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Christopher Thiem

Cross-Category, Trans-Pacific Spillovers of Policy Uncertainty and Financial Market Volatility

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Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

Editors

Prof. Dr. Thomas K. Bauer
RUB, Department of Economics, Empirical Economics
Phone: +49 (0) 234/3 22 83 41, e-mail: thomas.bauer@rub.de

Prof. Dr. Wolfgang Leininger
Technische Universität Dortmund, Department of Economic and Social Sciences
Economics – Microeconomics
Phone: +49 (0) 231/7 55-3297, e-mail: W.Leininger@tu-dortmund.de

Prof. Dr. Volker Clausen
University of Duisburg-Essen, Department of Economics
International Economics
Phone: +49 (0) 201/1 83-3655, e-mail: vclausen@vwl.uni-due.de

Prof. Dr. Roland Döhrn, Prof. Dr. Manuel Frondel, Prof. Dr. Jochen Kluge
RWI, Phone: +49 (0) 201/81 49-213, e-mail: presse@rwi-essen.de

Editorial Office

Sabine Weiler
RWI, Phone: +49 (0) 201/81 49-213, e-mail: sabine.weiler@rwi-essen.de

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Christopher Thiem¹

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Abstract

Using generalised variance decompositions from vector autoregressions, we analyse cross-country, cross-category spillovers of economic policy uncertainty (EPU) and financial market volatility between the US and Japan. Our model includes indices of monetary, fiscal and trade policy uncertainty for each country, as well as three measures of option-implied stock market and exchange rate volatility, respectively. We find that the financial market volatility indices are usually substantial net spillover transmitters towards the total group of EPU measures. However, the Japanese equity and especially the FX volatility index are typically more affected by EPU spillovers than the US VXO. Our results also reveal that, compared to within-country spillovers, cross-country spillovers of EPU are relatively small and less volatile. Finally, we show that the direction of net EPU spillovers between the US and Japan is both time- and category-dependent with different EPU categories acting as strong sources of uncertainty spillovers throughout the sample period.

JEL Classification: C32, D80, F42, G18

Keywords: Economic policy uncertainty; exchange rate volatility; Japan; spillovers; stock market volatility; United States; vector autoregression

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¹ Christopher Thiem, Chair of International Economics, University of Duisburg-Essen, Universitätsstr. 12, 45117 Essen, Germany, e-mail: christopher.thiem@vwl.uni-due.de

1. Introduction

Trust and predictability have become increasingly important for the functioning of the modern world economy. In the absence of these factors, that is, in an environment of uncertainty, banks cease to lend to their peers and across borders, financial conditions deteriorate, and companies refrain from making new investments or hiring workers at home or abroad. What followed in 2008/09 was a global economic crisis. Since then, academic research has come surprisingly far in terms of measuring economic uncertainty, quantifying its effects, and thereby providing proof for this chain of reactions. Nevertheless, we have yet to make satisfactory progress when it comes to understanding the nature of economic uncertainty. What events or mechanisms typically give rise to economic uncertainty? Is there only one type of uncertainty or are there many? If it is the latter, how do these different kinds of uncertainty interact? To what extent do they spread through the economy or across borders?

Motivated by such questions, Thiem (2018) investigates the relationship between different kinds of economic *policy* uncertainty (EPU) in the United States. Using the Diebold and Yilmaz (2012, 2014) spillover index approach, he not only finds that there are strong cross-category uncertainty spillovers but also that each policy area exhibits individual characteristics in terms of these spillovers. Moreover, the intensity and direction of cross-category EPU connectedness may change significantly over time, mostly depending on the nation's political environment.

In this paper, we expand Thiem's empirical study in two dimensions: First, we move from a categorical, but only domestically-focused perspective to a cross-country cross-category analysis. We accomplish this by incorporating category-specific measures of Japanese EPU into the Diebold and Yilmaz (DY) framework and its underlying vector autoregressive (VAR) model.² Second, we also add measures of option-implied volatility (IV), which allows us to investigate cross-type uncertainty spillovers between financial markets and category-specific EPU. Moreover, since IV indices are widely regarded as proxies for overall economic uncertainty (see, e.g., Bloom 2009, Nodari 2014 or Baker et al. 2016), by including these measures we are also able to control for fluctuations in non-policy related uncertainty when investigating within-country or trans-Pacific EPU spillovers.³

In short, we estimate a system of nine variables: Three newspaper-based measures of monetary (MPU), fiscal (FPU) and trade policy uncertainty (TPU) for the US and Japan, respectively (see Baker et al. 2016 and Arbatli et al. 2017), two indices of option-implied stock market volatility, again one for each country, and one measure of foreign-exchange (FX) market volatility. Afterwards, we compute bilateral, multilateral, and system-wide measures of spillover intensity to characterise the variables' relationships. Our analysis covers the static, fundamental properties of the uncertainty network as well as the dynamics of the spillovers throughout the 1987-2017 sample period. To examine the latter, we use a rolling-window approach with window averaging (WinAve) – see also DY (2012, 2014) and Thiem (2018).

Our main results can be summarised as follows. First, with respect to the relationship between the IV and EPU indices, we find that the former group is typically a strong net transmitter of uncertainty spillovers towards the latter. There are only a few instances in which the cross-type net spillover index points in the other direction and these phases are usually dominated by a specific EPU category. Nevertheless, we also find that the overall result is mostly driven by the US stock market IV index and that its Japanese counterpart, and especially the Yen/USD volatility index, are much more susceptible

² Our choice of the US and Japan as objects of study is largely determined by the limited availability of category-specific EPU measures for other countries. However, as these are the world's two largest developed economies, their relationship is also fundamentally of interest.

³ Krol (2014) also highlights the need to control for general economic uncertainty when investigating the effects of EPU on other financial variables such as foreign-exchange market volatility, for instance.

to EPU spillovers. Second, despite the institutional and cultural differences between the US and Japan, our network graphs show that the structure of within-country, cross-category EPU spillovers is similar on both sides of the Pacific. In addition, our dynamic analysis reveals that within-country EPU spillovers are almost constantly larger and more volatile than cross-country spillovers, with the Asian (AFC) and global financial crises (GFC) being the only exceptions. Third, while trans-Pacific EPU spillovers are largely balanced from a bird's eye perspective, there are also several multi-year periods during which the relevant net spillover index tilts towards either of the two countries. Japan, for instance, turns out to have been a net transmitter vis-à-vis the US during the AFC and the subsequent late-1990s recession, but a net spillover receiver during the 2011-2015 US fiscal policy battles and partisan conflicts. However, even these episodes are better described as category-driven rather than country-driven. We find that, in most cases, one country's FPU or MPU measure acts as a net source of international EPU spillovers, while the country's remaining EPU categories, particularly TPU, are often close to neutral or even net receivers.

Apart from the connection to Thiem (2018), our study relates to three strands of literature. The first consists of recent articles that investigate the underlying causes of political uncertainty, such as Baker et al. (2014), Funke et al. (2016), Davis (2017) and Azzimonti (2018). Collectively, these papers point towards regulatory complexity, voter polarisation and partisan conflict as important drivers of EPU. Second, there is previous research on international EPU spillovers. Klößner and Sekkel (2014), for example, find significant spillovers between *overall* EPU indices for the US, Canada and several European economies, while Yin and Han (2014), Balli et al. (2017) and Liow et al. (2018) obtain similar results for broader sets of countries, including Japan.⁴ Colombo (2013), Belke and Osowski (2018), and Clausen et al. (forthcoming) do not exclusively focus on cross-country EPU spillovers, but nonetheless also document their significance. Likewise, Husted et al. (2016) find considerable MPU spillovers from the US to other advanced economies. Finally, there is a fast-growing literature on the relationship between EPU and financial markets. The majority of studies is concerned with EPU's (unidirectional) impact on equity markets (e.g. Pastor and Veronesi 2013, Brogaard and Detzel 2015, Amengual and Xiu 2018), but there are also a few exceptions. Most notably, Beckmann and Czudaj (2017) examine the impact of US EPU, MPU and FPU on exchange rate expectations and forecast errors for various currencies, while Belke et al. (2018) investigate spillovers between stock volatility, FX volatility and aggregate EPU in the context of Brexit.⁵ All these studies find a significant influence of EPU on the financial markets – albeit with varying degrees of strength.

Overall, our work differs from the existing literature in that we bring together different EPU categories and financial market variables in a coherent, dynamic and above-country level framework. In our model, all variables are treated as endogenous, and their relationships are estimated simultaneously. Not only does this allow us to analyse the intensity and direction of cross-category, cross-type or trans-Pacific uncertainty spillovers while controlling for the remaining variables' influence, but it also enables us to directly compare the size of these effects.

The paper is structured as follows. Section 2 describes the category-specific EPU and the option-implied volatility indices. Section 3 introduces the econometric framework, the DY spillover measures and the WinAv procedure. Section 4 reports the main results of our static analysis and Section 5 of our dynamic analysis. Section 6 investigates the robustness of our findings to changes in model parameters and the inclusion of European uncertainty measures. Section 7 concludes.

⁴ Liow et al. (2018) also investigate the link between a cross-country EPU spillover index and a cross-financial market volatility spillover index they compute and find weak evidence for the former leading the latter. However, since their framework does not allow for direct EPU-volatility spillovers, they are only looking at third-round spillovers at best, and at generally biased results at worst.

⁵ Other examples of studies on the link between EPU and FX volatility are Krol (2014) and Kido (2016).

