

Quantifying the Federal Reserve’s Objectives Using a Structural Vector Autoregressive Model

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Abstract

The Federal Reserve’s (Fed’s) objective, namely, its dovish stance, is often blamed for the so-called Great Inflation. A popular proxy for the former is constructed using the inflation coefficients in estimated Taylor rules. However, for a welfare-optimizing central bank, the estimated Taylor coefficients are not sufficient for inferring its underlying preference. We quantify Fed’s objective—the targeting rule—relying on a conditional estimator (Galí and Gambetti 2018) that is free of the classical simultaneity problem. We discover that Fed’s targeting rule remained stable during the pre- and post-Volcker periods—the opposite of what is implied through a Taylor rule estimation.

Keywords: Targeting Rule, Central Bank Preference, Structural Vector Autoregressive (SVAR) Model, Sign Restrictions, Great Inflation, Great Moderation

JEL Classification: E31, E32, E52, E58 and E65

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1 Introduction

The United States (US) Federal Reserve’s (Fed’s) attitude toward inflation, particularly its dovish stance during the pre-Volcker periods, is widely believed to be responsible for the Great Inflation (e.g., [Clarida *et al.* 2000](#); [Lubik and Schorfheide 2004](#); [Cecchetti *et al.* 2007](#); [Bianchi 2012](#)).¹ A common empirical proxy for a central bank’s attitude toward inflation is its coefficient in the Taylor rule. A dovish central bank is considered to react less strongly to inflation than a hawkish central bank. However, the estimated Taylor coefficients are not sufficient to infer the underlying preferences² of a central bank ([Svensson 1997](#); [Favero and Rovelli 2003](#)), and the estimation of a Taylor-type instrument rule can be problematic if the central bank conducts policy optimally.

The goal of this paper is to provide a direct estimate of Fed’s objective, namely, the targeting rule, which determines the central bank’s relative tolerance between inflation and output gap³, using a structural vector autoregressive (SVAR, hereafter) model. Further, we evaluate whether there is a break in Fed’s attitude toward inflation during the pre- and post-Volcker periods.

The estimation of a central bank’s targeting rule is a non-trivial exercise as it is subject to a simultaneity problem; see [McLeay and Tenreyro \(2018\)](#). To overcome this issue, we rely on the conditional estimate that is recently advocated by [McLeay and Tenreyro \(2018\)](#), [Galí and Gambetti \(2018\)](#) and [Barnichon and Mesters \(2018a,b\)](#). We construct an environment in which the central bank’s targeting curve is fixed over time.

In this environment, the realized equilibrium outcomes are driven only by shocks that

¹[Clarida *et al.* \(2000\)](#) discussed self-fulfilling equilibria that could arise when the Fed’s reaction does not satisfy the Taylor principle. Based on a regime-switching model, [Davig and Leeper \(2007\)](#) confirmed the uniqueness of the model solution even when the central bank deviates from the Taylor principle for short periods.

²The welfare loss associated with inflation volatility relative to that associated with output gap volatility.

³A targeting rule includes a constant term that reflects the inflation target. In this paper, we focus on the slope of the targeting rule. Unless otherwise specified, the “targeting rule” in this paper refers to its slope.

shift the New Keynesian (NK) Philipps curve (NKPC). In other words, the output gap growth and inflation are distributed along with the central bank's targeting rule. We construct this desired environment by identifying cost-push shocks and constructing conditional measures of the output gap and inflation driven by those shocks. The identification assumption is that cost-push shocks, for example, price markup shocks, only shift the NKPC, but do not move the targeting rule. The identification of cost-push shocks is achieved by relying on sign restrictions implied by the NK model. Therefore, the ordinary least squares (OLS) estimator based on those conditional variables, denoted as a conditional estimate, is free of the simultaneity issue. We conduct a simulation exercise that validates this methodology.

We apply this methodology to US data. The following results stand out. First, in the presence of cost-push shocks, the Fed is willing to decrease output gap growth by roughly two and a half percentage points for each percentage point increase in (quarterly) inflation. This suggests that the Fed indeed operates on a dual mandate as claimed in its policy objectives. Our estimate quantifies Fed's objective, which is not fully transparent to the public.

Second, Fed's targeting rule, in other words, Fed's attitude toward inflation, remains stable during the pre- and post-Volcker periods.⁴ This finding is consistent with several interpretations of the Great Moderation that do not attribute the phenomenon to a change in monetary policy conduct. Alternative interpretations include the "Good Luck" view (e.g., [Bernanke and Mihov 1998](#), [Stock and Watson 2003](#), [Primiceri 2005](#), [Sims and Zha 2006](#)), as well as explanations like the one proposed by [McConnell and Perez-Quiros \(2000\)](#), which attributes the moderation to improved inventory management.

One strong advocate of the "Good Policy" hypothesis was [Clarida *et al.* \(2000\)](#). In their

⁴However, the estimated inflation target changed from 5% during the pre-Volcker periods to 2.5% during the second half of our sample.

estimation of the Taylor rule, [Clarida *et al.* \(2000\)](#) discovered a break in the Fed's response to inflation for the pre- and post- Volcker periods. Our analysis differs from theirs in terms of two important dimensions. First, we estimate a targeting rule rather than a Taylor rule. Second, our approach relies on a conditional estimate rather than the use of raw data. We investigate which of the two differences drives the disagreement regarding the stability of monetary policy rule. To this end, we first empirically demonstrate that a similar break in the point estimates of the Fed's Taylor rule can be found using conditional variables. Second, based on a model simulation, we show that the estimated Taylor coefficients using the GMM method can vary significantly between two random samples when the data is generated from a model that follows the targeting rule.

One limitation of this study is that we cannot test whether the Fed has been conducting monetary policy optimally (i.e., following a targeting rule) or merely following an interest rate rule. Our estimation results suggest that conditional on the Fed following a targeting rule, the data support a stable monetary policy. On the contrary, the data hint on a possible break in Fed's conduct of monetary policy if the latter can be characterized by a simple interest rate rule. Our preferred interpretation is the former, as it is shown in the literature that a dynamic stochastic general equilibrium (DSGE) model with optimal monetary policy fits the data better than that with a simple interest rate rule ([Adolfson *et al.* 2011](#), [Chen *et al.* 2017](#)).

Literature Review Theoretical discussions on the targeting rule are vast; see, e.g., [Rudebusch and Svensson \(1999\)](#), [Svensson \(1999\)](#), and [Svensson and Woodford \(2004\)](#) for the discussions on the targeting rule versus instrument rules. To the best of our knowledge, this is the first paper that provides an empirical estimate for a central bank's targeting rule and uses it to assess a potential break in the Fed's objective.

This paper contributes to the literature that estimates the welfare loss function of a cen-

tral bank; see, e.g., [Ozlale \(2003\)](#), [Favero and Rovelli \(2003\)](#), [Dennis \(2006\)](#), [Ilbas \(2012\)](#), [Lakdawala \(2016\)](#), [Chen *et al.* \(2017\)](#) and [Debortoli *et al.* \(2017\)](#). Our paper extends this literature in the following dimensions. First, instead of estimating the deep parameters in the welfare loss function, we provide an estimate for the central bank’s targeting rule. Second, because of the nature of the central bank’s preference defined in the literature, most estimations are based on a DSGE model. In this paper, we estimate the central bank’s targeting rule using an SVAR model that relies on less structural assumptions. Exceptionally, [Cecchetti *et al.* \(2002\)](#) and [Cecchetti and Ehrmann \(1999\)](#) estimated a central bank’s preference using a VAR model. However, they did not address the simultaneity issue. [Surico \(2007\)](#) estimated the Fed’s preference using the Generalized Method of Moments. However, as documented by [Mavroeidis *et al.* \(2014\)](#), and we will show later, their instruments are weak.

