Does uncertainty matter for the effectiveness of monetary policy?*

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Abstract

Uncertainty can affect the monetary policy through its influence on macroeconomic variables. In this paper, we examine the extent to which uncertainty affects the effectiveness of the monetary policy in a monthly sample over the period 1985:1-2020:12 for the U.S. economy. Using threshold regression models, we find evidence of threshold effects where an uncertainty threshold around 109.8 of the uncertainty variable is estimated, which defines two regimes: high and low uncertainty. By estimating a 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 findings are robust to the use of other uncertainty measures.

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1 Introduction

In the last decade there is a growing literature that states the importance of uncertainty on macroeconomic variables. Uncertainty can influence on 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).

In 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 exactly 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.

On related literature, Vavra (2014) constructs price-setting models with CPI micro data, 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 than these previous works. First, we postulate that uncertainty affects the effectiveness of the U.S. monetary policy by splitting the sample following a threshold regression model (Hansen, 2000), where uncertainty is a threshold variable that endogenously splits the sample into two or more regimes. That is, the 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 a SVAR model in each 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 uncertainty threshold is estimated by splitting the sample in high and low uncertainty regimes, we estimate the effectiveness of the U.S. monetary policy in each 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).

We find strong evidence of uncertainty threshold effects; that is, in a threshold model of the monetary policy equation, the uncertainty measure splits the sample into two regimes -which we will call "low-uncertainty" and "high-uncertainty". In the low-uncertainty regime, the U.S. monetary policy is effective since it drops economic activity and inflation. In contrast, in the high uncertainty regime, the U.S. monetary policy loses its effectiveness in the sense that it does not affect or has a lesser 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 examine the regression model where uncertainty is the threshold variable, and the SVAR model in the high and low uncertainty regimes. In Section 4, we discuss certain robustness exercises. Finally, in Section 5, we conclude.

2 Methodology and data

In this section, we briefly discuss our methodology and database. We postulate that 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 uncertainty is the threshold variable that splits the sample in 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 1985:1-2020:12. The data are retrieved from the Federal Reserve Bank of St. Louis database (FRED).

2.1 U.S. economy SVAR

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

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

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 $0 \le \ell \le v$ 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

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

where $\mathbf{A}_+' = \begin{bmatrix} \mathbf{A}_1' & \ldots & \mathbf{A}_v' & \mathbf{c}' \end{bmatrix}$ and $\mathbf{x}_t' = \begin{bmatrix} \mathbf{y}_{t-1}' & \ldots & \mathbf{y}_{t-v}' & 1 \end{bmatrix}$ for $1 \le t \le T$. 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

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

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

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

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

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

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

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

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).

It is assumed that the central bank have 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 parameter: $UNIW(v, \phi, \psi, \Omega)$, 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:

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

   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 time 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.

In order to asses whether or not the 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 uncertainty of the U.S. economy, and 1(.) is an indicator variable which takes the value of 1 if uncertainty level is lower (or greater) than a threshold parameter and 0 otherwise. γ is the 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 test for non-linearity). 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 uncertainty regime, when $q_{t-\ell} \leq \gamma$, than in the high 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 $T \rightarrow \infty$ 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 $c(\rho)$.

In regard to 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 $T \rightarrow \infty$.

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 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 federal funds rate. 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, Federal Reserve Bank of St. Louis, using the following mnemonics: NONBORRES (nonborrowed reserves of depository institution), CPIAUCSL (consumer price index), FEDFUNDS (the federal funds rate), GDPC1 (real GDP), GDPDEF (GDP deflator), INDPRO (industrial production index), PPIACO (producer price index by commodity) and TOTRESNS (total reserves of depository institutions). All variables are seasonally adjusted except for the commodity price index, reserves and the federal funds rate. Also, all the variables except the federal funds rate are expressed in logarithms.

The sample starts in January 1985 and ends in December 2020. This sample was chosen because the uncertainty data only are available since January 1985. So, for the monthly uncertainty level of the U.S. economy, we use the Economic Policy Uncertainty Index, which is constructed from three types of underlying components: newspaper coverage of policy-related economic uncertainty, number of federal tax code provisions set to expire in future years, and disagreement among economic forecasters.

