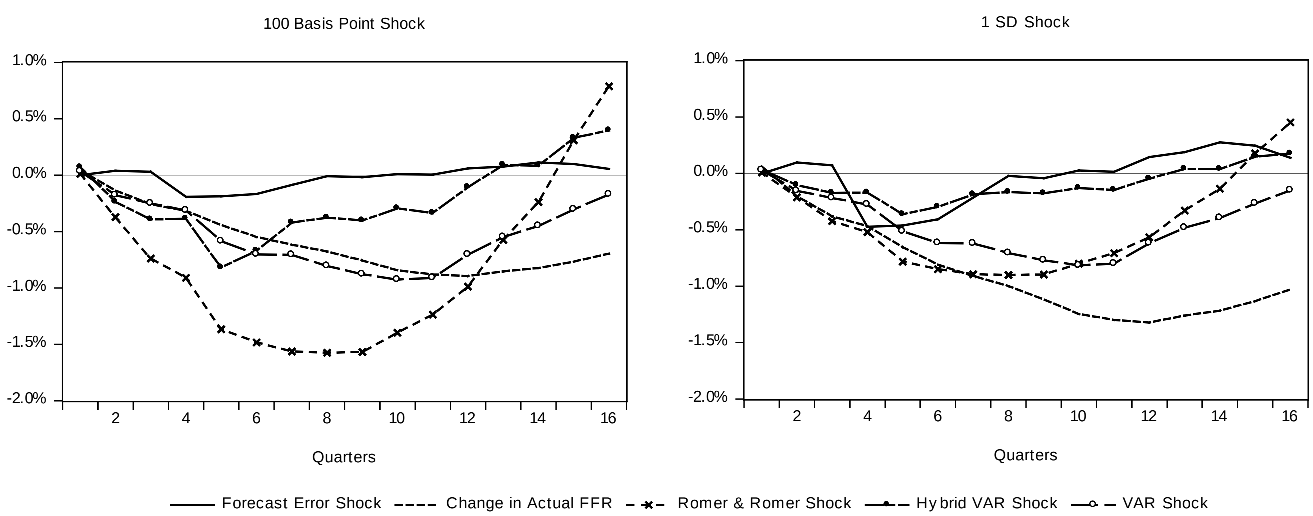
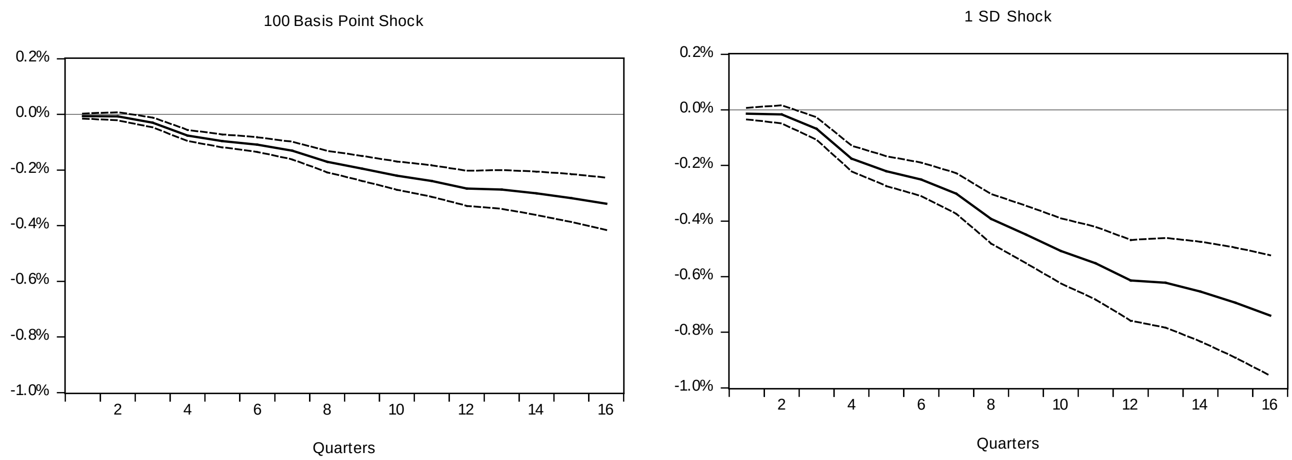


FIGURE 3

EFFECT OF SHOCKS ON GDP DEFLATOR

Panel 1: Impact of Forecast Error Shock on GDP Deflator



Note: Solid lines display the cumulative effect of the shock on the macroeconomic variable up to 16 quarters. Dashed lines are 1 standard error bands computed using Monte Carlo methods drawing from a multivariate normal distribution.

