On the Transmission Mechanism of Country-Specific and International Economic Uncertainty Spillovers: Evidence from a TVP-VAR Connectedness Decomposition Approach^{*}

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June 25, 2018

Abstract

We investigate the internal and external categorical economic policy uncertainty (EPU) spillovers between the US and Japan using a novel extension of the TVP-VAR connectedness approach of Antonakakis and Gabauer (2017). The decomposition of our approach gives us insights about the dynamics with and without international spillovers which has essential policy implications. Our results suggest that monetary policy uncertainty is the main driver, followed by uncertainties associated with fiscal, currency market and trade policies. Furthermore, we find that the Fukushima Daiichi accident can be interpreted as a negative trade shock that spread internationally.

Keywords: Dynamic Connectedness, TVP-VAR, Spillover Decomposition

<u>JEL codes</u>: C32, C50, F42

 $^{^{\}ast} \rm We$ would like to thank an anonymous referee for many helpful comments. However, any remaining errors are solely ours.

1 Introduction

The Great Recession has led to the emergence of a large international literature that analyzes the impact of uncertainty on macroeconomic variables and financial markets (see Antonakakis et al. (2013), Castelnuovo et al. (2017), Chuliá et al. (2017), and Gupta et al. (2016a,b) for detailed literature reviews). Simultaneously, studies have also analyzed the spillover of uncertainty across economies (see, for example, Colombo (2013), Ajmi et al. (2014), Klößner and Sekkel (2014), Yin and Han (2014), Biljanovska et al. (2017), Caggiano et al. (2017), Antonakakis et al. (2018)). This is an important line of research, since if the uncertainties across economies are indeed interrelated, as the above-mentioned studies show, then a particular economy can witness the negative impacts of uncertainty, even when there is no change in its domestic levels of uncertainty, through the linkages that exists in a modern globalized world. Also, if domestic uncertainty does increase, then international uncertainty feedbacks are likely to prolong the effects on the domestic economy.

Against this backdrop, we revisit the issue of uncertainty spillovers between two major economies of the world, namely the US and Japan, and add to the literature along the following dimensions: (a) Unlike the above-mentioned studies that utilize aggregate measures of economic uncertainty, we analyze categorical uncertainty, associated with monetary, fiscal, trade and currency market policies. Uncertainty related with alternative policies is not only likely to have heterogeneous impact, but it is also possible that some form of uncertainty plays a dominant role (Mumtaz and Surico, 2013). (b) Deviating from the above literature, the usage of categorical data, also allows us to look at spillovers across domestic policy uncertainties, while acknowledging the simultaneous existence of the international linkage between these two economies. In light of this, it makes more sense to analyze spillovers of uncertainty at a disaggregated-level, so that the policy makers in the domestic economy know how strongly to react to movements in different types of foreign uncertainties. Clearly, if domestic policy uncertainties are interlinked, econometric models analyzing the impact of one time changes of policy uncertainty are likely to yield misleading results, in terms of its underestimated impact of a change in a particular domestic policy-related uncertainty; (c) Unlike the rolling-window estimation of the popular Diebold and Yılmaz (2012) model used to capture spillovers over time, we use a full-fledged time-varying parameter vector autoregressivion (TVP-VAR) suggested by Antonakakis and Gabauer (2017). This improves the methodology of Diebold and Yılmaz (2012) substantially, because there is no need to arbitrarily set the rolling window-size and there is no loss of observations, and; (d)

Finally, from a methodological perspective, in the context of the TVP-VAR model our paper develops a new technique which decomposes shocks in within and between country to analyze the contribution of international and within-country spillovers associated with policy uncertainties. In sum, to the best of our knowledge, this is the first attempt to analyze spillovers of categorical policy uncertainties within and across two important developed economies using a pure time-varying approach.