2. EPU & Volatility Indices

To measure monetary, fiscal and trade policy uncertainty in the US and Japan, we use the newspaper-based EPU indices of Baker et al. (2016) and Arbatli et al. (2017), respectively. In order to construct these indices, both research teams scan local-language newspaper archives for articles that meet predefined keyword criteria. More specifically, each relevant article has to contain at least one keyword from each of four different term sets pertaining to the economy, policy in general, uncertainty, and the respective policy category. The authors then compute the relative frequency of articles about category-specific EPU in relation to the total number of monthly newspaper reports and track its evolution over time. Since there are no a priori constraints on how journalists may address policy uncertainty, the resulting indices potentially cover many crucial aspects of EPU such as uncertainty about the *who*, *what*, *when* and the effects of policy decisions (see Baker et al. 2016).

Another important argument in favour of the Baker et al. and Arbatli et al. indices is that they are the only EPU measures available for both countries, all three policy categories and an extended period, allowing us to work with a sample of monthly data from January 1987 to December 2017.⁶ In addition, the similar construction approach ensures the comparability of the indices across countries and categories, and both groups of authors also conduct country-specific human audit studies to select optimal keyword criteria and minimise classification errors. Indeed, the widespread use of the EPU indices by practitioners and in academic research seems to confirm the measures' information value (Baker et al. 2016).

To capture financial market volatility and general economic uncertainty, respectively, we prefer measures of option-implied volatility, as the underlying (options) contracts reflect the views of a broad base of market participants and are also forward-looking in nature. For the US, we use the CBOE's VIX index, which reflects the expected volatility of the S&P 100 stock market index over a 30-day horizon.⁷ In the case of Japan, no option-implied volatility index is available for the entire sample period. We thus follow Bloom (2009) and use a measure of realised volatility for the missing periods. More precisely, we compute the monthly standard deviation of daily returns of the Nikkei 225 stock market index and standardise the resulting time series so that it has the same mean and variance as the related option-implied volatility measure (during the period for which the latter is available). Afterwards, we splice the two series to obtain our measure of Japanese stock market volatility (NVI). Using the same procedure and data on the Yen/USD exchange rate, we also construct a measure of uncertainty about the two countries' relationship and relative economic position (JYVIX).⁸

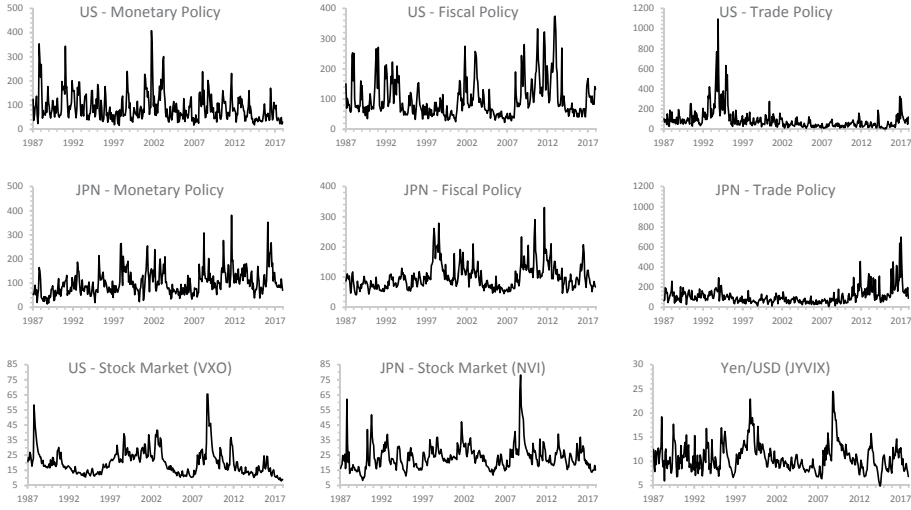
Figure 1 provides a graphical representation of the nine uncertainty indices, while Table A1 in the appendix contains a more detailed account of the data sources and the volatility series' construction.

⁶ By including measures of MPU, FPU and TPU, we arguably cover the policy categories that are the most relevant for the two countries' economies and their economic relationship. We decide against the inclusion of other EPU indices or sub-categories, as these variables are only available for one of the two countries, which raises potential concerns regarding the cross-country balance and comparability of our spillover indices. In some cases, there are also non-negligible technical barriers. Arbatli et al.'s (2017) exchange rate policy uncertainty index, for instance, shows many isolated jumps, making it difficult to reconcile the index with the DY framework's assumptions – see the next section and *JPN_FX* in Appendix Figure A1.

⁷ The VIX index as the “most commonly used proxy for overall economic uncertainty” (Baker et al. 2016, p. 1620) is not computed before 1990. However, during the available period, the VXO and the VIX correlate at 0.99 on a monthly basis.

⁸ The monthly correlations of the computed realised volatilities and the option-implied indices are 0.83 for the Nikkei 225 stock market index and 0.81 for the Yen/USD exchange rate, respectively.

Figure 1: Category-specific EPU & Volatility Indices for the US and Japan



Notes: See Table A1 for information on data sources and series construction.

3. Empirical Framework

In this section, we introduce the DY spillover index (or connectedness measurement) approach. Since the methodology is widely known and applied by researchers in both empirical finance and macroeconomics, we keep its discussion very brief and refer the reader to DY (2012, 2014) and also to Thiem (2018) for further details.

The main building block of the DY framework is an N -variable vector-autoregressive (VAR) model with p lags: $\mathbf{y}_t = \sum_{i=1}^p \Phi_i \mathbf{y}_{t-i} + \boldsymbol{\varepsilon}_t$, where $\mathbf{y}_t$ is an $N \times 1$ vector of endogenous variables, Φ_i are $N \times N$ coefficient matrices, and $\boldsymbol{\varepsilon}_t \sim (\mathbf{0}, \Sigma)$ is an $N \times 1$ vector of i.i.d. disturbances. Under the assumption that the $VAR(p)$ process is covariance stationary, we can rewrite the approximating model as $\mathbf{y}_t = \sum_{i=0}^{\infty} \mathbf{A}_i \boldsymbol{\varepsilon}_{t-i}$, which constitutes its moving average representation. The $N \times N$ coefficient matrices $\mathbf{A}_i$ are recursively defined as $\mathbf{A}_i = \Phi_1 \mathbf{A}_{i-1} + \Phi_2 \mathbf{A}_{i-2} + \dots + \Phi_p \mathbf{A}_{i-p}$ with $\mathbf{A}_0 = \mathbf{I}_N$ and $\mathbf{A}_{i<0} = \mathbf{0}$, and, according to DY (2012), are crucial to understanding the system's dynamics.

In particular, they can be used to compute generalised forecast error variance decompositions (GFEVD) – the second important element of the DY connectedness framework. Variance decompositions break down the H -step ahead forecast error variance of each variable y_i into fractions that can be attributed to its own shock and to those in other variables y_j (with $i, j = 1, \dots, N$). To identify both types of shocks from the usually contemporaneously correlated VAR innovations $\boldsymbol{\varepsilon}_t$, we follow DY (2012, 2014) and use the generalised approach of Koop et al. (1996) and Pesaran and Shin (1998) (KPPS). The KPPS framework is largely data-driven, requires no a priori assumptions regarding the variables' relationships, and produces variance decompositions that are independent of the variable ordering. At the same time, it accounts appropriately for any observed correlation in $\boldsymbol{\varepsilon}_t$ and has a conclusive theoretical basis (cf. Pesaran and Shin 1998).

The elements of the resulting $N \times N$ GFEVD matrix θ^g can be written as follows:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (\mathbf{s}_i' \mathbf{A}_h \boldsymbol{\Sigma} \mathbf{s}_j)^2}{\sum_{h=0}^{H-1} (\mathbf{s}_i' \mathbf{A}_h \boldsymbol{\Sigma} \mathbf{A}_h' \mathbf{s}_i)},^9 \quad (1)$$

where σ_{jj} is the variance of ε_j and $\mathbf{s}_i, \mathbf{s}_j$ are selection vectors. Because the individual rows of $\boldsymbol{\theta}^g$ do not necessarily sum to one ($\sum_{j=1}^N \theta_{ij}^g(H) \neq 1$), DY (2012) further normalise the matrix entries by their corresponding row sums, i.e.

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)}. \quad (2)$$

Now each $\tilde{\theta}_{ij}^g(H)$ represents the share of y_i 's total variation over the forecast horizon (caused by initial shocks to all N variables) that is explained by an initial shock to y_j (see Lanne and Nyberg 2016). Consequently, for $i = j$, we obtain y_i 's own-effect share, while for $i \neq j$, we get cross-variable effect shares or, in other words, measures of spillover intensity.

Since we now also have $\sum_{j=1}^N \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H) = N$, the normalised GFEVD can be used to construct various indices that characterise the intensity and direction of spillovers for individual variables, within and across different subgroups, and even for the system as a whole (see also DY 2012, 2016). Simply writing $C_{i \leftarrow j} = \tilde{\theta}_{ij}^g(H) \cdot 100$, for instance, gives us a measure of pairwise spillover intensity. Aggregating this further, we obtain $C_{i \leftarrow \blacksquare} = \sum_{j=1, j \neq i}^N C_{i \leftarrow j}$ as a measure of the total intensity of uncertainty spillovers that variable (or subgroup) i receives from all other variables (*From Others*), and $C_{\blacksquare \leftarrow i} = \sum_{j=1, j \neq i}^N C_{j \leftarrow i}$ as a measure of the overall intensity of spillovers that it transmits (*To Others*). Nonetheless, due to the nature of our research agenda, we are mostly interested in

average connectedness, e.g.

$$\bar{C}_i = \frac{C_{\blacksquare \leftarrow i} + C_{i \leftarrow \blacksquare}}{2(N-1)}, \quad (3)$$

which measures the average intensity of all spillovers that variable (or subgroup) i either transmits to or receives from the rest of the system (or another subgroup) (cf. Thiem 2018),

net uncertainty spillovers, e.g.

$$C_{ij} = C_{j \leftarrow i} - C_{i \leftarrow j}, \quad (4)$$

which, as highlighted by DY (2014, p. 120), are analogous to bilateral or multilateral trade balances ("exports of future uncertainty, less imports of future uncertainty"),¹⁰ and, finally,

the system's *total spillover* (or *connectedness*) *index* (SOL),

$$C = \frac{1}{N} \sum_{i,j=1, i \neq j}^N C_{i \leftarrow j}, \quad (5)$$

⁹ This notation implies that we condition on the information set Ω_t – see also Thiem (2018).

