



Research Program on Forecasting

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Abstract

There is a large literature evaluating the forecasts of the Federal Reserve by testing their rationality and measuring the size of their forecast errors. There is also a substantial literature and debate on the impact of the Fed's monetary policy on the economy. We know little, however about the impact of the Fed's 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, we treat the Fed's forecast errors as a shock, analogous to a monetary policy shock. Our shock, however, is different in that it is completely unintended by the monetary authority rather than simply unanticipated by the public. 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 absolute magnitude of the forecast error shock is large, the impact of the shock on the macroeconomy is quite small. This finding is robust across a range of different specifications. The maximum impact suggests a decline of less than 0.3 percent of real GDP and less than 0.4 percent of GDP deflator in response to a 100 basis point contractionary forecast error shock.

¹ The views expressed in this paper are the authors' and should not be interpreted as those of the Congressional Budget Office, the U.S. Bureau of Economic Analysis, or the U.S. Department of Commerce. Corresponding author: Pao-Lin Tien: Pao-Lin.Tien@bea.gov. 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, the University at Albany Economics Seminar, and the University of Texas at Austin macroeconomics 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.

I. Introduction

This paper presents an approach for measuring the potential economic impact of the forecast errors made by the Federal Reserve (Fed). There has been a considerable debate about the impact of monetary policy generally on the economy and there has been parallel research on the quality of the Federal Reserve's forecasts, but little is known about the impact of the Fed's forecast errors on economic outcomes. In this paper we investigate this important question.

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. Given this exogenous shock, we can implement methods typical in the monetary policy shock literature to evaluate the impact of the shock on the economy. We document that the forecast error shock is large in absolute value, consistent with the findings of Sinclair et al. (2012), where the mean absolute error (MAE) of the shock is over 175 basis points as transformed into fed funds rate units.³ Furthermore, these shocks are spread throughout the sample rather than concentrated in a

² See, for example, Romer and Romer (2000), Gamber and Smith (2009), and El-Shagi et al. (2014).

³ 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.

few key time periods. Although the Fed is on target on average, the federal funds rate is far away 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, however Romer and Romer (2008) and Nunes (2013) have found that the Greenbook forecasts are of higher quality than the FOMC forecasts.⁴ 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.⁵ Thus we focus on the Greenbook forecasts in this paper.

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 to economic events then they should be a valid shock measure. Our approach differs from the line of literature focused on capturing *unexpected* monetary policy. This research on measuring

⁴ 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. One reason why the FOMC projections may be less accurate is that they are released immediately. Therefore, they may be used for communication purposes and/or experience political pressures in a way that the Greenbook forecasts are not, since the Greenbook forecasts are released with a 5 year lag.

⁵ 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. 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).

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. Our shock 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.⁶

We examine the role of our forecast error shock using the same regression methodology as Romer and Romer (2004, henceforth R&R).⁷ To interpret the size of the impact we find, we compare the effect of our shock on output and prices to the effects generated by 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.⁸ In the baseline model, our results are consistent with the literature in that we find the R&R shock 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. Thus our unintended shock has a much smaller economic effect than unanticipated shocks.

Section II presents a review of monetary policy shock measures that we use for comparison to interpret the magnitude of the impact of the Fed's forecast errors on the economy. Section III presents our methodology for constructing the shock. Section IV describes the data and our regression methodology, Section V details our baseline empirical results, and Section VI

⁶If the Federal Reserve attempts to minimize monetary policy surprises then the unexpected component of monetary policy is likely to be small. 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. In this case our forecast error measure might also be an appropriate measure of a monetary policy shock.

⁷ 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).

⁸ Using the terminology coined by Coibion (2012).

presents various alternative specifications and robustness checks of our analysis. We offer concluding remarks and discuss the implications of our results in Section VII.

II. A Brief Review of Monetary Policy Shock Measures

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

$$(1) \quad r_t = r_{t|t-i} + shock_t,$$

where r_t is the policy instrument and $r_{t|t-i} = E[r_t | \Omega_{t-i}]$ is the public's expectation of the policy instrument based on information set Ω_{t-i} , $i = 1, 2, 3, \dots$. The difference between the expectation and the actual values of the instrument, $shock_t$ measures the unanticipated movement in policy.

The measure of monetary policy shocks described by equation (1) is clearly sensitive to the researcher's choice of information set. Different approaches make different choices. For example, in the VAR approach, 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. Forecasters may also include forecasts of macroeconomic variables in Ω_{t-i} . In Romer and Romer (2004) and Thapar (2008), for example, Ω_{t-i} contains the Federal Reserve's Greenbook forecasts.

There are two dimensions to the choice of information set: 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.⁹ 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) argue 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 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.

⁹ 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, et al. (2005) adopts the FAVAR (factor-augmented VAR) approach that incorporates a balanced panel of 120 macroeconomic time series.

Kuttner (2001), Poole and Rasche (2003), Lange et al. (2003), Swanson (2006), and Barakchian and Crowe (2013) 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 after 1994 in the proportion of federal funds interest rate targets that is due to monetary surprises.

Nevertheless 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 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. Similar to Coibion (2012), we look at:

- R&R narrative monetary policy shock¹⁰
- Monetary policy shock extracted from a standard 3 variable (output, price, fed funds rate) VAR identified using short-run Cholesky decomposition.¹¹ 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 but with the cumulated R&R shock replacing the fed funds rate.

¹⁰ 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.

¹¹ 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.

III. 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 (2) below, where the superscript “ f ” denotes that the target is based on forecasted variables.¹² The Fed’s interest rate target (i_t^{Tf}) is written as:

$$(2) \quad i_t^{Tf} = r^* + \pi_{t+h|t}^f + 0.5(\pi_{t+h|t}^f - \pi^*) + 0.5(y_{t+h|t}^f - y^*),$$

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.¹³ The Fed forecasts both inflation, $\pi_{t+h|t}^f$, and output growth, $y_{t+h|t}^f$, h periods ahead. We note that this baseline specification assumes fixed weights and does not include smoothing, but we explore a range of weights and a range of smoothing parameters in Section VI.

¹² 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).

¹³ 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 $\ln(Y_t^f) - \ln(Y_{t-1}^f)$. Thus, when we subtract one from the other for the policy forecast error, we have $\ln(Y_t) - \ln(Y_t^f)$. Approximating the output gaps in the same manner, we have $\ln(Y_t) - \ln(Y^*)$ and $\ln(Y_t^f) - \ln(Y^*)$, so again we have $\ln(Y_t) - \ln(Y_t^f)$. 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).

