International monetary policy spillovers: Evidence from a time-varying parameter vector autoregression

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Abstract

This study examines the transmission of international monetary policy spillovers across developed economies based on a Bayesian time-varying parameter vector autoregressive (TVP-VAR) connectedness methodology. The analysis is based on daily shadow short rates over the period of January 2, 1995 to December 20, 2018. The empirical findings suggest that the magnitude of international monetary policy spillovers behaves heterogeneously over time, with unprecedented heights reached during the Great Recession of 2009, suggesting potential gains unconventional monetary policy coordination. In addition, the results indicate that the dominant transmitters of international monetary policy spillovers are the Euro Area and the US, while Japan and the UK are the dominant receivers of spillovers. Our results are robust to alternative experimentations in terms of estimation and prior choices used to estimate the TVP-VAR

Keywords: Monetary policy spillovers; Dynamic connectedness; TVP-VAR

JEL codes: C32; C50; E52

1 Introduction

The issue of monetary policy spillovers can be traced as far back as to the 18th century in David Hume's *Essays, Moral, Political, and Literary* (Coeuré, 2016). Theoretical models have rigorously analyzed the international spillovers of monetary policy, and reviewed the case for and against monetary policy coordination since the mid-1980s (see Taylor, 2013, for a detailed review of this literature). In general, as noted by Engel (2016), this literature tends to point towards limited spillovers, with the desirability of cooperation across monetary authorities being highly model specific, and some potentially important shocks causing the propagation poorly understood.

In addition, from a political economy perspective, the complexity of cooperation due to differences in legal and institutional frameworks is also believed to prevent cooperation (Ostry and Ghosh, 2016). In the wake of recent global financial crisis and the "Great Recession", Cook and Devereux (2016) focussing on the effects of the Zero Lower Bound (ZLB) and related unconventional monetary policy actions (such as Quantitative Easing, QE), tends to suggest that spillovers, during the ZLB, can be larger than in normal times and the gains from monetary policy coordination possibly greater. In sum, a relevant empirical hypothesis that needs to be tested is: whether monetary policy spillovers are higher during episodes of crises when compared to normal times?

This is exactly the question we aim to answer by analysing the spillover of monetary policy across the United States (US), the Euro Area, Japan and the United Kingdom (UK), using a full-fledged time-varying parameter vector autoregressive (TVP-VAR) model of Antonakakis and Gabauer (2017). This approach is an extension of the popular rolling-window method of Diebold and Yılmaz (2012), which has been used widely to analyze spillovers across variables and countries over time. The TVP-VAR improves the methodology provided by Diebold and Yılmaz (2012) substantially, because (i) there is no need to arbitrarily set the rolling window-size, wherein the latter case the spillover measures might overreact (underreact) when the rolling window-size is set too small (big). (ii) As there is no rolling window analysis involved, there is no loss of valuable observations (equal to the window size) at the beginning of the sample. (iii) Finally, Monte Carlo simulations indicate that the TVP-VAR-based approach is not sensitive to outliers.

As indicated above, in the wake of global financial crisis and the ZLB situation that ensued thereafter, central banks in the economies of our concern pursued unconventional monetary policies, such as QE. QE in turn involves a multitude of measures such as large scale asset purchases, maturity extension programs, and efforts of forward guidance in order to manage expectations of a prolonged period of low policy rates (Tillmann, 2016). But understandably, to compare across the conventional and unconventional regimes of monetary policy decisions, we would need a common metric capturing the stance of monetary policy. We circumvent this apparent empirical difficulty by considering the Shadow Short Rate (SSR), which is the nominal interest rate that would prevail in the absence of its effective lower bound, with it derived by modelling the term structure of the yield curve.

The main advantage of the SSR is that it is not constrained by the ZLB and thus allows us to combine the monetary policy instrument data from the ZLB (unconventional) period with the data from the non-ZLB (conventional) era. For our spillovers analysis we rely on the daily SSR data, as developed by Krippner (2013), over the period of January 2, 1995 to September 22, 2017. Note that, alternative measures of the SSR for the US, the Euro Area and the UK have also been developed by Wu and Xia (2016). However, besides being only available at monthly frequency and unavailable for Japan (which also witnessed the ZLB situation), the SSR estimates derived by Krippner (2013) have been shown to be relatively more robust (Krippner, 2017). In addition, given the large literature that exists on the impact of domestic and international (conventional and unconventional) monetary policy on macroeconomic variables are primarily at lower (monthly or quarterly) frequency (see, Claessens et al., 2016, for a detailed literature review in this regard), knowledge of monetary policy spillovers at a higher frequency is likely to be more beneficial to policy makers in determining the direction in which the economy is headed in the future. Further, with asset prices available at higher frequencies and deemed as leading indicators for economic activity (Armesto et al., 2010) and inflation (Breitung and Roling, 2015), the likely effect of the daily movements of the monetary policy instrument on asset market movements, is also going to carry valuable information for decision makers of the economy. Hence, the decision to use daily SSRs to conduct our spillover analysis is well warranted.