This paper is also closely related to the literature that estimates central banks’ instrument rules, see, e.g., seminal works by [Taylor \(1993\)](#) for the interest rate rule⁵ and by [McCallum \(1988\)](#) for the money supply rule. Estimated instrument rules such as the Taylor rule are merely an approximations of a central bank’s reaction function, whereas the targeting rule describes a central bank’s preference. The estimated Taylor coefficients are not sufficient to derive the underlying preference of a central bank as it is presented by [Svensson \(1997\)](#) and [Favero and Rovelli \(2003\)](#). Our estimated targeting rule, therefore, complements existing instrument rules as it provides a direct measure of a central bank’s “desired allocation.”

By evaluating whether or not there was a break in the Fed’s targeting rule during the pre- and post- Volcker periods, our paper complements the discussion of a potential break in the Fed’s monetary policy implementation. [Clarida *et al.* \(2000\)](#) and [Coibion and Gorodnichenko \(2011\)](#) presented some evidence supporting a break in the Taylor rule.

⁵See also [Carvalho *et al.* \(2018\)](#) for the most recent estimation.

Conversely, [Orphanides \(2001, 2002, 2004\)](#) argued in favor of no change in the conduct of the Fed’s policy using real-time data.⁶ Our contribution with respect to the literature is to demonstrate empirically that the Fed’s targeting rule remained stable during the pre- and post-Volcker’ periods although the estimated Taylor coefficients using the same approach suggests a break. We reconcile these two seemingly contradictory results based on a simple NK model. Our results highlight the importance of the direct estimation of a central bank’s objective in the examination of possible changes in a central bank’s attitude toward inflation and the output gap.

The remainder of this paper is organized as follows. Section [\(2\)](#) defines the targeting rule, the simultaneity problem associated with its estimation and its relationship with the Taylor rule. Section [\(3\)](#) describes our estimation methodology. Section [\(4\)](#) provides empirical results. Section [\(5\)](#) conducts a simulation exercise that validates our methodology, and Section [\(7\)](#) concludes.

2 The Targeting Rule

2.1 The Targeting Rule and the Simultaneity Problem

In this section, we briefly discuss the central bank’s targeting rule and the simultaneity problem associated with its estimation through the lens of the NK model presented by [Galí \(2015\)](#). [McLeay and Tenreyro \(2018\)](#) presented a more formal discussion of the simultaneity issue.

In a standard NK model, the period welfare loss function of a central bank derived as the second-order approximation of the representative household’s utility function is the

⁶See also [Cogley and Sargent \(2005\)](#), [Primiceri \(2005\)](#), [Stock and Watson \(2002\)](#), [Canova and Gambetti \(2009\)](#) and [Sims and Zha \(2006\)](#).

following:

$$L_t = \pi_t^2 + \lambda x_t^2,$$

where π_t denotes inflation, x_t is the output gap, and λ is the deep parameter that characterizes the central bank's preference. It describes the relative weight that the central bank attaches to the volatility of the output gap and inflation in its loss function. Theoretically, the central bank's targeting rule—the growth rate of the output gap that a central bank is willing to lower if inflation is one percentage point higher than its target—is closely related to λ . To observe this, we solve for the central bank's optimization problem.

The optimization problem of the central bank is as follows:

$$\min_{\{\pi_t, x_t\}_{t=0}^{\infty}} E_t \sum_{t=0}^{\infty} L_t = E_t \sum_{t=0}^{\infty} \gamma^t (\pi_t^2 + \lambda x_t^2),$$

where γ is the discount factor, subject to the sequence of constraints, namely the NKPC:

$$\pi_t = \gamma E \pi_{t+1} + \kappa x_t + \epsilon_t^\pi, \forall t \geq 0. \quad (1)$$

The solution to this problem under commitment is:

$$\pi_t = -\beta \Delta x_t, \text{ for } t \geq 1, \quad (2)$$

where $\Delta x_t \equiv x_t - x_{t-1}$, and $\beta \equiv \frac{\lambda}{\kappa}$. Equation (2) is referred as the central bank's targeting rule. It describes the central bank's desired allocation in the presence of cost-push shocks. The parameter of interest is $-\beta$, which is interpreted as follows: the central bank is willing to lower the output gap growth by $\frac{1}{\beta}$ percentage points for each percentage point increase in inflation. The goal of the rest of the paper is to provide an empirical estimate of β .

As discussed by [McLeay and Tenreyro \(2018\)](#), Equation (2) represents the central bank's desired allocation from which it might deviate for many reasons. For example, the central bank observes the state of the economy subject to measurement errors. The central bank only observes an $\hat{x}_t$ in real-time that is a noisy measure of the unobservable x_t ; i.e. $\hat{x}_t = x_t + e_t$, where e_t denotes the real-time measurement error. Therefore, the targeting rule is as follows:

$$\pi_t = -\beta \Delta x_t + \epsilon_t^m, \quad (3)$$

where $\epsilon_t^m \equiv -\beta \Delta e_t$ denotes the monetary policy shock. This relaxes the assumption that the central bank is always capable of achieving the desired allocation. Notice that ϵ_t^m is serially correlated. Even if e_t was independent and identically distributed, ϵ_t^m would follow a moving average (MA)(1) process. In general, if e_t follows an autoregressive (AR)(p) process, the monetary policy shock ϵ_t^m follows an autoregressive moving average (ARMA)($p,1$) process.

In the model, the equilibrium outcomes of the economy are jointly determined using the NKPC (1) and the central bank's targeting rule (3). As a solution, π_t and Δx_t depend on both ϵ_t^π and ϵ_t^m . Thus, the econometrician who uses OLS to estimate Equation (3) directly will obtain a biased estimate as the regressors and residuals are correlated.

Intuitively, this problem arises if the central bank's targeting curve shifts over time. Therefore, the solution to this problem is to shut down the central bank's targeting rule shifters and to allow only for NKPC shifters in the data. We achieve this goal by constructing variables that are conditional on cost-push shocks.⁷

⁷It is clear that monetary policy shocks are the central bank's main targeting rule shifters and that price markup shocks are the NKPC's shifters. It is less clear, however, how demand and technology shocks shift those curves. In fact, in the basic model examined above, those shocks are perfectly stabilized by the central bank, and therefore, neither of these curves shift in response to the shocks. To use the least number of structural assumptions possible, we focus exclusively on cost-push shocks.

An alternative solution to the simultaneity problem is to estimate Equation (3) using instrumental variables.⁸ Candidates for instruments include lagged inflation and the lagged output gap. This approach is subject to two drawbacks. First, it is well known, see, e.g., [Mavroeidis *et al.* \(2014\)](#), and we will demonstrate later, that those instruments are weak. Second, the exclusion assumption is likely to be violated by using the first few lags as instruments. As discussed previously, ϵ_t^m follows a moving average process with at least one lag, and, therefore, $E(\epsilon_t^m x_{t-1}) \neq 0$. In other words, x_{t-1} and π_{t-1} are not valid instruments. Similarly, x_{t-2} or π_{t-2} cannot be used as instruments if the real-time measurement error is serially correlated. Overall, it is unclear which lagged variables satisfy the exclusion restriction. In addition, excluding the first few lags as instruments exacerbates the first problem (relevance). [Zhang and Clovis \(2010\)](#) formally addressed this issue in their estimation of the NKPC.

3 Estimation Methodology

The objective is to estimate the targeting rule of the form (3). Our estimation methodology can be summarized in the following steps. First, we identify cost-push shocks (shocks to the NKPC) by means of sign restrictions ([Uhlig 2005](#)). Second, we construct variables conditional on the identified shocks. The resulting conditional measures of inflation and the output gap are generated from shocks that only shift the Philips Curve. Therefore, the generated data are free of the simultaneity problem. Last, we project the conditional inflation on to conditional output gap growth.

