PERUVIAN ECONOMIC ASSOCIATION

Effectiveness of monetary policy under economic uncertainty regimes

Nelson R. Ramírez-Rondán

Luis Yépez

Working Paper No. 204, September 2024

Effectiveness of monetary policy under economic uncertainty regimes*

Nelson R. Ramírez-Rondán
CEMLA

Luis Yépez
University of Chicago & Central Reserve Bank of Peru

September, 2024

Abstract

Uncertainty can affect monetary policy through its influence on macroeconomic variables. In this paper, we examine the extent to which economic policy uncertainty influences the effectiveness of monetary policy in the 1965:1-2023:12 period for the U.S. economy. Using a threshold regression model, we find evidence of threshold effects where an uncertainty threshold of around 145 of the economic policy uncertainty variable is estimated –the 62th percentile of the economic policy uncertainty variable distribution–, which defines two regimes: high and low uncertainty. By estimating a Structural Vector Autoregression (SVAR) model with sign and zero restrictions in each uncertainty regime, we find that the monetary policy is effective during low-uncertainty periods but loses its effectiveness during high-uncertainty ones. These results are robust to the addition of more restrictions.

JEL Classification: C11, C24, E52, E58.
Keywords: monetary policy; economic uncertainty; threshold model; SVAR.

*We thank Pablo Guerron-Quintana, Carlos Molina, Alejandro Vicondoa, Tânia Saraiva, Juan Carlos Aquino, Alfredo Salgado and the participants of the 2022 CEMLA-FRBNY-ECB Conference, the Annual Event of Finance Research Letters 2022, the University of St. Gallen's Workshop on Applied Macroeconomics and Monetary Policy, the 2021 Annual Meeting of the Economic Society of Chile, and the CEMLA Research Seminar for useful comments. We also thank Jonas Arias and Juan Rubio-Ramirez for sharing their MATLAB codes. The views expressed in this paper are those of the authors and do not necessarily represent the views of the institutions they are affiliated with.
Corresponding author: Nelson R. Ramírez-Rondán, CEMLA, Durango 54, Mexico City 06700, Mexico. E-mail address: nramron@gmail.com.

1 Introduction

In the last decade, a growing literature has stated the importance of uncertainty on macroeconomic variables. Uncertainty can influence aggregate saving and investment since it produces a partial irreversibility of investments in high uncertainty periods (see Bernanke, 1983; Bloom, 2009; Dixit and Pindyck, 1994); that is, as greater uncertainty increases the real option value of postponing non-reversible investment (Bloom et al., 2018) as well as increasing precautionary saving. In other words, uncertainty motivates agents to postpone decisions, awaiting more precise information or more pressing needs, and this cautiousness makes them less responsive to changes in the interest rate (Aastveit et al., 2017).

Uncertainty can also influence financial and credit market conditions and currency risk. Specifically, financial market liquidity as portfolio rebalances and funds move internationally, there is evidence that periods of heightened uncertainty are associated with lower asset trade volumes (Rehse et al., 2019); uncertainty has detrimental effects on market functioning since it hurts credit growth (Bordo et al., 2016); and increased uncertainty is associated with higher excess returns to the currency carry trade operations (Husted et al., 2018; Berg and Mark, 2018).

On the other hand, there is a large literature on the identification of the monetary policy (see Bernanke and Blinder, 1992; Christiano et al., 1996; Leeper et al., 1996; Bernanke and Mihov, 1998; Smets and Wouters, 2007, among others). Most of the literature uses Structural Vector Autoregression (SVAR) models, where identification of the monetary policy shock plays a key role. The identification scheme restricts only the monetary policy equation; thus the structural parameters are not fully identified. Identifying only one shock or subset of shocks follows the work of Bernanke and Mihov (1998), Christiano et al. (1999), Uhlig (2005), Arias et al. (2019) among others.

In related literature, Vavra (2014) constructs price-setting models with CPI microdata, and then shows that these models imply output responds less to monetary policy during times of high volatility; whereas, Tillmann (2020) shows that a policy tightening leads to a weaker reaction of long-term interest rates when uncertainty is high; while, Aastveit et al. (2017) show that policy uncertainty reduces the transmission of Fed monetary policy on investment and consumption; similarly, Castelnuovo and Pellegrino (2018) find that monetary policy exerts a substantially milder impact in presence of high uncertainty for the US economy, and Pellegrino (2018) for the Euro area; likewise, Mehmet et al. (2016) find that both price and output reacting more significantly to monetary policy shocks when the level of U.S. policy uncertainty is low. Nonetheless, Blot et al. (2020) do not find any significant difference in the response function of inflation to monetary policy in low and high uncertainty periods for the Euro area.

Those papers that used an SVAR framework fix a certain *ad hoc* percentile of the historical distribution for the uncertainty measure to define high uncertainty; nonetheless, two drawbacks arise: first, when a very high threshold is imposed (for instance the 90th percentile), the number of observations in the high uncertainty regime is significantly reduced; and thus, in Bayesian methods, the confidence bands tend to be wide; second, Donayre (2014) shows that if the uncertainty threshold is misspecified by imposing an *ad hoc* definition, tests for asymmetry have low power, leading to an inability to reject the null hypothesis of linearity; that is, there is no difference on the monetary policy effects under the high and low uncertainty regimes.

Our framework differs from these previous works. First, we postulate that economic policy uncertainty affects the effectiveness of the U.S. monetary policy by splitting the sample following a threshold regression model (Hansen, 2000), where economic uncertainty is a threshold variable that endogenously splits the sample into two or more regimes. That is, the economic uncertainty threshold parameter is estimated within the model, in contrast to the exogenous sample split following *ad hoc* rules. In addition, in our framework, the number of regimes in which the sample could be split might exceed two -as dictated by the sample.

Second, we estimate an SVAR model in each economic uncertainty regime by using the recent algorithms on sign and zero restrictions and identification scheme of the monetary policy shock developed by Arias et al. (2018) and Arias et al. (2019). That is, once the economic uncertainty threshold is estimated by splitting the sample into high and low economic uncertainty regimes, we estimate the effectiveness of the U.S. monetary policy in each economic uncertainty regime, where the U.S. monetary policy shock is identified by imposing sign and zero restrictions on the systematic component of monetary policy (Taylor rule equation) as in Arias et al. (2019).

Unlike Arias et al. (2019), we use the two-year Treasury bond yield to identify monetary policy shocks as it captures the market's immediate reactions to monetary policy announcements and reflects expectations about the near future; contrary to longer-term yields, which long-term growth expectations or risk premiums can influence, the two-year Treasury bond yield is more directly tied to monetary policy actions (Gürkaynak et al., 2006; Kuttner, 2001);[1] and, therefore, this measure is effective in isolating the impact of unexpected policy changes, as they react sharply to actual policy rate adjustments and shifts in forward guidance (Campbell et al., 2012). Moreover, their higher variability compared to short-term rates (such as the overnight rate) allows for more accurate identification of monetary policy shocks, as highlighted in studies such as Gertler and Karadi (2015) and Bernanke et al. (2005).[2]

We find strong evidence of economic policy uncertainty threshold effects; that is, in a threshold model of the monetary policy equation, the economic policy uncertainty measure splits the sample into two regimes -which we will call "low-uncertainty" and "high-uncertainty". The U.S. monetary policy is effective in the low-uncertainty regime since it drops economic activity and inflation. In contrast, in a high uncertainty regime, the U.S. monetary policy becomes less effective because it has no or minor effect on economic activity and inflation.

The remainder of this paper is organized as follows. In Section 2, we discuss the methodology and dataset we use in this study. In Section 3, we estimate a threshold regression model where economic policy uncertainty is the threshold variable, then we estimate an SVAR model in the high and low economic policy uncertainty regimes. In

[1]We found quite similar results when we used the one-year Treasury bond yield to measure monetary policy shock.