To the best of our knowledge, this is the first attempt to compare international monetary policy spillovers across conventional and unconventional monetary policy regimes for four developed economies using a TVP-VAR model. The only study that is to some extent similar to ours is that by Claus et al. (2016), whereby the authors used a constant parameter latent factor model, and hence, a sub-sample based analysis to show that there is significant evidence of spillovers across monetary policies of the US and Japan, with the effect being stronger during the unconventional monetary policy regime.

The results of our empirical analysis suggest that, the transmission of international monetary policy ~~shocks~~ is an important source of domestic monetary policy fluctuations. Moreover, the magnitude of international monetary policy spillovers behaves heterogeneously overtime, with unprecedented heights reached during the "Great Recession". In addition, the dominant transmitters of international monetary policy ~~shocks~~ are the Euro Area and the US, while Japan and the UK are the dominant receivers of international monetary policy ~~shocks~~. Interestingly enough, international monetary policy ~~shocks~~ spillovers originating from the US are the largest during the zero lower bound and the related unconventional monetary policy actions era, indicating potential gains from monetary policy coordination.

The rest of the paper is organized as follows: Section 2 lays out the basics of the methodology, while Section 3 presents the data and discusses the results. Finally, Section 5 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, 2014), by allowing the variances to vary via a stochastic volatility Kalman Filter estimation with forgetting factors. By doing so, the TVP-VAR approach overcomes the burden of the often arbitrarily chosen rolling-window-size, that could lead to very erratic or flattened parameters, and loss of valuable observations.

In particular, the TVP-VAR model can be written as follows,

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

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

where $\boldsymbol{Y}_t$ represents an $N \times 1$ conditional volatilities vector, $\boldsymbol{Y}_{t-1}$ is an $Np \times 1$ lagged conditional vector, $\boldsymbol{\beta}_t$ 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, $\boldsymbol{S}_t$. The parameters $\boldsymbol{\beta}_t$ depend on their own values $\boldsymbol{\beta}_{t-1}$ and on an $N \times Np$ dimensional error matrix with an $Np \times Np$ variance-covariance matrix. The time-varying coefficients and error covariances are used to estimate the generalised connectedness procedure of Diebold and Yılmaz (2014) that is based on generalised impulse response functions (GIRF) and generalised forecast error variance decompositions (GFEVD) developed by Koop et al. (1996) and Pesaran and Shin (1998). In order to calculate the GIRF and GFEVD, we transform the VAR to its vector moving average (VMA) representation, based on the Wold representation theorem as follows:

$$\boldsymbol{Y}_t = \boldsymbol{\beta}_t \boldsymbol{Y}_{t-1} + \boldsymbol{\epsilon}_t \tag{3}$$

$$\boldsymbol{Y}_t = \boldsymbol{A}_t \boldsymbol{\epsilon}_t \tag{4}$$

$$\boldsymbol{A}_{0,t} = \boldsymbol{I} \tag{5}$$

$$\boldsymbol{A}_{i,t} = \boldsymbol{\beta}_{1,t} \boldsymbol{A}_{i-1,t} + ... + \boldsymbol{\beta}_{p,t} \boldsymbol{A}_{i-p,t} \tag{6}$$

where $\boldsymbol{\beta}_t = [\boldsymbol{\beta}_{1,t}, \boldsymbol{\beta}_{2,t}, ..., \boldsymbol{\beta}_{p,t}]'$ and $\boldsymbol{A}_t = [\boldsymbol{A}_{1,t}, \boldsymbol{A}_{2,t}, ..., \boldsymbol{A}_{p,t}]'$ and hence $\boldsymbol{\beta}_{i,t}$ and $\boldsymbol{A}_{i,t}$ are $N \times N$ dimensional parameter matrices. 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

$$GIR_t(J, \boldsymbol{\delta}_{j,t}, \boldsymbol{F}_{t-1}) = E(\mathbf{Y}_{t+J} | \boldsymbol{\epsilon}_{j,t} = \boldsymbol{\delta}_{j,t}, \boldsymbol{F}_{t-1}) - E(\mathbf{Y}_{t+J} | \boldsymbol{F}_{t-1}) \tag{7}$$

$$\boldsymbol{\Psi}^g_{j,t}(J) = \frac{\boldsymbol{A}_{J,t} \boldsymbol{S}_t \boldsymbol{\epsilon}_{j,t}}{\sqrt{S_{jj,t}}} \frac{\boldsymbol{\delta}_{j,t}}{\sqrt{S_{jj,t}}} \qquad \boldsymbol{\delta}_{j,t} = \sqrt{S_{jj,t}} \tag{8}$$

$$\boldsymbol{\Psi}^g_{j,t}(J) = S_{jj,t}^{-\frac{1}{2}} \boldsymbol{A}_{J,t} \boldsymbol{S}_t \boldsymbol{\epsilon}_{j,t} \tag{9}$$

where $\boldsymbol{\Psi}^g_{j,t}(J)$ represent the GIRFs of variable j and J represents the forecast horizon, $\boldsymbol{\delta}_{j,t}$ the selection vector with one on the jth position and zero otherwise, and $\boldsymbol{F}_{t-1}$ the information set until $t-1$. Afterwards, we compute the GFEVD that can be interpreted as the variance share one variable has on others. These variance shares are then normalised, so that each row sums up to one, meaning that all variables together explain 100% of variable's i forecast error variance. This is calculated as follows

$$\tilde{\phi}^g_{ij,t}(J) = \frac{\sum_{t=1}^{J-1} \Psi^{2,g}_{ij,t}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \Psi^{2,g}_{ij,t}} \tag{10}$$