¹⁰ Consequently, the sum of all bilateral (and multilateral) net uncertainty spillovers is equal to zero: $\sum_{i,j=1, i \neq j}^N C_{ij} = \sum_{i=1}^N C_i = 0$.

which is a gauge of the average intensity of spillovers per variable.¹¹ Since it is possible to rewrite the SOI as either $C = \frac{1}{N} \sum_{i=1}^N C_{\blacksquare \leftarrow i}$, $C = \frac{1}{N} \sum_{i=1}^N C_{i \leftarrow \blacksquare}$, or $C = \frac{N-1}{N} \sum_{i=1}^N \bar{C}_i$, the index can also be interpreted from a transmitter perspective, a receiver perspective, or a combination of both (Thiem 2018).

As pointed out by DY (2014, p. 123), “variance decompositions are networks”, and the GFEVD matrix is the adjacency matrix of a weighted directed network. Therefore, our spillover indices are essentially measures of connectedness among the uncertainty network’s components. This not only further strengthens their theoretical footing but also allows us to use tools similar to those employed in the analysis of network topologies. More specifically, we will use the open-source software Gephi and Jacomy et al’s (2014) ForceAtlas algorithm to convert the computed variance decomposition matrices into network graphs. The resulting diagrams then make it easy to analyse the various types of uncertainty (nodes) and their spillovers (edges).

In a similar vein, DY suggest using rolling-window estimations to study spillover dynamics. There are indeed many reasons why the relationships in the uncertainty network may change – both fast and slowly – over time (e.g., various types of unexpected events, transformations of institutions and governments, etc.), and characterising these changes constitutes an important part of our analysis. The rolling-window approach has the advantage that it is simple in construction, yet consistent with many possible data-generating processes, and thus very general with respect to its domain (see DY 2015). Moreover, we decide to use the window-averaging procedure (WinAv) of Thiem (2018), which preserves the original approach’s simplicity and generality, but, at the same time, improves it in terms of robustness and flexibility.

Before we proceed to the discussion of our results, we still need to determine the specific parameters of our empirical approach: Regarding the data transformation, we decide to work with the natural logarithms of the implied volatilities and EPU indices, as they are approximately Gaussian (see also DY 2014, 2016, Diebold et al. 2017). In the case of the EPU measures, we also linearly detrend the series to ensure stationarity.¹² Appendix Figure A1 plots the variables’ empirical distributions both before and after the transformations. For the VAR model, we choose $p = 1$ lags, which is the optimal lag length according to all common information criteria (Akaike, Schwarz-Bayes and Hannan-Quinn). Furthermore, our preferred horizon for the study of cross-category and trans-Pacific uncertainty spillovers is one year, so $H = 12$ months. Finally, to determine the window range for the WinAve procedure, we follow Thiem’s (2018) suggestion and set w_{Min} and w_{Max} so that we avoid any clear signs of under- or oversmoothing. This is the case for $w_{Min} = 36$ and $w_{Max} = 72$, respectively. We later examine the robustness of our results to the choice of model parameters in Section 6.

4. Static, Full-sample Analysis

We begin by characterising the static, unconditional structure of the trans-Pacific EPU and volatility system. To this end, we estimate the VAR model for the full sample period from 1987 to 2017, calculate the $N \times N$ GFEVD matrix and the corresponding spillover measures, and, as indicated in the previous section, translate the resulting information into an easy-to-read spillover network graph (Figure 2).¹³

The various uncertainty measures form three different groups: The Japanese and US EPU categories on the left and right of the diagram – as if reflecting the two countries’ geographic separation – and the group of financial market indices in the upper-mid between them. Indeed, as the system’s

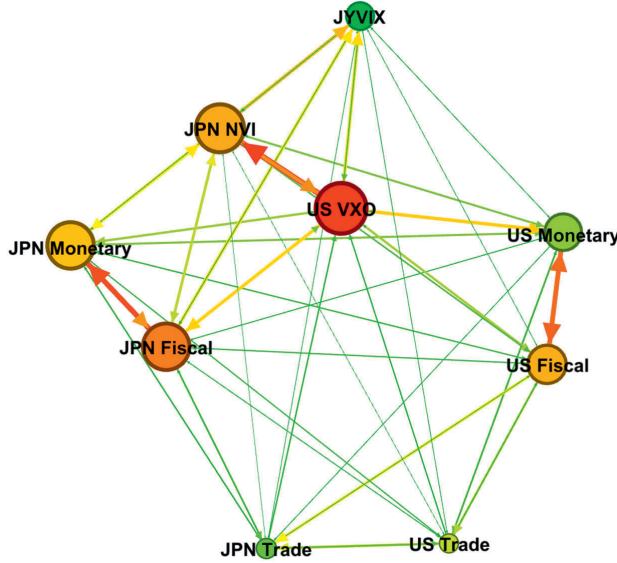
¹¹ Mechanically, the SOI is defined as the ratio of the sum of θ^g ’s off-diagonal elements to the sum of all its elements (cf. DY 2016): $C = \left[\frac{\sum_{i,j=1, i \neq j}^N \bar{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \bar{\theta}_{ij}^g(H)} \right] \cdot 100$.

¹² However, as shown in Section 6, this has hardly any influence on our results.

¹³ See also Table A2 in the appendix for a numerical representation.

strongest net total transmitter of uncertainty spillovers, the volatility index for the US stock market lies right at the centre of the uncertainty network ($C_{VXO} = 32.4$). It transmits significant spillovers to both monetary and fiscal policy EPU in the two countries, whereby, in the case of Japan, FPU is more strongly affected ($C_{FPU \leftarrow VXO}^{JPN,US} = 12.0\%$), and, in the case of the US, MPU is found to be more susceptible ($C_{MPU \leftarrow VXO}^{US} = 12.2\%$). The impact of US volatility shocks on the two TPU indices, on the other hand, is relatively small, which is also mirrored in their nodes' distant locations. Similarly, individual spillovers in the other direction, i.e. from any of the six EPU measures to the VXO, are rather limited.¹⁴

Figure 2: Full-sample Uncertainty Spillover Network



Notes: Node locations are determined in Gephi using Jacomy et al.'s (2014) ForceAtlas algorithm. Edge thickness and colour mirror the intensity of individual spillovers (thin, deep green – weakest; yellow; thick, deep red – strongest); node colour reflects each variable's relative strength as a net spillover transmitter; node size indicates average connectedness.

Next, we have the Nikkei 225 option-implied volatility index, which is relatively strongly connected to the local EPU measures. In fact, it is not only a notable transmitter of spillovers to Japanese fiscal and monetary policy uncertainty ($C_{FPU \leftarrow NVI}^{JPN} = 8.5\%$, $C_{MPU \leftarrow NVI}^{JPN} = 10.5\%$), but an even more significant spillover receiver ($C_{NVI \leftarrow FPU}^{JPN} = 9.6\%$, $C_{NVI \leftarrow MPU}^{JPN} = 11.7\%$). Local MPU and FPU are thus important factors in the Japanese stock market, revealing a key difference in the underlying nature of the EPU-IV relationship across the two countries.

The Yen/USD IV index, as the third member of the financial markets group, turns out to be the network's most distinct net receiver of uncertainty spillovers ($C_{JYVIX} = -33.3$). Apart from its own-effect, the largest share of its total forecast variation is explained by shocks to the NVI (12.9%), closely followed by shocks to the US VXO (11.9%), and Japanese FPU (11.7%) and MPU (9.8%). Japanese TPU and the US EPU categories, on the other hand, have only a weak influence on the expected degree of FX rate movements. In other words, even after controlling for general uncertainty shocks, spillovers from the two main Japanese EPU categories to the foreign exchange market are strong and, by far, eclipse those of their US counterparts. International investors may want to pay attention to this result.

¹⁴ When taken together, however, the EPU variables account for 21.8% of the VXO's total variation over the forecast horizon.

Within the two EPU clusters, we observe quite similar spillover structures. Despite the two countries' fundamentally different cultures, political institutions and economic orientations, in both cases, MPU and FPU strongly influence each other ($\bar{C}_{MPU,FPU}^{US} = 17.4$, $\bar{C}_{MPU,FPU}^{JPN} = 16.9$). The only difference is that, in Japan, spillovers between the two types of EPU are less balanced ($C_{MPU,FPU}^{JPN} = -5.0$), which likely reflects the Bank of Japan's lower degree of independence.¹⁵ Also similar in both countries, there is a significant distance between the TPU node and the other two categories' nodes, indicating the former's status as a (moderate) net spillover receiver within both EPU groups ($C_{TPU,[EPU]}^{US} = -9.6$, $C_{TPU,[EPU]}^{JPN} = -5.4$).

Finally, our static, full-sample analysis yields no evidence of particularly strong trans-Pacific EPU spillovers, with two exceptions: First, US FPU exerts a sizeable influence on Japanese TPU ($C_{TPU \leftarrow FPU}^{JPN \leftarrow US} = 10.3\%$), and, second, there is a relatively strong connection between TPU on both sides of the Pacific ($C_{TPU,TPU}^{US,JPN} = 7.5\%$). The latter also becomes apparent from the short distance between the two corresponding nodes.

