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Nonlinear Effects of Uncertainty Shocks: State-dependency and Asymmetry

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Abstract

The nonlinear effects of uncertainty shocks on U.S. macroeconomic activity are examined using a smooth transition VAR model in which the dynamic relationship between the variables changes with the level of economic policy uncertainty. We find that the responses of the variables change with the level of uncertainty, and in particular, the sign of the response of the inflation rate reverses. The empirical evidence suggests that the behaviors of the shifts in aggregate demand and aggregate supply functions induced by uncertainty shocks depend on the current uncertainty level.

Keywords: Uncertainty shocks, Nonlinear dynamics, VAR model.

JEL classification: C32, D80, E32.

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1 Introduction

Since the invention of the Economic Policy Uncertainty (EPU) index by Baker et al. (2016), numerous studies investigate the macroeconomic effects of economic policy uncertainty. Along with this literature, this paper studies the nonlinear effects of economic policy uncertainty on U.S. macroeconomic variables. More specifically, we address the questions as follows: Do responses of macroeconomic variables to uncertainty shocks depend on the current level of uncertainty? Is there asymmetry in these responses against positive or negative uncertainty shocks? To assess these questions, we estimate a Smooth Transition Vector Autoregressive (STVAR) model with a U.S. dataset including the EPU index, production, inflation rate, unemployment rate, and federal funds rate. Our specification of a STVAR model allows dynamic relations among variables to vary depending on the level of economic policy uncertainty.

Our estimated impulse responses to uncertainty shocks imply the presence of uncertainty state-dependency effects. Uncertainty shocks have recessionary effects regardless of the current state of uncertainty, as previous empirical studies suggested. The persistence of each response to uncertainty shock varies with changes in the current level of uncertainty. Furthermore, the response of the inflation rate on the shock hit is positive when the current state of uncertainty is relatively high although it is negative when low. These results suggest that behaviors of shifts in aggregate demand and aggregate supply functions induced by uncertainty shocks depend on the current uncertainty level. On the asymmetry of responses, forecast error variance decomposition (FEVD) indicates that the contribution of positive and negative uncertainty shocks to explaining forecast errors in macroeconomic variables is slightly different but almost equal, irrespective of the current uncertainty level.

There is a strand of literature exploring how economic uncertainty affects macroeconomic variables (e.g., Mumtaz and Theodoridis, 2015; Baker et al., 2016; Leduc and Liu, 2016; Caggiano et al., 2017; Alessandri and Mumtaz, 2019). Some empirical studies find that the propagation mechanism of uncertainty shock depends on the state of the business cycle (Caggiano et al., 2017) or the conditions of financial markets (Alessandri and Mumtaz, 2019). Another strand of literature investigates whether the propagation mechanism of macroeconomic shocks may change depending on the state of macroeconomic uncertainty. For instance, the dependency of monetary policy transmission on the current level of uncertainty is reported in Aastveit et al. (2017), Schmidt (2020), and Hauzenberger et al. (2021), while that of fiscal policy is discussed in Berg (2017).[1]

Jones and Enders (2016), a closely related study to ours, estimate univariate smooth transition autoregressive models in which the level of uncertainty can change autoregressive parameters. They conclude that uncertainty shocks have non-linear effects on U.S. macroeconomic variables from the perspective of univariate time series analysis. Our STVAR specification is a VAR version of their univariate models. This paper contributes to the literature by providing STVAR evidence in favor of the existence of non-linear effects of economic policy-related uncertainty shocks on macroeconomic variables of the U.S. economy.

The rest of this paper is organized as follows: Section 2 proposes our econometric framework and Section 3 describes estimation results. Finally, Section 4 offers concluding remarks.