In the first step, we construct cost-push shocks by relying on sign restrictions. In our

⁸For example, [Clarida *et al.* \(2000\)](#) used lagged macroeconomic variables as instruments in their estimation of the Taylor rule, and, more recently, [Caldara *et al.* \(2019\)](#) combined narrative analysis with a panel of observations on country-specific oil production and consumption as instruments to estimate oil supply and demand elasticities.

baseline, we consider a VAR model with the following variables $Y_t = \begin{bmatrix} \pi_t & x_t & i_t \end{bmatrix}'$, which denote inflation, the output gap, and the nominal interest rate, respectively. The system is assumed to follow a VAR with p lags as follows:

$$Y_t = A_0 + A_1 Y_{t-1} + \dots + A_p Y_{t-p} + U_t, \quad (4)$$

where $U_t = \begin{bmatrix} u_t^\pi & u_t^x & u_t^i \end{bmatrix}'$ includes the reduced form residuals, which are linear combinations of structural shocks as follows:

$$\begin{bmatrix} u_t^\pi \\ u_t^x \\ u_t^i \end{bmatrix} = B_0^{-1} \begin{bmatrix} \epsilon_t^\pi \\ \epsilon_t^i \\ \epsilon_t^x \end{bmatrix}, \quad (5)$$

where $\begin{bmatrix} \epsilon_t^\pi & \epsilon_t^i & \epsilon_t^x \end{bmatrix}'$ denote the structural shocks. We estimate the VAR model using Bayesian techniques; the details can be found in Appendix (C). One could compute the structural shocks once B_0^{-1} is estimated. Under the normalization assumption that structural shocks have unit variances, we obtain $(B_0^{-1})' B_0^{-1} = \Sigma_u$, where Σ_u is the covariance matrix of the reduced form residuals. It is trivial to get an unbiased estimate $\hat{\Sigma}_u$. However, the identification issue then arises because there are more parameters to be estimated in B_0^{-1} than the number of knowns contained in $\hat{\Sigma}_u$.

Structural assumptions regarding B_0^{-1} are required to overcome this identification issue. For our purpose, the key is to identify NKPC shifters, i.e., cost-push shocks. To this

end, we impose the following restrictions:

$$B_0^{-1} = \begin{bmatrix} + & + & * \\ - & + & * \\ * & * & * \end{bmatrix}. \quad (6)$$

The first identified shock is labeled as the “cost-push shock”. It is defined as a shock that pushes the output gap and inflation in the opposite directions. One example of such a shock is the markup shock. In an extended exercise, we identify markup shocks in a larger VAR model, and the results are similar to those we obtain here for the baseline model. Crucial to the estimation of the targeting rule is that those identified shocks do not contain targeting rule shifters, which we interpret as monetary policy shocks. Monetary policy shocks generate positive co-movement of the output gap and inflation, i.e., the second shock identified in the aforementioned system.

As we identify the shocks using sign restrictions, we obtain a set for the structural matrix B_0^{-1} and thus a set of shock series consistent with the identification restrictions (“set identified”). In the second step, for each time series of cost-push shocks j contained in the set identified above, we purge out the remaining shocks by constructing a new dataset j that is driven only by cost-push shocks. That is, we take the fitted values from the structural form of Equation (4), in which all of the remaining shocks in the whole sample are set to zero.

In the third step, we estimate the following regressions using the purged dataset as follows:

$$\hat{\pi}_t(j) = \alpha(j) + \beta(j)\Delta\hat{x}_t(j) + e_t(j). \quad (7)$$

This is done for each dataset j constructed from each time series of cost-push shocks j

belonging to the set identified in the first step. $\hat{\pi}_t(j)$ and $\hat{x}_t(j)$ denote inflation and the output gap conditional on past cost-push shocks through time t , respectively. Therefore, $\beta(j)$ provides an estimate of the targeting rule that is not subject to simultaneity bias.

Instead of this third step, one might attempt to back up the targeting rule, i.e., determine $\beta(j)$ directly from the structural matrix B_0 together with the reduced form parameter A_0 . We postpone discussing of the fallacy of this approach and confirming the validity of our methodology based on a simulation exercise in Section (5).

4 Estimation Results

The national income and product accounts variables are drawn from the Federal Reserve Economic Data database for the 1960Q1-2017Q4 period. We use the following variables: (log) real gross domestic product (GDP) (y_t), (log) GDP deflator (p_t), (log) hours of all persons in the non-farm business sector (n_t), the Fed funds rate (i_t), (log) wage earnings of production and non-supervisory workers (w_t). To overcome the zero lower bound issue, we replace the Fed funds rate with its shadow rate as estimated by [Wu and Xia \(2016\)](#) for the 2009Q1-2015Q4 period.

Our baseline VAR model consists of three variables as follows: output gap, inflation, and the Fed funds rate. The output gap is the difference between (log) real GDP and the (log) real efficient GDP. The latter is proxied by the potential real GDP provided by the Congressional Budget Office (CBO). Inflation is defined as the first difference of the (log) GDP deflator.

For the larger VAR that we will introduce later, we additionally utilize the following series. Labor productivity is defined as the difference between (log) real GDP and (log) hours, i.e. $(y_t - n_t)$. The price markup is defined as the difference between labor productivity and real wage, i.e. $\mu_t = (y_t - n_t) - (w_t - p_t)$.

Data occur on a quarterly frequency, and four lags are chosen for the VARs.

4.1 Estimation of Fed’s Targeting Rule

Figure 2 in Appendix A presents the impulse response functions of the output gap and inflation to an exogenous cost-push shock and a monetary policy shock, respectively. Inflation increases and the output gap decreases when there is a positive markup shock. In response to a contractionary monetary policy shock, inflation and the output gap decrease simultaneously. These results reflect our identification scheme that utilizes sign restrictions.

Table 1 reports our estimation results for the central bank’s targeting rule. For comparison, the first three columns report the mean estimate and a 95% confidence interval for β using a simple OLS approach and the middle columns report the two-stage least squares estimate using the first four lags of inflation and the output gap as instruments. The last three columns present the conditional estimates using our methodology. We first obtain a set of conditional estimates by estimating (7) using 50,000 time series generated by cost-push shocks times 1,000 bootstrapped resamples for each conditional regression. Table 1 reports the median, the 2.5th, and the 97.5th quantiles of conditional estimates.

Our estimate of the targeting rule coefficient is -0.37 , suggesting that the Fed is willing to take a roughly 2.5 percentage points decrease in the growth rate of the output gap for each percentage point increase in inflation. Moreover, our estimations highlight the aforementioned problems concerning other estimation strategies. The OLS estimate of the targeting rule (β) is less than the median of the absolute value of our conditional estimate. This is consistent with the fact that the OLS estimate is biased downward (in terms of its absolute value) because of the simultaneity problem and that the NKPC is positively sloped. In the instrumental variable approach, the first stage F-statistic is 4.21 and is thus smaller than the rule-of-thumb value of 10 proposed by Stock and Yogo (2005),

which suggests that instruments are indeed weak.

Table 1: Baseline Results

	OLS			IV			Conditional estimate			
	95% Interval			95% Interval			First Stage	95% Interval		
	Mean	Low	High	Median	Low	High	F-statistics	Median	Low	High
$\hat{\beta}$	-0.12	-0.23	-0.01	-0.42	-0.89	0.05	4.12	-0.37	-1.44	-0.13

Note: This table reports the regression results from estimating the regression $\pi_t = \alpha + \beta \Delta x_t + e_t$, where we use raw data for the OLS and IV estimations and by estimating the equation $\hat{\pi}_t = \alpha + \beta \Delta \hat{x}_t + e_t$, where a variable with hat denotes variables that are conditional on cost-push shocks for the conditional estimate. We estimate the conditional regression for each set of cost-push shocks identified using a VAR with sign-restrictions. The confidence interval for the conditional estimate ($\hat{\beta}$) is constructed on the basis of 50,000 draws times 1,000 bootstrap resampling for each draw.

Note: OLS, ordinary least squares; VAR, vector autoregression; IV, instrumental variable.

4.2 Did the Fed Change its Targeting Rule in the 1980s?

We now assess whether there was a change in the Fed's policy objective after Volcker's appointment. To address this question, we repeat our exercise using the following data: pre-Volcker (pre-1979) and post-Volcker (post-1979). Table 2 reports the results. Panel A reports the estimation results based on our baseline specification. The key parameter—the slope of the targeting rule, $\hat{\beta}$, which describes the Fed's desired trade-off between the output gap and inflation—is shown to have remained stable across the two subsamples analyzed. The constant parameter $\hat{\alpha}$ has changed from 1.21 in the pre-1979 sample to 0.67 in the post-1979 sample. This reflects the change in the target inflation rate throughout the sample and explains, at least partially, the drop in inflation after Volcker's appointment as the Fed chairman. However, the identification of the precise sources underlying the

Great Inflation and the Great Moderation that followed is beyond the scope of this paper. This finding supports several interpretations of the Great Moderation that do not rely on changes in monetary policy conduct. Among these are the "Good Luck" hypothesis (e.g., [Bernanke and Mihov 1998](#); [Stock and Watson 2003](#); [Primiceri 2005](#); [Sims and Zha 2006](#)), as well as explanations such as that proposed by [McConnell and Perez-Quiros \(2000\)](#), which attributes the moderation to advancements in inventory management.