Overall, our results are well in line with Thiem (2018), who not only highlights the relative importance of *within*-country, cross-category EPU spillovers but also describes a similar EPU spillover structure for the isolated case of the US.

5. Dynamic, Rolling-sample Analysis

The previous section gave us a useful overview of the underlying or unconditional structure of the uncertainty network. However, during our long sample period of more than 30 years, both countries saw many events and political changes that may have, temporarily or permanently, altered the size and direction of trans-Pacific and cross-category uncertainty spillovers (cf. DY 2009). Between 1990 and 2017, for instance, Japan alone went through fifteen changes in its political leadership, going as far as having four different prime ministers (PMs) in a one-year period between 1993 and 1994.

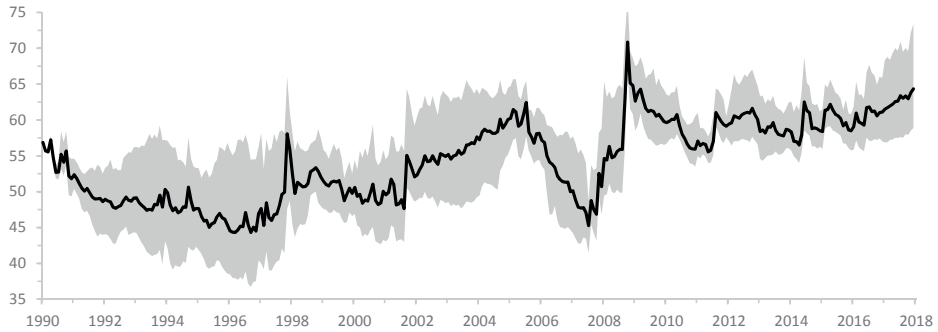
To characterise the spillover dynamics potentially resulting from such events, we now use the rolling-window estimation approach combined with WinAve. We first assess the overall importance of the time dimension by looking at the total spillover index. Afterwards, we focus on the evolution of the relationships between the volatility indices and the group of EPU measures as well as on *cross*-country, cross-category EPU spillovers.

5.1 Total Spillover Index

Figure 3 shows the dynamic total uncertainty spillover index. Starting from a relatively high value of 56.9% in January 1990, the SOI declines during the US economic recovery of the early 1990s and, despite the ongoing troubles in the Japanese banking sector, bottoms out at 44.3% in early 1996. Following this, we can discern three extended periods of high or rising spillover intensity that, when taken together, form a positive long-run trend: First, the index rises in the run-up to the AFC and jumps to a local maximum of 58.1% as the crisis reached its critical stage in November 1997. Second, the dynamic SOI reacts strongly to the September 2001 attacks and, from then on, climbs further until it arrives at another high of 62.5% in July 2005. Finally, the system is hit by the GFC in 2007/2008, which results in an unprecedented increase in system-wide connectedness. More specifically, the dynamic spillover index reaches its sample maximum of 70.9% in October 2008 – just shortly after the collapse of Lehman Brothers.

¹⁵ Even after the revision of the Bank of Japan Act in 1998, the Japanese government retains a relatively strong control over certain central bank functions and aspects of monetary policy (see, for instance, Mikitani and Kuwayama 1998).

Figure 3: Dynamic Total Uncertainty Spillover Index



Notes: Rolling-window estimation with window averaging, $w = [36, 72]$. The grey shaded area indicates the 90% interval of the distribution across window sizes.

During the post-crisis years, various (political) events that created further economic uncertainty unfolded in both the US and Japan. Examples include the continued utilisation of untested policy instruments by the two countries' central banks, a number of partisan clashes over fiscal policy in the US, and the introduction of "Abenomics" in Japan – an ambitious reform package by PM Shinzo Abe that entailed fundamental changes to both monetary and fiscal policy (see, e.g., Baker et al. 2016, Davis 2017 or Arbatli et al. 2017). Likely as a result, system-wide connectedness fluctuates around a relatively high level of about 58% between 2010 and 2016. Most recently, there also seems to be a renewed upward trend in the SOI, leading to a value of 64.3% at the end of our sample period.

In sum, it becomes clear that the total intensity of spillovers in the system varies substantially over time. The SOI does not only exhibit different kinds of secular movements throughout the sample period but also reacts significantly to major economic events. This provides grounds for a more in-depth analysis of the dynamics of spillovers within and, more importantly, across the different groups of uncertainty measures.

5.2 Volatility-EPU Spillovers

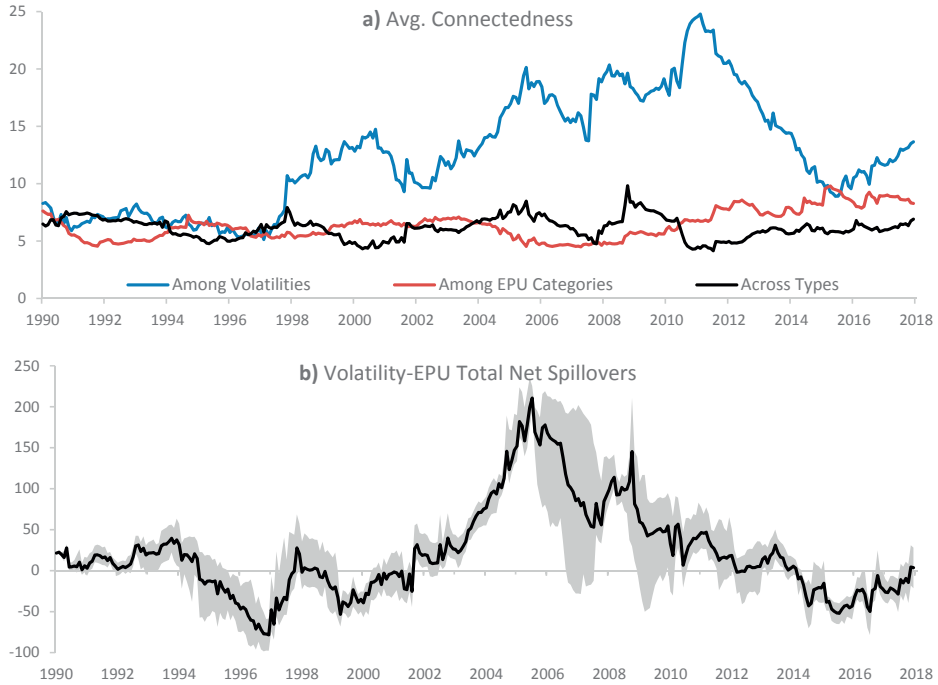
We begin the more granular dynamic analysis by mentally separating the nine-variable system into two subgroups consisting of the three option-implied volatility indices and the six US and Japanese EPU measures, respectively. Accordingly, Figure 4 a) plots the dynamic average connectedness for three different kinds of uncertainty spillovers: spillovers within the first group (*Among Volatilities*), spillovers within the second group (*Among EPU Categories*), and, finally, spillovers between the two groups (*Across Types*).

It first becomes clear that the average intensity of uncertainty spillovers within the financial markets group (blue line) is much higher and more erratic than the average spillover intensity within the EPU group or across the two. Interestingly, this has not been the case for the entire sample period. During most of the 1990s, all three connectedness measures fluctuate between 5 and 8% and display a similar variance. Only in November 1997 the *Among Volatilities* index suddenly jumps to almost 11% and, from then on, follows a steady upward trend with a significantly greater variation.

By contrast, average connectedness within the EPU group (red line) barely changes during the AFC or immediately thereafter. It does rise considerably in the wake of the GFC, however, and then continues to follow a positive trend until the end of the sample period. For a short time in 2015, it even exceeds the average connectedness in the volatilities group (9.5 vs 9.1%). Nevertheless, since the *Among EPU categories* index summarises EPU spillover intensity within and across two separate countries, it would

be premature to draw any definitive conclusions from this. Before that, we need to investigate the different kinds of relationships within the EPU group in more detail. We will thus revisit this question in the next section.

Figure 4: Dynamic Spillovers Between Financial Market Volatilities and US & Japan EPU Categories