[2]Following the global financial crisis and the COVID-19 pandemic, both the overnight rate and the effective federal funds rate displayed limited variability over the zero lower bound period.

Section 4, we add a further restriction as a robustness exercise. Finally, in Section 5, we conclude.

2 Methodology and data

In this section, we briefly discuss our methodology and database. We postulate that economic policy uncertainty affects the effectiveness of the U.S. monetary policy by separating the sample into two or more regimes. In particular, we embed the Taylor rule equation within a threshold regression model, whereby economic policy uncertainty is the threshold variable that splits the sample into uncertainty regimes; later on, we estimate a Structural Vector Autoregression (SVAR) model in each regime to see the effectiveness of the U.S. monetary policy. The dataset comprises monthly information for the U.S. economy over the period 1965:1-2023:12. The data are retrieved from the Federal Reserve Bank of St. Louis database (FRED), the Global Financial Database (GFD) and the Economic Policy Uncertainty website.

2.1 U.S. economy SVAR

As in Arias et al. (2018) we begin with an SVAR model which takes the form

$$\mathbf{y}_t'\mathbf{A}_0 = \sum_{\ell=1}^{v} \mathbf{y}_{t-\ell}'\mathbf{A}_\ell + \mathbf{c} + \varepsilon_t' \text{ for } 1 \leq t \leq T, \tag{1}$$

where $\mathbf{y}_t$ is an $n \times 1$ vector of endogenous variables of the U.S. economy, ε_t is an $n \times 1$ vector of structural shocks and $\mathbf{A}_\ell$ is an $n \times n$ matrix of structural parameters for $0 \leq \ell \leq v$ with $\mathbf{A}_0$ invertible, $\mathbf{c}$ is a $1 \times n$ vector of parameters, v is the lag length, and T is the sample size. The vector ε_t is Gaussian with mean zero and covariance matrix I_n, conditional in $\mathbf{y}_0, \ldots, \mathbf{y}_{t-v}$.

The SVAR described in equation (1) can be written as

$$\mathbf{y}_t'\mathbf{A}_0 = \mathbf{x}_t'\mathbf{A}_+ + \varepsilon_t' \text{ for } 1 \leq t \leq T, \tag{2}$$

where $\mathbf{A}_+' = \left[\begin{array}{ccc} \mathbf{A}_1' & \ldots & \mathbf{A}_v' \ \mathbf{c}' \end{array}\right]$ and $\mathbf{x}_t' = \left[\begin{array}{cccc} \mathbf{y}_{t-1}' & \ldots & \mathbf{y}_{t-v}' & 1 \end{array}\right]$ for $1 \leq t \leq T$. The dimension of $\mathbf{A}_+'$ is $m \times n$, where $m = nv + 1$. We call $\mathbf{A}_0$ and $\mathbf{A}_+$ the structural parameters. The reduce form vector autoregression (VAR) implied by equation (2) is

$$\mathbf{y}_t' = \mathbf{x}_t'\mathbf{B} + \mathbf{u}_t' \text{ for } 1 \leq t \leq T, \tag{3}$$

where $\mathbf{B} = \mathbf{A}_+\mathbf{A}_0^{-1}, \mathbf{u}_t' = \varepsilon_t'\mathbf{A}_0^{-1}$, and $\mathbb{E}\left[\mathbf{u}_t\mathbf{u}_t'\right] = \Sigma = \left(\mathbf{A}_0\mathbf{A}_0'\right)^{-1}$.

The impulse response function (IRF) of the variable i to the structural shock j in the horizon k correspond to the element (i, j) of the matrix $\mathbf{L}_0\left(\mathbf{A}_0, \mathbf{A}_+\right)$, where $\mathbf{L}_k$ is recursively defined by

$$\mathbf{L}_0 = \left(\mathbf{A}_0^{-1}\right)', \tag{4}$$

$$\mathbf{L}_k = \sum_{\ell=1}^{k} \left(\mathbf{A}_\ell\mathbf{A}_0^{-1}\right)' \mathbf{L}_{k-\ell} \text{ for } 1 \leq k \leq v, \tag{5}$$

$$\mathbf{L}_k = \sum_{\ell=1}^{v} \left(\mathbf{A}_\ell \mathbf{A}_0^{-1}\right)' \mathbf{L}_{k-\ell} \text{ for } v < k < \infty. \tag{6}$$

As in Arias et al. (2019), we impose sign and zero restrictions directly on the structural coefficients. Since the identification scheme restricts only the monetary policy equation and less than $n-1$ zero restrictions, the structural parameters are not exactly identified. Identifying only one shock or subset of shocks follows the work of Bernanke and Mihov (1998), Christiano et al. (1999) and Uhlig (2005). Similarly, the specification of the systematic component of monetary policy is consistent with the works of Leeper et al. (1996), Leeper and Zha (2003), and Sims and Zha (2006). Without loss of generality, we let the first shock be the monetary policy shocks. Thus, the first equation of the SVAR

$$\mathbf{y}_t' \mathbf{a}_{0,1} = \sum_{\ell=1}^{v} \mathbf{y}_{t-\ell}' \mathbf{a}_{\ell,1} + \varepsilon_{1,t} \text{ for } 1 \leq t \leq T \tag{7}$$

is the monetary policy equation, where ε_{1t} denotes the first entry of ε_t, $\mathbf{a}_{\ell,1}$ denotes the first column of $\mathbf{A}_\ell$ for $0 \leq \ell \leq v$, and $a_{\ell,ij}$ denotes the (i,j) entry of $\mathbf{A}_\ell$ and describes the systematic component of the monetary policy. The restrictions are impose on $\mathbf{a}_{\ell,1}$ for $0 \leq \ell \leq v$.

The identification scheme is motivated by Taylor-type monetary policy rules identical to Arias et al. (2019). The reduced-form VAR specification consists of six endogenous variables ordered in the following form: output, y_t; prices, p_t; commodity prices, $p_{c,t}$; total reserves, tr_t; nonborrowed reserves, nbr_t; and the federal funds rate, r_t. These variables have been used by, among others, Christiano et al. (1996), Bernanke and Mihov (1998), Uhlig (2005) and Arias et al. (2019). The following two restrictions are imposed:

Restriction 1. The federal funds rate is the monetary policy instrument and it only reacts contemporaneously to output, prices, and commodity prices; and

Restriction 2. The contemporaneous reaction of the federal funds rate to output and prices is positive.

Restriction 1 implies that the Fed's interest rate does not react to changes in reserves. The second restriction is on the qualitative response of the Fed's interest rate to economic conditions. Restriction 2 implies that the central bank contemporaneously increases the federal funds rate in response to a contemporaneous increase in output and prices while leaving the response to commodity prices unrestricted as in Christiano et al. (1996).

As in Arias et al. (2019), it is assumed that the central bank has access to an enormous amount of real-time indicators to learn about the current state of real activity and prices. So we can rewrite equation (7), abstracting from lag variables, as

$$r_t = \psi_y y_t + \psi_p p_t + \psi_{p_c} p_{c,t} + \psi_{tr} tr_t + \psi_{nbr} nbr_t + \sigma \varepsilon_{1,t}, \tag{8}$$

where $\psi_y = -a_{0,61}^{-1} a_{0,11}$, $\psi_p = -a_{0,61}^{-1} a_{0,21}$, $\psi_{p_c} = -a_{0,61}^{-1} a_{0,31}$, $\psi_{tr} = -a_{0,61}^{-1} a_{0,41}$, $\psi_{nbr} = -a_{0,61}^{-1} a_{0,51}$ and $\sigma = a_{0,61}^{-1}$. Therefore, the Restriction 1 implies that $\psi_{tr} = \psi_{nbr} = 0$ and the Restriction 2 implies that $\psi_y, \psi_p > 0$. At the same time, the coefficient ψ_{p_c} remains unrestricted.