Panel 2: Impact of All Shocks on GDP Deflator

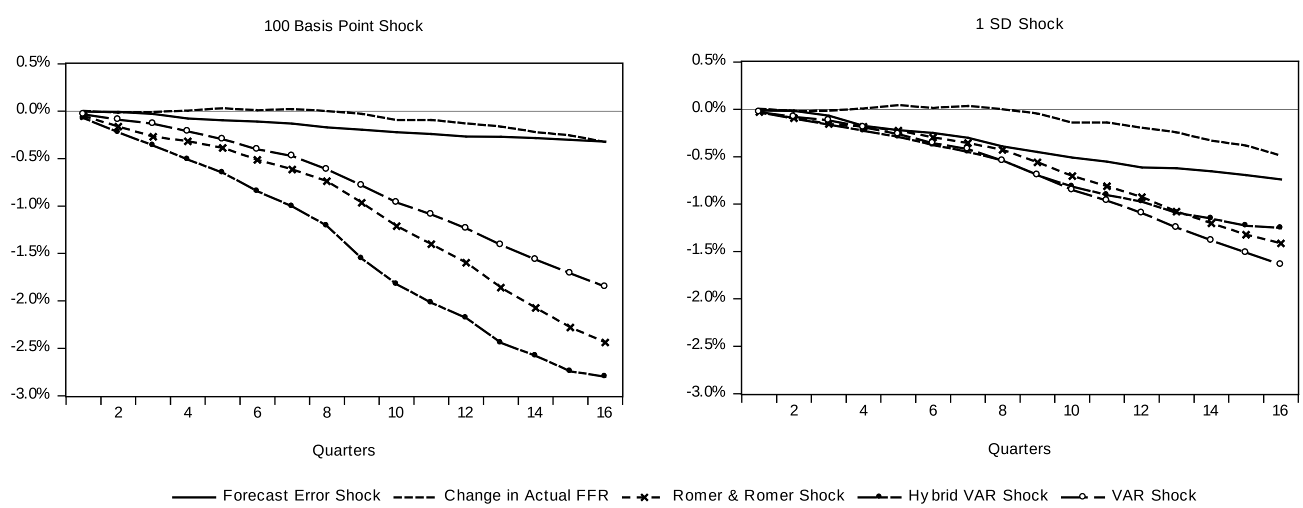
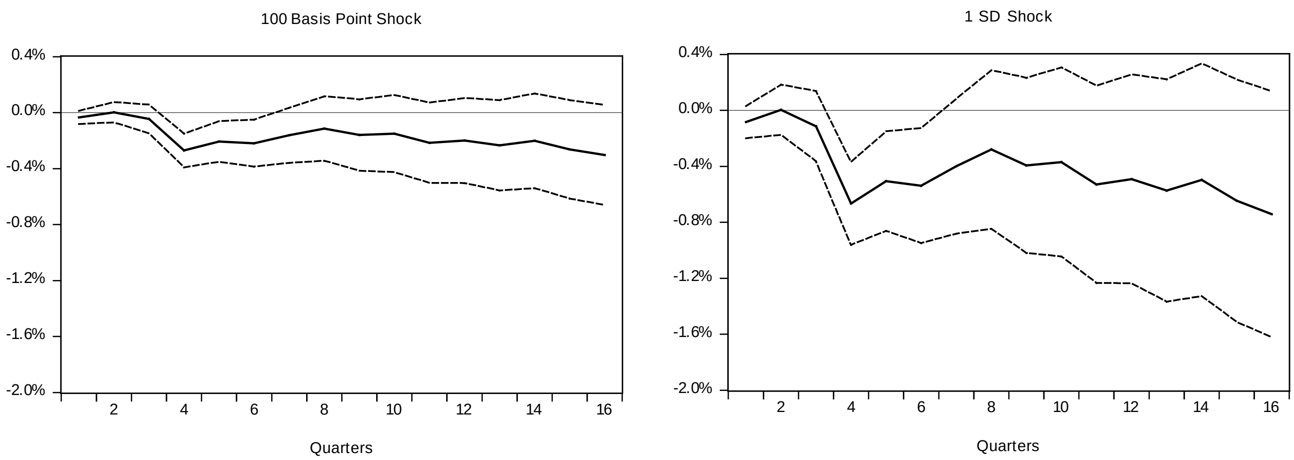


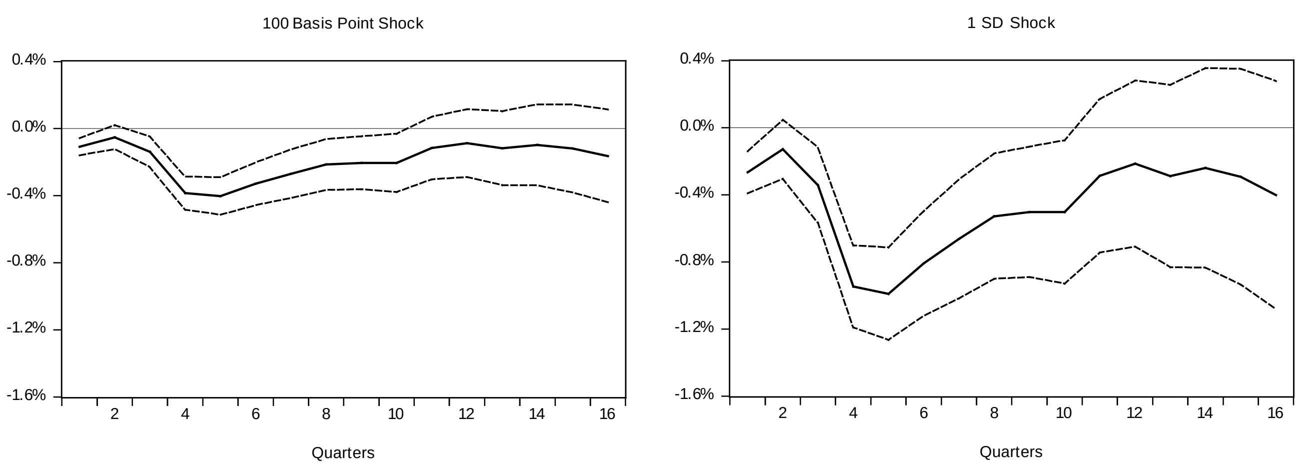
FIGURE 4

EFFECT OF FORECAST ERROR SHOCK ON GDP WITH RECESSION DUMMIES

Panel 1: Impact of Forecast Error Shock with Contemporaneous Recession Dummy



Panel 2: Impact of Forecast Error Shock with Forward Looking Recession Dummy

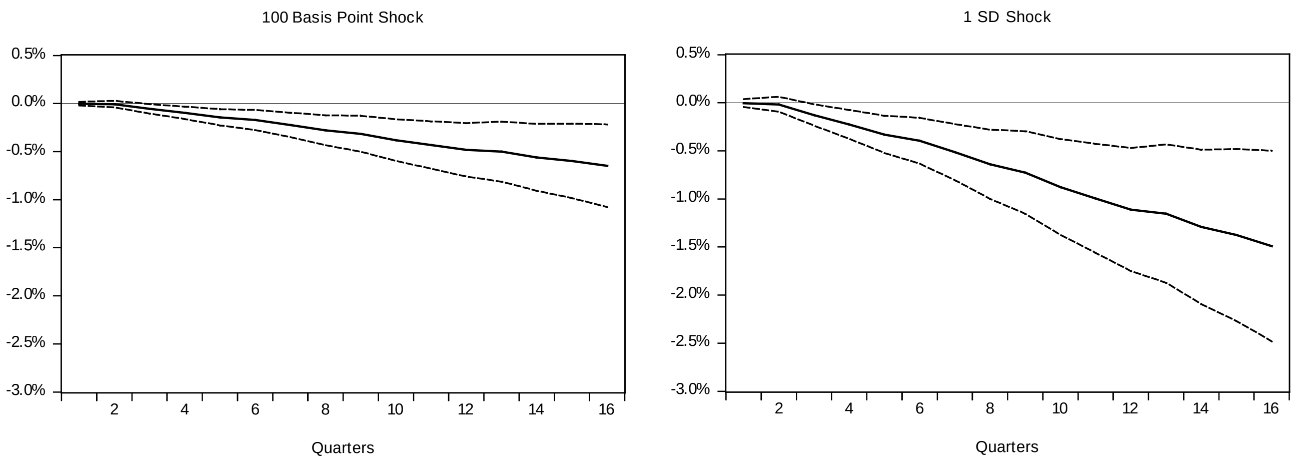


Note: Solid lines display the cumulative effect of the shock on the macroeconomic variable up to 16 quarters. Dashed lines are 1 standard error bands computed using Monte Carlo methods drawing from a multivariate normal distribution.