The results of our empirical analysis reveal that, in both countries, the monetary policy uncertainty (MPU) spillovers are the most dominant ones, followed by the fiscal policy uncertainty (FPU), then the currency policy uncertainty (CPU), and finally the trade policy uncertainty (TPU). Furthermore, the findings suggest that the US TPU is dominating the Japanese TPU and that the MPU of one country is consistently driving the TPU of the other country. Analyzing the aggregated international spillovers between both countries reveal that the US was the uncertainty transmitter until the Japanese nuclear power plant accident.

The remainder of this study is organized as follows. Section 2 describes the empirical methodology employed. The empirical results of our analysis are presented in Section 3. Finally, Section 4 summarizes and concludes this study.

2 Methodology

2.1 TVP-VAR

In order to explore the transmission mechanism of monetary policy in a time-varying fashion, we use the TVP-VAR methodology of Antonakakis and Gabauer (2017) that extends the originally proposed connectedness approach of Diebold and Yılmaz (2009, 2012), by allowing the variances to vary via a stochastic volatility Kalman Filter estimation with forgetting factors. The TVP-VAR model can be written as follows,

$$\boldsymbol{y}_t = \boldsymbol{\beta}_t \boldsymbol{z}_{t-1} + \boldsymbol{\epsilon}_t \qquad \qquad \boldsymbol{\epsilon}_t | \boldsymbol{F}_{t-1} \sim N(\boldsymbol{0}, \boldsymbol{S}_t) \tag{1}$$

$$vec(\boldsymbol{\beta}_t) = vec(\boldsymbol{\beta}_{t-1}) + \boldsymbol{\nu}_t$$
 $\boldsymbol{\nu}_t | \boldsymbol{F}_{t-1} \sim N(\boldsymbol{0}, \boldsymbol{R}_t)$ (2)

where \boldsymbol{y}_t and $\boldsymbol{z}_{t-1} = [\boldsymbol{y}_{t-1}, ..., \boldsymbol{y}_{t-p}]'$ represent $N \times 1$ and $Np \times 1$ dimensional vectors, respectively. $\boldsymbol{\beta}_t$ is an $N \times Np$ dimensional time-varying coefficient matrix and $\boldsymbol{\epsilon}_t$ is an $N \times 1$ dimensional error disturbance vector with an $N \times N$ time-varying variance-covariance matrix, \boldsymbol{S}_t . $vec(\boldsymbol{\beta}_t)$, $vec(\boldsymbol{\beta}_{t-1})$ and $\boldsymbol{\nu}_t$ are $N^2p \times 1$ dimensional vectors and \boldsymbol{R}_t is an $N^2p \times N^2p$ dimensional matrix. In order to calculate the generalized impulse response functions (GIRF) and generalized forecast error variance decomposition (GFEVD) (Koop et al., 1996; Pesaran and Shin, 1998), we transform the VAR to its vector moving average (VMA) representation:

$$\boldsymbol{y}_t = \sum_{j=0}^{\infty} \boldsymbol{L}' \boldsymbol{W}_t^j \boldsymbol{L} \boldsymbol{\epsilon}_{t-j}$$
(3)

$$\boldsymbol{y}_t = \sum_{j=0}^{\infty} \boldsymbol{A}_{it} \boldsymbol{\epsilon}_{t-j} \tag{4}$$

where $\boldsymbol{L} = [\boldsymbol{I}_N, ..., \boldsymbol{0}_p]'$ is an $Np \times N$ dimensional matrix, $\boldsymbol{W} = [\boldsymbol{\beta}_t; \boldsymbol{I}_{N(p-1)}, \boldsymbol{0}_{N(p-1)\times N}]$ is an $Np \times Np$ dimensional matrix, and \boldsymbol{A}_{it} is an $N \times N$ dimensional matrix. The GIRFs represent the responses of all variables following a shock in variable *i*. Since we do not have a structural model, we compute the differences between a *J*-step-ahead forecast where once variable *i* is shocked and once where variable *i* is not shocked. The difference can be accounted to the shock in variable *i*, which can be calculated by