Algorithm

For the estimation of the model, we use a uniform-normal-inverse-Wishart distribution for the priors over the orthogonal reduced-form, that is characterized by four parameters: $UNIW(v, \phi, \psi, \Omega)$, with $v = 0, \phi = \mathbf{0}_{n\times n}, \psi = \mathbf{0}_{nv\times n}, \Omega^{-1} = \mathbf{0}_{nv\times nv}$. This parameterization results in prior densities that are equivalent to those in Uhlig (2005), as shown in Arias et al. (2018).

The algorithm described in Arias et al. (2018) is used to make independent draws subject to zero and sign constraints. This algorithm has two main advantages. The first is that it ensures that draws are subject only to the desired restrictions. This is important because other methods, such as the popular penalty function algorithm in Mountford and Uhlig (2009), introduce additional zero constraints and the identification does not come only from the desired constraints (Arias et al., 2018).

The second important advantage is that this algorithm offers greater computational efficiency compared to other methods, such as Baumeister and Hamilton (2015), which uses Metropolis-Hastings sampling to draw directly in the structural parameterization. It is also important to note that the results obtained by this algorithm are invariant to the ordering of the variables.

The following algorithm makes independent draws from the normal-generalized-normal $\mathrm{NGN}(v, \phi, \psi, \Omega)$ distribution over the structural parameterization conditional on the zero and sign constraints:

1. Draw (B, Σ), which are the parameters of the reduced orthogonal form from the $\mathrm{UNIW}(\mathrm{v}, \phi, \Psi, \Omega)$ distribution.

2. Draw an orthogonal matrix $\mathbf{Q}$ such that $(\mathbf{A}_0, \mathbf{A}_+) = \mathrm{f}_{\mathrm{h}}^{-1}(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q})$ satisfies the zero constraints.

3. If $(\mathbf{A}_0, \mathbf{A}_+)$ satisfies the sign constraints, then set its importance weight to:

$$\frac{\mathrm{NGN}_{(v,\mathbf{\Phi},\boldsymbol{\psi},\mathbf{\Omega})}\left(\mathbf{A}_0, \mathbf{A}_+\right)}{\mathrm{NIW}_{(v,\mathbf{\Phi},\boldsymbol{\psi},\Omega)}(\mathbf{B}, \mathbf{\Sigma}) v_{(g\circ f_h)|z}\left(\mathbf{A}_0, \mathbf{A}_+\right)} \propto \frac{\left|\det\left(\mathbf{A}_0\right)\right|^{-(2n+m+1)}}{v_{(gof_h)|z}\left(\mathbf{A}_0, \mathbf{A}_+\right)}$$

   where the denominator is the density over the conditional structural parameterization on the zero constraints. Otherwise, set its importance weight to zero.

4. Return to step 1 until the required number of draws has been obtained.

5. Re-sample with replacement with the importance weights and keep with the desired number of draws.

To ensure that we have a large enough sample size relative to the desired number of independent draws. First, we take 100,000 parameters that satisfy the zero constraints and then we hold 10,000 after resampling the draws that satisfy the sign constraints. Then the IRFs for the U.S. economy are calculated and saved.

2.2 Threshold Equation

The first equation, the monetary policy equation, of the SVAR (7) in its reduced form is given by

$$\mathbf{y}_{1t} = \sum_{\ell=1}^{v} \mathbf{y}'_{t-\ell}\mathbf{b}_{\ell,1} + \mathbf{u}_{1t} \text{ for } 1 \leq t \leq T, \tag{9}$$

where $\mathbf{y}_{1t}$ and $\mathbf{u}_{1t}$ denote the first entry. Equation (9) describes our specification for the Taylor rule as a time series regression, where $\mathbf{y}_{1t}$ is the federal funds rate, $\mathbf{y}_t$ is a vector which contains the intercept and lags of the six variables, $\mathbf{u}_{1t}$ is the error term of the Taylor rule equation, and t indexes periods (months). The variables in $\mathbf{y}_t$ are the federal funds rate, output, prices, commodity prices, total reserves, and nonborrowed reserves. $\mathbf{b}_{\ell,1}$ are the parameters to be estimated.

To assess whether or not economic policy uncertainty can affect the monetary policy equation, we estimate the following time series regression with a threshold variable as in Hansen (2000)

$$\mathbf{y}_{1t} = \sum_{\ell=1}^{v} \mathbf{y}'_{t-\ell}\mathbf{b}_{1\ell,1}1(q_{t-\ell} \leq \gamma) + \sum_{\ell=1}^{v} \mathbf{y}'_{t-\ell}\mathbf{b}_{2\ell,1}1(q_{t-\ell} > \gamma) + \mathbf{u}_{1,t} \text{ for } 1 \leq t \leq T, \tag{10}$$

where q_t is the economic policy uncertainty of the U.S. economy, and $1(.)$ is an indicator variable that takes the value of 1 if the economic policy uncertainty level is lower (or greater) than a threshold parameter and 0 otherwise. γ is the economic policy uncertainty threshold parameter to be estimated. $\mathbf{b}_{1\ell,1}$ and $\mathbf{b}_{2\ell,1}$ are the slope coefficients; that is, in this specification the effects of the lags of the six variables mentioned above on the monetary policy depend on the uncertainty regime.

The empirical analysis of these models involves estimation, inference, and testing for threshold effects (or testing for non-linearity). The theory for these models is developed in Hansen (2000). In particular, he proposes a method to construct confidence intervals for the threshold parameter, γ, in a simple closed-form expression. After estimating model (10), we need to test whether the threshold parameter is statistically significant, whether $\mathbf{b}_{1\ell,1} = \mathbf{b}_{2\ell,1}$ which is the hypothesis of no threshold effect. We expect that the monetary policy is effective in the low economic policy uncertainty regime when $q_{t-\ell} \leq \gamma$, than in the high economic policy uncertainty regime when $q_{t-\ell} > \gamma$.

Parameters estimation

Using the notation of equation (3), (10) is equivalent to

$$\mathbf{y}_{1t} = \mathbf{x}'_t\mathbf{B}_1 1(q_{t-\ell} \leq \gamma) + \mathbf{x}'_t\mathbf{B}_2 1(q_{t-\ell} > \gamma) + \mathbf{u}_{1,t} \text{ for } 1 \leq t \leq T, \tag{11}$$

and let $\mathbf{x}_t(\gamma)' = [\mathbf{x}'_t 1(q_{t-\ell} \leq \gamma) \quad \mathbf{x}'_t 1(q_{t-\ell} > \gamma)]$ and $\mathbf{B} = [\mathbf{B}_1 \quad \mathbf{B}_2]$. Thus, with this notation (11) can be written in vector notation stacked over time as

$$\mathbf{Y}_1 = \mathbf{X}(\gamma)'\mathbf{B} + \mathbf{U}. \tag{12}$$

The estimation procedure starts considering a given γ, within the empirical support of the threshold variable -in our case the uncertainty variable. The coefficients $\mathbf{B}_1$ and $\mathbf{B}_2$ can then be estimated using ordinary least squares, conditional on the given value for γ

$$\widehat{\mathbf{B}}(\gamma) = (\mathbf{X}(\gamma)'\mathbf{X}(\gamma))^{-1}X(\gamma)'\mathbf{Y}_1, \tag{13}$$

and the regression residuals are given by

$$\widehat{\mathbf{U}}(\gamma) = \mathbf{Y}_1 - \mathbf{X}(\gamma)'\widehat{\mathbf{B}}(\gamma); \tag{14}$$

finally, the sum of squared errors to be minimized is

$$S(\gamma) = \widehat{\mathbf{U}}(\gamma)'\widehat{\mathbf{U}}(\gamma). \tag{15}$$

The criterion function (15) is not smooth, so conventional gradient algorithms are not suitable for its maximization. Following Hansen (2000), the minimization of this sum of squared errors is carried out using a grid search over the threshold variable space. This involves constructing an evenly spaced grid on the empirical support of uncertainty, q_t, and minimizing the concentrated sum of squared errors (15). Finally, once $\widehat{\gamma}$ the uncertainty threshold parameter is estimated, the slope coefficient estimates are $\widehat{\mathbf{B}}_1 = \widehat{\mathbf{B}}_1(\widehat{\gamma})$, and $\widehat{\mathbf{B}}_2 = \widehat{\mathbf{B}}_2(\widehat{\gamma})$.