2 Econometric framework

2.1 STVAR model

A STVAR model, developed by Granger and Terasvirta (1993), allows us to analyze nonlinear effects of uncertainty shocks on the macroeconomic variables. Let y_t and u_t be a vector of endogenous variables and reduced-form residuals, respectively. A STVAR model with p-th lags can be specified as:

$$y_t = \{1 - G(z_{t-1})\} \left[b_0 + \sum_{j=1}^{p} B_{0,j} y_{t-j} \right] + G(z_{t-1}) \left[b_1 + \sum_{j=1}^{p} B_{1,j} y_{t-j} \right] + u_t, \tag{1}$$

$$u_t \sim N\left(0, \{1 - G(z_{t-1})\} \Omega_0 + G(z_{t-1})\Omega_1\right), \tag{2}$$

[1] In the studies referenced above, economic uncertainty is regarded as an exogenous variable in the sense that there is no simultaneous causal effect from other variables to uncertainty. Our study follows the same exogenous assumption on uncertainty. On the other hand, there exist recent studies, such as Fajgelbaum et al. (2017), that allow uncertainty to fluctuate endogenously in response to business cycles.

where b_i, $B_{i,j}$, and Ω_i denote the constant term, VAR coefficients, and variance-covariance matrix in each polar situation ($i = 0, 1$). Both of the VAR coefficients and variance-covariance matrix smoothly change depending on a transition function $G(z_{t-1})$, whose value varies between 0 and 1 according to the transition variable z_{t-1}.[2] To be specific, we adopt the logistic transition function as $G(z_{t-1})$:

$$G(z_{t-1}) = \frac{1}{1 + \exp\{-\gamma(z_{t-1} - c)\}}, \gamma > 0, \tag{3}$$

where the parameters γ and c determine the "smoothness" and "threshold" of transition between two polar situations.

By incorporating a uncertainty measure into y_t and z_{t-1}, we examine two types of nonlinear dynamic effects of uncertainty shocks: state-dependency and asymmetry. As for state-dependency, the dynamic responses allow change depending on z_{t-1} because, as discussed above, the VAR coefficients and variance-covariance matrix are different according to z_{t-1}. Moreover, the dynamic responses drawn from the STVAR model possibly become asymmetric depending on the sign of the shocks. This is because, as described in equation (3), the function $G(z_{t-1})$ is an increasing function of z_{t-1}, so that $G(z_{t-1})$ should be different depending on whether z_{t-1} increases or decreases from an arbitrary value. Therefore, both the size of uncertainty at the time of the shock and the sign of the uncertainty shock may lead to different shapes of impulse responses. Exploiting these nonlinear properties of the STVAR model, we evaluate the dynamic effects of uncertainty shocks under the following four possible cases: (i) positive shock in high uncertainty, (ii) negative shock in high uncertainty, (iii) positive shock in low uncertainty, and (iv) negative shock in low uncertainty.

2.2 Estimation method

The parameters in STVAR model are estimated by the Random-Walk Metropolis-Hastings (RH-MH) sampler of the Bayesian MCMC algorithm because the conditional posteriors of γ and c in equation (3) cannot be derived analytically. In addition, we estimate the

[2]In general, transition variable is inserted in transition function at period $t-1$ to avoid the contemporaneous interaction.

lower triangular elements of $A_i = chol(\Omega_i), i = 0, 1$ instead of Ω_i ($\Omega_i = A_i A_i'$). Table 1 summarizes the prior distributions for the estimated parameters.

We run a total of 100,000 MCMC iterations and the first 50,000 iterations are discarded as the burn-in. To mitigate the auto-correlation between each draw, only every tenth sample is saved, resulting in an inference based on 5,000 samples. Moreover, we select the draws in which the roots of the VAR coefficients are inside the unit circle throughout the sample in order to ensure the stationarity of the VAR system.

Table 1: Prior distributions

Parameters	Descriptions	Distribution	Mean	Std.
γ	Smoothness parameter	Gamma	10	2
c	Threshold parameter	Normal	Ave. of z_{t-1}	Std. of z_{t-1}
$\boldsymbol{\alpha_i}$	Off-diagonal elements in A_i	Normal	0	1
$\boldsymbol{\omega_i^{-1}}$	Inv. of diagonal elements in A_i	Gamma	1	1
b_i	Constant term	Normal	0	Inf.
$B_{i,j}$	VAR matrices	Normal	0	1

Notes: Prior distributions for the parameters that take only positive values are assumed to be the Gamma distribution, while the priors for the parameters with no range restrictions are imposed are assumed to be the Normal distribution.