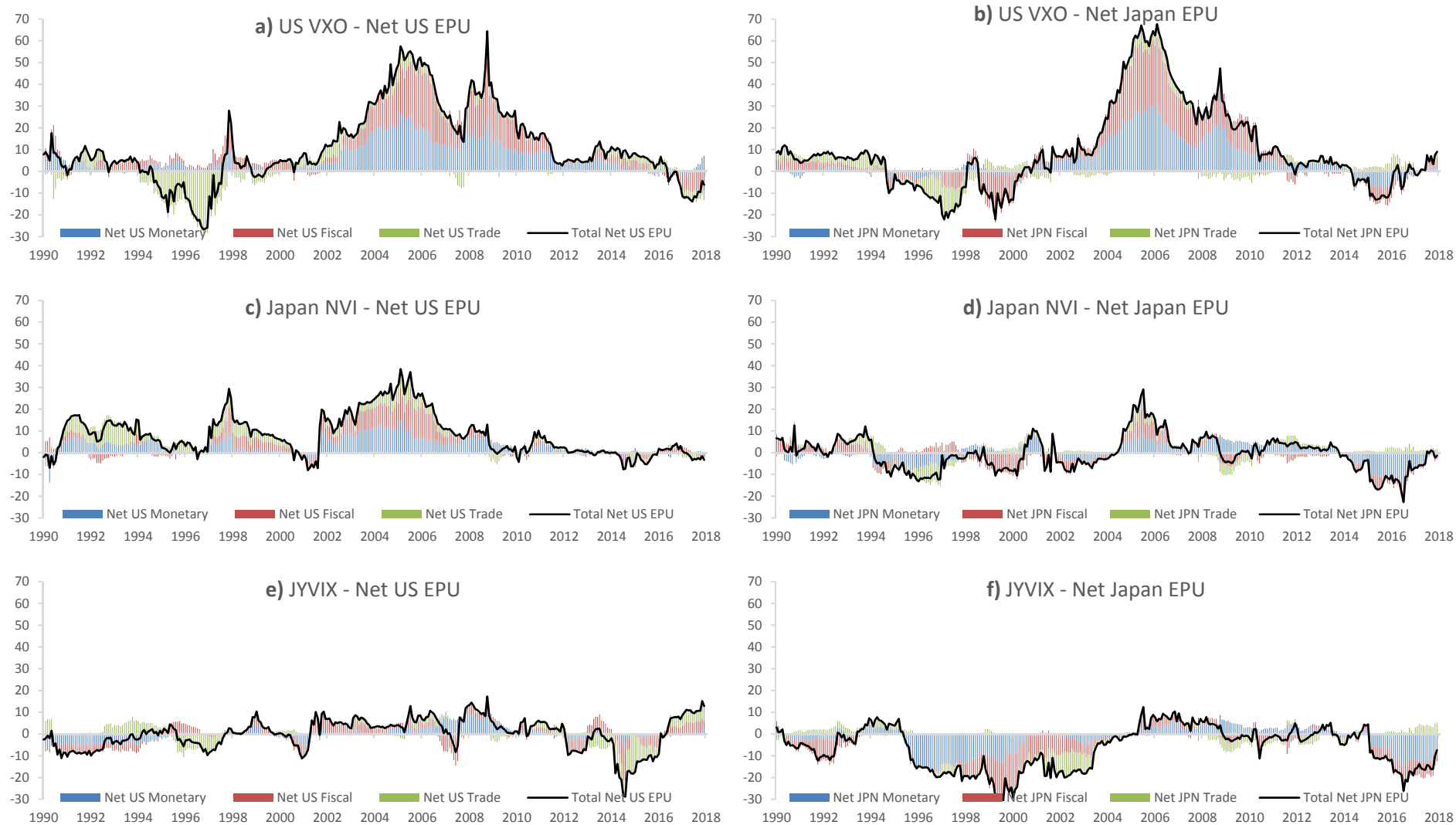
Notes: Rolling-window estimation with window averaging, $w = [36, 72]$. The grey shaded area in Panel b) indicates the 90% interval of the distribution across window sizes.

For now, let us focus on the volatility-EPU spillovers: As shown by the black line in Figure 4 a), *Across Types* connectedness is particularly high during the AFC (7.9%), during the early to mid-2000s (between 6.2 and 8.5%) and, once more, during the GFC (up to 9.8%). At most other times, the index moves around a similar level as the within-EPU connectedness measure. The only exception is 2010 during which volatility-EPU connectedness suddenly drops to 4.2%, only to rise again slowly after mid-2011.

Figure 4 b) plots the net direction of the spillovers. As we can see, the three peaks in *Across Types* connectedness are all associated with rising net spillovers from financial market volatility – i.e. general economic uncertainty – to policy uncertainty. After the burst of the dotcom bubble in 2000, for instance, the net spillover index increases markedly for several years and, coinciding with the peak in cross-type connectedness, climbs to its sample maximum of +210.6 in mid-2005. Obviously, both the financial market turbulences of the early 2000s as well as the following, synchronised decline in volatility after 2002 had a substantial impact on policy uncertainty.¹⁶ Indeed, for most of the sample period, the volatility-EPU net spillover index is positive, and hence financial markets transmit significantly more uncertainty spillovers towards the policy sphere than vice versa.

¹⁶ By July 2005 all three option-implied volatility indices had declined to multi-year lows.

Figure 5: Dynamic Volatility-EPU Net Spillovers – Breakdown by Country & Volatility Index



Notes: Rolling-window estimation with window averaging, $w = [36, 72]$.

Nonetheless, from 1994 to 1997, 1998 to 2000, and more recently from 2014 to 2017, we also observe large negative values (up to -78.3, -53.3, and -52.0, respectively). To see which financial markets or policy categories are responsible for these swings, we compute the net cross-type spillovers individually for each IV measure and decompose them by country and EPU category. Figure 5 presents the results.

Expectedly, Panels a) and b) show that the US stock market is a distinct net transmitter of uncertainty spillovers vis-à-vis the US as well as the Japanese EPU categories. The two dynamic graphs now additionally reveal that this characteristic is most pronounced between 2000 and 2010 / 11. Regarding US EPU, the VXO's strongest impact can be observed at the height of the GFC ($C_{VXO,[EPU]}^{US,US} = 64.4$), while, in the case of Japanese EPU, net spillovers are most intense in mid-2005 and early 2006 ($C_{VXO,[EPU]}^{US,JP} = 67.0$ and 67.7 , respectively).

Consistent with the overall picture, net spillovers in the other direction are much less common. Most notably, the VXO receives net spillovers of up to -28.4 from US TPU between 1994 and early-1997 due to the NAFTA and WTO agreements. In hindsight, both treaties were important milestones in global economic development, but at the time, they were surrounded by considerable uncertainty regarding their negotiation and implementation processes as well as their complex economic effects (cf. Lawrence 2002). As to the other two EPU categories, we observe strong net spillovers from Japanese FPU (up to -21.5) shortly after the Twisted Diet election in 1998, and from Japanese FPU and MPU between 2014 and 2016 (up to -15.7 combined). Also, following the 2016 presidential election, the VXO-US FPU net spillover index becomes persistently negative for the first time in its history (between -6.8 and -8.9 during 2017). This suggests that the current dominance of political issues in the US stock market is a relatively recent, or at least rather infrequent, phenomenon.

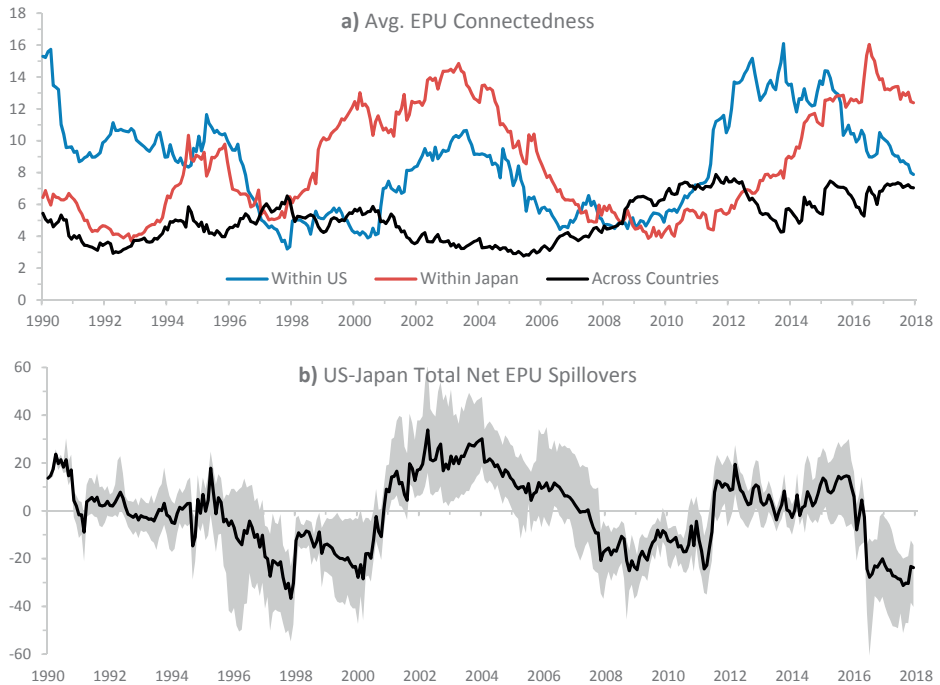
The next two panels depict the net cross-type spillovers from the Nikkei option-implied volatility index. In Panel c), the evolution of the NVI-US EPU relationship resembles, to a large extent, the dynamic patterns observed in the previous two cases, albeit with a generally lower level of net spillovers and only until the GFC. After that, the total net spillover index falls abruptly and then stays close to zero until the end of 2017. In Panel d), the relationship between the NVI and the Japanese EPU categories is even more balanced. Throughout the sample period, we can discern several longer phases in which the total net cross-type spillover index is either unambiguously positive or negative, and the same applies to the category-specific net spillover indices. For example, the NVI is a distinct net spillover receiver vis-à-vis Japanese MPU during the mid-1990s banking crisis (up to -10.1), a strong net transmitter for an entire decade after 2004 (up to +9.6), and then again, a substantial net receiver of uncertainty spillovers after the profound shift in the BoJ's monetary policy strategy in 2013 (up to -15.6).

Finally, among the three financial market indicators included in our system, foreign exchange volatility turns out to be the strongest net receiver of EPU spillovers. As shown in Panel e), for instance, the FX market is strongly affected by US TPU between 2013 and 2016 (up to -17.7). At the time, talks about the Trans-Pacific Partnership (TPP) agreement were well underway and, even before TPP was finally signed in early 2016, several political events had already cast doubt on the treaty's future ratification – see, e.g., Arbatli et al. (2017). Similarly, between March and December 1995, the JYVIX's net spillover index in Panel f) falls by more than twenty points (from +6.9 to -15.9) before settling well into negative territory. Consistent with the historical narrative, our results show that this is mostly driven by Japanese MPU. Not only did a coordinated FX intervention by the major central banks fail to prevent a surge in the Yen in early 1995 but also the Japanese banking crisis intensified during that year. Eventually, the BoJ was forced to cut interest rates and started acting as a lender of last resort by providing emergency loans to various financial institutions (cf. Kuttner 2014, Arbatli et al. 2017).