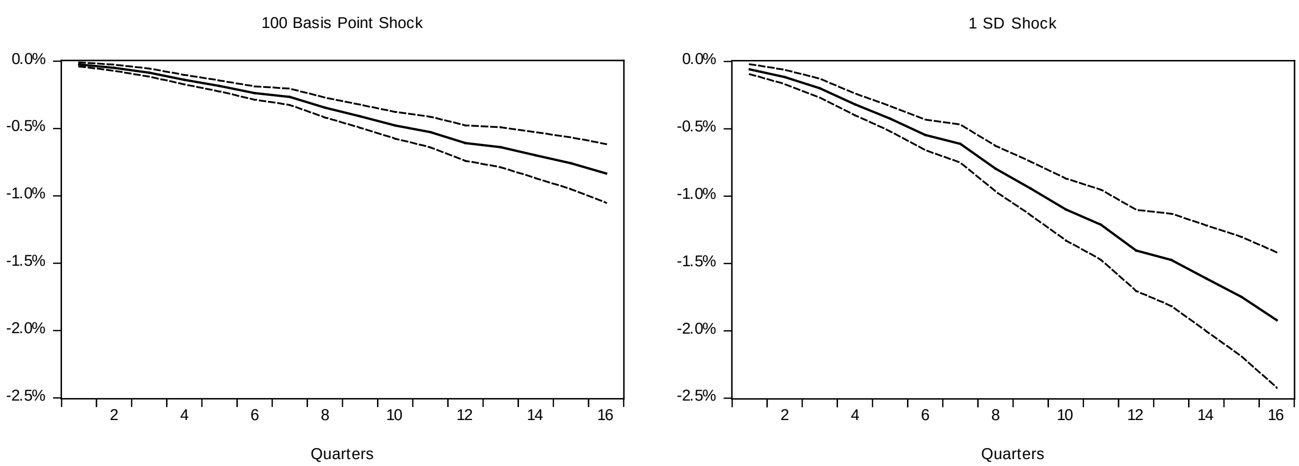
FIGURE 5

EFFECT OF FORECAST ERROR SHOCK ON GDP DEFLATOR WITH RECESSION DUMMIES

Panel 1: Impact of Forecast Error Shock with Contemporaneous Recession Dummy



Panel 2: Impact of Forecast Error Shock with Forward Looking Recession Dummy

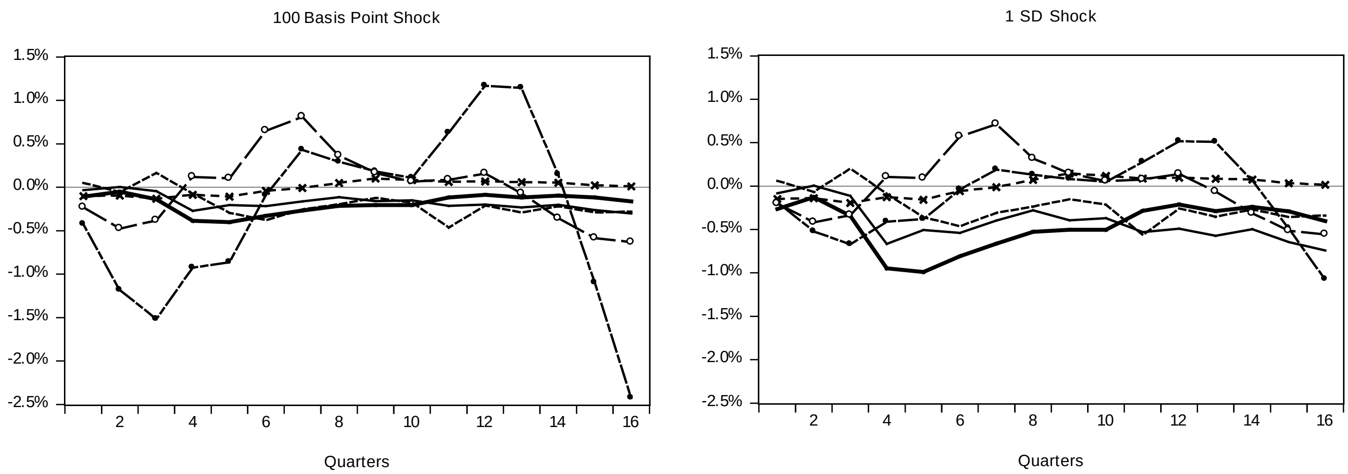


Note: Solid lines display the cumulative effect of the shock on the macroeconomic variable up to 16 quarters. Dashed lines are 1 standard error bands computed using Monte Carlo methods drawing from a multivariate normal distribution.