This result is robust to the use of the alternative specifications reported in Table 2. First, our conclusion is robust to the use of an alternative measure of the output gap. In particular, the (log) real efficient GDP is estimated by fitting a sixth-degree polynomial for the logarithm of real GDP. Panel B shows the results obtained using this measure. There are not any statistically or economically significant differences in the targeting rule between the two subsamples. The point estimate is slightly higher in absolute value in the post-1979 sample which suggests that, if anything, the Fed is willing to accept higher inflation for the same amount of changes in the output gap—the diametric opposite of what the traditional view suggests.

Similar results hold when a measure of the unemployment gap is used rather than the output gap, where the former is constructed using CBO's measure of potential unemployment. In this case, as compared with the baseline, the targeting rule coefficient is multiplied by a factor of three, consistent with the relationship between GDP and unemployment implied by Okun's law.

The Fed conducts its policy based on real-time data rather than the revised data that we utilize in the baseline. Therefore, it is sensible to re-conduct our analysis based on real-time data. However, those real-time measures of economic activity have the shortcoming of featuring additional significant measurement errors. To mitigate this issue, we use the second revised measure of quarterly real GDP and the GDP deflator. In Panel D, we illustrate that our results are robust to the use of real-time data.

Table 2: Pre- v.s. post- Volcker Periods

	Pre-Volcker			Post-Volcker		
	95% Interval			95% Interval		
	Median	Low	High	Median	Low	High
Panel A: Baseline Specification						
$\hat{\alpha}$	1.21	0.38	2.00	0.67	0.38	0.97
$\hat{\beta}$	-0.39	-0.99	-0.13	-0.43	-1.31	-0.13
Panel B: Alternative Measure of Output Gap						
$\hat{\alpha}$	1.25	0.58	1.99	0.67	0.39	1.00
$\hat{\beta}$	-0.46	-1.15	-0.15	-0.50	-1.31	-0.17
Panel C: Unemployment Gap						
$\hat{\alpha}$	1.18	0.49	1.84	0.67	0.37	1.00
$\hat{\beta}$	-1.26	-3.03	-0.47	-1.28	-3.36	-0.38
Panel D: Real-Time Data						
$\hat{\alpha}$	1.58	1.25	1.89	0.66	0.36	1.03
$\hat{\beta}$	-0.33	-0.66	-0.03	-0.32	-1.04	0.00
Panel E: Pre- financial crisis sample						
$\hat{\alpha}$	1.21	0.38	2.00	0.76	0.48	1.03
$\hat{\beta}$	-0.39	-0.99	-0.13	-0.39	-1.04	-0.13
Panel F: Larger VAR						
$\hat{\alpha}$	1.25	-1.98	3.62	0.67	0.35	1.15
$\hat{\beta}$	-0.42	-5.78	-0.01	-0.44	-1.16	-0.10
Panel G: Oil Shocks						
$\hat{\alpha}$	1.22	0.30	2.24	0.66	0.31	0.10
$\hat{\beta}$	-0.43	-1.11	-0.12	-0.35	-0.89	-0.10

Note: Table (2) reports regression results obtained from estimating $\hat{\pi}_t = \alpha + \beta \Delta \hat{x}_t + e_t$ for the pre-1979 and post-1979 subsamples. Panel A reports the results using the baseline specification for the two subsamples separately. Panel B reports regression results using an alternative measure of efficient real GDP constructed by fitting a sixth-degree polynomial for the logarithm of real GDP. In panel C, we use the unemployment gap instead of the output gap. In panel D, we use real-time measures of output gap and inflation. In panel E, we truncate the sample to 2007Q3. In panel F, we rely on a larger VAR to construct price markup shocks. In panel G, we report conditional estimates based on oil shocks.

In Panel E, we report the estimation results using the sample through the recent financial crisis that occurred in 2007Q3—during which the zero lower bound was not an issue. The same result holds.

Evidence from a Larger VAR Model We now check whether the results obtained above using three variables of VAR can be extended to a larger VAR. We consider a VAR with the following variables $[\Delta(y_t - n_t), \pi_t, y_t, i_t, \mu_t]'$, which denote the first difference in labor productivity, inflation, output, the nominal interest rate, and the price markup, respectively. We identify four shocks—namely, technology shocks, price markup shocks, monetary policy shocks, and other demand shocks—relying on the following restrictions. The first is that a technology shock is assumed to be the only shock that has the long-run impact on productivity. The second is that a price markup shock positively influences inflation and the price markup and negatively effects output. The third is that a monetary policy shock has a negative impact on both inflation and the output, and a positive effect on the interest rate. The fourth is that a demand shock is assumed to have a positive impact on inflation, the output gap, and the nominal interest rate. Furthermore, both monetary policy shocks, price markup shocks, and demand shocks are all assumed to have no long-run impact on labor productivity. Appendix D provides additional details regarding our identification assumptions. Those restrictions are consistent with predictions of NK models, which are a standard practice in the SVAR literature: see, e.g., [Galí and Gambetti \(2018\)](#) for a recent application. As before, we estimate the targeting rule using variables conditional on markup shocks.

Panel F in Table 2 reports the conditional estimates based on markup shocks. The results are similar to those obtained in the baseline.

Evidence based on Oil Shocks We investigate whether the results are robust to an alternative measure of cost-push shocks. To this end, we make use of [Hamilton \(2003\)](#) oil price shock series. [Hamilton \(2003\)](#) constructs oil_t as the percentage increase in the quarterly oil price, where negative changes are excluded. This shock is calculated based on the difference between the current oil price and the maximum oil price observed over the preceding 12 quarters:

$$oil_t = 100 \times \max(0, \log p_t - \max(\log p_{t-1}, \log p_{t-2}, \dots, \log p_{t-12}))$$

Here, p_t represents the producer price index for crude petroleum. Oil price shocks are constructed in a VAR using a recursive identification assumption, where macroeconomic variables do not contemporaneously affect oil_t . Recent studies employing this shock include [Loria *et al.* \(2024\)](#).

Specifically, we consider a VAR model with the following variables: $[oil_t, \pi_t, y_t, i_t]'$, with oil_t ordered first. Oil shocks are identified by imposing that B_0^{-1} is a lower triangular matrix:

$$B_0^{-1} = \begin{bmatrix} * & 0 & 0 & 0 \\ * & * & 0 & 0 \\ * & * & * & 0 \end{bmatrix}. \quad (8)$$

Note that this identification approach does not require imposing a sign restriction.

Panel G in [Table 2](#) presents the conditional estimates based on oil price shocks. The estimated $\hat{\beta}$ coefficients are consistent with those obtained in the baseline model. Furthermore, there is no statistically significant difference in the estimated $\hat{\beta}$ coefficients across the two periods under consideration.

5 Validation of our Methodology: Simulation Evidence

The simulation exercise conducted in this section serves two purposes. First, it shows that our methodology delivers an unbiased estimate. Second, it demonstrates that the structural relationship between π_t , x_t , and x_{t-1} , which is implied by the structural matrix B_0 together with the reduced form coefficient A_1 is not a good approximation of the true targeting rule.

We simulate three times series for 232 periods (the same as our data sample) using the simple model discussed in Section 3—the output gap, inflation, and the interest rate. The parameter of interest β is calibrated to be -0.4 , i.e. the true targeting rule is $\pi_t = -0.4\Delta x_t + \epsilon_t^m$. The remaining calibration, as well as the details of the model, can be found in Appendix E. We apply our methodology to each simulated data for 1,000 times and keep the median estimate from each simulation. Table 4 in Appendix E reports the simulation results. The left and the middle columns report the conditional estimated that we emphasize in this paper. The median of the conditional estimates from the 1,000 simulations coincides with the true value of -0.4 .