However, it is also important to mention that, even though the BoJ's intervention continued for several more years, there is a distinct change in the composition of the net spillover index from as early as 1997. In April of that year, the Japanese government underestimated the fragile state of the banking system and the economy, leading it to raise the consumption tax prematurely. The officials then added to their mistake by deciding to continue fiscal consolidation amidst the height of AFC and from 1998 to 2000, fiscal policy remained inconsistent and mostly ineffective. As a result, we observe strongly growing net spillovers from Japanese FPU to the financial markets coinciding with one of the country's worst recessions (cf. Kuttner and Posen 2002, Iwaisako 2014, Arbatli et al. 2017).¹⁷

Overall, the diagrams in Figure 5 clearly highlight the dynamic and category-specific nature of the IV-EPU spillovers. However, our results also point to an important country dimension as the differences in the financial markets' dynamic net spillover indices reach from (minor) variations in relative magnitude – e.g., the VXO's net indices vis-à-vis the US and Japan between 2004 and 2010 – to substantial differences in the direction and composition of the net spillovers – e.g., the JYVIX's indices between 1996 and 2004.

Figure 6: Dynamic Spillovers of Category-specific EPU Across the Pacific



Notes: Rolling-window estimation with window averaging, $w = [36, 72]$. The grey shaded area in Panel b) indicates the 90% interval of the distribution across window sizes.

¹⁷ Note that, while the impact on the JYVIX is strongest and most persistent, we also find increased net spillovers from Japanese FPU to the US and Japanese stock markets during the 1998-2000 period.

5.3 US-Japan EPU Spillovers

As indicated in the previous section, we now return to the group of EPU measures and examine its inner workings in more detail. Figure 6 a) plots the average connectedness of the EPU indices within and across the US and Japan.

As can be seen, within-country EPU spillovers (red and blue lines) are usually much larger and more dynamic than cross-country EPU spillovers (black line) and their evolution also clearly varies by country. The three US EPU categories, for instance, are highly connected at the sample beginning, but their average connectedness declines significantly during the 1990s (from 15.2% in 1990 to 4.2% in 2000). It then jumps up again and continues to increase following the election of George W. Bush in November 2000, only to decline once more and almost return to its pre-Bush level by the end of 2006.¹⁸ Perhaps surprisingly, the group's average connectedness does not visibly change during the ensuing GFC, suggesting that much of the observable rise in EPU levels can be attributed to a combination of simultaneous shocks in each EPU category and the strong financial market uncertainty spillovers that we found earlier. Instead, US EPU spillover intensity surges from 7.4 to 11.6% following the 2011 Debt Ceiling Dispute and, due to similar events such as the 2012 Fiscal Cliff or the 2013 Government Shutdown (see, e.g., Baker et al. 2016), climbs even further thereafter (up to 16.1% in October 2013). Putting the GFC aside, the evolution of our US average connectedness index is again largely consistent with earlier descriptions of FPU, MPV and TPU spillovers by Thiem (2018).

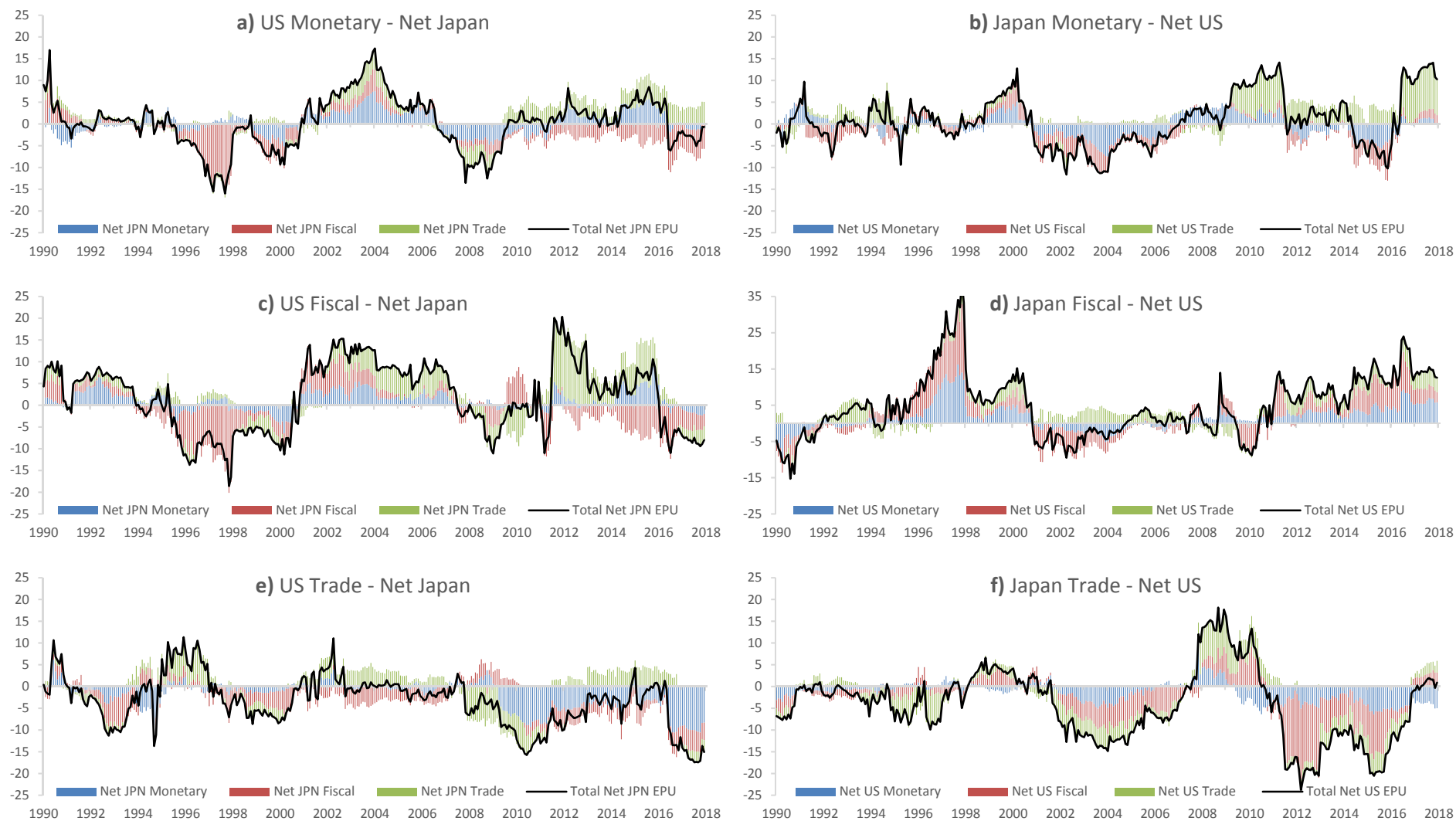
The connectedness index for the Japanese EPU categories shows its first substantial increase from 1993 onwards (from 4.3 to 10.3%) and then remains elevated until late 1995. In addition to the intensification of the Japanese banking crisis, two PMs had to resign during this short period with one, PM Hata, being just two months in office. Japanese EPU connectedness declines from 1996 to mid-1997, but afterwards, embarks on yet another strong upward trend that takes the relevant index to 14.9% in mid-2003. From the fiscal policy side, this second surge in spillover intensity is likely fuelled by the Twisted Diet election of 1998, the government's fiscal consolidation plans we discussed earlier, and several other tight elections afterwards. From the monetary policy side, the BoJ's unsuccessful battle against deflation with zero interest rate policy (ZIRP) and quantitative easing (QE) likely injected further uncertainty into the political-economic system (cf. Kuttner 2014, Arbatli et al. 2017). Similar to its US counterpart, the *Within Japan* connectedness index falls during the second half of the 2000s and shows no exceptional rise during the GFC. A third secular increase only begins with the premiership of Yoshihiko Noda, 2011-2012, and continues throughout the first years of Abenomics. One example of how PM Abe's reform plans created uncertainty is the repeated postponement of a consumption tax hike originally planned for 2015 (cf. Arbatli et al. 2017). Indeed, Japanese EPU connectedness rises further amid the first rumours of a second tax hike delay in mid-2016 and reaches its sample maximum of 16.0% in July of that year – just shortly after the delay's announcement.¹⁹

Finally, cross-country EPU connectedness rises slowly but persistently during the 1990s and reaches a local peak of 6.5% at the height of the AFC. Indeed, the Asian market turmoil marks one of only two occasions on which international EPU connectedness exceeds both countries' internal EPU connectedness. The second time is the GFC, during which the *Across Countries* index also jumps to levels above six percent after September 2008. Nevertheless, at this point, the intensity of trans-Pacific EPU spillovers has already been increasing since the beginning of 2006, and this trend continues until the end of our sample period.

¹⁸ Halfway through the cycle (August 2003), the *Within US* connectedness index reaches a local peak of 10.6%.

¹⁹ By including an aggregate index for European EPU in the system, we rule out the possibility that this result is somehow driven by the outcome of the Brexit referendum, which sent large waves of uncertainty through the global economy in June/July 2016. See Section 6 for further details.

Figure 7: Dynamic US-Japan Net EPU Spillovers – Breakdown by Country & EPU Category



Notes: Rolling-window estimation with window averaging, $w = [36, 72]$.