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+h}^T) would have been:

$$(3) \quad i_{t+h}^T = r^* + \pi_{t+h} + 0.5(\pi_{t+h} - \pi^*) + 0.5(y_{t+h} - y^*),$$

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+h}^T and i_{t+h}^{Tf} 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:

$$(4) \quad shock_t = i_{t+h}^T - i_{t+h}^{Tf} = 1.5(\pi_{t+h} - \pi_{t+h|t}^f) + 0.5(y_{t+h} - y_{t+h|t}^f).$$

The differences, $(\pi_{t+h} - \pi_{t+h|t}^f)$ and $(y_{t+h} - y_{t+h|t}^f)$, are the Fed's forecast errors for the inflation rate and real output growth respectively. In equation (4) 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

$$(5) \quad shock_t = -\left(i_{t+h}^T - i_{t+h}^{Tf}\right) = 1.5\left(\pi_{t+h|t}^f - \pi_{t+h}\right) + 0.5\left(y_{t+h|t}^f - y_{t+h}\right)$$

to be directly comparable with the monetary policy shock measures.¹⁴ Throughout the results section we will be focusing on a contractionary shock.

IV. Data and Regression Methodology

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)¹⁵ 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 for comparison. 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

¹⁴ A negative innovation in the forecast error shock described by equation (4) 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 the shock series should be equivalent to a contractionary monetary policy shock. However, for the commonly used measures of monetary policy shocks, a negative innovation in the shock series represents expansionary monetary policy. Therefore, to be comparable with the literature on monetary policy shocks, we work with the inverse of the shock series in equation (4).

¹⁵ The last forecast in the fourth quarter of 1991 was the first forecast of GDP.

deflator price index (seasonally adjusted, 2009 = 100) as our price measure.¹⁶ The sample period we consider goes from 1974Q2 to 2008Q2. The basic specification is set up as follows:

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

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). We then 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. We provide baseline results in Section V and then follow with alternative specifications and robustness checks in Section VI.

V. Results

¹⁶ Alternative measures of output and prices are considered in Section VI.

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 forecast error shock and the others is that it has a much larger magnitude. 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.

a. The Impact of Forecast Error Shocks on Output

Figure 2 illustrates the impact of the forecast error shock on output. 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.¹⁷ 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 only about 0.19%, and this number is statistically significant with two standard error confidence interval.

¹⁷ 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.

To put this result in context, Panel 2 illustrate the impact of a 1 standard deviation forecast error shock, along with the monetary policy shocks we're including for comparison, on output. We use one standard deviation innovation here because a 100 basis point shock is a rather small forecast error. 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 considered are all smaller than 100 basis points. Hence we believe that a one standard deviation shock provides a more appropriate comparison. Not surprisingly, the estimated impact of the forecast error shock on GDP reported in Panel 2 is larger than that reported in Panel 1 (the maximum decline in output is just below 0.5% at the maximum). But the response of GDP is quite muted, particularly over longer horizons, when compared with the other shocks used in the literature. The R&R narrative shock have the largest impact (0.9% decline at the peak) on GDP, the VAR shock's effect is similar in magnitude to the R&R narrative shock, but the hybrid VAR shock generates a much milder response. All the shocks produce similar dynamics where the declines in output eventually dissipate.

b. The Impact of Forecast Error Shocks on Prices

Panel 1 in Figure 3 illustrates the impulse response of price 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 Panel 2 the IRFs of price for the commonly used monetary policy shocks along with the forecast error shock on a 1 standard deviation scale. From both of these panels 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 (16th quarter, 1 standard deviation shock). The R&R narrative

shock 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).

Overall, given these baseline estimations, the macroeconomic cost of forecast errors, in terms of output and price as measured by GDP and GDP deflator, appears to be small.

VI. Alternative Specifications and Robustness Checks

c. 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.

The impulse responses are presented in Figures 4. Our result for IP (Panel 1) is very similar to that reported for GDP, though IP appears to react more strongly than GDP to the same 100 basis point increase in the forecast error shock.¹⁸ For PCE (Panel 2), the dynamics of the impulse response is again similar to that exhibited by the benchmark price variable: the GDP deflator. The magnitude of the IRF in this case does 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.

d. Limiting the Sample Size

¹⁸ Though not shown in Figure 4, IP reacts more strongly to all other monetary policy shocks considered.

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 used the shocks constructed for the full sample (1974Q2 to 2008Q2) and removed the data prior to 1988Q4 to re-estimate equation (6) for the shorter sample. Figure 5 presents the restricted sample results for GDP and Figure 6 presents the results for GDP deflator. We also include an additional monetary policy shock constructed by B&C here for comparison.¹⁹

Panel 1 in both Figures 5 and 6 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

¹⁹ 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 inherent in the other monetary policy shocks under consideration here post 1988.

similar to using full sample (maximal decline in GDP is 0.19% for the full sample versus 0.17% 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 (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 5 and 6 shows some interesting comparisons of our shock against the other monetary policy shocks. Similar to what is reported in B&C, a contractionary impulse in many of the popular monetary policy shocks cause an increase in output. The exceptions are the VAR shock and the B&C shock. As for the price variable, the hybrid VAR shock generates the expected decline in price along with our shock series, but all other shocks end up with a price puzzle over some or all horizons.

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.

e. The Role of Forecast Horizon

There is not consensus 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.²⁰ We considered here an alternative forecast horizon, the two quarter ahead forecast. The two quarter horizon is within the range of the “six to twelve months” that former Fed Chair Alan Greenspan

²⁰ 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.

mentioned as being critical in formulating monetary policy in a 1997 testimony before the Senate Committee on the Budget (Orphanides 2001). The results of replacing the 4 quarter ahead forecasts with the 2 quarter ahead forecasts of GDP and GDP deflator are presented in Figure 7. In general, the results presented here are almost identical to those presented in Figures 2 and 3. So our observation that the forecast error shock has little macroeconomic impact on output and price remains robust to a change in the forecast horizon of the data that we feed into the monetary policy rule.

f. Reducing the Lags of the Shock Series

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 8. For both GDP and GDP deflator, the results are qualitatively similar to those using 12 (for output) or 16 (for price) lags. Both output and price decline in response to a contractionary forecast error shock. Quantitatively, the peak effects on the macro variables are smaller than that reported for the benchmark specification. So the economic significance of the forecast error shock remains small under this alternative specification.

g. Alternative Weights for the Taylor Rule

There have been many different estimates of the weights placed on the inflation and output components of the Taylor Rule. We cannot estimate the weights and still have an

exogenous shock measure which is why we initially took the original Taylor weights for our baseline. Here we explore a range of weight options by varying the weights in the forward looking Taylor Rule we use to construct our shock (equations 2 and 3) from no weight on the inflation gap and full weight on the output gap to full weight on inflation gap and no weight on output gap in increments of 0.1. Given the way the shock (equation 5) is constructed, this means the weights on the inflation and output components for the shock series will vary from 1:1 (1 on the inflation component in equation 5 and 1 on the output component) to 2:0 (2 on the inflation component in equation 5 and 0 on the output component). Note that the benchmark specification has a 1.5:0.5 weight, and the weights have to add up to 2.