$$GIRF_t(J, \boldsymbol{\delta}_{j,t}, \boldsymbol{F}_{t-1}) = E(\boldsymbol{Y}_{t+J} | \boldsymbol{\epsilon}_{j,t} = \boldsymbol{\delta}_{j,t}, \boldsymbol{F}_{t-1}) - E(\boldsymbol{Y}_{t+J} | \boldsymbol{F}_{t-1})$$
(5)

$$\Psi_{j,t}^{g}(J) = \frac{\boldsymbol{A}_{J,t}\boldsymbol{S}_{t}\boldsymbol{\epsilon}_{j,t}}{\sqrt{S_{jj,t}}} \frac{\boldsymbol{\delta}_{j,t}}{\sqrt{S_{jj,t}}} \qquad \boldsymbol{\delta}_{j,t} = \sqrt{S_{jj,t}}$$
(6)

$$\Psi_{j,t}^g(J) = S_{jj,t}^{-\frac{1}{2}} \boldsymbol{A}_{J,t} \boldsymbol{S}_t \boldsymbol{\epsilon}_{j,t}$$
(7)

where $\Psi_{j,t}^g(J)$ represent the GIRFs of variable j and J represents the forecast horizon, $\delta_{j,t}$ the selection vector with one on the jth position and zero otherwise, and F_{t-1} the information set until t-1. Afterwards, we compute the GFEVD that can be interpreted as the variance share one variable has on others. This is calculated as follows

$$\tilde{\phi}_{ij,t}^{g}(J) = \frac{\sum_{t=1}^{J-1} \Psi_{ij,t}^{2,g}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \Psi_{ij,t}^{2,g}}$$
(8)

with $\sum_{j=1}^{N} \tilde{\phi}_{ij,t}^{g}(J) = 1$ and $\sum_{i,j=1}^{N} \tilde{\phi}_{ij,t}^{N}(J) = N$. Using the GFEVD, we construct the total connectedness index (TCI) by

$$C_t^g(J) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\phi}_{ij,t}^g(J)}{\sum_{i,j=1}^N \tilde{\phi}_{ij,t}^g(J)} * 100$$
(9)

$$=\frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}_{ij,t}^{g}(J)}{N} * 100$$
(10)

This connectedness approach shows how a shock in one variable spills over to other variables. First, we look at the case where variable i transmits its shock to all other variables j, called total directional connectedness to others and defined as

$$C^{g}_{i \to j,t}(J) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\phi}^{g}_{ji,t}(J)}{\sum_{j=1}^{N} \tilde{\phi}^{g}_{ji,t}(J)} * 100$$
(11)

Second, we calculate the directional connectedness variable i receives it from variables j, called total directional connectedness from others and defined as

$$C^{g}_{i \leftarrow j,t}(J) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\phi}^{g}_{ij,t}(J)}{\sum_{i=1}^{N} \tilde{\phi}^{g}_{ij,t}(J)} * 100$$
(12)

Finally, we subtract *total directional connectedness to others* from *total directional connectedness* from others to obtain the net total directional connectedness:

$$C_{i,t}^{g} = C_{i \to j,t}^{g}(J) - C_{i \leftarrow j,t}^{g}(J)$$
(13)

The sign of the net total directional connectedness illustrates if variable i is driving the network $(C_{i,t}^g > 0)$ or driven by the network $(C_{i,t}^g < 0)$. Finally, we break down the net total directional connectedness to examine the bidirectional relationships by computing the net pairwise directional connectedness (NPDC),

$$NPDC_{ij}(J) = \frac{\tilde{\phi}_{ji,t}^{g}(J) - \tilde{\phi}_{ij,t}^{g}(J)}{T} * 100$$
(14)