3 Estimation results

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

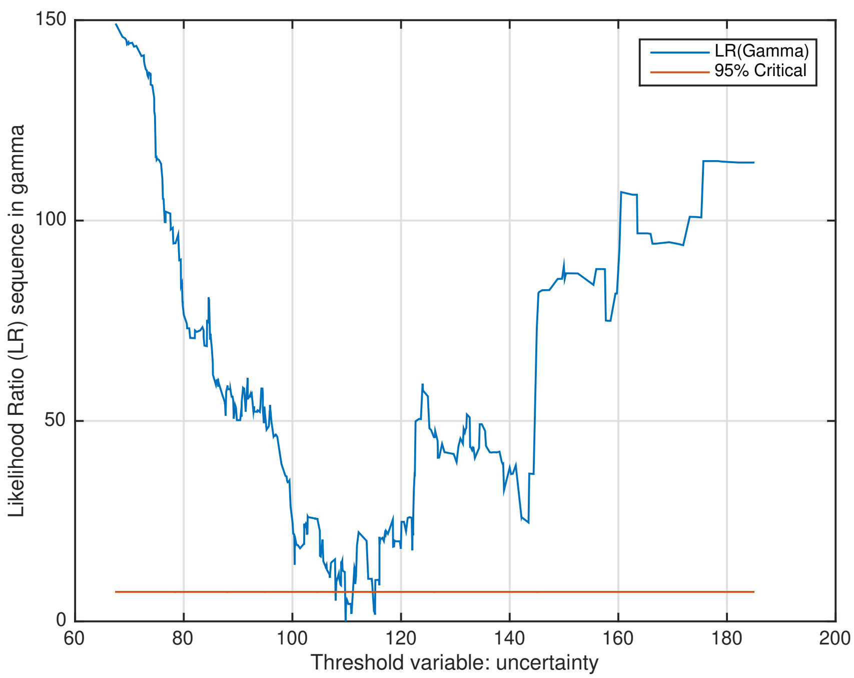
3.1 Threshold estimation results

Are there 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.[1] 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 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 uncertainty regimes.

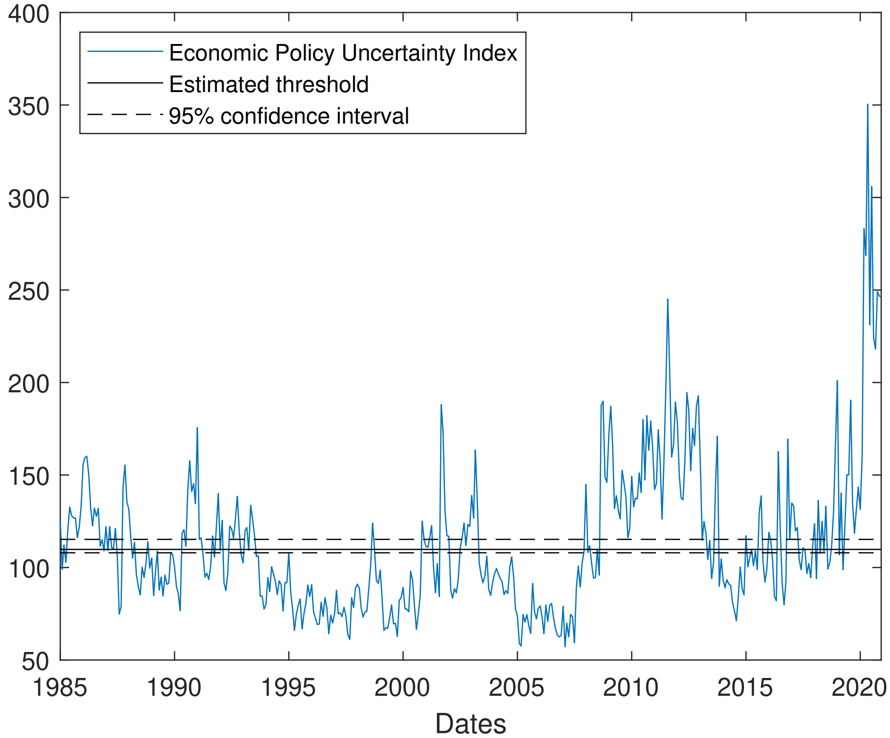
Figure 1 shows a renormalization of the objective function (concentrated likelihood ratio function $LR(\gamma)$) on the space of the uncertainty threshold parameter, where the function is minimized at zero when the estimated threshold is $\widehat{\gamma} = 109.789$. Thus, the two regimes separated by the threshold estimate are denoted as low and high uncertainty regimes, respectively. Note that, most of the periods above the uncertainty estimated threshold are after the financial crisis of 2008 (see Figure 2).

Figure 1: Confidence interval construction for threshold



[1]The test of null of no uncertainty threshold model against alternative of a single uncertainty threshold model was performed by allowing heteroskedastic errors (White corrected).