Figure 9 illustrates the range of effects on output and price in response to a 100 basis point contractionary forecast error shock with varying weights. To make the presentation more succinct, we display the IRF of the benchmark specification and the IRFs of the weighting scheme that gives us minimal as well as maximal peak effect on the macro variables. In general, as the weight on output increases, the effect of the forecast error shock on output increases (and becomes more persistent). However, the maximum peak effect for a 100 basis point shock is still just -0.24%. For the deflator, as we increase the weight on the output gap, the impact of the shock becomes slightly larger until the benchmark weights, then it starts to shrink. Hence the peak effect on deflator is generated by the benchmark weight which is -0.32% at the 16th quarter for a 100 basis point shock.²¹

h. Interest Rate Smoothing

²¹ We also tried this exercise on the shortened sample period (1988Q4 to 2008Q2) considered in part b of this section. It has been argued that the Fed began placing heavier weights on the inflation component in the Taylor Rule during this latter period (e.g. Clarida, Gali, Gertler, 1999). Changing the weights for the shorter sample period generated quantitatively and qualitatively similar results. The peak effect of the forecast error shock on output and price remain small.

There has also been debate in the literature about the amount of interest rate smoothing implemented by the Fed. If we include smoothing in our Taylor Rule we get the following equation for our shock:

$$(7) \quad shock_t = \rho \left(i_{t-1|t-1}^{Tf} - i_{t-1|t-1+h}^T \right) + (1 - \rho) \left[1.5 \left(\pi_{t+h|t}^f - \pi_{t+h} \right) + 0.5 \left(y_{t+h|t}^f - y_{t+h} \right) \right],$$

Similar to the exercise for the weights in the Taylor rule, we consider a range of values for the smoothing parameter, ρ , from 0 to 1 in 0.1 unit increments. Note that $\rho = 0$ gives us the benchmark case. Here again we find that smoothing makes little difference in terms of the economic impact of the forecast error shock. In Figure 10 we present, for simplicity, just the benchmark case as well as a large value for the smoothing parameter (0.8), which is one of the values proposed by Clarida et al (2000).

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, our forecast error measure

should be a valid exogenous shock. 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 from traditional monetary policy shocks. That is reassuring, as we would hope that forecast errors do 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. Our findings are robust to a range of specifications of the Taylor rule and do not appear sensitive to the sample chosen. Thus despite the large errors of the Fed, these forecasting mistakes appear to have little impact on economic outcomes.

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TABLE 1

RATIONALITY TEST RESULTS FOR FORECAST ERROR SHOCK

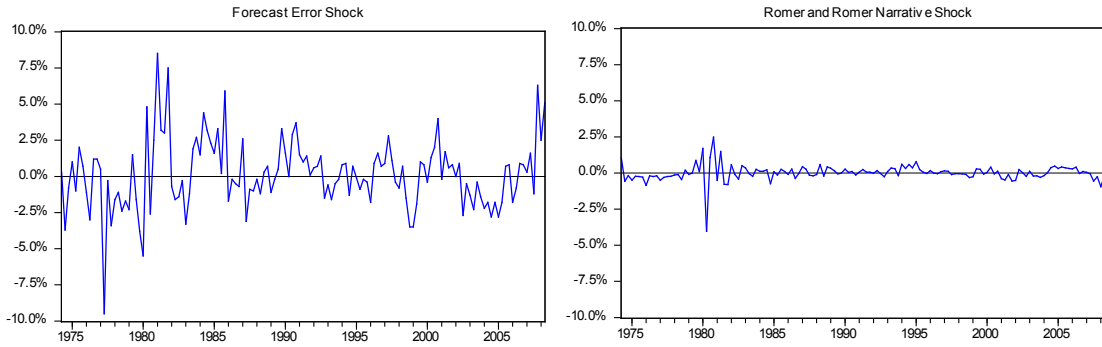
Dependent Variable	Constant	AR(1)	AR(2)
Forecast error shock	-0.137226 (0.205085)		
Forecast error shock	-0.225745 (0.356776)	0.231489** (0.085040)	0.224262** (0.085365)