Inference

When there is a threshold effect ($\mathbf{B}_1 \neq \mathbf{B}_2$), then the threshold estimate $\widehat{\gamma}$ is a consistent estimator for γ_0 (the true value of γ), and it has an asymptotic distribution, which is nonstandard (Hansen, 2000). Thus, the best way to produce confidence intervals for the threshold parameter is to form the no-rejection region using the likelihood ratio statistic for the test on $\widehat{\gamma}$ (Hansen, 2000). To test the null hypothesis H_0: $\gamma = \gamma_0$, the likelihood ratio test is to reject large values of $LR(\gamma_0)$ where

$$LR(\gamma) = T\frac{S(\gamma) - S(\widehat{\gamma})}{S(\widehat{\gamma})}, \tag{16}$$

where $S(\gamma)$ is defined in (15), and T is the sample size.

The LR test converges in distribution as $T \to \infty$ to a random variable ξ with distribution function $P(\xi \leq z) = (1 - exp(-z/2))^2$. Furthermore, the distribution function ξ has the inverse

$$c(\rho) = -2ln(1 - \sqrt{1-\rho}), \tag{17}$$

where ρ is the significance level. The "no-rejection region" for a confidence level $1 - \rho$ is the set of values of γ such that $LR(\gamma) \leq c(\rho)$. This is found by plotting $LR(\gamma)$ against γ and drawing a flat line at $c(\rho)$.

Regarding the estimates of the slope parameters $\widehat{\mathbf{B}}_1$ and $\widehat{\mathbf{B}}_2$, the threshold regression model conditional on a given threshold parameter is a linear regression model. Furthermore, the asymptotic distribution of the estimates of the slope parameters converges to the traditional normal distribution as $T \to \infty$.

Testing for threshold effects

It is critical to determine whether the threshold effect is statistically significant or not. The null hypothesis of no threshold effects in (11) can be represented by the linear constraint $H_0 : \mathbf{B}_1 = \mathbf{B}_2$. Nonetheless, under the null hypothesis, H_0, the threshold γ is not identified, so classical tests have non-standard distributions. For this reason Hansen (2000) suggests a bootstrap to simulate the asymptotic distribution of the likelihood ratio test for this model so that the p-values constructed from the bootstrap procedure are asymptotically valid.

Therefore, under the null hypothesis of no threshold, the time series model is

$$\mathbf{y}_{1t} = \mathbf{x}_t'\mathbf{B}_1 + \mathbf{u}_{1,t} \text{ for } 1 \leq t \leq T, \tag{18}$$

or in a vector form

$$\mathbf{Y}_1 = \mathbf{X}'\mathbf{B}_1 + \mathbf{U}, \tag{19}$$

where the parameter $\mathbf{B}_1$ can be estimated using ordinary least squares, yielding an estimate of $\widehat{\mathbf{B}}_1$, and residuals $\widehat{\mathbf{U}}$. Let $S_0 = \widehat{\mathbf{U}}'\widehat{\mathbf{U}}$ be the sum of squared residuals of the linear time series model. In this case, the likelihood ratio test of H_0 is based on

$$F = T\frac{S_0 - S(\widehat{\gamma})}{S(\widehat{\gamma})}; \tag{20}$$

moreover, the null hypothesis is rejected if the percentage of draws for which the simulated statistic exceeds the actual value is less than a given critical value.

2.3 Data

As mentioned above, our dataset contains monthly U.S. data for the following variables: real Gross Domestic Product (GDP), the GDP deflator, a commodity price index, total reserves, nonborrowed reserves and the two-year Treasury bond yield. The monthly time series for real GDP and the GDP deflator are constructed using interpolation of the corresponding quarterly time series, as in Bernanke and Mihov (1998) and Mönch and Uhlig (2005). Real GDP is interpolated using the industrial production index, while the GDP deflator is interpolated using the consumer price index.

All the variables are retrieved from FRED (except the Treasury bond yield), Federal Reserve Bank of St. Louis, using the following mnemonics: NONBORRES (nonborrowed reserves of depository institution), CPIAUCSL (consumer price index), GDPC1 (real GDP), GDPDEF (GDP deflator), INDPRO (industrial production index), PPIACO (producer price index by commodity) and TOTRESNS (total reserves of depository institutions). The two-year Treasury bond yield (IGUSA2D) is from GFD, Global Financial Database. All variables are seasonally adjusted except for the commodity price index, reserves and the Treasury bond yield. Also, all the variables except the Treasury bond yield are expressed in logarithms.

The sample starts in January 1965 and ends in December 2023. This sample was chosen following and extending Arias et al. (2019). For the monthly uncertainty level of the U.S. economy, we used the News-Based Economic Policy Uncertainty Index and the News-Based Historical Economic Policy Uncertainty, which are constructed from newspaper coverage of policy-related economic uncertainty. Specifically, for the period from January 1965 to October 2010, we used the News-Based Historical Economic Policy Uncertainty and then we spliced the series using the News-Based Economic Policy Uncertainty Index, from November 2010 to December 2023.[3]

3 Estimation results

In this section, we discuss our main empirical findings on the relationship between economic policy uncertainty and the effectiveness of the U.S. monetary policy. That is, it contains the resulting economic policy uncertainty threshold estimation, and IRFs to a contractionary monetary policy for the U.S. economy under low and high economic policy uncertainty regimes, and compares them with findings from previous research.

3.1 Threshold estimation results

Are there economic policy uncertainty threshold effects in the Taylor rule (monetary policy) regression equation? To address this question, we need to test for the existence of an uncertainty threshold effect in the Taylor rule regression equation using the F test given in equation (20). This step typically involves estimating equation (11) and computing the residual sum of squares for the different uncertainty values. As it was mentioned before, the test has non-standard distributions, to this end we use 2,000 bootstrap replications to perform the threshold effects test.

The bootstrap p-value of the test is 0.000.[4] Thus, the null hypothesis of no uncertainty threshold effect (linear model) against a single uncertainty threshold model is rejected at the one percent significance level. Therefore, there is strong evidence that economic policy uncertainty affects the Taylor rule equation by splitting the regression sample into two regimes. In addition, we perform tests for the existence of two or more uncertainty threshold effects (more than two uncertainty regimes), but we do not find evidence of more than two economic policy uncertainty regimes.

Figure 1 shows a renormalization of the objective function (concentrated likelihood ratio function $LR(\gamma)$) on the space of the economic policy uncertainty threshold parameter, where the function is minimized at zero when the estimated threshold is $\widehat{\gamma} = 145.017$ (the 62th percentile of the economic policy uncertainty variable distribution). Thus, the two regimes separated by the threshold estimate are denoted as low and high uncertainty regimes, respectively. Note that, most of the periods above the economic policy uncertainty estimated threshold are after the financial crisis of 2008 (see Figure 2).

How precise is this uncertainty threshold estimate? To answer this question, we construct a confidence interval for the estimated uncertainty threshold. The estimation

[3]Note that the correlation between the two indices in the common sample from 1985:01 to 2014:10 is 0.98.

[4]The null test that the model is linear, where uncertainty plays no role, against the alternative of a single uncertainty threshold model was performed by allowing heteroskedastic errors (White corrected).