FIGURE 6

COMPARISONS OF THE EFFECTS OF SHOCKS WITH CONTEMPORANEOUS RECESSION DUMMY ON OUTPUT AND PRICE

Panel 1: GDP



Panel 2: GDP Deflator

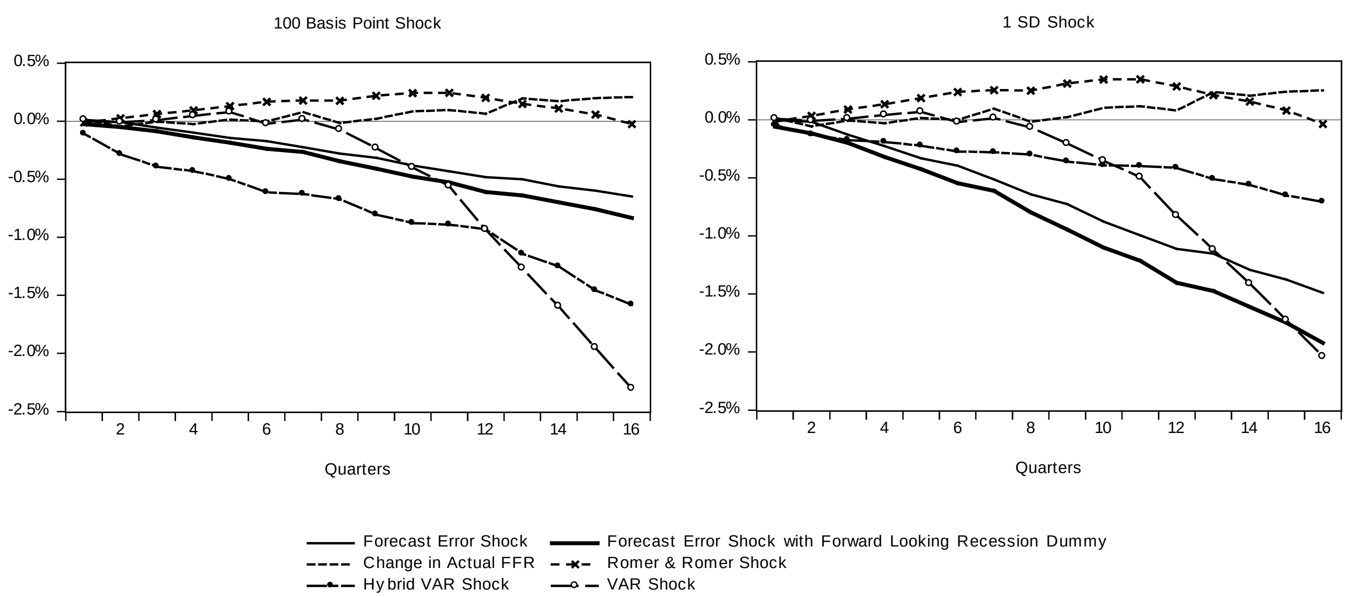
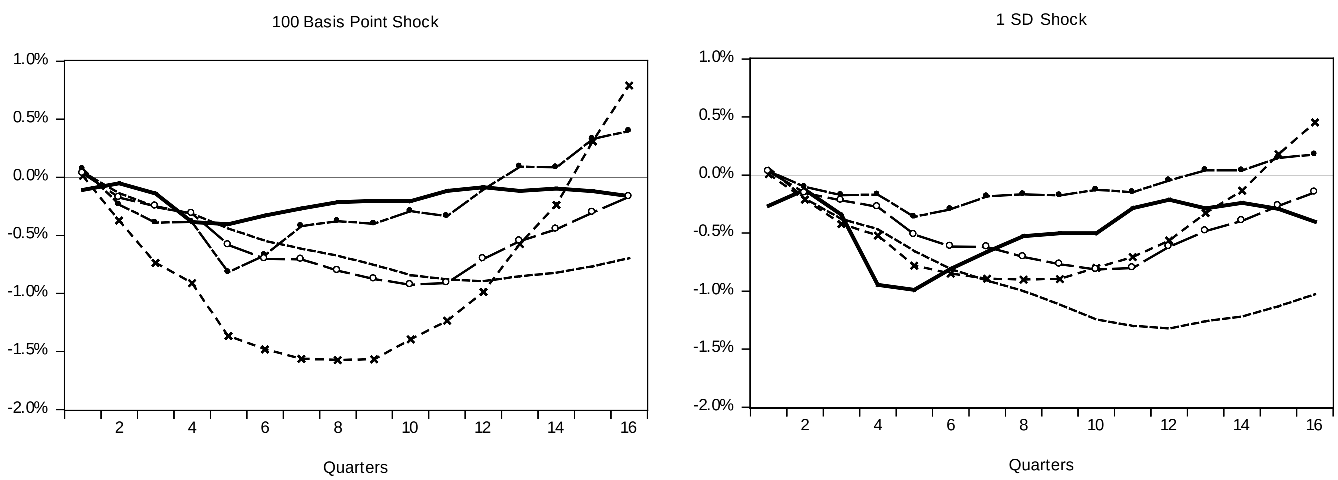


FIGURE 7

COMPARISONS OF THE EFFECTS ON OUTPUT AND PRICE OF MONETARY POLICY SHOCKS WITHOUT RECESSION DUMMIES AGAINST FORECAST EFFOR SHOCK WITH FORWARD LOOKING RECESSION DUMMY

Panel 1: GDP



Panel 2: GDP Deflator

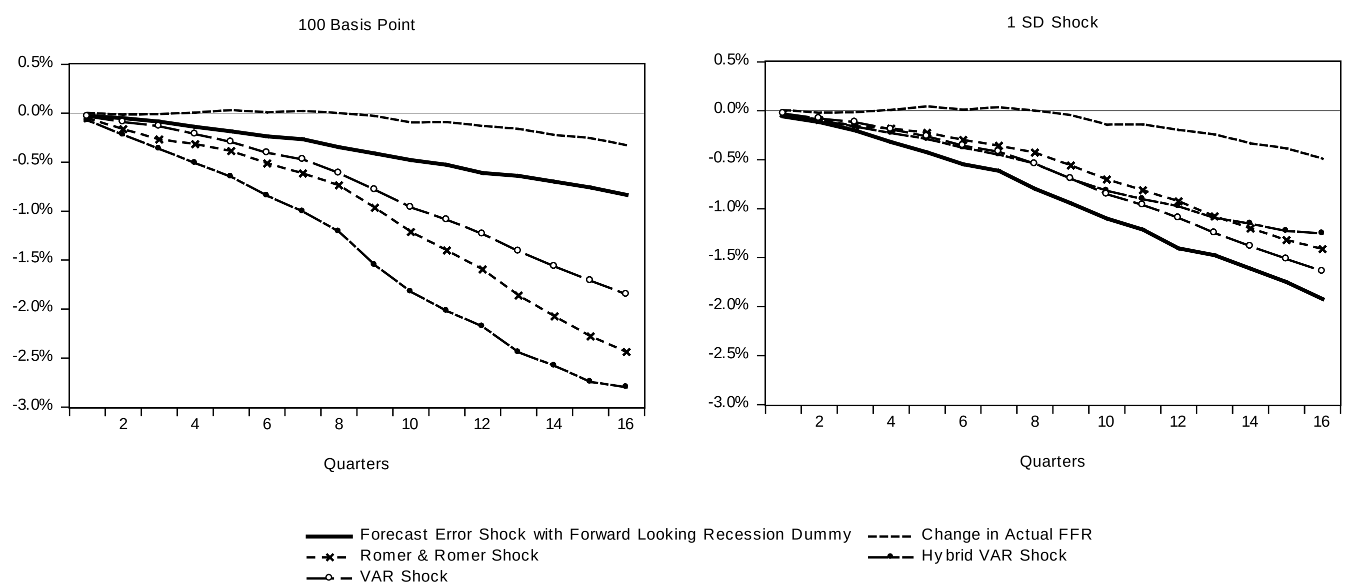
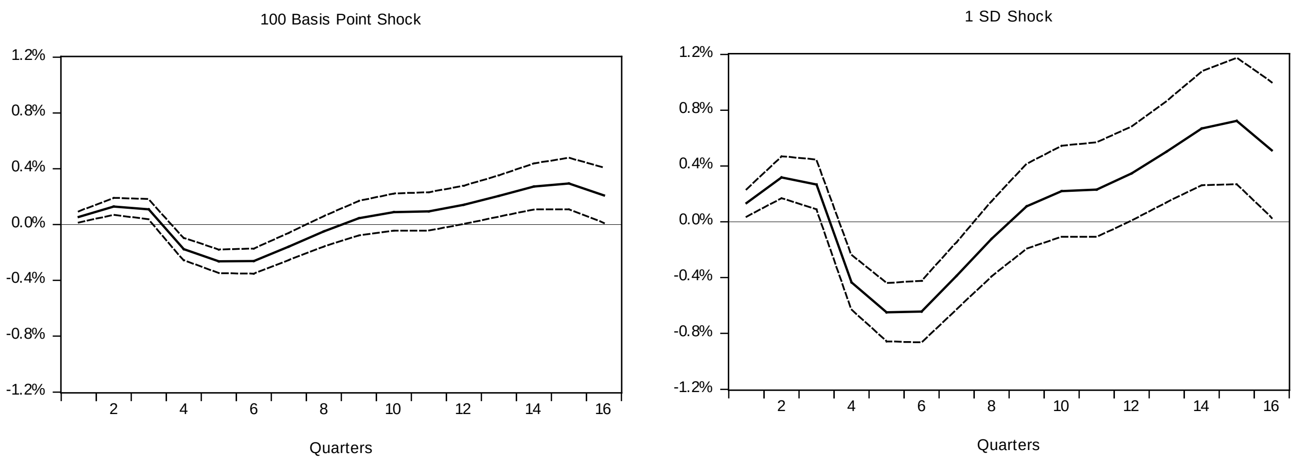