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

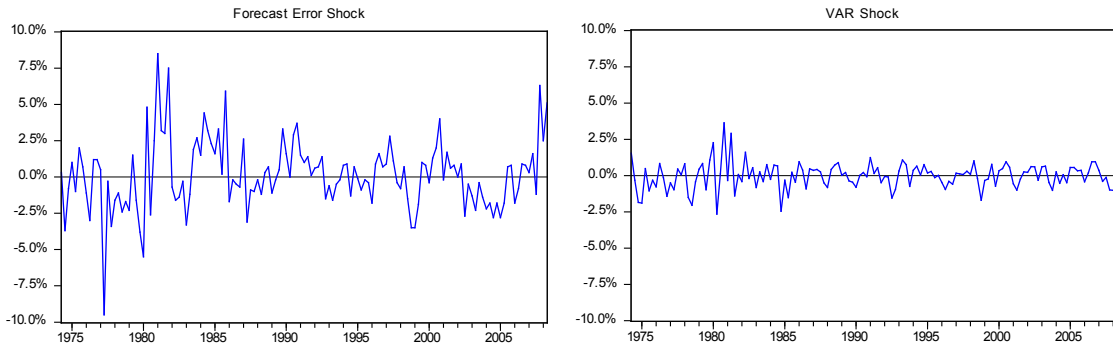
FIGURE 1

MEASURES OF MONETARY POLICY SHOCKS VERSUS FORECAST ERROR SHOCK

Panel 1



Panel 2



Panel 3

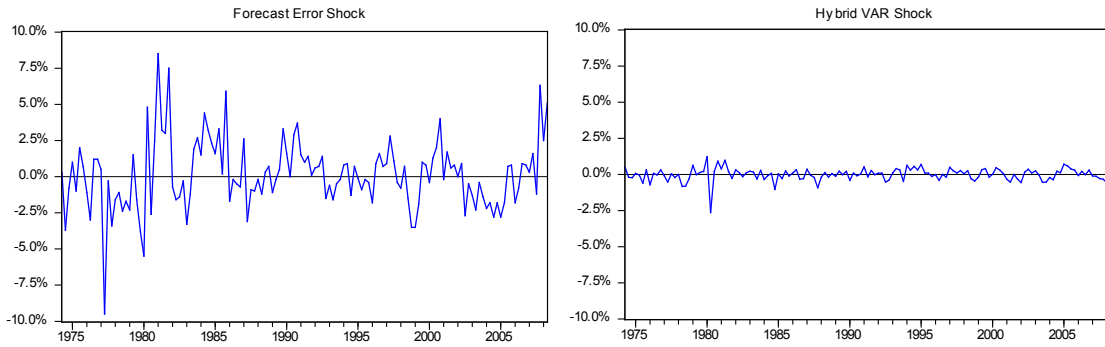
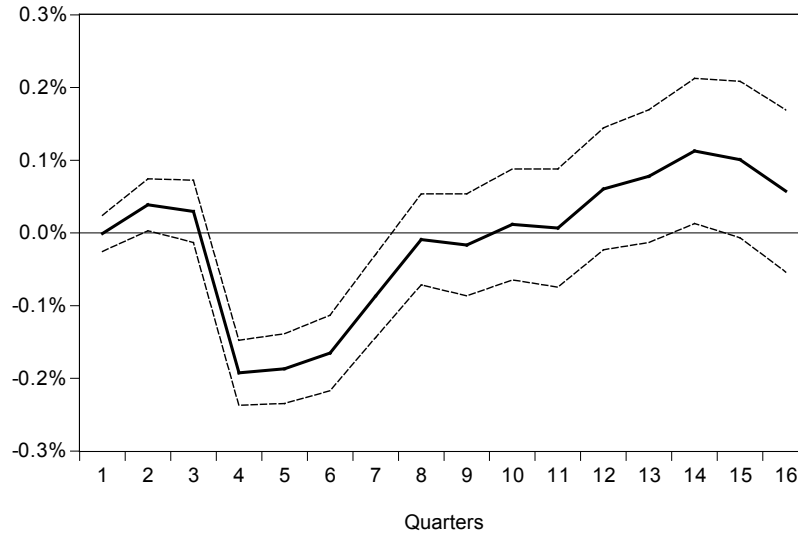


FIGURE 2

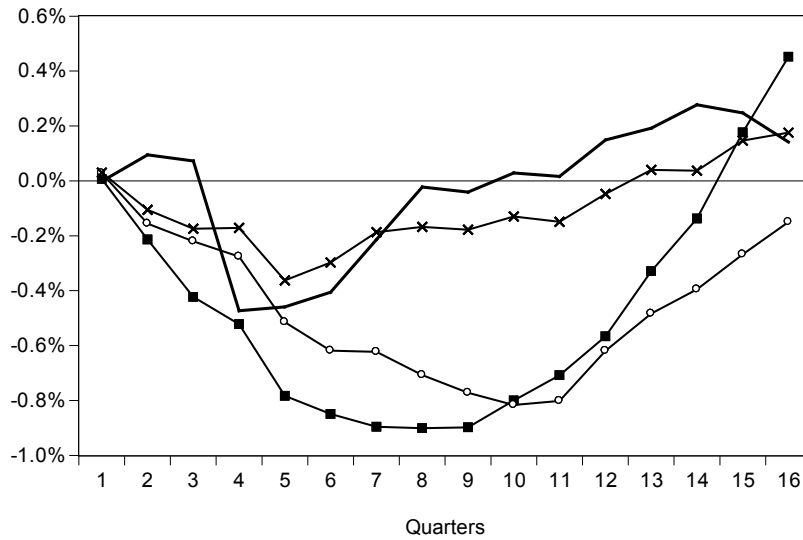
EFFECT OF SHOCKS ON GROSS DOMESTIC PRODUCT (GDP)

Panel 1: Impact of Forecast Error Shock (100 basis point) 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 (1 standard deviation) on GDP

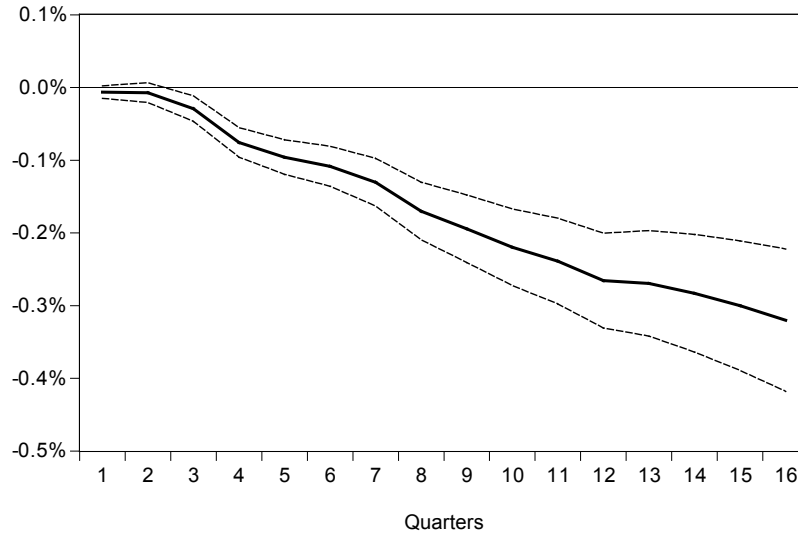


— Forecast Error Shock —■— Romer & Romer Shock —○— VAR Shock —×— Hybrid VAR Shock