Figure 1: Confidence interval construction for threshold

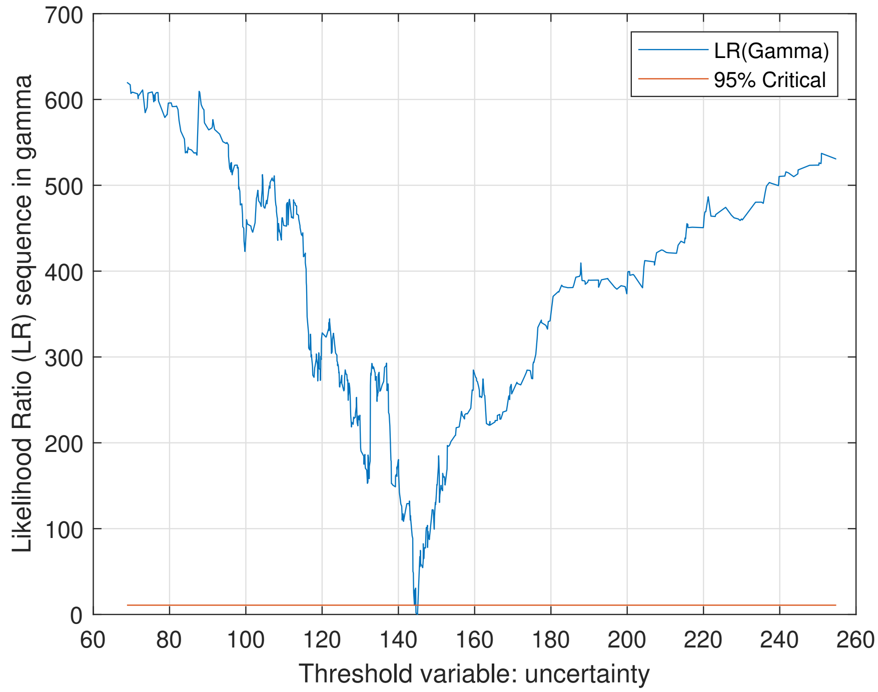
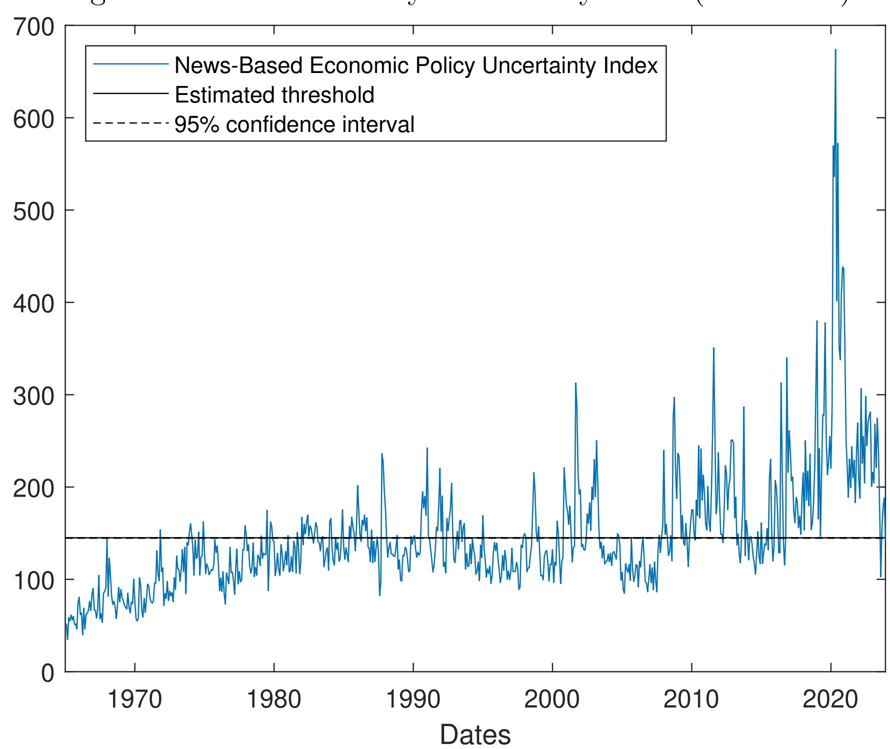


Figure 2: Economic Policy Uncertainty Index (1985-2020)

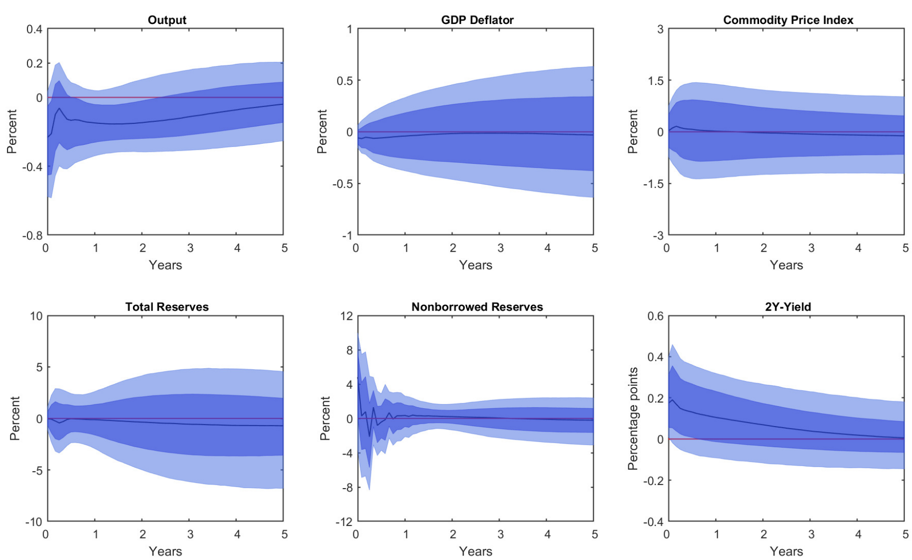


precision is high because the 95 percent confidence interval, the set of values below the dotted line in Figure 1, is $[144.609, 145.017]$; which is tight and indicates a high precision in the uncertainty threshold estimation.[5] Note that the threshold estimate is placed at the 62th percentile of the economic policy uncertainty variable distribution, this estimate and its corresponding confidence interval are much smaller than those obtained under the *ad hoc* rule of the 75th or 90th percentile, which suggests the unfitness of the later.

3.2 SVAR results

Figure 3 shows the posterior-wise median IRFs of the endogenous variables to a contractionary policy shock in the entire sample, while the blue-shaded bands represent the corresponding 68 and 95 percent posterior probability bands. A contractionary monetary policy shock leads to an immediate median increase in the two-year Treasury bond yield of around 17 basis points. The significant tightening in monetary policy leads to an immediate drop in output of around 5 basis points with a high posterior probability and a zero response with a 95 percent posterior probability for all periods. After the first month, the output shows a zero response with a high posterior probability for five months. Subsequently, it exhibits a negative response for nearly one and a half years. While the median response of output is negative for the five years. The rest of the variables have a zero response with a high posterior probability and 95 percent posterior probability.

Figure 3: Impulse responses to a monetary policy shock



Note: IRFs to a one standard deviation contractionary monetary policy shock identified using Restrictions 1 and 2. The solid lines depict the point-wise posterior medians and the shaded bands represent the 68 and 95 percent equal-tailed point-wise posterior probability bands.