As previously mentioned, one might find our second stage regression ($\hat{\pi}_t = \alpha + \beta_1 \hat{x}_t + \beta_2 \hat{x}_{t-1} + e_t$) abundant. The reasoning is that one can pin down β_1 and β_2 from the structural matrix B_0 together with the reduced form coefficient A_1 . This approach is shown to be incorrect in our simulation exercise. The right panel of Table 4 reports the simulated results using such an approach. β_1 is significantly different from the truth and β_2 is approximately equal to zero, whereas the data are simulated on the basis of a model in which $\beta_1 = -\beta_2 = -0.4$. In general, the VAR is an approximation of the true model. The fact that we can back up the true structural equation (the targeting rule) from the VAR indicates that the latter is indeed a good approximation. However, it takes the entire VAR system to approximate the true data generation process, and none of the individual

equations from the VAR mimics the true structural equation.

6 Targeting Rule or Taylor Rule

In their estimation of the Taylor rule, [Clarida *et al.* \(2000\)](#) discovered a break in the Fed's response to inflation during the pre- and post- Volcker periods. Our analysis differs from theirs in terms of two important dimensions. First, we estimate a targeting rule rather than a Taylor rule. Second, our approach relies on a conditional estimate rather than using raw data.

This Section investigates which of the two differences drives the disagreement regarding the stability of the monetary policy rule. Specifically, Section [6.1](#) revisits the estimation of the Taylor rule using conditional estimates. Section [6.2](#) theoretically reconciles the differences in the estimated stable Targeting rules with the estimated Taylor rule, which implies changing coefficients.

6.1 Conditional Targeting Rule vs. Conditional Taylor Rule in the Data

Using our conditional variables, we estimate a Taylor rule of the following type— $\hat{i}_t = c + \rho \hat{i}_{t-1} + (1 - \rho)(\phi_\pi \hat{\pi}_t + \phi_x \hat{x}_t) + e_t$ —using the maximum likelihood estimator, separately for the underlying subsamples.

The estimation results are reported in Table [\(3\)](#). The difference in the point estimates of the conditional Taylor rule is similar to those calculated by [Clarida *et al.* \(2000\)](#), namely $\hat{\phi}_\pi$ increased from 0.83 in the pre-1979 sample to 1.54 in the post-1979 sample. However, the change in the Taylor rule is statistically insignificant—a result that is shared by the work of [Cogley and Sargent \(2005\)](#), [Primiceri \(2005\)](#) and [Sims and Zha \(2006\)](#) using a time-varying or regime-switching framework.

Table 3: Conditional Taylor Rule

	Pre-Volcker			Post-Volcker		
	95% Interval			95% Interval		
	Median	Low	High	Median	Low	High
$\hat{\rho}$	0.61	0.05	1.00	0.93	0.62	1.00
$\hat{\phi}_{\pi}$	0.81	0.00	4.42	1.66	0.00	4.75
$\hat{\phi}_x$	0.48	0.10	4.54	0.22	0.00	3.98
$\hat{c}$	0.77	0.05	1.88	0.02	-0.74	0.74

Note: Table (3) reports the regression results obtained by estimating $\hat{i}_t = c + \rho \hat{i}_{t-1} + (1 - \rho)(\phi_{\pi} \hat{\pi}_t + \phi_x \hat{x}_t) + e_t$, where a variable with a hat denotes that it is conditional on cost-push shocks. We estimate the aforementioned regression using the maximum likelihood estimator for each set of cost-push shocks identified through a VAR with sign-restrictions. The confidence interval for the conditional estimates is constructed based on 50,000 draws times 1,000 bootstrap resampling for each draw.

This exercise demonstrates that the differences in conclusions between our paper and *Clarida et al. (2000)* are not attributable to differences in estimation strategies. Rather, they stem from the fundamental difference in the assumed nature of monetary policy: an optimal policy (Targeting rule) versus a simple Taylor rule.

6.2 The Issue with a Taylor Rule when Central Bank follows a Targeting Rule

Finally, we now discuss the relationship between the targeting rule and the Taylor rule and present our interpretation of the breaks in the Taylor coefficients between a pre-1979 sample and the post-1979 sample as documented in the literature.

Proposition 1. *A stable targeting rule can be implemented by a Taylor rule with time-varying inflation and output gap targets:*

$$i_t = \rho_t + \phi_\pi(\pi_t - \pi_t^*) + \phi_x(x_t - x_t^*) \quad (9)$$

for any combination of ϕ_π and ϕ_x that satisfies the *Blanchard and Kahn (1980)* conditions, where

$$\begin{aligned} \rho_t &\equiv r_t^e + \sigma\psi_{x,1}(x_t - x_{t-1}) - \sigma(1 - \rho_v\psi_{x,2})\left(\frac{x_t - \psi_{x,1}x_{t-1}}{\psi_{x,2}}\right), \\ \pi_t^* &\equiv \psi_{\pi,1}x_{t-1} + \psi_{\pi,2}\frac{x_t - \psi_{x,1}x_{t-1}}{\psi_{x,2}}, \\ x_t^* &\equiv \psi_{x,1}x_{t-1} + \psi_{x,2}\frac{x_t - \psi_{\pi,1}x_{t-1}}{\psi_{\pi,2}}, \end{aligned}$$

$$\text{with } \psi_{\pi,1} = -\frac{\lambda}{\kappa}(\delta - 1), \psi_{\pi,2} = -\frac{\delta}{1 - \delta\beta\rho_v}, \psi_{x,1} = \delta, \psi_{x,2} = -\frac{\kappa\delta}{\lambda(1 - \delta\beta\rho_v)}, \delta = \frac{1 - \sqrt{1 - 4\beta\gamma^2}}{2\gamma\beta}, \gamma = \frac{\lambda}{\lambda(1 + \beta) + \kappa^2}.$$

Proof. See Appendix B. □

Proposition 1 establishes that a Taylor-type instrument rule with a time-varying inflation target and output gap target can achieve the same outcome as the targeting rule. However, there are two important lessons. First, the Taylor rule coefficients, ϕ_π and ϕ_x , are undetermined.

Second, and more importantly for the empirical estimation of Taylor rules, in this variant of the Taylor rule, the inflation target π_t^* and the output gap target x_t^* are state-dependent and depend on the previous output gap x_{t-1} . When estimating the following time-invariant simple rule $\hat{i}_t = c + \rho\hat{i}_{t-1} + (1 - \rho)(\phi_\pi\hat{\pi}_t + \phi_x\hat{x}_t) + e_t$, the time-varying inflation target and output gap target π_t^* are considered unobserved residuals. Therefore, if we estimate the coefficients using lags of macroeconomic variables as instrumental variables, the coefficients will be biased because these instruments are correlated with the unobserved residuals.