Turning to the lower panel of Figure 6, we find that net EPU spillovers between the two economies are largely balanced if viewed over the entire sample. In between, however, there are constantly strong and persistent swings in either direction. For example, the three US EPU categories are moderate net transmitters of uncertainty shocks vis-à-vis the three Japanese categories in the first half of the 1990s (up to +23.7), strong spillover transmitters during the Bush years after 2000 (up to +33.8), and again moderate but persistent net transmitters during the US fiscal policy battles and partisan conflicts from 2011 to 2015 (up to +19.4). Japan's exports of future EPU, in contrast, are relatively large throughout the late 1990s (up to -36.6), during the GFC (up to -25.0), and from 2016 onwards (up to -26.4). Also notable: While average trans-Pacific EPU connectedness changes rather slowly, transitions from one phase to the next in the net spillover index often happen suddenly and are concluded within just a few months.

In Figure 7, we present the decomposition of net US-Japan EPU spillovers by country and policy category. As before, let us highlight the most important findings: First of all, there are several episodes during which one EPU category in either country suddenly becomes a material source of trans-Pacific uncertainty spillovers and, accordingly, assumes responsibility for a large share of the movement in the total net spillover index. As a case in point, after 1995, the Japanese FPU - Net US EPU index (Panel d)) swiftly climbs to +18.6 points in late 1996 and, from there on, to an unprecedented high of +39.2 in November 1997. Apparently, Japan's inconsistent fiscal policy mix did not only affect the volatility of the Yen/USD exchange rate in the course of the AFC but, even before that, generated strong uncertainty spillovers to US fiscal and monetary policy EPU.

In a similar manner, concerns about the long-run sustainability of US government debt appear to be lifting the country's FPU net spillover index to unusual highs in 2011 (Fig. 7 c)). Following S&P's first-time announcement of a negative rating outlook for US treasuries in April, the index rises by 28 points during the 2011 Debt Ceiling Dispute and then peaks at +20.1 after the actual debt downgrade in August. Likely due to the subsequent political conflicts (see above), US FPU remains an influential transmitter of international spillovers until late 2015.

Second, the 2011-15 episode in Figure 7 c) also shows that, on the receiver side, spillovers can be equally concentrated. According to our results, Japanese TPU is by far the largest net receiver of US FPU spillovers during this period (up to -16.2), and we can find comparable episodes with the same or other EPU categories acting as (almost) sole net spillover receivers in each of the remaining panels.

Third, TPU is generally the strongest net receiver of foreign policy uncertainty in both countries. While the total net spillover measures in the upper four panels of Figure 7 either show a positive tendency or are essentially balanced, the net indices in panels e) and f) are typically below zero. Possibly this is because TPU governs the respective country's long-run ties to the foreign economy, being affected by a public debate about the appropriate strength of these ties whenever any kind of foreign economic policy becomes less predictable. We leave the investigation of this hypothesis to future research.

Fourth, we do find evidence of structural changes with respect to the net direction and composition of cross-country EPU spillovers. Again, this can be best seen from Figure 7's lower two panels. The US TPU index on the left, for instance, is relatively volatile during the 1990s but, in absolute terms, rarely exceeds the 10 point-mark. After 2002, however, the measure first becomes more persistent, and then, following the GFC, there are lengthier periods during which it remains close to or significantly below -10. Particularly from 2009 onwards, there is a permanent change in the relationship between US TPU and Japanese MPU, with the former starting to receive strong net spillovers from the latter (up to -10.6). In Panel f), the structural changes become even more apparent: Before 2001, the Japanese TPU net spillover measure typically fluctuates between -5.0 and +5.0, but afterwards, it exceeds that

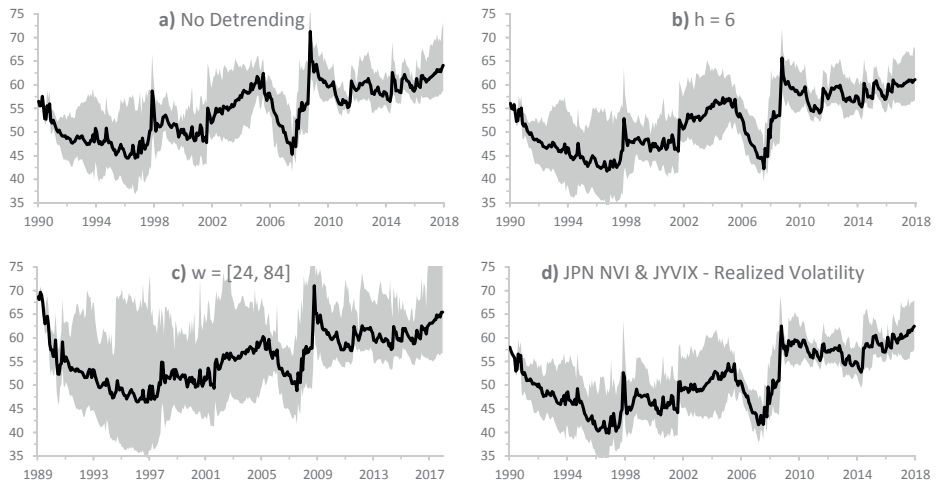
range frequently and often substantially. Indeed, because of strong US FPU spillovers, the index reaches values as low as -20.0 on several occasions between 2011 and 2015.

In summary, the spillover plots in this section again highlight the importance of *category*-driven as opposed to *country*-driven uncertainty spillovers. Except during financial crises, within-country, cross-category EPU spillovers are typically stronger than cross-country spillovers. In addition, the net direction of the latter is often determined by an individual EPU category acting as a substantial net transmitter or receiver of spillovers. The fact that TPU is frequently such a net receiver is not only intuitive but may also explain why international EPU transmissions are comparatively weak: Since trade issues are, at least in the short-run, relatively unimportant for domestic economic policies and policymaking, this type of EPU's capability to cause knock-on effects and second-round uncertainty spillovers is somewhat limited.

6. Sensitivity Analysis

We examine the sensitivity of our results with respect to several aspects of our model and empirical approach. More specifically, we recalculate the spillover indices without the detrending of the EPU data, using a different forecast horizon and a broader window range, and using realized volatility for the Japanese stock and FX market variables over the entire sample period. Figure 8 plots the dynamic SOI for each of these cases and, in light of space limitations, representative of all other spillover measures. While there are some minor differences across the resulting time profiles and compared to our main results, the basic character of our findings is clearly robust to all modifications.

Figure 8: Sensitivity Analysis – Dynamic Total Uncertainty Spillover Index



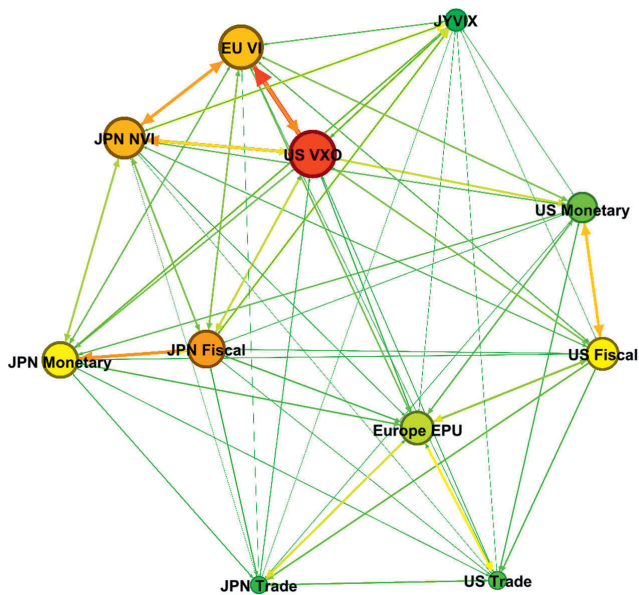
Notes: Rolling-window estimation with window averaging, $w = [36, 72]$. The grey shaded area in Panel b) indicates the 90% interval of the distribution across window sizes.

Another potential concern is to what extent our results are influenced by events in Europe due to the region's economic size and strong trading ties with both the US and Japan. To evaluate this, we include measures of European EPU and stock market volatility (EU VI) in our model.²⁰ Figure 9 shows the

²⁰ Since category-specific EPU measures are not available for Europe, we use Baker et al.'s (2016) aggregate European EPU index. Apart from not providing categorical information, one drawback of this measure is that it

extended uncertainty spillover network.²¹ Consistent with its membership in the financial markets group, the EU VI lies in the upper-left of the diagram. It has significant connections to the US VXO and Japanese NVI, which, to a large extent, seem to have replaced the strong trans-Pacific stock market link that we discovered earlier. Apart from that, however, the inclusion of the EU VI does not seem to alter the structure of the uncertainty network as it exerts a moderate and almost equally sized influence on the US and Japanese EPU indices, and a relatively weak influence on the JYVIX.

Figure 9: Full-sample Uncertainty Spillover Network including European Indices



Notes: See Figure 2.

Similarly, the European EPU measure is located almost directly between the US and Japanese EPU indices. Due to its influence on both countries, the connectedness among the remaining six EPU indices declines from 5.6% to 4.8%. Nevertheless, the strongest spillovers that the new EPU index transmits affect the two countries' TPU measures, which is in line with our previous findings. In summary, also controlling for European uncertainty spillovers does not change our main conclusions.²²

is not based on the same group of countries over the entire sample period – see www.policyuncertainty.com for further details. Regarding European stock market volatility, we use the VSTOXX for the period from 1999 onwards and the standardised realized volatility of the Eurostoxx 50 for the earlier part of the sample. We obtain data on the former from www.stoxx.com and data on the latter from Yahoo Finance.

²¹ See also Table A3 in the appendix.

²² We obtain similar results for our dynamic analysis: While the intensity of spillovers among the US and Japanese variables is generally weaker after including the European uncertainty measures, the direction and evolution of the time-varying spillover indices hardly changes.