2.3 Data and specifications

Following Caggiano et al. (2017), we estimate a six-variables VAR model including the log of EPU index, the annualized growth rate of industrial production, unemployment rate, year-on-year CPI index, and the federal fund rate in this order.[3] Unlike Caggiano et al. (2017), the EPU index is included in the VAR model without transforming it into a dummy variable because the EPU index is also the transition variable in the transition function. The sample period is from January 1985 to December 2019. The EPU index is only released from January 1985 in the data source. Furthermore, the post-COVID-19 period is excluded because of the rapid hike in uncertainty observed in that period. The lag length in the VAR model is set to six by taking into account the compatibility of degree of the freedom and sufficient dynamics of the variables.

[3]The EPU index is obtained from https://www.policyuncertainty.com/, while the other endogenous variables are downloaded from the Federal Reserve Economic Data provided by St. Louis Fed.

Regarding the identification of the shock, we rely on the recursive restrictions using the Cholesky decomposition, as in Caggiano et al. (2017). In other wards, the EPU index is assumed to be the most exogenous variable among the variables in the VAR system. The shock to the EPU index has simultaneous effects on all variables, while the EPU index is not contemporaneously affected by the shocks that occurred in the rest of the variables.

3 Empirical evidence

3.1 GIRFs

Figure 1 displays impulse response functions (IRFs) to EPU shocks of different signs in two uncertainty levels of EPU. The IRFs are computed using the method of generalized IRFs (GIRFs) proposed by Koop et al. (1996) due to the nonlinearity of the STVAR model. The first row in Figure 1 depicts impulse responses when the level of EPU is high, and the second is when it is low, in both of which the solid and dashed lines indicate the median responses and the shaded areas are 68% credible intervals for the IRFs to positive shock. In addition, the sign of the IRFs to negative EPU shock is reversed for comparative purpose.

First, we can find evidence for state-dependent responses, but no strong evidence for asymmetric responses. The responses of IIP, unemployment rates, and CPI imply that EPU shocks have similar effects to negative aggregate demand shocks irrespective of the current state of EPU, in line with the findings of Leduc and Liu (2016). The FF rate also reacts negatively under each level of uncertainty, suggesting that the counter-cyclical nature of the traditional monetary policy rule is relevant to this reaction. In comparison with the IRFs between high and low uncertainty, the differences are present in the persistence of each response. To be specific, statistically significant responses of IIP and unemployment rates are longer-lasting with low uncertainty than high uncertainty. Furthermore, the state-dependency on CPI is eye-catching: around when the shock hits, the directions of impulse responses depend on the current value of the EPU index. When EPU is high, uncertainty shocks decrease CPI in the short run. When EPU is low, however, CPI reacts to the EPU shocks negatively around when the shock occurs.

These results can be a consequence of the state-dependency of timings or speeds of shifts in aggregate demand and supply functions. When the current level of uncertainty is high, uncertainty shocks cause the aggregate demand function to shift to the left, and its effect on CPI becomes dominant in the short run. As a result, CPI decreases in the period when the shock occurs. In contrast, the uncertainty shock under the low current uncertainty level moves the aggregate supply function to the left in the first place, and consequently, CPI increases.