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



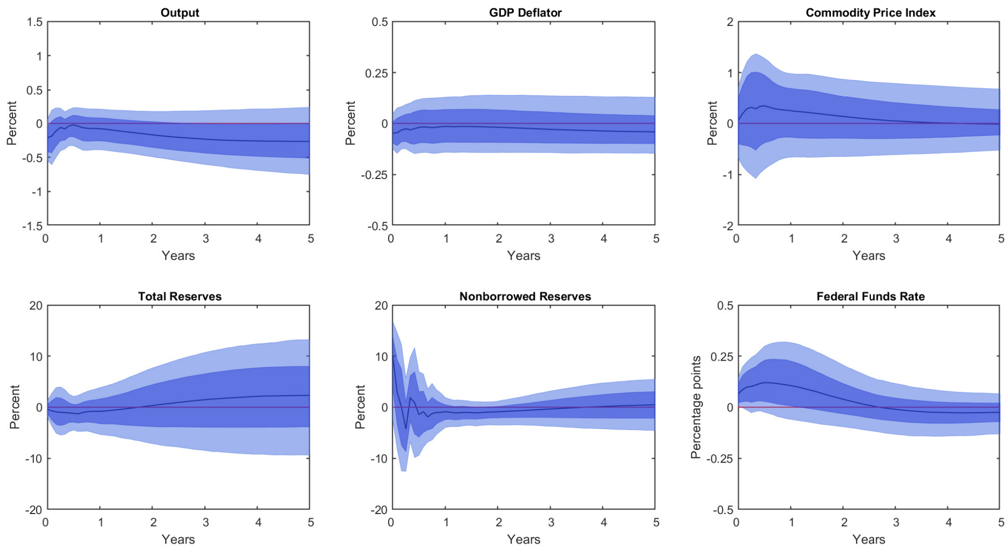
How precise is this uncertainty threshold estimate? In order to answer this question, we construct a confidence interval for the estimated uncertainty threshold. The estimation precision is high because the 95 percent confidence interval, the set of values below the dotted line in Figure 1, is $[107.955, 115.214]$; which is tight and indicates a high precision in the uncertainty threshold estimation. Note that the threshold estimate is placed at the 57th percentile of the uncertainty variable distribution, this estimate and its corresponding confidence interval are much smaller than those obtained under the *ad hoc* rule of the 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 federal funds rate of around 6 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 95 percent posterior probability for all the period. After the first month, the output has a zero response also with a high posterior probability. While the median response of output is negative for the five years. And the rest of the variables have a zero response with a high posterior probability and 95 percent posterior probability.

This result loses the effectiveness to drop the economic activity than the estimate

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.

in Arias et al. (2019), who use data from 1965 to 2007. In order to check the influence of other factors, we estimate the SVAR model from 1965 to 2017; from 1983 to 2017, to exclude the years in which the Fed explicitly targeted non-borrowed reserves; from 1983 to June 2007, to exclude the Great Recession; to account for the period of unconventional monetary policy, the model is also estimated replacing the Fed funds rate with the shadow rate estimated in Wu and Xia (2016) from 1965 to 2017. All of them yield similar results (figures not showed), with the response of output remaining contractionary as in Arias et al. (2019). Thus, our result in the entire sample loses the effectiveness, that might be by the inclusion of years 2018-2020, periods in which uncertainty was high (see Figure 2).

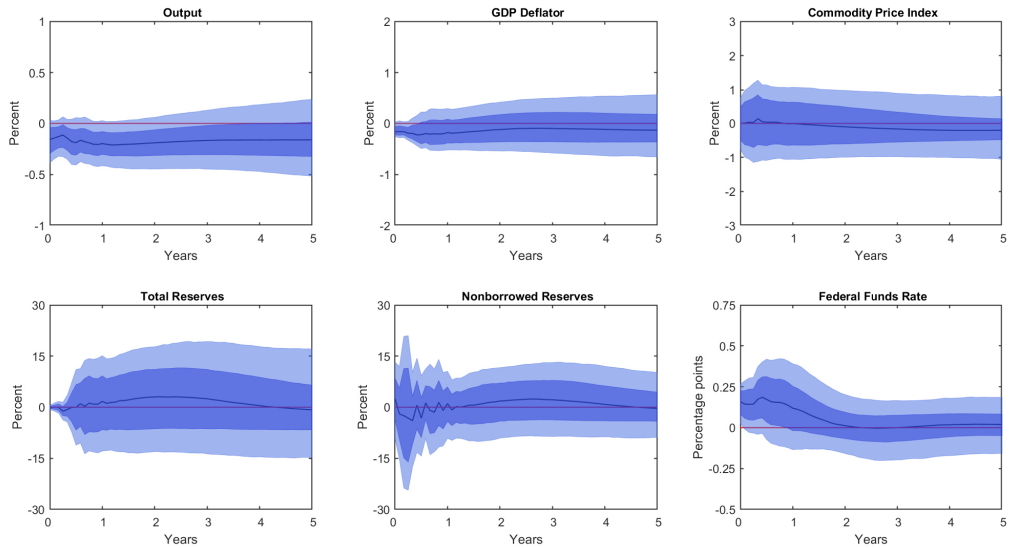
Monetary policy under low uncertainty regime