FIGURE 3

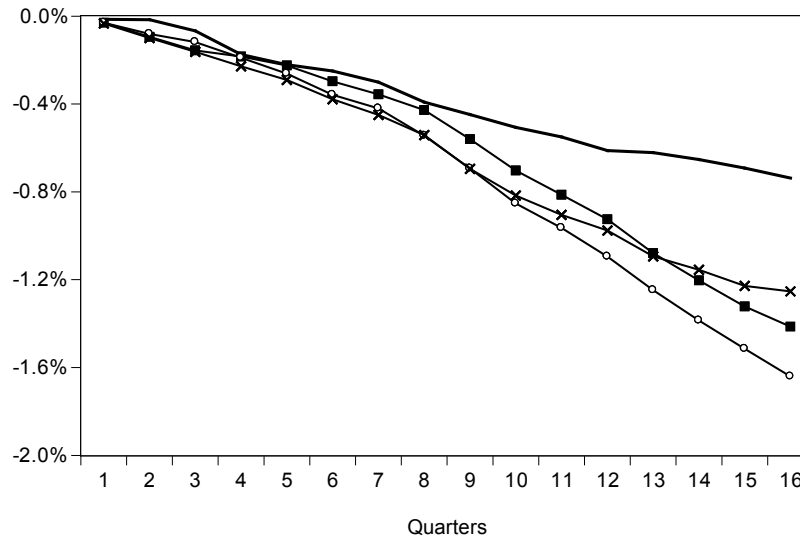
EFFECT OF SHOCKS ON GDP DEFLATOR

Panel 1: Impact of Forecast Error Shock (100 basis point) 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 (1 standard deviation) on GDP Deflator

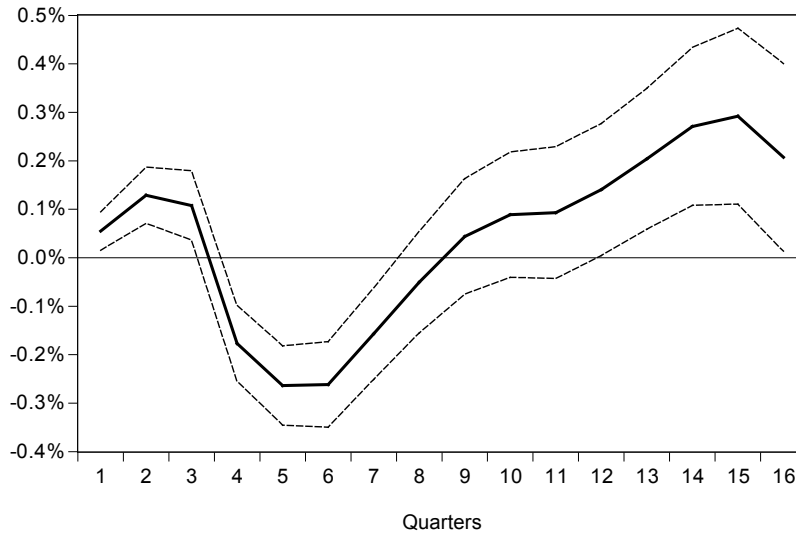


— Forecast Error Shock —■— Romer & Romer Shock —○— VAR Shock —×— Hybrid VAR Shock

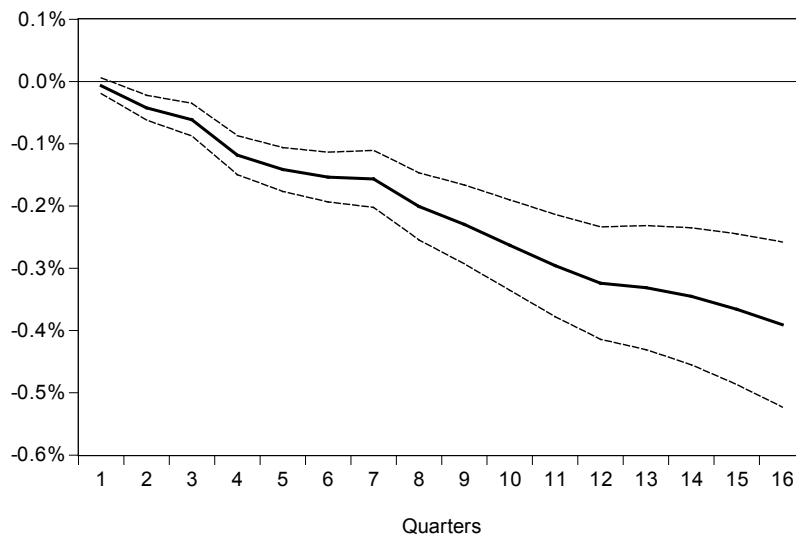
FIGURE 4

EFFECT OF FORECAST ERROR SHOCK ON ALTERNATIVE OUTPUT AND PRICE MEASURES

Panel 1: Impact of Forecast Error Shock (100 basis point) on IP



Panel 2: Impact of Forecast Error Shock (100 basis point) on PCE

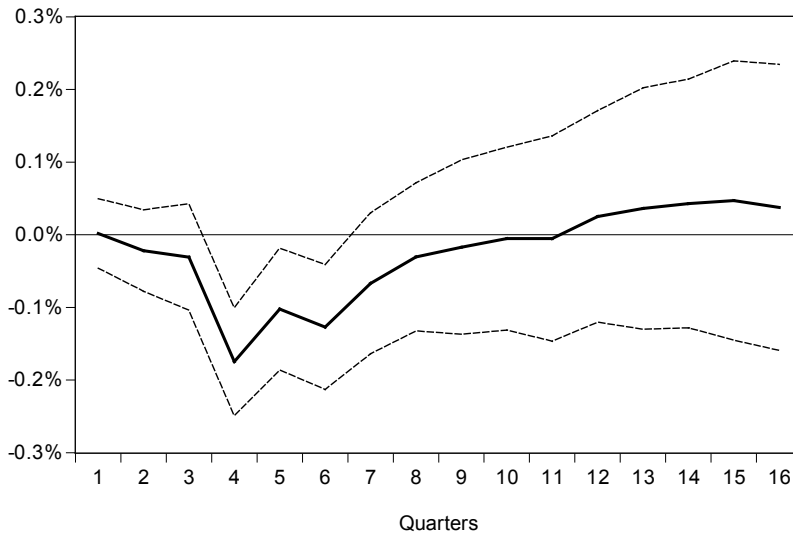


Note: Solid lines display the cumulative effect of the shock on the macroeconomic variable up to 16 quarters. Dashed lines are 1 standard error bands computed using Monte Carlo methods drawing from a multivariate normal distribution.