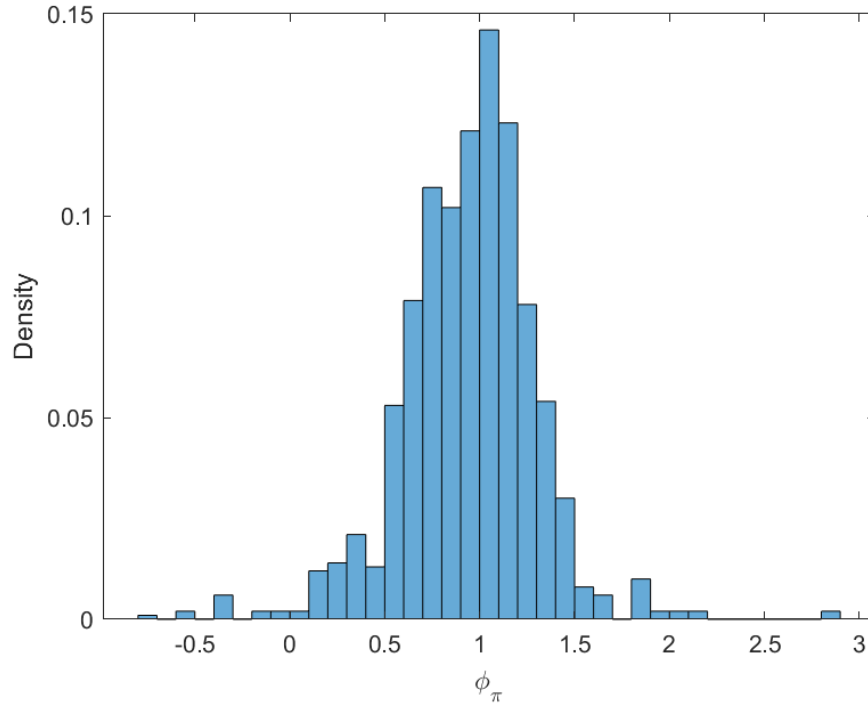


Figure 1: The figure presents the estimated coefficients of ϕ_π obtained from estimating the equation $\hat{it} = c + \rho\hat{it} - 1 + (1 - \rho)(\phi_\pi\hat{\pi}_t + \phi_x\hat{x}_t) + e_t$ using model-simulated data with a sample size of 76 (pre-Volcker sample size) and the GMM method. Four lags of nominal interest rates, inflation, and the output gap are used as instruments.

Next, we demonstrate that the estimated coefficients of the Taylor rule can exhibit significant variability when a small sample of data is generated from a model that follows a constant targeting rule.

Figure 1 presents the estimated coefficients for the Taylor rule using the model-simulated data from Section 5, where monetary policy follows the targeting rule. The figure shows that the coefficients ϕ_π can range from values less than 1 to greater than 1. This exercise demonstrates that even if the central bank conducts a stable targeting rule, the estimated Taylor coefficients using small samples can vary significantly between two random samples. This variability suggests that the difference in Taylor coefficients between the pre-1979 and post-1979 samples can be attributed to invalid instrumental variables and the random draw of two sample periods in a world where the central bank follows a time-

invariant targeting rule.

7 Conclusion

The inflation coefficient in an estimated Taylor rule is widely accepted as a proxy for a central bank's attitude toward inflation. However, this is not true when the central bank conducts monetary policy optimally. Departing from the widespread assumption that the Fed follows a simple Taylor rule, we assumed a welfare-maximizing Fed and estimated its targeting rule. The latter serves as a direct measure of Fed's policy stance—namely, its attitude toward inflation relative to the output gap. Surprisingly, we discovered that Fed's targeting rule remained stable during the pre- and post-Volcker periods—the opposite of what is implied by estimating a Taylor rule.

Our results highlight the importance of directly estimating a central bank's objectives when examining possible changes in a central bank's attitude toward inflation or the output gap, assuming that the central bank conducts monetary policy optimally rather than by following a simple interest rate rule. However, the novelty of this paper is also a limitation. If a simple instrument rule better describes the conduct of monetary policy, the findings uncovered in this study could be biased or misleading. [Adolfson *et al.* \(2011\)](#) and [Chen *et al.* \(2017\)](#) provide evidence in support of a welfare-maximizing central bank. However, it remains an open question whether the Fed and/or other central banks in advanced economies follow a simple rule or conduct monetary policy optimally.

References

ADOLFSON, M., LASÉEN, S., LINDÉ, J. and SVENSSON, L. E. (2011). Optimal monetary policy in an operational medium-sized dsge model. *Journal of Money, credit and Banking*,

43 (7), 1287–1331.

BARNICHON, R. and MESTERS, G. (2018a). Direct estimation of the inflation-unemployment tradeoff. *Working Paper*.

— and — (2018b). Identifying the phillips curve from shifts in demand. *Working Paper*.

BERNANKE, B. S. and MIHOV, I. (1998). Measuring monetary policy. *The quarterly journal of economics*, **113** (3), 869–902.

BIANCHI, F. (2012). Regime switches, agents’ beliefs, and post-world war ii us macroeconomic dynamics. *Review of Economic studies*, **80** (2), 463–490.

BLANCHARD, O. J. and KAHN, C. M. (1980). The solution of linear difference models under rational expectations. *Econometrica: Journal of the Econometric Society*, pp. 1305–1311.

CALDARA, D., CAVALLO, M. and IACOVIELLO, M. (2019). Oil price elasticities and oil price fluctuations. *Journal of Monetary Economics*, **103**, 1–20.

CANOVA, F. and GAMBETTI, L. (2009). Structural changes in the us economy: Is there a role for monetary policy? *Journal of Economic dynamics and control*, **33** (2), 477–490.

CARVALHO, C., NECHIO, F. and TRISTAO, T. (2018). Taylor rule estimation by ols. *Available at SSRN 3265449*.

CECCHETTI, S. G. and EHRMANN, M. (1999). *Does inflation targeting increase output volatility? An international comparison of policymakers’ preferences and outcomes*. Tech. rep., National bureau of economic research.

—, HOOPER, P., KASMAN, B. C., SCHOENHOLTZ, K. L. and WATSON, M. W. (2007). Understanding the evolving inflation process. In *US Monetary Policy Forum*, vol. 8.

- , MCCONNELL, M. M. and PEREZ-QUIROS, G. (2002). Policymakers' revealed preferences and the output–inflation variability trade–off: Implications for the european system of central banks. *The Manchester School*, **70** (4), 596–618.
- CHEN, X., KIRSANOVA, T. and LEITH, C. (2017). How optimal is us monetary policy? *Journal of Monetary Economics*, **92**, 96 – 111.
- CLARIDA, R., GALÍ, J. and GERTLER, M. (2000). Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory. *The Quarterly Journal of Economics*, **115** (1), 147–180.
- COGLEY, T. and SARGENT, T. J. (2005). Drifts and volatilities: monetary policies and outcomes in the post wwii us. *Review of Economic dynamics*, **8** (2), 262–302.
- COIBION, O. and GORODNICHENKO, Y. (2011). Monetary policy, trend inflation, and the great moderation: An alternative interpretation. *American Economic Review*, **101** (1), 341–70.
- DAVIG, T. and LEEPER, E. M. (2007). Generalizing the taylor principle. *American Economic Review*, **97** (3), 607–635.
- DEBORTOLI, D., KIM, J., LINDÉ, J. and NUNES, R. (2017). Designing a simple loss function for central banks: Does a dual mandate make sense? *The Economic Journal*.
- DENNIS, R. (2006). The policy preferences of the us federal reserve. *Journal of Applied Econometrics*, **21** (1), 55–77.
- FAVERO, C. A. and ROVELLI, R. (2003). Macroeconomic stability and the preferences of the fed: A formal analysis, 1961-98. *Journal of Money, Credit and Banking*, pp. 545–556.
- GALÍ, J. (2015). *Monetary Policy, Inflation, and the Business Cycle: An Introduction to the New Keynesian Framework*. Princeton University Press.

- GALÍ, J. and GAMBETTI, L. (2018). Has the u.s. wage phillips curve flattened? a semi-structural exploration. *Working Paper*.
- HAMILTON, J. D. (2003). What is an oil shock? *Journal of Econometrics*, **113** (2), 363–398.
- ILBAS, P. (2012). Revealing the preferences of the us federal reserve. *Journal of Applied Econometrics*, **27** (3), 440–473.
- KILIAN, L. and LÜTKEPOHL, H. (2017). *Structural vector autoregressive analysis*. Cambridge University Press.
- LAKDAWALA, A. (2016). Changes in federal reserve preferences. *Journal of Economic Dynamics and Control*, **70**, 124–143.
- LORIA, F., MATTHES, C. and ZHANG, D. (2024). Assessing macroeconomic tail risk. *The Economic Journal*, p. ueae066.
- LUBIK, T. A. and SCHORFHEIDE, F. (2004). Testing for indeterminacy: An application to u.s. monetary policy. *American Economic Review*, **94** (1), 190–217.
- MAVROEIDIS, S., PLAGBORG-MØLLER, M. and STOCK, J. H. (2014). Empirical evidence on inflation expectations in the new keynesian phillips curve. *Journal of Economic Literature*, **52** (1), 124–88.
- MCCALLUM, B. T. (1988). Robustness properties of a rule for monetary policy. In *Carnegie-Rochester conference series on public policy*, Elsevier, vol. 29, pp. 173–203.
- MCCONNELL, M. M. and PEREZ-QUIROS, G. (2000). Output fluctuations in the united states: What has changed since the early 1980's? *American Economic Review*, **90** (5), 1464–1476.