Figure 4 shows the IRFs to a contractionary monetary policy shock for months where the level of uncertainty is below the threshold previously found. This shock leads to an immediate median increase in the federal funds rate of around 16 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 16 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 four years after the shock.

Furthermore, Figure 4 shows a protracted 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 and nonborrowed reserves is virtually zero with a high posterior probability and with 95 percent posterior probability.

The contractive response of output is consistent with the findings of Bernanke and

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.

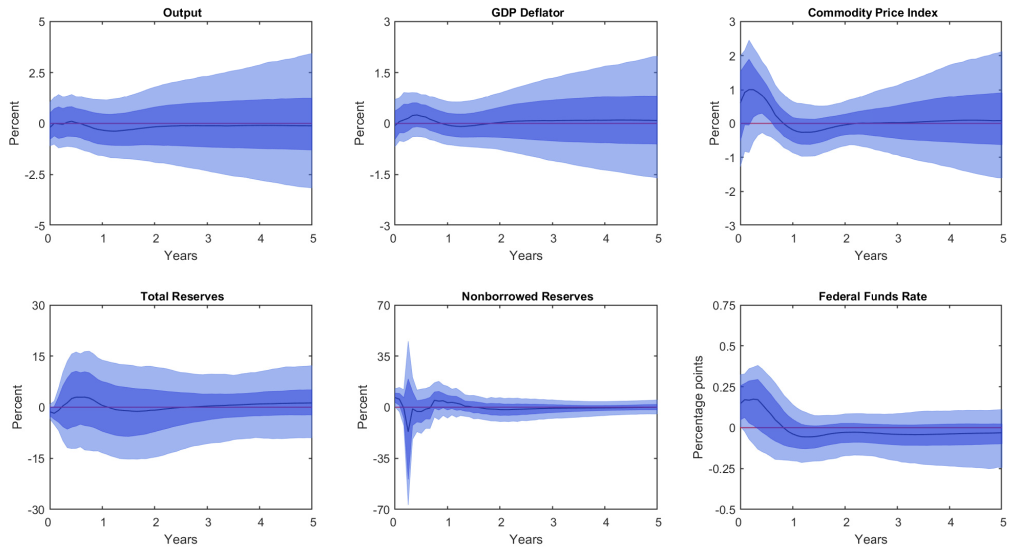
Blinder (1992), Christiano et al. (1996), Leeper et al. (1996), Bernanke and Mihov (1998) and Smets and Wouters (2007). In particular, the form of the output response and the undershooting of the federal funds rate is similar to those obtained by Smets and Wouters (2007), who estimated a Bayesian DSGE 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 uncertainty is above the threshold previously found. In this case, the monetary policy shock leads to an immediate median increase in the federal funds rate of around 15 basis points. Similar to the case where we use all the 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 a high posterior probability and with 95 percent posterior probability for all the period. Also, in the case of commodity prices there are some periods during the first year that present a positive response with a high posterior probability. Whereas prices and reserves have a zero response, similar to the case when we analyze all the sample.

When a very high uncertainty threshold is imposed, for example, the 90th percentile, 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 due to the few observations that exist in that regime and not because of the level of uncertainty itself.

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.

Compared with related empirical literature

Our main results are in line with previous literature that investigate the differentiated responses to a monetary policy shock in both low and high uncertainty regimes. For instance, Vavra (2014) studies if monetary policy is less effective at increasing output during periods of high volatility than during normal times by using CPI micro data, where he shows that this micro-founded model predicts weaker effects of policy when firm-level volatility is high; while Tillmann (2020) studies the nonlinear response of the term structure of interest rates to monetary policy shocks, where he shows that uncertainty about monetary policy changes the way the term structure responds to monetary policy. In line with our SVAR framework, 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).