FIGURE 5

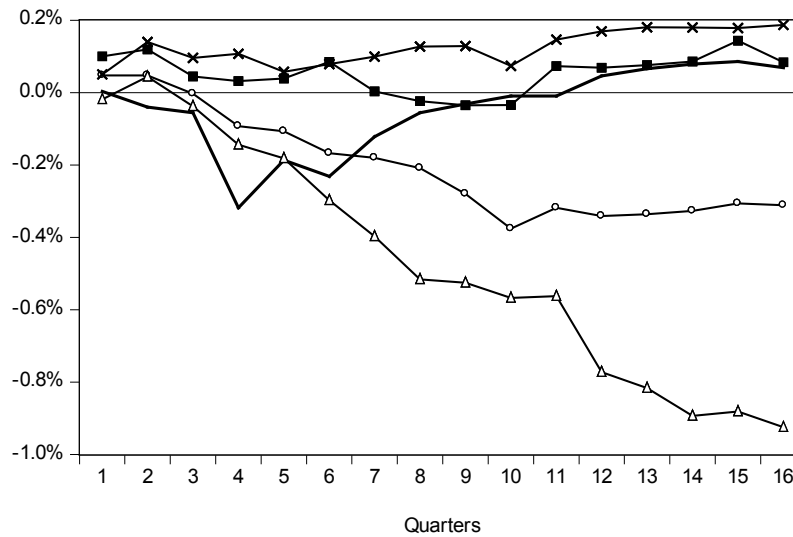
EFFECT OF SHOCKS ON GROSS DOMESTIC PRODUCT (1988Q4-2008Q2)

Panel 1: Impact of Forecast Error Shock (100 basis point) 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 (1 standard deviation) on GDP

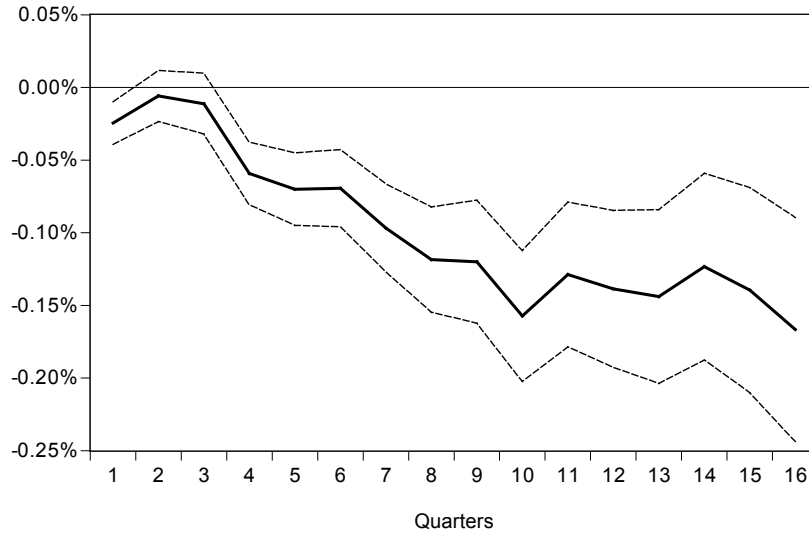


— Forecast Error Shock ■ Romer & Romer Shock ○ VAR Shock × Hybrid VAR Shock △ Barakchian & Crowe Shock

FIGURE 6

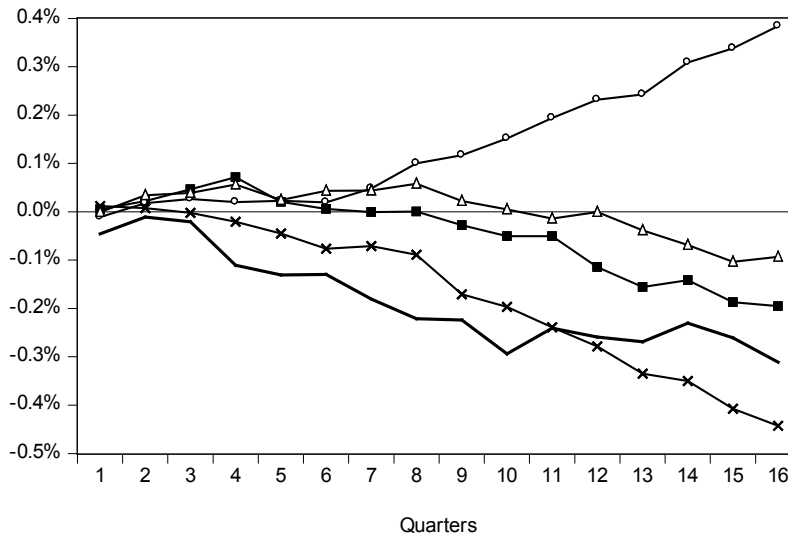
EFFECT OF SHOCKS ON GDP DEFLATOR (1988Q4-2008Q2)

Panel 1: Impact of Forecast Error Shock (100 basis point) 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 (1 standard deviation) on GDP Deflator

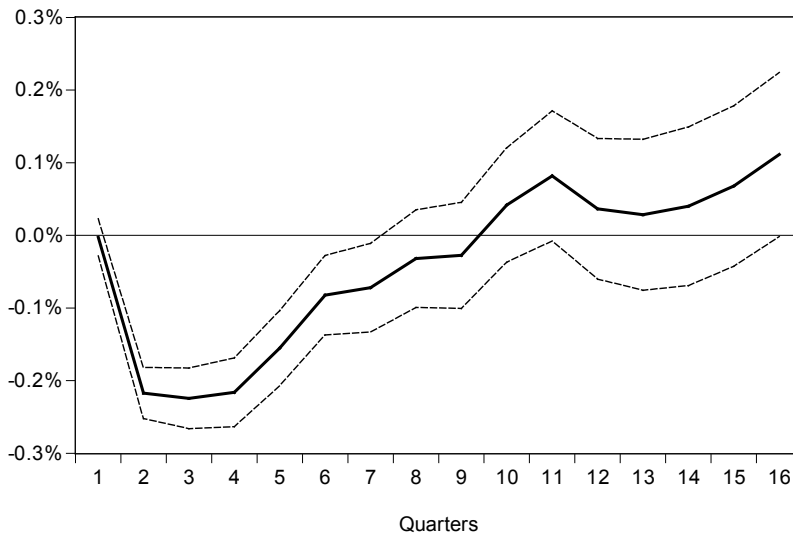


— Forecast Error Shock ■ Romer & Romer Shock ○ VAR Shock × Hybrid VAR Shock △ Barakchian and Crow e Shock