- MCLEAY, M. and TENREYRO, S. (2018). Optimal inflation and the identification of the phillips curve. *Working Paper*.
- ORPHANIDES, A. (2001). Monetary policy rules based on real-time data. *American Economic Review*, **91** (4), 964–985.
- (2002). Monetary-policy rules and the great inflation. *American economic review*, **92** (2), 115–120.
- (2004). Monetary policy rules, macroeconomic stability, and inflation: A view from the trenches. *Journal of Money, Credit and Banking*, pp. 151–175.
- OZLALE, U. (2003). Price stability vs. output stability: tales of federal reserve administrations. *Journal of Economic Dynamics and Control*, **27** (9), 1595–1610.
- PRIMICERI, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies*, **72** (3), 821–852.
- RUDEBUSCH, G. and SVENSSON, L. E. (1999). Policy rules for inflation targeting. In *Monetary policy rules*, University of Chicago Press, pp. 203–262.
- SIMS, C. A. and ZHA, T. (2006). Were there regime switches in us monetary policy? *American Economic Review*, **96** (1), 54–81.
- STOCK, J. and YOGO, M. (2005). *Testing for Weak Instruments in Linear IV Regression*, New York: Cambridge University Press, pp. 80–108.
- STOCK, J. H. and WATSON, M. W. (2002). Has the business cycle changed and why? *NBER macroeconomics annual*, **17**, 159–218.
- and — (2003). Has the business cycle changed? Evidence and explanations. *Monetary policy and uncertainty: adapting to a changing economy*, pp. 9–56.

- SURICO, P. (2007). The fed's monetary policy rule and us inflation: The case of asymmetric preferences. *Journal of Economic Dynamics and Control*, **31** (1), 305–324.
- SVENSSON, L. E. (1997). Inflation forecast targeting: Implementing and monitoring inflation targets. *European economic review*, **41** (6), 1111–1146.
- (1999). Inflation targeting as a monetary policy rule. *Journal of monetary economics*, **43** (3), 607–654.
- and WOODFORD, M. (2004). Implementing optimal policy through inflation-forecast targeting. In *The inflation-targeting debate*, University of Chicago Press, pp. 19–92.
- TAYLOR, J. B. (1993). Discretion versus policy rules in practice. In *Carnegie-Rochester conference series on public policy*, Elsevier, vol. 39, pp. 195–214.
- UHLIG, H. (2005). What are the effects of monetary policy on output? results from an agnostic identification procedure. *Journal of Monetary Economics*, **52** (2), 381–419.
- WU, J. C. and XIA, F. D. (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, **48** (2-3), 253–291.
- ZHANG, C. and CLOVIS, J. (2010). The new keynesian phillips curve of rational expectations: A serial correlation extension. *Journal of Applied Economics*, **13** (1), 159–179.

A Figures

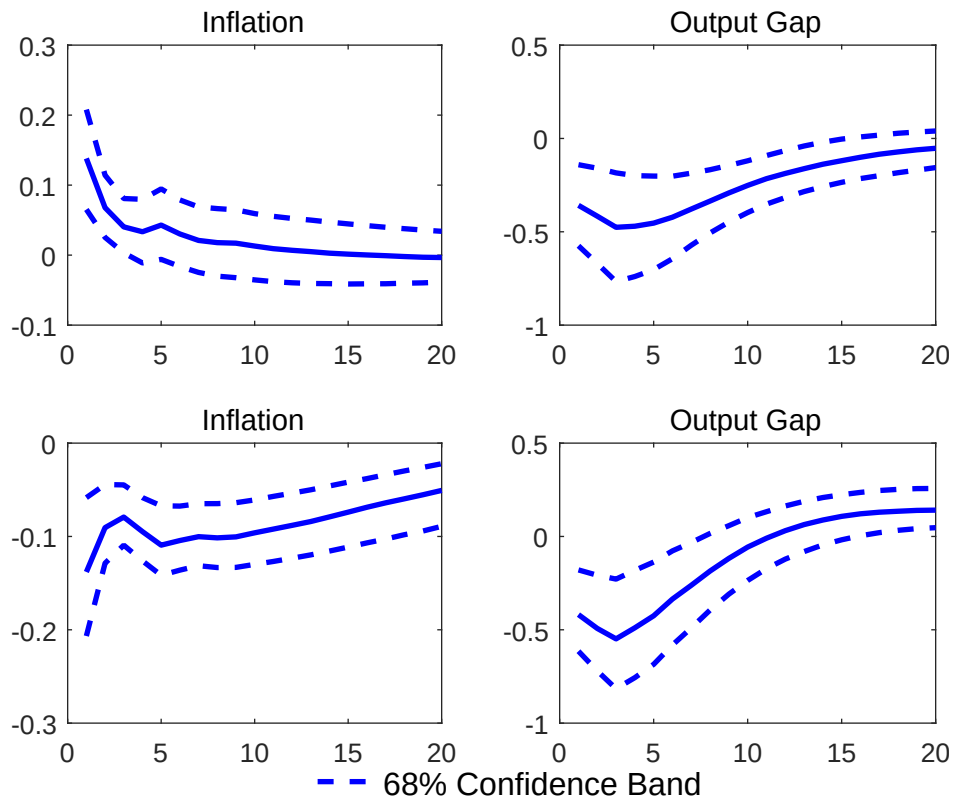


Figure 2: This figure presents the impulse response function of inflation and the output gap to the identified shocks. The first row corresponds to the response to the markup shock, and the second row represents the response to the monetary policy shock. The solid blue line is the median estimate, and the blue dashed line is the 68% confidence band.

B Relationship between the Targeting Rule and Taylor Rule

We now discuss the relationship between the targeting rule and the Taylor rules. The central bank minimizes the following loss function:

$$\min_{\{\pi_t, x_t\}_{t=0}^{\infty}} = \sum_{t=0}^{\infty} \beta^t (\pi_t^2 + \lambda x_t^2)$$

subject to

$$\pi_t = \kappa x_t + \beta E \pi_{t+1} + v_t, \forall t = 0, 1, 2, \dots$$

$$v_t = \rho_v v_{t-1} + \epsilon_t, \forall t = 0, 1, 2, \dots$$

The solution to this problem is as follows:

$$\pi_t = \psi_{\pi,1} x_{t-1} + \psi_{\pi,2} v_t, \quad x_t = \psi_{x,1} x_{t-1} + \psi_{x,2} v_t,$$

where $\psi_{\pi,1} = -\frac{\lambda}{\kappa}(\delta - 1), \psi_{\pi,2} = -\frac{\delta}{1 - \delta\beta\rho_v}, \psi_{x,1} = \delta, \psi_{x,2} = -\frac{\kappa\delta}{\lambda(1 - \delta\beta\rho_v)}, \delta = \frac{1 - \sqrt{1 - 4\beta\gamma^2}}{2\gamma\beta}, \gamma = \frac{\lambda}{\lambda(1 + \beta) + \kappa^2}$.