The interest rate has a weaker reaction and less persistent in high uncertainty periods than in low uncertainty ones, in this line Castelnuovo and Pellegrino (2018) find that the interest rate response is less persistent during uncertain times, while 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 about policy 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.

The drop in output is negative at a high posterior probability in low uncertainty periods, but not in high uncertainty ones. Castelnuovo and Pellegrino (2018) find that real activity indicators such as real GDP, consumption, investment, and hours worked display a lower peak response and persistence in high uncertainty times. Similarly, Aastveit et al. (2017) and Mehmet et al. (2016) find that monetary policy shocks affect economic activity considerably weaker when uncertainty is high for the U.S. economy and Euro area, respectively. 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; and hence, 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 drop in prices, and no response under the high uncertainty regime. Unlike this result, in one hand, Castelnuovo and Pellegrino (2018) find that inflation raises quicker when uncertainty is high, while no significant response of inflation when uncertainty is low. On the other hand, 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. Nonetheless, our results in the low uncertainty regime are in line with Arias et al. (2019).

4 Robustness

In this section we check the robustness of the results reported in Section 3 by using other measures of uncertainty. In particular,[2] (i) first, we use the Categorical Economic Policy Uncertainty Index which is derived using results from the Access World News database of over 2,000 US newspapers; and (ii) second, we use the US Equity Market Volatility Index, which is a tracker that moves with the CBOE Volatility Index (VIX) and with the realized volatility of returns on the S&P 500.

4.1 Categorical Economic Policy Uncertainty Index

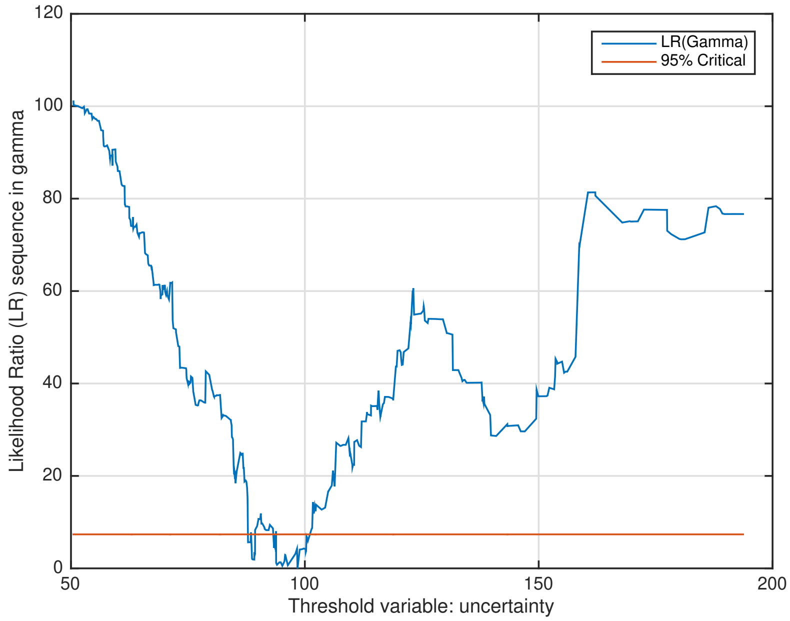
Threshold estimation results

By using the categorical Economic Policy Uncertainty Index as the uncertainty measure, the bootstrap p-value of the test is 0.000, which means that we reject the test of null of the monetary policy linear model in favor of the alternative monetary policy threshold model. Therefore, there is strong evidence with this measure that uncertainty affects the Taylor rule equation by splitting the regression sample into two regimes. The uncertainty threshold estimate is $\widehat{\gamma} = 98.434$ (see Figure 6), which is placed at the 58th percentile of the observed uncertainty variable, estimate that is broadly similar to the baseline estimation.

The 95 percent confidence interval are the set of values below the dotted line in Figure 9 and it is $[87.850; 100.654]$; this confidence interval is tight, which indicates

[2] There are several uncertainty measures used in the literature, but most of them start long after 1985.