These results are quite similar to the estimates of Arias et al. (2019) in the sense that monetary policy is effective in bringing down economic activity at a 68 percent

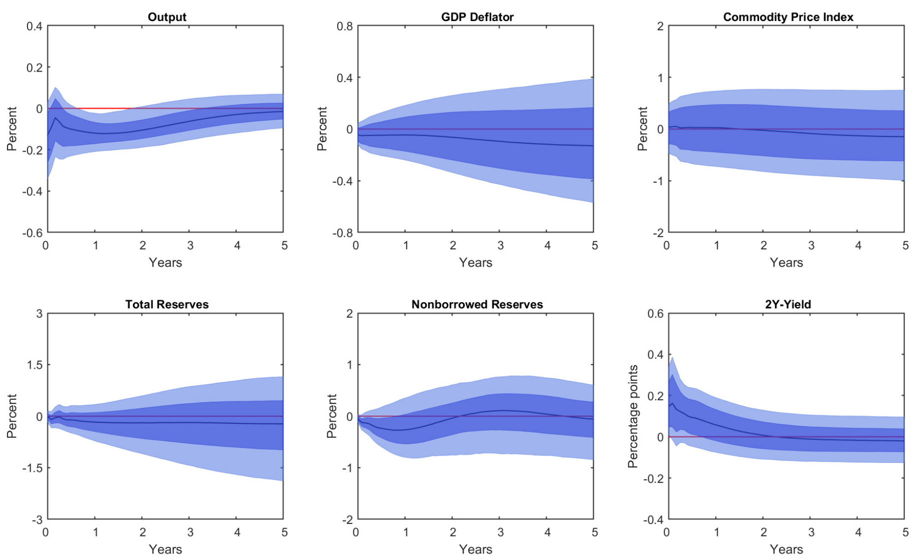
[5]Note that the upper quota of the 95 percent confidence interval coincides with the estimated threshold, because the asymptotic distribution of the estimated threshold is asymmetric.

confidence level, but there is no effect on GDP deflator; note that Arias et al. (2019) use data from 1965 to 2007 in their estimation results. Nonetheless, the result for the entire sample indicates that the effectiveness of U.S. monetary policy is lost at the 95 percent confidence level; we argue that this could be due to the inclusion of periods of high uncertainty (see Figure 2).

Monetary policy under low uncertainty regime

Figure 4 shows the IRFs to a contractionary monetary policy shock for months where the level of economic policy uncertainty is below the threshold previously found. This shock leads to an immediate median increase in the two-year Treasury bond yield of around 15 basis points that is then corrected. In this case, the significant tightening in monetary policy leads to a more pronounced immediate median drop in output of around 13 basis points and also this fall is persistent for the rest of the period. The response of output is negative with a high posterior probability for the first forty months after the shock, except for months 1 to 3.

Figure 4: Impulse responses to a monetary policy shock - low uncertainty regime



Note: IRFs to a one standard deviation contractionary monetary policy shock identified using Restrictions 1 and 2. The solid lines depict the point-wise posterior medians and the shaded bands represent the 68 and 95 percent equal-tailed point-wise posterior probability bands.

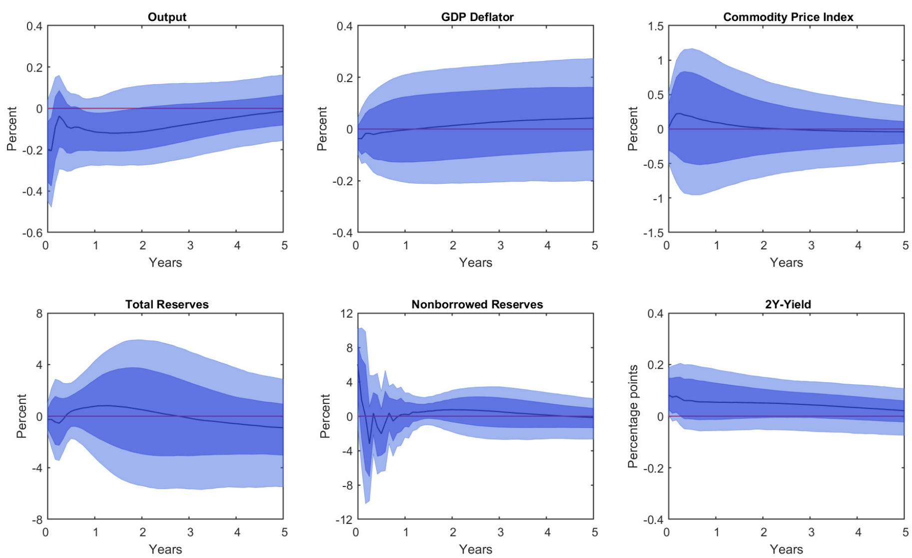
Furthermore, Figure 4 shows a protracted median decline in prices, and the response of commodity prices is close to zero and not precisely estimated. On the reserves side, the response of total reserves is virtually zero with a high posterior probability and with 95 percent posterior probability. The nonborrowed reserves show an immediate decrease with a high posterior probability, which extends over the next nine months.

The contractive response of output is consistent with the findings of Bernanke and Blinder (1992), Christiano et al. (1996), Leeper et al. (1996), Bernanke and Mihov (1998) and Smets and Wouters (2007). In particular, the form of the output response and the undershooting of the monetary policy rate (two-year Treasury bond yield) is similar to those obtained by Smets and Wouters (2007), who estimated a Bayesian DSGE with various restrictions.

Monetary policy under high uncertainty regime

Figure 5 shows the IRFs to a contractionary monetary policy shock for months where the level of economic policy uncertainty is above the threshold previously found. In this case, the monetary policy shock leads to an immediate median increase in the two-year Treasury bond yield of around 8 basis points. Similar to the case where we use the entire sample, the significant tightening in monetary policy leads only to an immediate median drop in output of around 20 basis points, and a zero response with 95 percent posterior probability for all periods. Furthermore, we observe a less pronounced drop in output with a high posterior probability; whereas prices, commodity prices, and reserves have a zero response.

Figure 5: Impulse responses to a monetary policy shock - high uncertainty regime



Note: IRFs to a one standard deviation contractionary monetary policy shock identified using Restrictions 1 and 2. The solid lines depict the point-wise posterior medians and the shaded bands represent the 68 and 95 percent equal-tailed point-wise posterior probability bands.

When a very high uncertainty threshold is imposed –for instance, the 90th percentile of the economic policy uncertainty variable distribution–, the number of observations that the SVAR method will use to analyze the high uncertainty regime is reduced. Therefore, the confidence bands of the IRFs in this case end up being very wide. This leads to monetary policy being ineffective; which might be due to the few observations that exist in such a regime and not because of the level of uncertainty itself.

The main result of declining output with a posterior probability of 95 percent in periods of low uncertainty, but not in periods of high uncertainty is consistent with previous literature. For instance, Pellegrino (2018), Castelnuovo and Pellegrino (2018), Aastveit et al. (2017), Mehmet et al. (2016), and Blot et al. (2020) study the responses of a monetary shock contingent to the low and high uncertainty regimes; all of them find differentiated effects except Blot et al. (2020). In this matter, Aastveit et al. (2017) argue that this result is consistent with the "cautiousness" effects suggested by economic theory, where there is more cautiousness when deciding whether to invest or not when uncertainty is high; therefore, a marginal change in investment incentives induced by a change in interest rate has a smaller impact.

Consistent with the drop in output under the low uncertainty regime, there is also a slight fall in prices, and no response in the high uncertainty regime; this result is in line with Arias et al. (2019), whose analysis goes up to 2007, after which uncertainty has been quite high. On the contrary, Castelnuovo and Pellegrino (2018) find that inflation rises quicker when uncertainty is high, while there is no significant response of inflation when uncertainty is low; Aastveit et al. (2017) find that in both the high and low volatility regimes, the prices initially increase in response to the monetary tightening, and decline only several periods later; while Mehmet et al. (2016) do not observe a significant difference in the impulse responses of prices under high and low uncertainty environments; however they observe a larger impact when uncertainty is low.