To solve for the equilibrium nominal interest rate, we make use of the dynamic IS equation:

$$x_t = E(x_{t+1}) - \frac{1}{\sigma}(r_t - r_t^e),$$

where $r_t^e = \rho + \sigma E \Delta y_{t+1}^e$ denotes the efficient real interest rate that follows an exogenous process. The nominal interest rate under this targeting rule is as follows:

$$i_t = r_t^e + \sigma \psi_{x,1} (x_t - x_{t-1}) - \sigma (1 - \rho_v \psi_{x,2}) v_t, \quad (1)$$

where $\Psi_i = \Psi[\kappa\sigma(1 - \rho_{\epsilon,\pi}) + \lambda\rho_{\epsilon,\pi}]$. Equation (1) is merely the solution to the model and does not represent the interest rate rule (i.e., the Taylor rule) that is employed by the central bank to achieve the target. In fact, if the central bank were setting interest rates following Equation (1), **Blanchard and Kahn (1980)** condition would be violated. Consequently, there would be multiple equilibria. In theory, there are an infinitely number of Taylor rules of the following form that satisfies the equilibrium allocations derived above:

$$i_t = \rho_t + \phi_\pi(\pi_t - \pi_t^*) + \phi_x(x_t - x_t^*). \quad (2)$$

With $\rho_t \equiv r_t^e + \sigma\psi_{x,1}(x_t - x_{t-1}) - \sigma(1 - \rho_v\psi_{x,2})(\frac{x_t - \psi_{x,1}x_{t-1}}{\psi_{x,2}})$, $\pi_t^* \equiv \psi_{\pi,1}x_{t-1} + \psi_{\pi,2}\frac{x_t - \psi_{x,1}x_{t-1}}{\psi_{x,2}}$, and $x_t^* \equiv \psi_{x,1}x_{t-1} + \psi_{x,2}\frac{x_t - \psi_{\pi,1}x_{t-1}}{\psi_{\pi,2}}$, for any combination of ϕ_π and ϕ_x that satisfies the **Blanchard and Kahn (1980)** condition.

C Estimation

We explain the estimation technique in this section. Let $Y \equiv [y_1, \dots, y_T]$, $A \equiv [A_0, A_1, \dots, A_p]$, and $Z \equiv [Z_0, \dots, Z_{T-1}]$ with $Z_{t-1} \equiv (1, y'_{t-1}, \dots, y'_{t-p})$. In matrix form, the system of equations is $Y = AZ + U$. In vector form, we have $y = (Z' \otimes I)\alpha + u$, where $\alpha \equiv \text{vec}(A)$, $y \equiv \text{vec}(Y)$, and $u \equiv \text{vec}(U)$. We assume the independent Gaussian-inverse Wishart prior. In particular, the priors are as follows:

$$\alpha \sim N(\alpha^*, V_\alpha) \quad (3)$$

and

$$\Sigma_u \sim IW(S_*, n). \quad (4)$$

Then the posterior distribution of α will be a conditional normal distribution,

$$\alpha|\Sigma_u, y \sim N(\bar{\alpha}, \bar{\Sigma}_\alpha) \quad (5)$$

and the posterior distribution of Σ_u will be an inverse Wishart distribution as follows:

$$\bar{\Sigma}_u|\alpha, y \sim IW(S, \tau), \quad (6)$$

where

$$\bar{\alpha} = [V_\alpha^{-1} + (ZZ' \otimes \Sigma_u^{-1})]^{-1}[V_\alpha^{-1}\alpha^* + (Z \otimes \Sigma_u^{-1})y] \quad (7)$$

$$\bar{\Sigma}_\alpha = [V_\alpha^{-1} + (ZZ' \otimes \Sigma_u^{-1})]^{-1} \quad (8)$$

and

$$S = S_\star + \sum_{t=1}^T (y_t - Z_t\alpha)(y_t - Z_t\alpha)' \quad (9)$$

$$\tau = T + n. \quad (10)$$

We use the Gibbs sampling algorithm to draw the posterior distribution. The detailed derivations can be found in [Kilian and Lütkepohl \(2017\)](#). With each draw, we identify the structural matrix, generate artificial data, and calculate the targeting rule as we describe in Section (3). The hyperparameters in the prior are specified as follows: $\alpha^* = 0$, $V_\alpha^{-1} = 0$, $S = 0$, and $n = 0$.

D Evidence from a Larger VAR Model

Consider a VAR with the following variables— $Y_t = \begin{bmatrix} \Delta(y_t - n_t) & \pi_t & y_t & i_t & \mu_t \end{bmatrix}'$,—which denote the first difference in labor productivity, inflation, output, the nominal interest rate, and the price markup, respectively. The system is assumed to follow a VAR with p lagged variables— $Y_t = A_1 Y_{t-1} + \dots + A_p Y_{t-p} + U_t$ —where $U_t = \begin{bmatrix} u_t^a & u_t^\pi & u_t^y & u_t^i & u_t^\mu \end{bmatrix}'$ includes the reduced form residuals, which are linear combinations of structural shocks as follows:

$$\begin{bmatrix} u_t^a \\ u_t^\pi \\ u_t^y \\ u_t^i \\ u_t^\mu \end{bmatrix} = B_0^{-1} \begin{bmatrix} \epsilon_t^a \\ \epsilon_t^\pi \\ \epsilon_t^y \\ \epsilon_t^i \\ \epsilon_t^\mu \end{bmatrix}, \quad (11)$$

where $\begin{bmatrix} \epsilon_t^a & \epsilon_t^\pi & \epsilon_t^y & \epsilon_t^i & \epsilon_t^\mu \end{bmatrix}'$ denote the structural shocks. We impose the following restrictions to identify the structural shocks:

$$B_0^{-1} = \begin{bmatrix} * & * & * & * & * \\ * & + & - & + & * \\ * & - & - & + & * \\ * & * & + & + & * \\ * & + & * & * & * \end{bmatrix}, \quad A_L \equiv \left(I - \sum_{i=1}^p A_i \right)^{-1} B_0^{-1} = \begin{bmatrix} * & 0 & 0 & 0 & 0 \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix}. \quad (12)$$

Specifically, we identify four shocks—technology shocks, price markup shocks, monetary policy shocks, and demand shocks. The first is the technology shock, which is assumed to be the only shock that has a long-run impact on labor productivity. The second is the price markup shock, which has a positive impact on inflation and the price markup,

and a negative effect on the output. The third is the monetary policy shock, which has a negative impact on both inflation and the output, and a positive effect on the interest rate. The fourth is the demand shock, which is assumed to have a positive impact on inflation, the output, and the nominal interest rate. Furthermore, both monetary policy shocks, price markup shocks, and demand shocks are assumed to have no long-run impact on labor productivity.

E Simulation

We simulate the output gap (x_t), inflation (π_t), and the interest rate (i_t) according to the following equations:

$$\pi_t = \beta \Delta x_t + u_t^m \quad (13)$$

$$\pi_t = \gamma E\pi_{t+1} + \kappa x_t + \epsilon_t^\pi \quad (14)$$

$$i_t = -\sigma(x_t - Ex_{t+1}) + E\pi_{t+1} + e_t, \quad (15)$$

where $u_t^m = \rho u_{t-1}^m + \epsilon_t^m$ and shocks ϵ_t^m , ϵ_t^π , and e_t are normally distributed with zero means and variances σ_m , σ_π , and σ_e , respectively. The last equation is the dynamic IS equation. We have added a shock e_t (which can be interpreted as a measurement error) to avoid the dynamic singularity. β is calibrated to be -0.4 to match our empirical estimates. The discount factor γ is set to 0.99 and κ is equal to 0.03 . We assume a log utility in consumption, i.e., $\sigma = 1$. Fed's preference is likely to be persistent, and therefore, ρ is set to be 0.95 . We assign an equal value to the volatility of structural shocks— $\epsilon_t^m = \epsilon_t^\pi = 0.02$ —and the measurement error. $\sigma_e = 0.0001$, is quite small.

Table 4: Simulation Results

	Conditional estimates			Conditional estimates			Structural VAR parameters		
	95% Interval			95% Interval			95% Interval		
	Median	Low	High	Median	Low	High	Median	Low	High
$\hat{\beta}$	-0.40	-0.44	-0.33						
$\hat{\beta}_1$				-0.40	-0.50	-0.25	- 0.34	-0.36	-0.32
$\hat{\beta}_2$				0.37	0.31	0.45	-0.01	-0.02	-0.01

Note: The left and the middle columns report conditional estimates using 1,000 sets of simulated data ($N = 232$) based on a model in which $\beta = \beta_1 = -\beta_2 = 0.40$. The right column reports the β_1 and β_2 that are implied by the structural VAR parameters B_0 and A_0 . For each simulation, we keep the median estimates. The Table (4) reports the median and the 95% interval of the saved estimates.