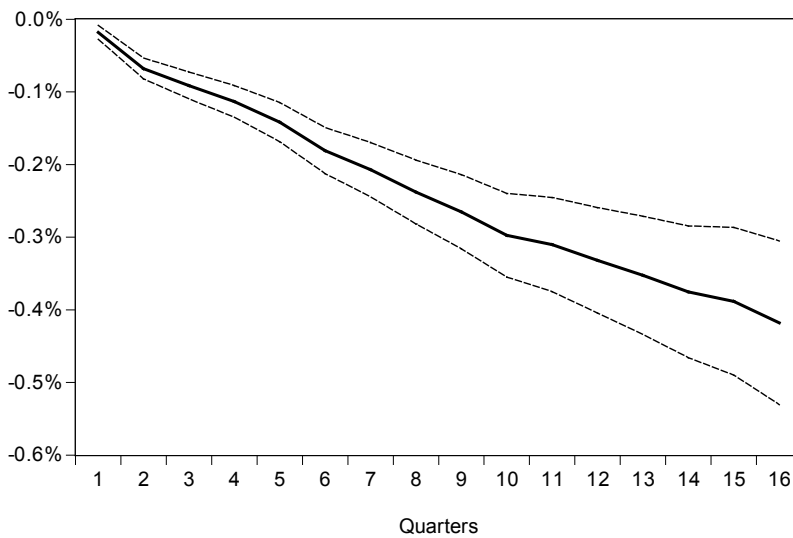
FIGURE 7

EFFECT OF FORECAST ERROR SHOCK USING 2Q AHEAD FORECAST ON GDP AND GDP DEFLATOR

Panel 1: Impact of Forecast Error Shock (100 basis point) on GDP



Panel 2: Impact of Forecast Error Shock (100 basis point) on GDP Deflator

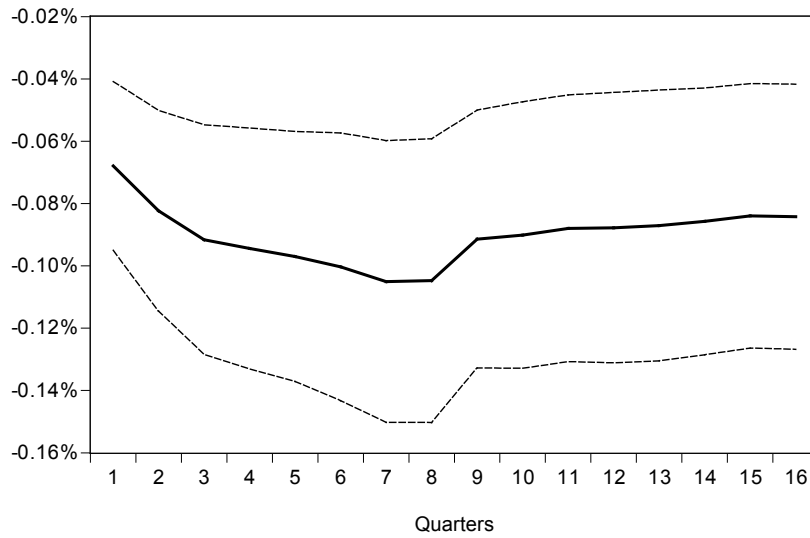


Note: Solid lines display the cumulative effect of the shock on the macroeconomic variable up to 16 quarters. Dashed lines are 1 standard error bands computed using Monte Carlo methods drawing from a multivariate normal distribution.

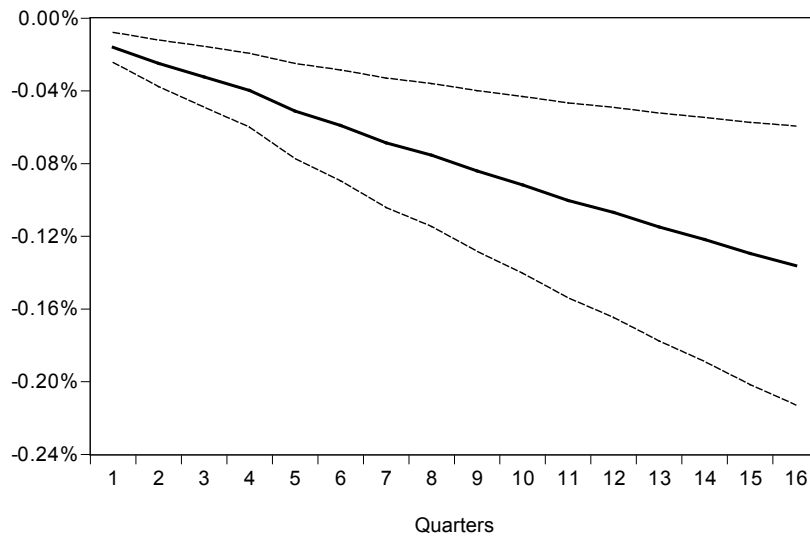
FIGURE 8

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

Panel 1: Impact of Forecast Error Shock (100 basis point) on GDP



Panel 2: Impact of Forecast Error Shock (100 basis point) on GDP Deflator

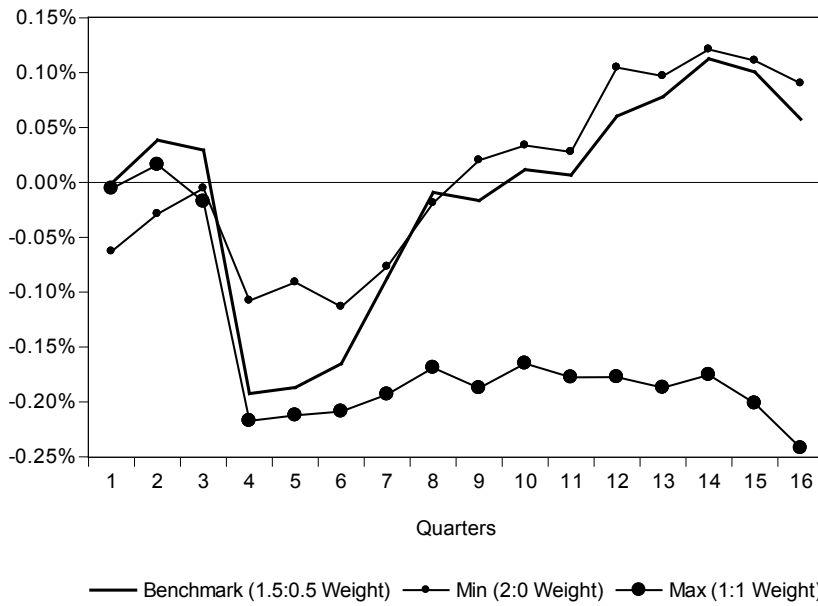


Note: Solid lines display the cumulative effect of the shock on the macroeconomic variable up to 16 quarters. Dashed lines are 1 standard error bands computed using Monte Carlo methods drawing from a multivariate normal distribution.