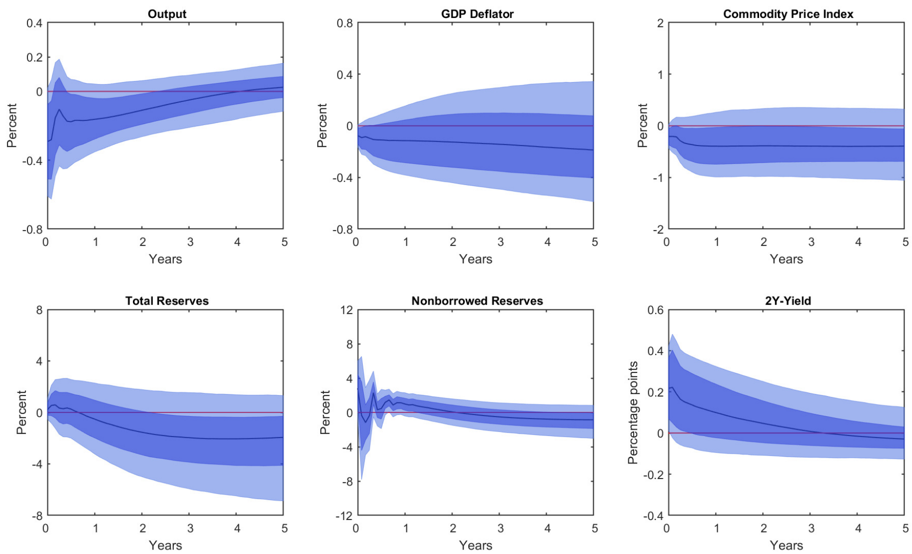
For its part, the interest rate has a weaker reaction and is less persistent in high uncertainty periods than in low uncertainty ones; in this regard, Castelnuovo and Pellegrino (2018) find that the interest rate response is less persistent during uncertain times; in the same manner, Tillmann (2020) finds that a policy tightening leads to a significantly smaller increase in long-term bond yields if policy uncertainty is high, where this weaker response is driven by the fall in term premia, which fall more strongly if uncertainty is high. Tillmann (2020) argues that a higher uncertainty about monetary policy tends to make securities with longer maturities relatively more attractive to investors; as a consequence, investors demand even lower term premia.

4 Restriction on commodity prices

In this section, we check the robustness of the results reported in Section 3 by using another specification following Arias et al. (2019). In particular, we will focus on the case when we add a further restriction for commodity prices to our identification. This is a zero restriction for commodity prices, $\psi_{p_c} = 0$ (Restriction 3). Since we are not changing any variables in the identification strategy, we maintain the economic policy uncertainty threshold estimated for this case.

Similar to the baseline case, Figure 6 displays the results of contractionary monetary policy shock for the entire sample. We observe greater effects, such as an immediate median increase of approximately 22 basis points in the two-year Treasury bond yield, an immediate output decrease of 8 basis points, and a prolonged negative output response with a high posterior probability. Other important results include a decrease in commodity prices throughout the entire period with a high posterior probability, an immediate price decrease of 2 basis points with a high posterior probability, and a negative long-term response of total reserves, also with a high posterior probability.

Figure 6: Impulse responses to a monetary policy shock



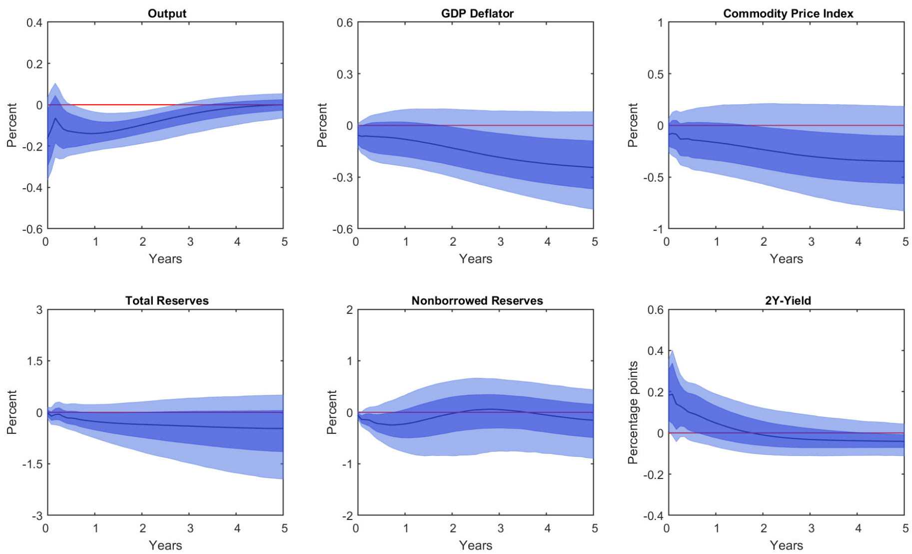
Note: IRFs to a one standard deviation contractionary monetary policy shock identified using Restrictions 1, 2 and 3. The solid lines depict the point-wise posterior medians and the shaded bands represent the 68 and 95 percent equal-tailed point-wise posterior probability bands.

In Figure 7, we observe an immediate median increase of approximately 18 basis points in the federal funds rate in response to a contractionary monetary policy shock when the uncertainty level is low. Additionally, the output response to this shock is negative with a high posterior probability for most of the entire period and with a 95 percent posterior probability for most of the first three years. We also find a long-term negative response in prices and commodity prices with a high posterior probability, and similar results for reserves as in the baseline case. Consequently, this drop is more persistent than in the case described in Section 3.2.

Figure 8 shows that when the uncertainty level is high, the output experiences a significant drop for the first two months with a high posterior probability, but then exhibits a near-zero response with both high and 95 percent posterior probability. Additionally, we observe a decrease in prices for the first five months and in commodity prices for the entire period, both with a high posterior probability. Meanwhile, the federal funds rate experiences an immediate median increase of approximately 10 basis points in response to this shock. As we can see, most of these results are in line with those described in the baseline case.

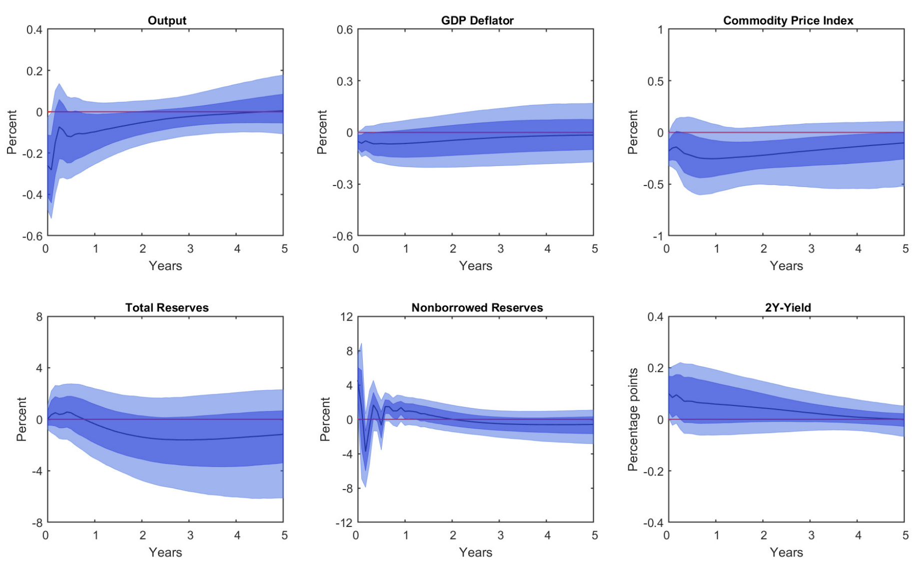
One could continue to add more constraints to the structural parameters or IRFs, but at the cost of further justification of each added constraint; which casts doubts on how agnostic and theory-driven the subsequent identification schemes are. Given that the methods used require large samples to obtain consistent results, no other uncertainty measures are available for large samples (the longest ones have been available since 1985); however, in the common sample, most uncertainty measures are highly correlated. Therefore, we expected similar results when using other measures of uncertainty.