Figure 6: Confidence interval construction for threshold



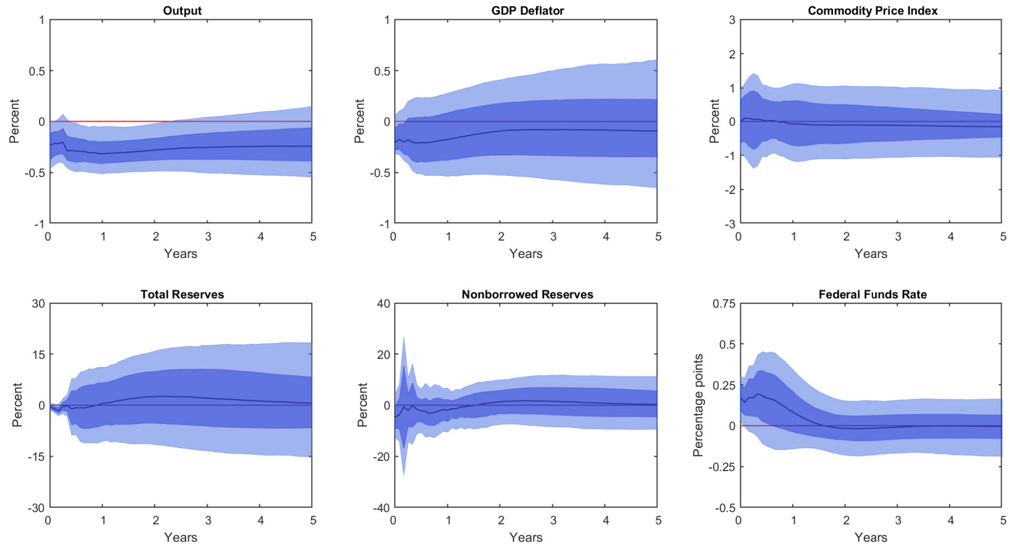
that the uncertainty threshold estimate is quite precise. This result is pretty similar to those obtained with other uncertainty measure and monetary policy threshold model specifications.

SVAR results

Similar to the other cases, we show in Figure 7 an immediate median increase in the federal funds rate of around 17 basis points as response to a contractionary monetary policy shock when the uncertainty level is low. Additionally, the response of output to this shock is negative with a high posterior probability for the entire period and with 95 percent posterior probability for the first two months. So, this drop is more persistent than in the case of Section 3.2. We also find a negative response in prices with a high posterior probability for the first three months and a zero response for commodity prices and reserves as in the baseline case.

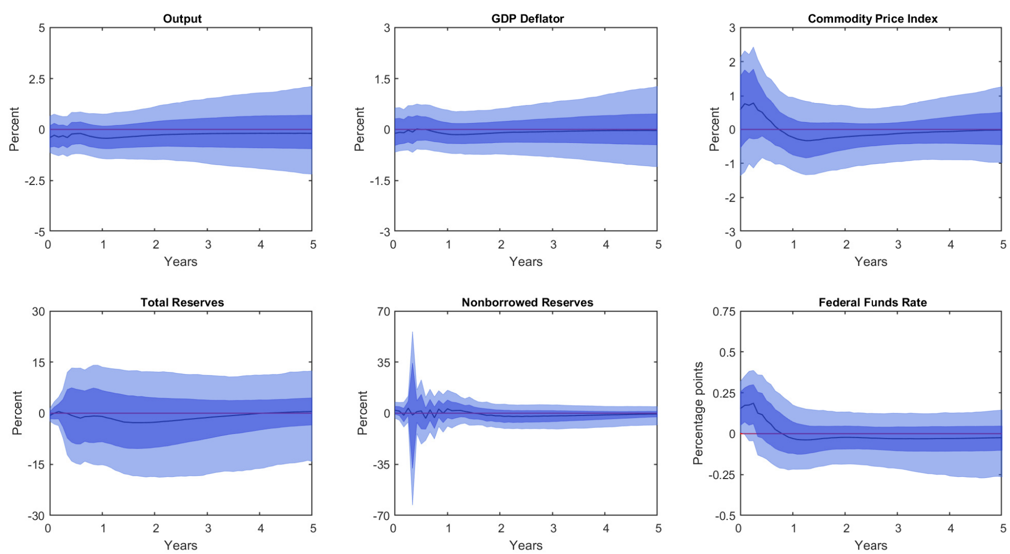
Figure 8 shows that when the uncertainty level is high, all the variables except the federal funds rate has a zero response to a contractionary monetary policy shock, with high and 95 percent posterior probability. Whereas the output has a negative median response for the five years as well, but this response is not statistically significant different from zero. Also, the federal funds rate suffers an immediate median increase of around 15 basis points as response to this shock.

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 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.

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 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.