FIGURE 9

EFFECT OF FORECAST ERROR SHOCK ON GDP AND GDP DEFLATOR WITH VARYING WEIGHTS IN THE TAYLOR RULE

Panel 1: Impact of Forecast Error Shock (100 basis point) on GDP



Panel 2: Impact of Forecast Error Shock (100 basis point) on GDP Deflator

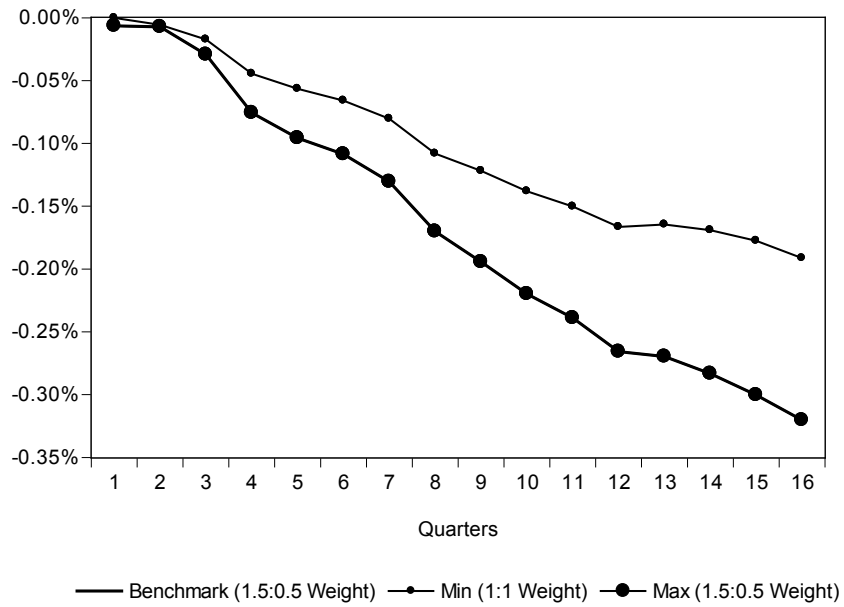
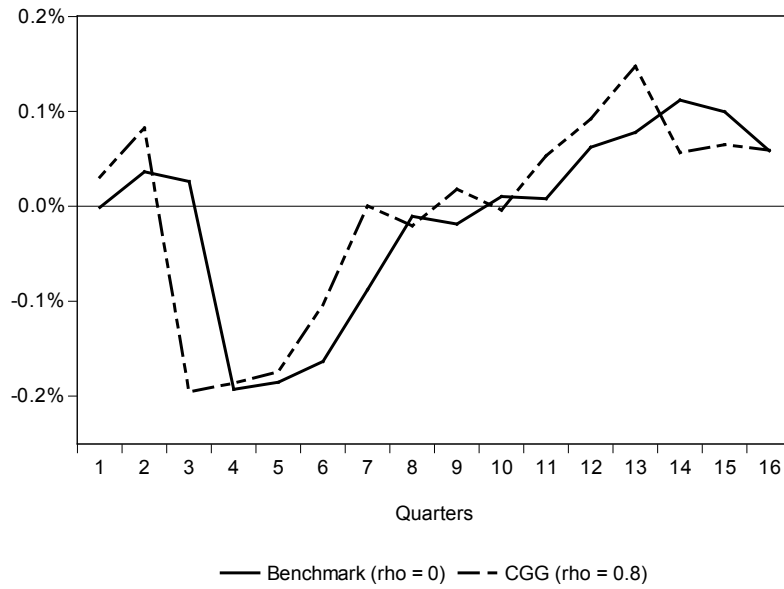


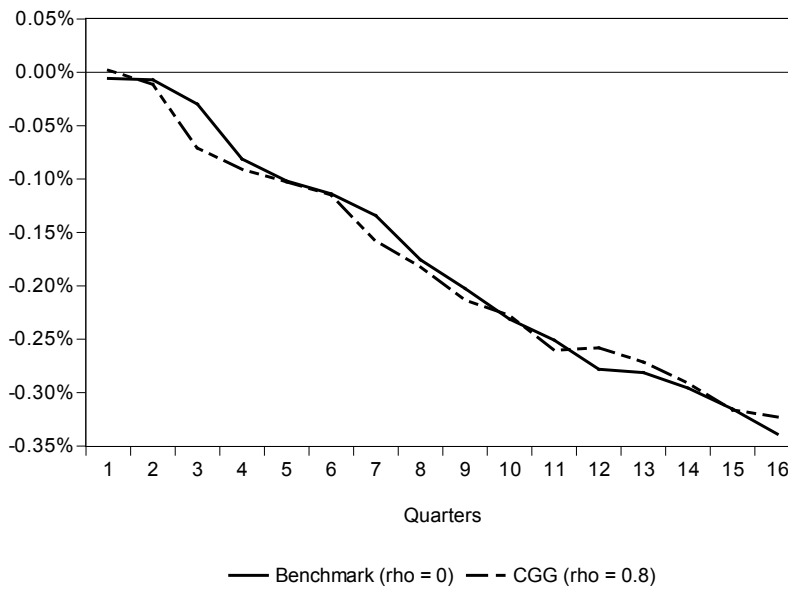
FIGURE 10

EFFECT OF FORECAST ERROR SHOCK ON GDP AND GDP DEFLATOR WITH SMOOTHING
IN THE TAYLOR RULE

Panel 1: Impact of Forecast Error Shock (100 basis point) on GDP



Panel 2: Impact of Forecast Error Shock (100 basis point) on GDP Deflator



Note: CGG refers to Clarida, Gali, and Gertler (2000). The value for the smoothing parameter $\rho = 0.8$ is taken from the estimates presented in the paper for post Volker period.