FIGURE 8

EFFECT OF SHOCKS ON INDUSTRIAL PRODUCTION (IP)

Panel 1: Impact of Forecast Error Shock on IP



Note: Solid lines display the cumulative effect of the shock on the macroeconomic variable up to 16 quarters. Dashed lines are 1 standard error bands computed using Monte Carlo methods drawing from a multivariate normal distribution.

Panel 2: Impact of All Shocks on IP

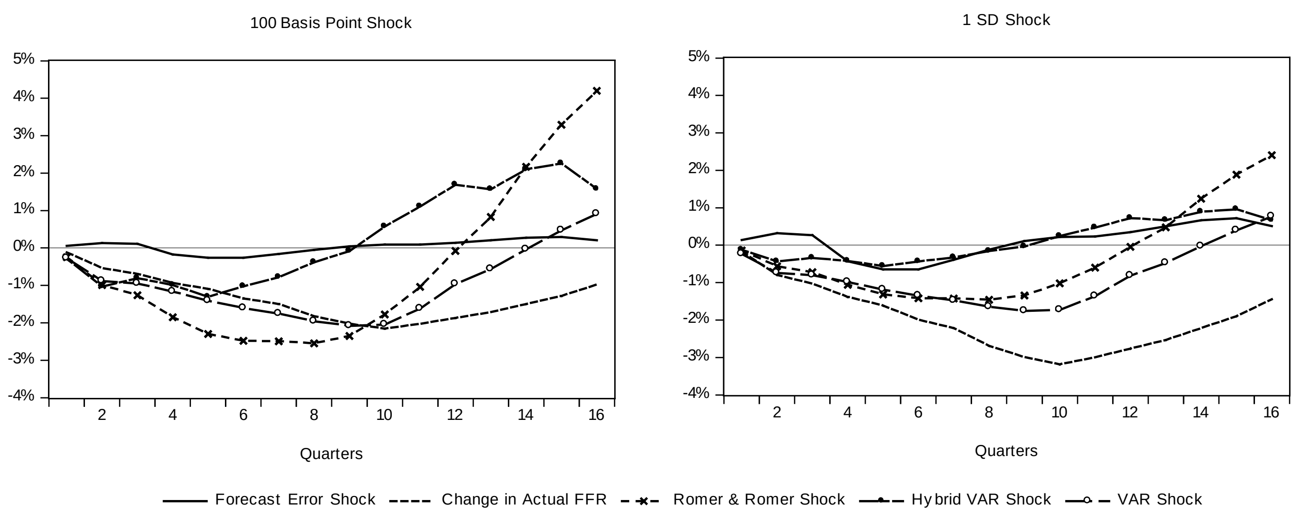
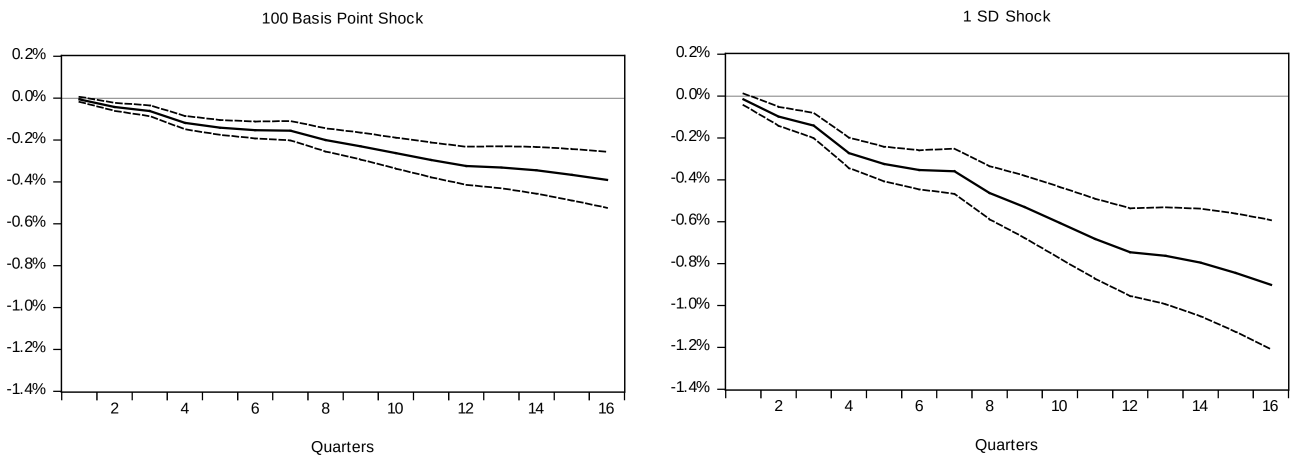


FIGURE 9

EFFECT OF SHOCKS ON PERSONAL CONSUMPTION EXPENDITURE PRICE INDEX (PCE)

Panel 1: Impact of Forecast Error Shock on PCE



Note: Solid lines display the cumulative effect of the shock on the macroeconomic variable up to 16 quarters. Dashed lines are 1 standard error bands computed using Monte Carlo methods drawing from a multivariate normal distribution.