7. Conclusions

We investigate cross-category, cross-type and trans-Pacific spillovers between different kinds of economic policy uncertainty and option-implied financial market volatility. To this end, we draw on the newspaper-based EPU indices of Baker et al. (2016) and Arbatli et al. (2017), and the Diebold and Yilmaz (2012, 2014) spillover index approach. We conduct both a static analysis where we focus on the overall structure of the US-Japanese uncertainty spillover network as well as a dynamic analysis where we characterise the evolution of spillovers between different groups of uncertainty measures throughout the previous three decades. We also decompose our dynamic spillover measures by country and category and relate their behaviour to various political-economic events.

Unlike most existing studies, our results highlight the bidirectional nature of the relationship between financial market volatility and policy uncertainty. We, therefore, conclude that there is a need for more empirical research on the political influence of financial markets – see, e.g., Funke et al. (2016). Similarly, given that international *EPU* spillovers are relatively small when compared to intranational *EPU* spillovers, the previous literature’s predominant focus on the former appears to be somewhat unjustified. While it is necessary to monitor the phenomenon, our results suggest that research on within-country, cross-category or cross-type spillovers may be more fruitful and important. This is especially so because *EPU* shocks in different categories may have different implications for the economy – a fact that our estimations already hint at.

From an investors’ perspective, it is important to recognise the elevated role of *EPU* in Japanese financial markets, as this may help to avoid – or even exploit – *EPU*-triggered volatility. In the same way, policymakers can profit from our research by recognising that a large fraction of *EPU* spillovers appears to be linked to political infighting and inconsistent, ideologically-driven policies. By avoiding these pitfalls, they can therefore not only reduce uncertainty in their own country’s economy but, to a certain extent, even in that of others.

Appendix

Table A1: Index Construction & Data Sources

Variable	Description	Sample / Series Description	Source
US Monetary, Fiscal & Trade Policy EPU	Baker et al. (2016) category-specific EPU indices for the US	1987:01-2017:12	policyuncertainty.com
JPN Monetary, Fiscal & Trade Policy EPU	Arbatli et al. (2017) category-specific EPU indices for Japan	1987:01-2017:12	policyuncertainty.com
US VXO	US option-implied stock market volatility index	1987:01-2017:12 – CBOE S&P 100 Volatility Index, monthly averages	Chicago Board Options Exchange
JPN NVI	Japan option-implied stock market volatility index	1987:01-1989:05 – Nikkei 225 Stock Average Index realized volatility (monthly standard deviation of daily returns), standardized to the same mean and variance as the corresponding option-implied volatility index after 1989:05 (see, e.g., Bloom 2009); 1989:06-2017:12 – Nikkei 225 Stock Average Volatility Index, monthly averages	Yahoo Finance; Datastream
JYVIX	Yen / USD option-implied exchange rate volatility index	1987:01-1994:12 – Japan / US Foreign Exchange Rate realized volatility (monthly standard deviation of daily returns), standardized to the same mean and variance as the corresponding option-implied volatility index after 1994:12 (see, e.g., Bloom 2009); 1995:01-2017:12 – Japanese Yen / US Dollar 1-month FX Volatility Index, monthly averages	Federal Reserve Bank of St. Louis; Datastream

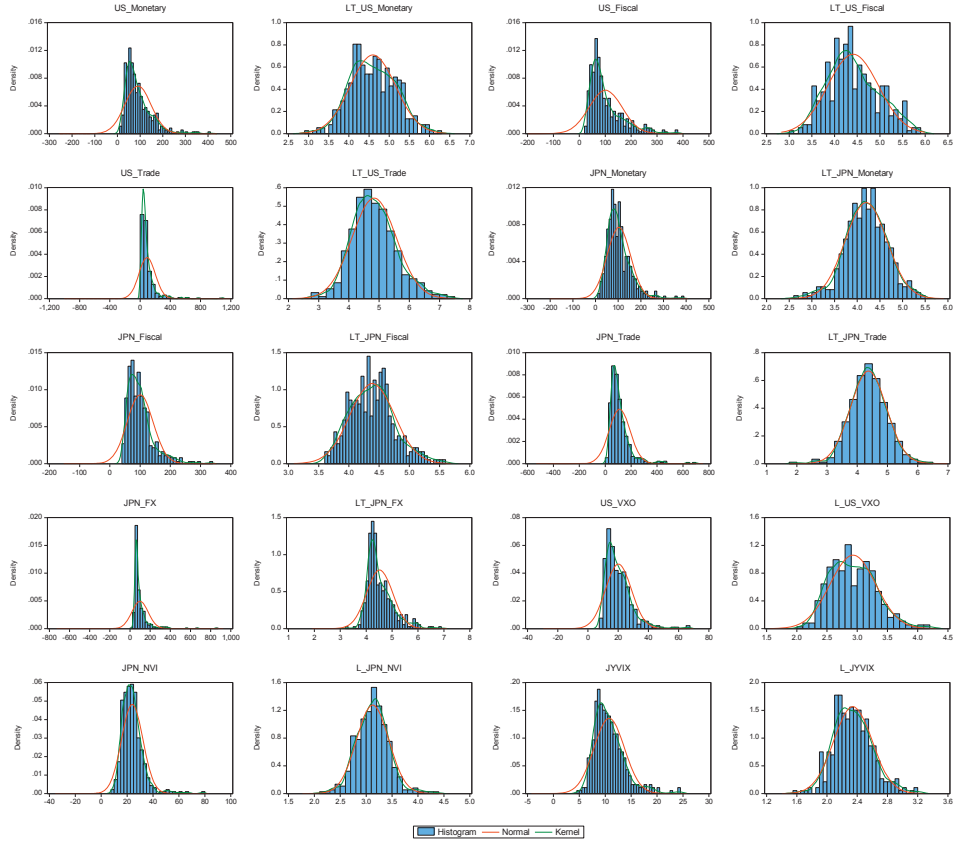
Table A2: Full-sample Uncertainty Spillover Table

To / From	US Monetary	US Fiscal	US Trade	JPN Monetary	JPN Fiscal	JPN Trade	US VXO	JPN NVI	JYVIX	From Others
US Monetary	51.2	17.0	2.6	6.7	2.5	0.2	12.2	6.4	1.2	48.8
US Fiscal	17.7	58.4	2.0	3.6	3.6	1.4	7.8	4.7	0.7	41.6
US Trade	6.0	8.2	72.1	3.4	2.1	5.5	0.7	0.8	1.3	27.9
JPN Monetary	5.0	3.9	0.6	48.9	19.4	2.1	7.7	10.5	1.9	51.1
JPN Fiscal	1.2	3.6	1.6	14.4	53.7	2.6	12.0	8.5	2.4	46.3
JPN Trade	1.6	10.3	9.4	4.5	5.6	66.8	0.5	0.3	0.9	33.2
US VXO	2.6	2.1	3.9	2.2	6.5	4.3	58.3	14.7	5.3	41.7
JPN NVI	1.9	2.4	0.7	11.7	9.6	0.6	21.4	48.5	3.3	51.5
JYVIX	1.6	1.1	0.3	9.8	11.7	1.1	11.9	12.9	49.6	50.4
To Others	37.7	48.6	21.2	56.2	61.0	17.9	74.2	59.0	17.1	43.6%
Net	-11.2	7.0	-6.8	5.0	14.7	-15.4	32.4	7.4	-33.3	
Avg. Conn.	5.4	5.6	3.1	6.7	6.7	3.2	7.2	6.9	4.2	

Table A3: Full-sample Uncertainty Spillover Table including European Indices

To / From	US Monetary	US Fiscal	US Trade	JPN Monetary	JPN Fiscal	JPN Trade	US VXO	JPN NVI	JYVIX	Europe EPU	EU VI	From Others
US Monetary	44.4	14.9	2.2	5.8	2.1	0.1	10.7	5.7	1.0	5.5	7.6	55.6
US Fiscal	15.3	49.8	1.4	3.1	3.2	0.9	7.6	4.6	0.6	8.2	5.3	50.2
US Trade	5.3	6.4	61.6	3.0	2.0	4.1	0.7	1.0	1.2	13.2	1.7	38.4
JPN Monetary	4.5	3.5	0.5	43.4	17.3	1.8	7.0	9.5	1.8	4.5	6.4	56.6
JPN Fiscal	1.1	3.4	1.3	12.7	47.7	2.3	10.6	7.5	2.4	2.9	8.1	52.3
JPN Trade	1.5	8.3	7.3	4.1	5.3	60.1	0.6	0.4	0.8	11.3	0.4	39.9
US VXO	2.3	2.1	2.7	1.9	5.3	3.3	46.3	11.6	4.7	2.2	17.7	53.7
JPN NVI	1.7	2.5	0.5	9.8	7.9	0.5	17.1	39.7	3.1	0.9	16.4	60.3
JYVIX	1.4	1.0	0.4	9.4	11.0	1.0	10.9	12.2	46.2	1.5	5.1	53.8
Europe EPU	7.0	11.3	5.2	6.9	6.6	3.4	5.1	3.0	0.6	44.0	6.9	56.1
EU VI	3.0	2.2	0.6	3.5	7.2	0.8	25.6	16.8	3.0	2.6	34.9	65.1
To Others	43.2	55.5	22.1	60.2	67.8	18.1	95.7	72.1	19.2	52.6	75.6	52.9%
Net	-12.4	5.3	-16.4	3.7	15.6	-21.8	42.0	11.8	-34.7	-3.5	10.5	
Avg. Conn.	4.9	5.3	3.0	5.8	6.0	2.9	7.5	6.6	3.7	5.4	7.0	

Figure A1: Distributions of the EPU and Volatility Indices Before and After the Data Transformation



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