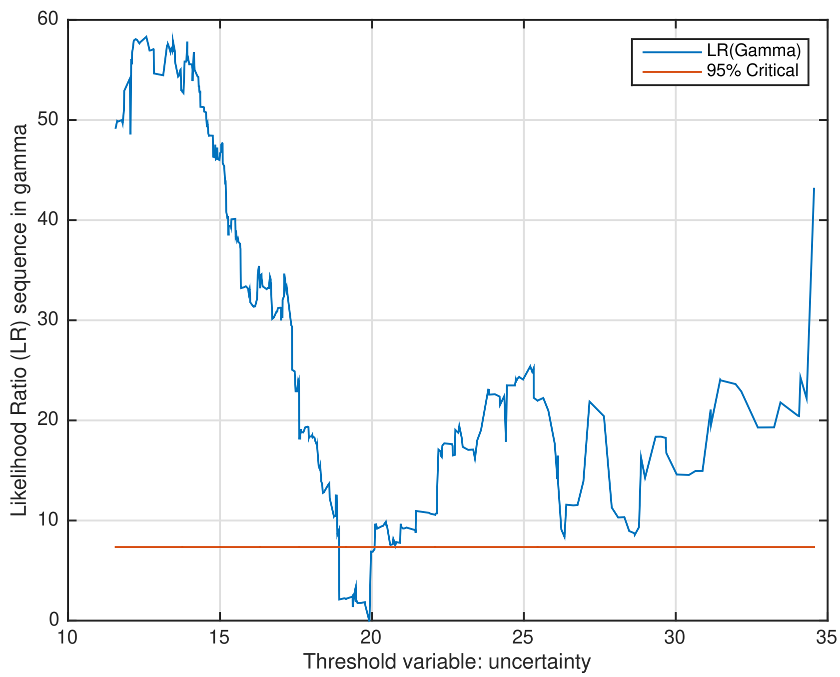
4.2 US Equity Market Volatility Index

Threshold estimation results

When we use the US Equity Market Volatility Index as the uncertainty measure, the bootstrap p-value of the test is 0.000, which means that we reject the test of null of no threshold (linear model) in favor of the alternative monetary policy threshold model. Therefore, there is evidence that uncertainty affects the Taylor rule equation by splitting the regression sample into two regimes.

Figure 9 shows the concentrated likelihood ratio function $LR(\gamma)$ on the space of the uncertainty threshold parameter, where the function is minimized at zero when the uncertainty estimated threshold is $\widehat{\gamma} = 19.913$, which is placed at the 65th percentile of the observed uncertainty variable. Thus, the two regimes separated by the threshold estimate are denoted as low and high uncertainty regimes, respectively.

Figure 9: Confidence interval construction for threshold

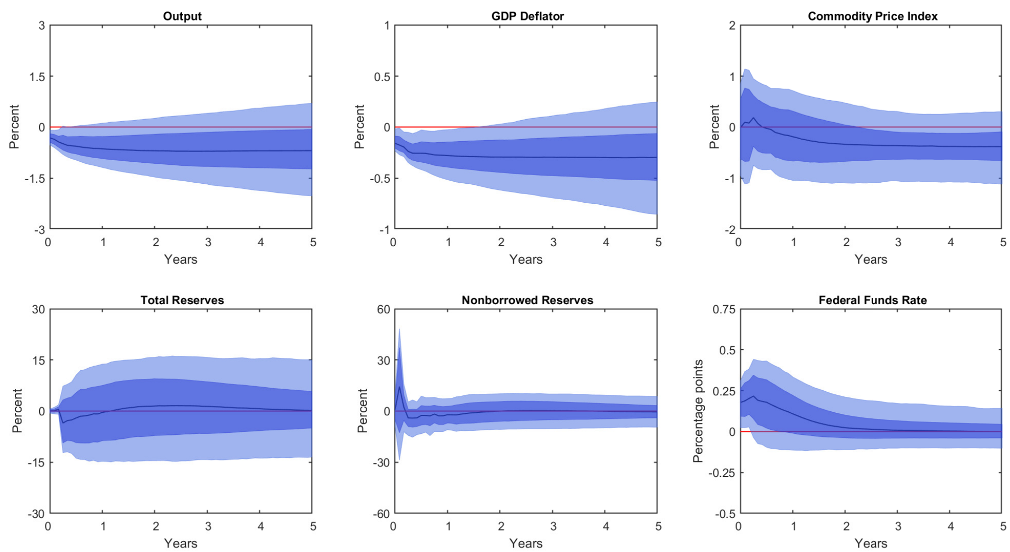


When we construct a confidence interval for the estimated uncertainty threshold, the estimation precision is high as in the baseline estimation. The 95 percent confidence interval, the set of values below the dotted line in Figure 9, is $[18.919, 20.087]$; which indicates a high precision in the uncertainty threshold estimation. Note that, the EPU Index quantifies policy-related uncertainty for the economy as a whole, while the EMV index quantifies the full range of volatility sources for the stock market in particular.