Panel 2: Impact of All Shocks on PCE

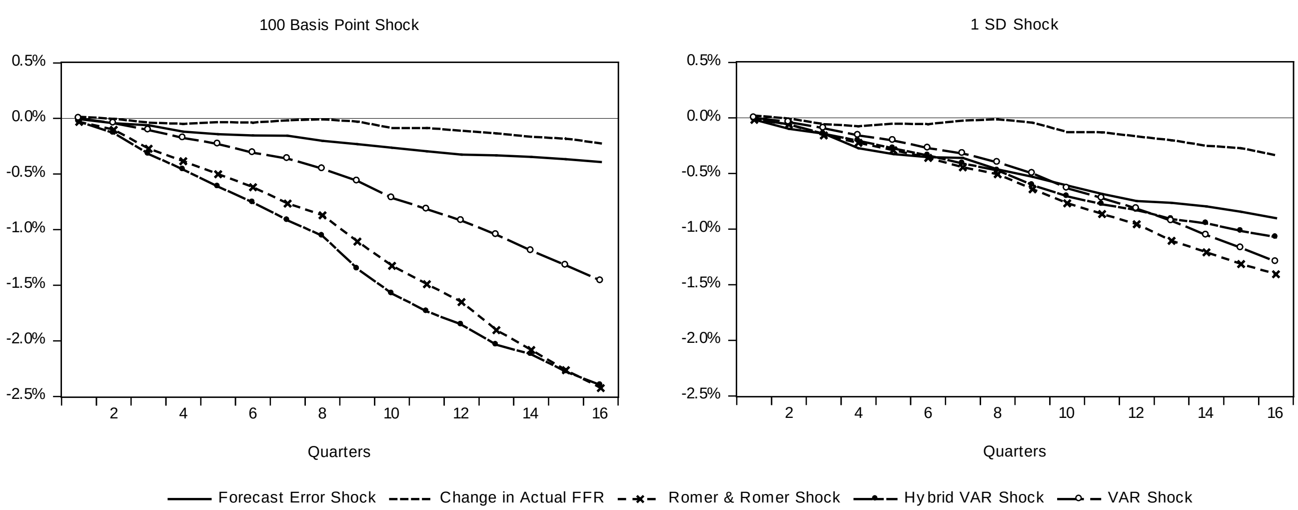
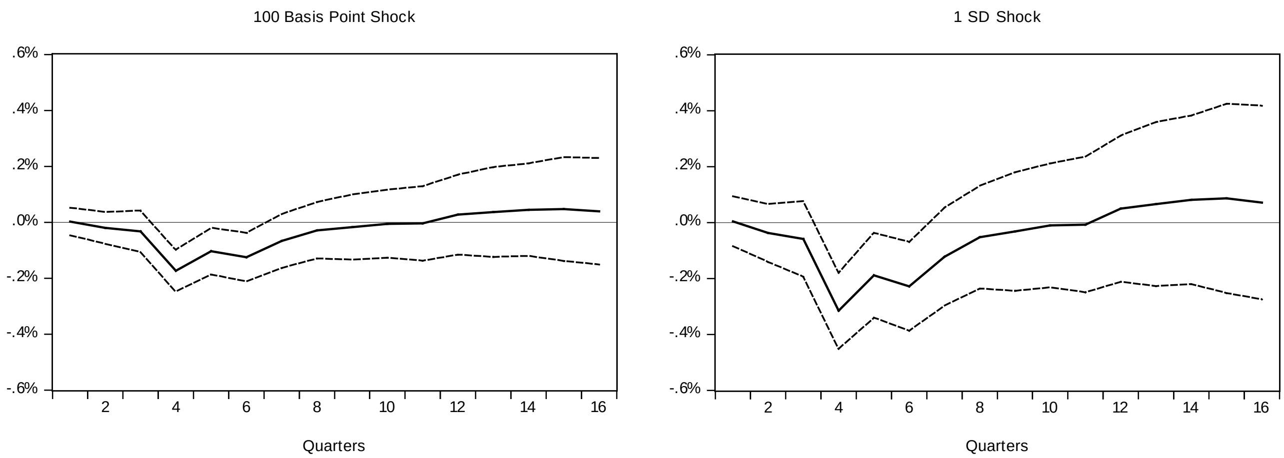


FIGURE 10

EFFECT OF SHOCKS ON GROSS DOMESTIC PRODUCT (1988Q4-2008Q2)

Panel 1: Impact of Forecast Error Shock on GDP



Note: Solid lines display the cumulative effect of the shock on the macroeconomic variable up to 16 quarters. Dashed lines are 1 standard error bands computed using Monte Carlo methods drawing from a multivariate normal distribution.

Panel 2: Impact of All Shocks on GDP

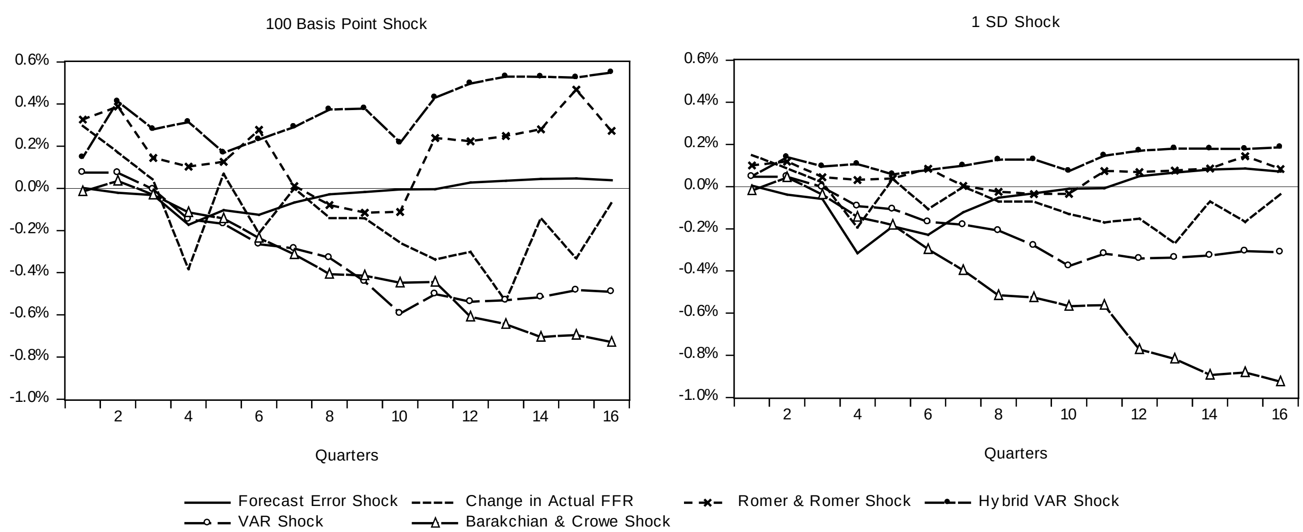
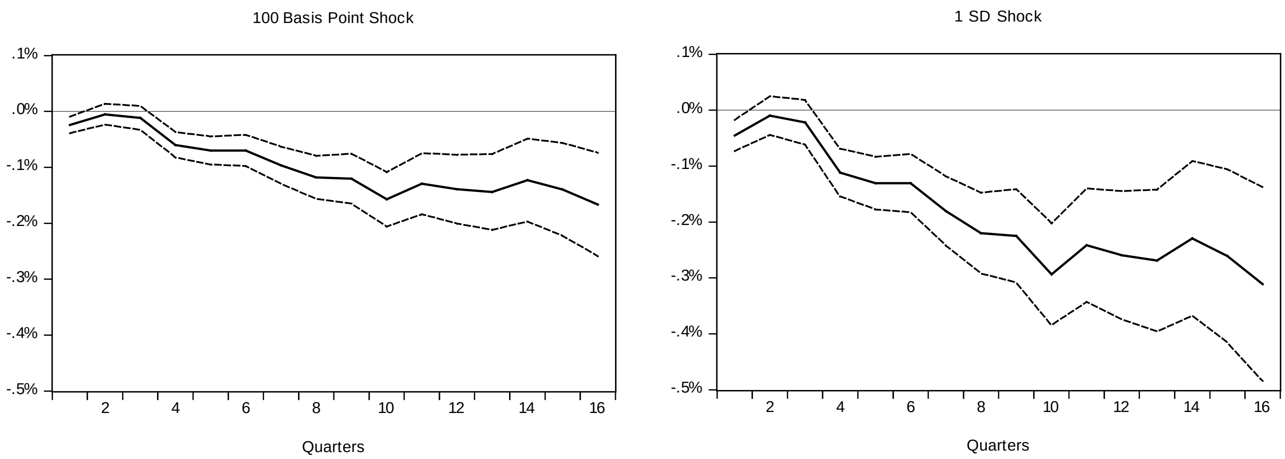