2.2 Connectedness Decomposition

Since we are analyzing the spillovers between two countries we are interested in how much of those spillovers is transmitted within the country and how much is transmitted from one country to another. The decomposition of k countries can be illustrated as follows:

$$\Phi(J) = [\tilde{\phi}^{g}]_{ij,t}(J) = \begin{bmatrix} C_{11} & C_{12} & \dots & C_{1k} \\ C_{21} & C_{22} & \dots & C_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ C_{k1} & C_{k2} & \dots & C_{kk} \end{bmatrix}$$

where C_{ii} includes the internal spillovers of country *i* and C_{ij} represents the spillovers of country *j* to country *i*. In a next step, to compute the internal and external spillovers we set $diag(C_{ii}) = 0$ and calculate:

$$TO_{ij} = \sum_{n=1}^{k} C_{ij,nm}$$

$$FROM_{ij} = \sum_{m=1}^{k} C_{ji,nm}$$

$$NET_{ij} = TO_{ij} - FROM_{ij}$$

$$NI_{ij} = \sum_{n=1}^{k} \sum_{m=1}^{k} C_{ij,nm} - \sum_{n=1}^{k} \sum_{m=1}^{k} C_{ji,nm}$$

where TO_{ij} is the total country-specific connectedness to others, $FROM_{ij}$ is the total countryspecific connectedness from others, NET_{ij} is the net total country-specific connectedness and NI_{ij} is the net international total country-specific connectedness.

3 Empirical Results

We compile a dataset of monthly news-based economic policy uncertainty indices for the US and Japan at the categorical level involving monetary policy uncertainty (MPU), fiscal policy uncertainty (FPU), trade policy uncertainty (TPU), and currency market-related policy uncertainty (CPU), based on the works of Baker et al. (2016) and Arbatli et al. (2017). Our data spans the period of January 1987 to December 2017 (based on data availability), which to the best of our knowledge, is the only available dataset at categorical level of policies.¹

Figure 1 visualizes the standardized data and Figure 2 the first differences time series.

Figure 3 shows that the total connectedness index (TCI) of the system varies over time. The most significant spike is observed in the beginning of 2010 when the Fukushima Daiichi nuclear disaster occurred. This conclusion can be derived by our proposed measure where we see that the Japanese TCI based on internal spillovers sharply increased whereas the US TCI did not. Interestingly, we observe that the overall TCI increased by much more than Japan increased which indicates that this shock spread over to the US. Further support of this hypothesis is granted by Figure 5 and 6 where jumps occur only in the decomposed Japanese total directional TO and FROM spillovers. Finally, Figure 4 visualizes the dominating transmission mechanism.

¹The data is available for download from: http://www.policyuncertainty.com/categorical_epu.html and http://www.policyuncertainty.com/japan_monthly.html for the US and Japan respectively.

The Japanese net directional connectedness are nearly the same with and without international spillovers except for the TPU. Besides, we find that the Japanese TPU is largely influenced by US spillovers starting in 2000 which increases after the Dotcom crisis (2001) and reaches its peak during the Great Recession (2007).

The internal net pairwise directional connectedness (Figure 7) suggest that US MPU is dominating the FPU, TPU and CPU. This is in line with economic theory since the decisions upon monetary policy is influencing the refinancing schemes of the government and hence the fiscal budget which highly depends on the interest rate provided by the financial market based on the policy rate plus the banking mark-up. Furthermore, through the uncovered interest rate parity, monetary policy is influencing the exchange rate, and finally the exchange rate is driving the relative prices among countries affecting exports and imports. The same relations hold true for Japan too until the Fukushima Daiichi nuclear disaster happened. This becomes evident as the FPU sharply increased its magnitude compared to TPU and CPU.