SVAR results

As in Section 3.2, Figures 10 and 11 show the main results in each uncertainty regime. We show in Figure 10 that a contractionary monetary policy shock leads to an immediate median increase in the federal funds rate of around 18 basis points, when the uncertainty level is low. Similarly, the response of output to this shock is negative with a high posterior probability for the entire period and with 95 percent posterior probability for the first three months. Furthermore, this drop is more persistent than in the case of Section 3.2. However, the protracted decline in prices is maintained and the rest of the variables have a zero response with high and 95 percent posterior probability.

Figure 10: Impulse responses to a monetary policy shock - low uncertainty regime

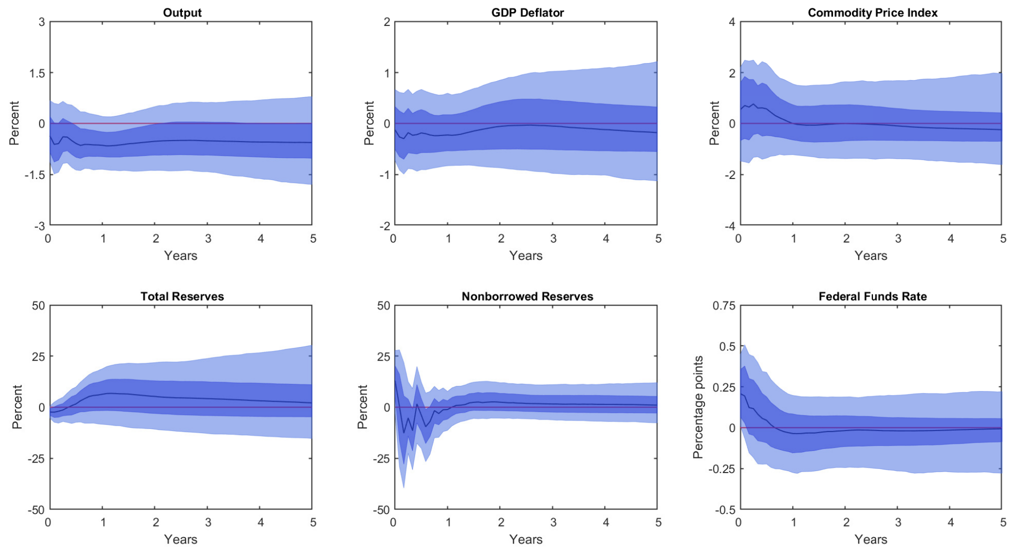


Note: IRFs to a one standard deviation contractionary monetary policy shock identified using Restrictions 1 and 2. The solid lines depict the point-wise posterior medians and the shaded bands represent the 68 and 95 percent equal-tailed point-wise posterior probability bands.

As before when the uncertainty level is high, we show in Figure 11 that a contractionary monetary policy shock leads to an immediate median increase in the federal funds rate of around 21 basis points. Nevertheless, the output has a zero response with 95 percent posterior probability for the entire period and a negative response with a high posterior for some months; While the median response of output is negative for the five years. In addition, the response of the rest of the variables is similar to the case when we analyze all the sample.

Unlike the EPU Index and the categorical EPU Index uncertainty measures, the response in prices is negative for more months (almost one year and half) in the low uncertainty regime. Thus, the effect is particularly larger in low uncertainty periods, when the uncertainty measure from financial markets is utilized; this could indicate that financial channels are playing an important role. However, the response in prices is not statistically significant different from zero in the high uncertainty regime, which is broadly similar when we use the EPU Index and the categorical EPU Index uncertainty measures.

Figure 11: 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.

5 Conclusion

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

More importantly, our SVAR analysis in each 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 different specifications of the threshold Taylor rule model and the use of different uncertainty measures.

What are the effects of the U.S. monetary policy in other countries in low and high uncertainty periods? This question is especially relevant in Latin American economies, where U.S. is one of the most important trade partners and the Latin American currencies are anchored to the U.S. dollar. What is the power of the monetary policy of Latin American economies under low and high uncertainty regimes? Is there any difference with the U.S. monetary policy? These questions and our findings suggest that this can be a fruitful area for future research.

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