FIGURE 11

EFFECT OF SHOCKS ON GDP DEFLATOR (1988Q4-2008Q2)

Panel 1: Impact of Forecast Error Shock on GDP Deflator



Note: Solid lines display the cumulative effect of the shock on the macroeconomic variable up to 16 quarters. Dashed lines are 1 standard error bands computed using Monte Carlo methods drawing from a multivariate normal distribution.

Panel 2: Impact of All Shocks on GDP Deflator

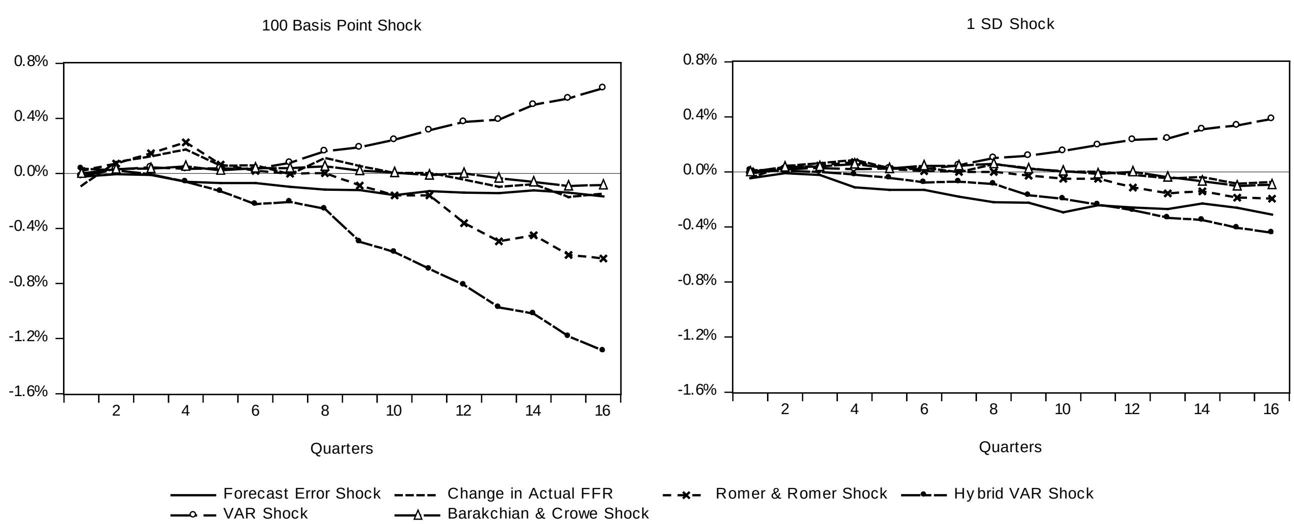
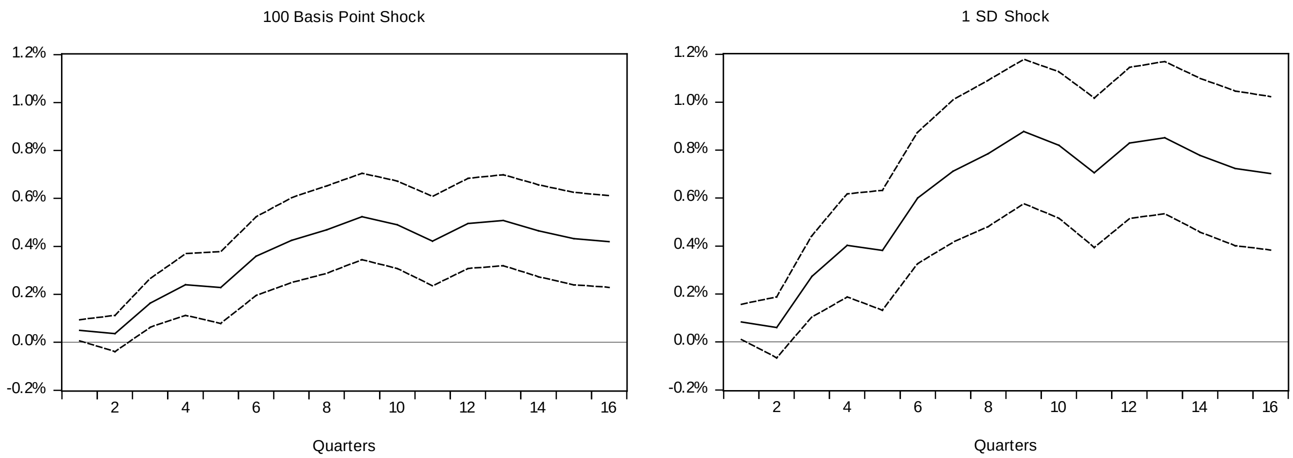