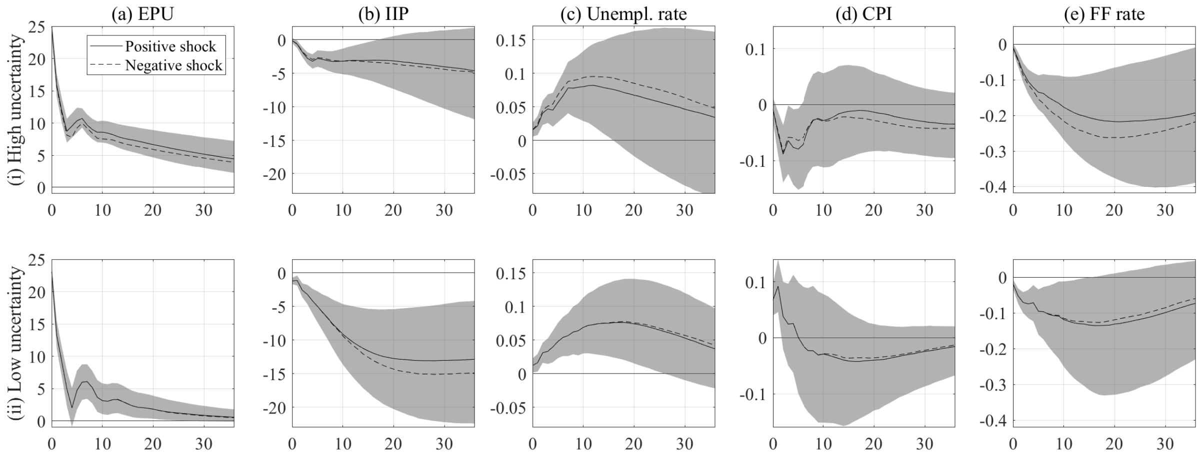

Figure 1: Impulse responses to uncertainty shocks

Notes: The top panels show the impulse responses in high uncertainty period, while the bottom panels show the ones in low uncertainty period. The solid and dashed lines indicate the median responses of the variables to positive and negative uncertainty shocks, respectively. The sign of the responses to negative shock is reversed. The shaded areas are 68% credible intervals corresponding to the responses to positive shock.

3.2 FEVD

Table 2 documents the result of the state-dependent FEVD on positive and negative uncertainty shocks. The FEVD allows us to quantitatively assess the contribution of uncertainty shock on the economy. Among all variables, there are little differences between contributions of positive and negative shocks regardless of the current state of uncertainty. For instance, the most sizable difference between contributions of the positive and negative shocks is 0.08, which appears in the EPU index with low uncertainty. This result indicates, as confirmed in the IRFs analysis, that uncertainty shocks barely have asymmetric effects through the uncertainty state-dependency mechanism of macroeconomic variables.

Table 2: Forecast error variance decomposition

(i) High uncertainty										
Horizons	(a) Positive shock					(b) Negative shock				
(months)	EPU	IIP	Unempl.	CPI	FF rate	EPU	IIP	Unempl.	CPI	FF rate
1	1.00	0.00	0.01	0.00	0.00	1.00	0.00	0.01	0.00	0.00
5	0.96	0.11	0.07	0.05	0.17	0.95	0.10	0.09	0.03	0.20
10	0.95	0.08	0.11	0.10	0.21	0.94	0.08	0.14	0.09	0.28
20	0.92	0.07	0.11	0.20	0.30	0.90	0.09	0.13	0.19	0.39
(ii) Low uncertainty										
Horizons	(a) Positive shock					(b) Negative shock				
(months)	EPU	IIP	Unempl.	CPI	FF rate	EPU	IIP	Unempl.	CPI	FF rate
1	1.00	0.03	0.01	0.04	0.01	1.00	0.03	0.01	0.04	0.01
5	0.49	0.14	0.15	0.02	0.19	0.33	0.14	0.12	0.02	0.13
10	0.77	0.17	0.23	0.13	0.26	0.77	0.20	0.23	0.13	0.20
20	0.66	0.18	0.19	0.22	0.31	0.58	0.23	0.21	0.21	0.25

Notes: The figures in the table indicates the median estimates of each variable in selected horizon.

4 Conclusion

This study estimates a STVAR model and examines the presence of the state-dependent and asymmetric effects of exogenous changes in economic policy uncertainty in U.S. macroeconomic variables. Our estimated model suggests that the current level of economic policy uncertainty alters responses of macroeconomic variables to economic policy uncertainty shocks. The short-term response of the inflation rate to uncertainty shocks can be positive or negative, depending on the current level of uncertainty. We also find that the contributions of positive and negative uncertainty shocks in the forecast error decomposition are almost the same, irrespective of the current levels of uncertainty. We conclude that economic policy uncertainty shocks have non-linear effects, which are uncertainty state-dependent and nearly symmetric.

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