Figure 7: Impulse responses to a monetary policy shock - low uncertainty regime



Note: IRFs to a one standard deviation contractionary monetary policy shock identified using Restrictions 1, 2 and 3. The solid lines depict the point-wise posterior medians and the shaded bands represent the 68 and 95 percent equal-tailed point-wise posterior probability bands.

Figure 8: Impulse responses to a monetary policy shock - high uncertainty regime



Note: IRFs to a one standard deviation contractionary monetary policy shock identified using Restrictions 1, 2 and 3. The solid lines depict the point-wise posterior medians and the shaded bands represent the 68 and 95 percent equal-tailed point-wise posterior probability bands.

5 Conclusion

In this paper, we study whether economic policy uncertainty matters for the effectiveness of monetary policy. We postulate that the link between economic uncertainty and the Taylor rule equation could be modeled using a threshold regression model, where economic uncertainty is the threshold variable, and then we modeled the U.S. economy into an SVAR model in each economic uncertainty regime.

Using times series data for the U.S. economy, we find that there is a statistically significant uncertainty threshold that splits the sample into two regimes: a low-uncertainty and a high-uncertainty regime. More importantly, the SVAR analysis in each economic uncertainty regime finds that the monetary policy shock declines the economic activity in the low-uncertainty regime but does not in the high-uncertainty one with 95 percent posterior probability, that is the monetary policy shock loses its power in high uncertainty periods. Our findings are robust to the addition of further restriction and the use of the one-year Treasury bond yield.

Other measures of uncertainty or volatility used in the literature can be used as robustness analyses; however, these measures are not available for a long period; however, Bayesian methods for SVAR estimation and, mainly, threshold models require many observations. Likewise, the analysis of sub-periods (before and after the global financial crisis or the pandemic) can be interesting, but at the cost of fewer observations. Therefore, other estimation methods such as local projections may be more suitable for short samples. Also, the analysis of other policies such as unconventional policies and reserve requirements in periods of high and low uncertainty would be relevant. These issues would be fruitful areas for future research.

References

Aastveit, K.A., G.J. Natvik and S. Sola (2017). "Economic uncertainty and the influence of monetary policy." *Journal of International Money and Finance* 76, 50-67.

Arias, J.E., D. Caldara and J.F. Rubio-Ramírez (2019). "The systematic component of monetary policy in SVARs: an agnostic identification procedure." *Journal of Monetary Economics* 101, 1-13.

Arias, J.E., J.F. Rubio-Ramírez and D.F. Waggoner (2018). "Inference based on structural vector autoregressions identified with sign and zero restrictions: theory and applications." *Econometrica* 86(2), 685-720.

Baumeister, C. and J. Hamilton (2015). "Sign restrictions, structural vector autoregressions, and useful prior information." *Econometrica* 83(5), 1963-1999.

Berg, K. and N. Mark (2018). "Where's the risk? The forward premium bias, the carry-trade premium, and risk-reversals in general equilibrium." *Journal of International Money and Finance* 95, 297-316.

Bernanke, B. (1983). "Irreversibility, uncertainty, and cyclical investment." *Quarterly Journal of Economics* 98(1), 85-106.

Bernanke, B. and A. Blinder (1992). "The federal funds rate and the channels of monetary transmission." *American Economic Review* 82(4), 901-921.

Bernanke, B., J. Boivin and P. Eliasz (2005). "Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach." *Quarterly Journal of Economics* 120(1), 387-422.

Bernanke, B. and I. Mihov (1998). "Measuring monetary policy." *Quarterly Journal of Economics* 113(3), 869-902.

Bloom, N. (2009). "The impact of uncertainty shocks." *Econometrica* 77(3), 623-685.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten and S.J. Terry (2018). "Really uncertain business cycles." *Econometrica* 86(3), 1031-1065.

Blot, C., P. Hubert and F. Labondance (2020). *Uncertainty and monetary policy in the Euro area*. Publication for the committee on Economic and Monetary Affairs, Policy Department for Economic, Scientific and Quality of Life Policies, European Parliament, Luxembourg.

Bordo, M.D., J.V. Duca and C. Koch (2016). "Economic policy uncertainty and the credit channel: aggregate and bank level U.S. evidence over several decades." *Journal of Financial Stability* 26, 90-106.

Campbell, J., C. Evans, J. Fisher and A. Justiniano (2012). "Macroeconomic effects of Federal Reserve forward guidance." *Brookings Papers on Economic Activity* 43(1), 1-80.

Castelnuovo E. and G. Pellegrino (2018). "Uncertainty-dependent effects of monetary policy shocks: a new-Keynesian interpretation". *Journal of Economic Dynamics and Control* 93, 277-296.

Christiano, L., M. Eichenbaum and C. Evans (1996). "The effects of monetary policy shocks: evidence from the flow of funds." *The Review of Economics and Statistics* 78(1), 16-34.

Christiano, L., M. Eichenbaum, and C. Evans (1999). "Monetary policy shocks: what have we learned and to what end?" In Taylor, J. and M. Woodford (Eds.), *Handbook of macroeconomics*, 65-148. Amsterdam: North-Holland.

Dixit, A. and R. Pindyck (1994). *Investment under uncertainty*. Princeton University Press.

Donayre, L. (2014). "Estimated thresholds in the response of output to monetary policy: are large policy changes less effective?" *Macroeconomic Dynamics* 18(1), 41-64.

Gertler, M. and P. Karadi. (2015). "Monetary policy surprises, credit costs and economic activity." *American Economic Journal: Macroeconomics* 7(1), 44-76.

Gürkaynak, R., B. Sack and E. Swanson. (2006). "The sensitivity of long-term interest rates to economic news: evidence and implications for macroeconomic models." *American Economic Review* 95(1), 425-436.

Hansen, B.E. (2000). "Sample splitting and threshold estimation." *Econometrica* 68(3), 575-603.

Husted, L., J. Rogers and B. Sun (2018). "Uncertainty, currency excess returns, and risk reversals." *Journal of International Money and Finance* 88, 228-241.

Kuttner, K. (2001). "Monetary policy surprises and interest rates: evidence from the Fed funds futures market." *Journal of Monetary Economics* 47(3), 523-544.

Leeper, E. and T. Zha (2003). "Modest policy interventions." *Journal of Monetary Economics* 50(8), 1673-1700.

Leeper, E., C. Sims and T. Zha (1996). "What does monetary policy do?" *Brookings Papers on Economic Activity* 27(2), 1-78.

Mehmet, B., R. Demirer, R. Gupta and R. van Eyden (2016). "Effectiveness of monetary policy in the Euro area: the role of US economic policy uncertainty." Working Papers 201620, University of Pretoria, Department of Economics.

Mönch E. and H. Uhlig (2005). "Towards a monthly business cycle chronology for the Euro area." *Journal of Business Cycle Measurement and Analysis* 2005/1, 43-69.

Mountford, A. and H. Uhlig (2009). "What are the effects of fiscal policy shocks?" *Journal of Applied Econometrics* 24(6), 960-992.

Pellegrino, G. (2018). "Uncertainty and the real effects of monetary policy shocks in the Euro area." *Economics Letters* 162, 177-181.

Rehse, D., R. Riordan, N. Rottke and J. Zietz (2019). "The effects of uncertainty on market liquidity: evidence from hurricane Sandy." *Journal of Financial Economics* 134(2), 318-332.

Sims, C. and T. Zha (2006). "Does monetary policy generate recessions?" *Macroeconomic Dynamics* 10(2), 231-272.

Smets, F. and R. Wouters (2007). "Shocks and frictions in US business cycles: a Bayesian DSGE approach." *American Economic Review* 97(3), 586-606.

Tillmann, P. (2020). "Monetary policy uncertainty and the response of the yield curve to policy shocks." *Journal of Money, Credit and Banking* 52(4), 803-833.

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.

Vavra, J. (2014). "Inflation dynamics and time-varying volatility: new evidence and an ss interpretation." *Quarterly Journal of Economics* 129(1), 215-258.