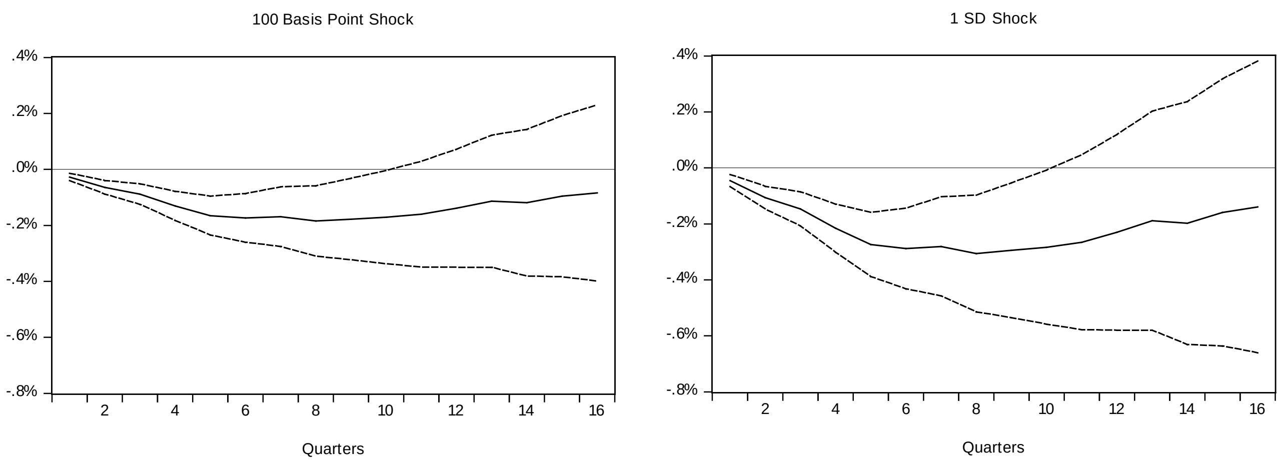
FIGURE 12

EFFECT OF FORECAST ERROR SHOCK USING NOWCAST ON GDP AND GDP DEFLATOR

Panel 1: Impact of Forecast Error Shock on GDP



Panel 2: Impact of Forecast Error Shock on GDP Deflator

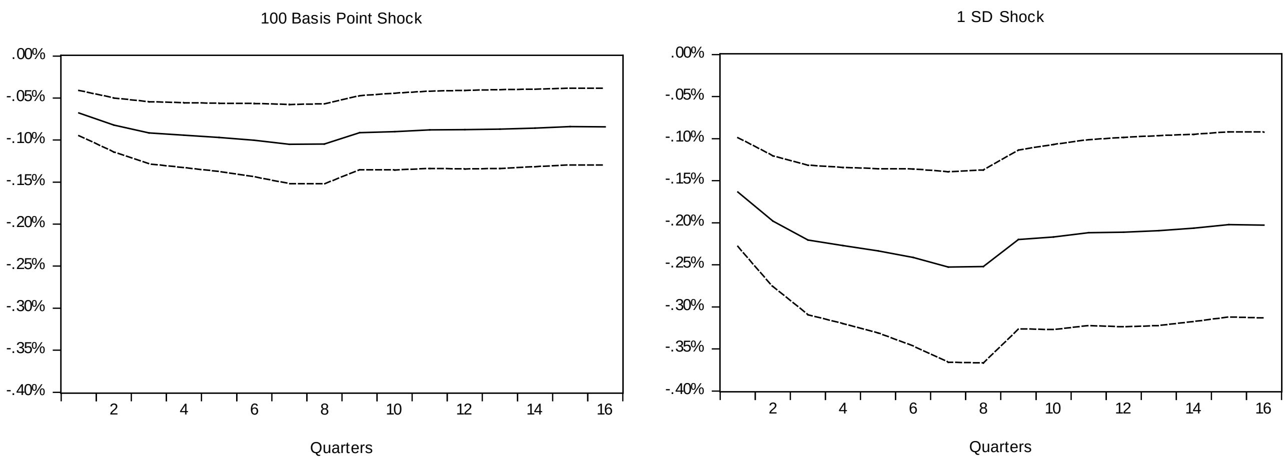


Note: Solid lines display the cumulative effect of the shock on the macroeconomic variable up to 16 quarters. Dashed lines are 1 standard error bands computed using Monte Carlo methods drawing from a multivariate normal distribution.

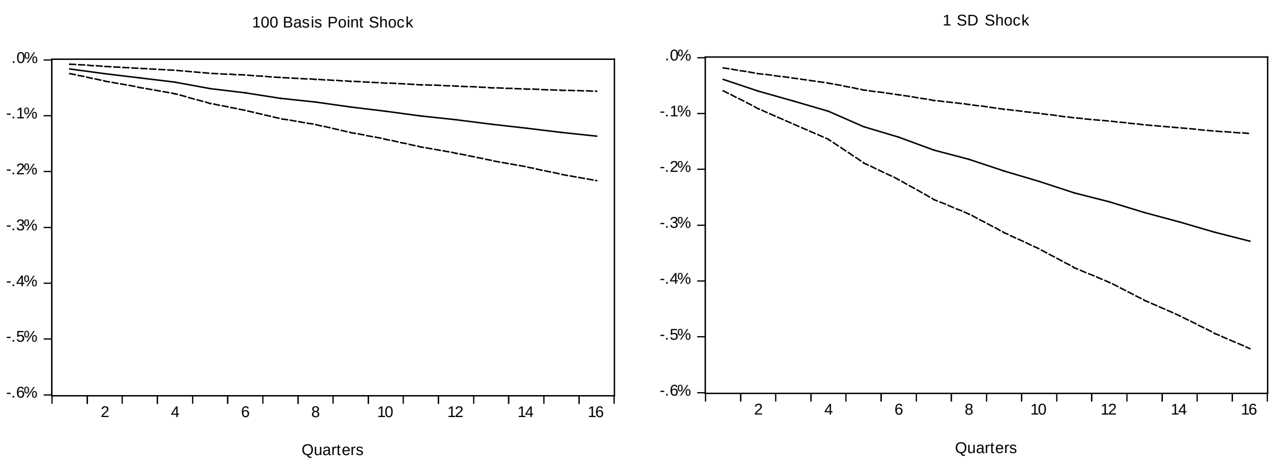
FIGURE 13

EFFECT OF FORECAST ERROR SHOCK WITH L_S = 1 ON GDP AND GDP DEFLATOR

Panel 1: Impact of Forecast Error Shock on GDP



Panel 2: Impact of Forecast Error Shock on GDP Deflator



Note: Solid lines display the cumulative effect of the shock on the macroeconomic variable up to 16 quarters. Dashed lines are 1 standard error bands computed using Monte Carlo methods drawing from a multivariate normal distribution.