Figure 8, illustrates the net external total connectedness where we find that US FPU and MPU pattern with the Japanese FPU and MPU are quite similar except for the US MPU and Japanese MPU spillovers starting in 1998 which could be explained by the fact that Japan reached the zero lower bound. After the Fukushima Daiichi accident, this pattern reverses so that Japan is influencing the US MPU and FPU more than vice versa. What is more, we find that MPU of one country has a dominant effect on the CPU and TPU of another country and that one country's CPU is dominating the TPU of the other country too, which is consistent with economic theory. Finally, the US TPU dominates the Japanese TPU. Figure 9, illustrates that from the beginning of our sample till the Fukushima Daiichi accident the US was the dominant transmitter whereas after the accident occurred the pattern reversed. Table 1 repeats the aforementioned examination in a quantitative manner.

4 Conclusion

This study is novel in several ways since it is the first of its kind looking on the categorical EPU spillovers using a TVP-VAR connectedness approach. In addition, the paper extends the connectedness literature by introducing a country-specific decomposition method to get further insights in the underlying transmission mechanism which opens new avenues to further research. We find that in both countries the MPU is the main driver of the categorical EPU followed by FPU then CPU and finally TPU. Furthermore, the findings suggest that that the MPU of

one country is consistently dominating the CPU and TPU of the other country. The external spillover analysis reveals that the US dominated Japan nearly almost permanently till the Japanese nuclear power plant accident. This indicate that the effect of Fukushima Daiichi spread internationally and can be interpreted as a permanent negative trade shock.



Figure 1: Macroeconomic policy uncertainty indices

Figure 2: First differences macroeconomic policy uncertainty indices





Figure 3: Dynamic total connectedness





Figure 4: Net total directional connectedness

Notes: Black shaded areas illustrate the connectedness with external spillovers whereas the grey lines represent the internal spillovers.



Figure 5: Total directional connectedness FROM others

Notes: Black shaded areas illustrate the connectedness with external spillovers whereas the grey lines represent the internal spillovers.



Figure 6: Total directional connectedness TO others

Notes: Black shaded areas illustrate the connectedness with external spillovers whereas the grey lines represent the internal spillovers.



Figure 7: Internal net pairwise total directional connectedness



Figure 8: External net pairwise total directional connectedness



Figure 9: Market net total directional connectedness

Notes: The light-grey shaded area illustrates dynamic international spillovers from Japan to the US, the dark-grey shaded area shows dynamic international spillovers from the US to Japan and the black area represents net international spillovers from the US to Japan.

	United States				Japan					
	FPU	MPU	TPU	CPU	FPU	MPU	TPU	CPU	FROM	$FROM_i$
TO United States	28.2	34.8	2.8	8.2					103.2	74.0
FPU	63.2	25.4	1.1	2.2	2.8	1.7	1.1	2.5	36.8	28.7
MPU	24.7	62.8	1.4	5.2	1.4	2.4	0.7	1.4	37.2	31.3
TPU	1.7	2.6	91.1	0.8	0.5	0.7	1.7	1.0	8.9	5.1
CPU	1.8	6.8	0.3	79.7	3.4	2.2	0.8	5.1	20.3	8.9
TO Japan					26.8	30.4	7.5	11.7	105.6	76.4
FPU	2.7	1.4	0.8	2.4	66.6	18.7	4.5	2.8	33.4	26.0
MPU	1.6	2.5	0.1	1.4	18.6	64.8	2.6	8.3	35.2	29.5
TPU	1.7	1.3	3.2	1.1	5.2	2.6	84.3	0.6	15.7	8.4
CPU	1.6	1.6	0.2	5.5	3.0	9.1	0.4	78.7	21.3	12.5
ТО	35.8	41.6	7.1	18.5	34.8	37.4	11.6	21.7	208.7	150.4
NET	-0.9	4.5	-1.8	-1.8	1.4	2.2	-4.1	0.4	TCI_A	TCI_I
NET_i	-0.5	3.5	-2.3	-0.7	0.8	0.9	-0.9	-0.8	26.1	18.8

 Table 1: Connectedness table

Notes: Results are based on a TVP-VAR with lag length of order 1 (BIC) and a 10-step-ahead forecast.

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