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 by

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

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

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

$$C_{i \rightarrow j,t}^{g}(J) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\phi}_{ji,t}^{g}(J)}{\sum_{j=1}^{N} \tilde{\phi}_{ji,t}^{g}(J)} * 100 \tag{13}$$

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

$$C_{i \leftarrow j,t}^{g}(J) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\phi}_{ij,t}^{g}(J)}{\sum_{i=1}^{N} \tilde{\phi}_{ij,t}^{g}(J)} * 100 \tag{14}$$

Finally, we subtract *total directional connectedness to others* from *total directional connectedness from others* to obtain the *net total directional connectedness*, which can be interpreted as the 'power' of variable i, or, its influence on the whole variables' network.

$$C_{i,t}^{g} = C_{i \rightarrow j,t}^{g}(J) - C_{i \leftarrow j,t}^{g}(J) \tag{15}$$

If the net total directional connectedness of variable i is positive, it means that variable i influences the network more than being influenced by that. By contrast, if the net total directional connectedness is negative, it means that variable i is driven by the network.

3 Data and Empirical Results

3.1 Data

With policy rates in the ZLB range for a prolonged period of time post the financial crisis, posed a great challenge to empirical researchers dealing with monetary policy to find alternative quantitative measures that are able to describe monetary policy at the ZLB. One such measure is the Shadow Short Rate (SSR). The SSR used in this paper is developed by Krippner (2013), based on a two-factor model of term-structure, at a daily frequency for the four economies of our concern, and is available for download from the website of the Reserve Bank of New Zealand.[1] The two-factor yield curve-based framework developed by Krippner (2013) essentially removes the effect that the option to invest in physical currency (at an interest rate of zero) has on yield curves, resulting in a hypothetical "shadow yield curve" that would exist if physical currency were not available. The process allows one to answer the question: "what policy rate would generate the observed yield curve if the policy rate could be taken negative?" The "shadow policy rate" generated in this manner, therefore, provides a measure of the monetary policy stance after the actual policy rate reaches zero.

We collect daily observations of the SSRs for the United States, the Euro Area, Japan and the United Kingdom over the period January 2, 1995 to September 22, 2017. The sample size is purely driven based on data availability. Figure 1 plots the shadow short rates.

[Insert Figure 1 around here]

[1]The data can be downloaded from the following link.

These rates are converted to stationary series by taking the first differences. The transformed series are plotted in Figure 2 and descriptive statistics are presented in Table 1.

[Insert Figure 2 around here]

[Insert Table 1 around here]

3.2 Empirical Results

In Table 2, we report the estimates of the connectedness indices for each series based on the TVP-VAR methodology. Summarizing the information in Table 2, we observe that own-country monetary policy spillovers explain the highest share of forecast error variance, as the diagonal elements receive higher values compared to the off-diagonal elements. For instance, innovations in monetary policy in the Euro Area explain 15.3% and 14.3% of the 10-day-ahead forecast error variance of monetary policy in the UK and the US, respectively, but only 4.4% in Japan. Moreover, the most important transmitters of monetary policy ~~shocks~~ are the Euro Area followed by the US, while UK and Japan are the most important receivers of monetary policy ~~shocks~~spillovers. These results are supported by the estimated net directional spillovers reported in the last row of Table 2. In addition, according to the total directional connectedness index (TCI) reported at the lower right corner of Table 2, which effectively distils the various directional spillovers into one single index, on average, 17.9% of the forecast error variance in monetary policy ~~shocks~~ comes from spillovers ~~of shocks~~ across countries. Put differently, the transmission of international monetary policy ~~shocks~~ is an important source of domestic monetary policy fluctuations.

[Insert Table 2 around here]

We now turn our attention to the interpretation of the spillover plots based on the time-varying estimates of the various spillover indices according to the TVP-VAR model. Figure 3 presents the results for the time-varying total connectedness index. According to this figure, we observe a large variation in the total connectedness index, which turns out very responsive to (extreme) economic events such as the Asian crisis in 1997, the introduction of the Euro, the Great Recession and the subsequent European sovereign debt crisis. In particular, monetary policy spillovers reached unprecedented heights during the Great Recession, a period characterized by intense unconventional monetary policy interventions primarily.

[Insert Figure 3 around here]

Figure 4 presents the dynamic directional connectedness of monetary policy ~~shocks~~ from each of the series to others, while Figure 5 presents the dynamic directional connectedness of monetary policy ~~shocks~~ to each series from others. According to these two figures, directional spillovers from or to each series range between 0% to 25% and are of bilateral nature. Nevertheless, they behave rather heterogeneously overtime and follow a similar pattern as the one found for the total connectedness index. For instance, directional monetary policy spillovers peak during the Great Recession, especially those originating from the Euro Area and the US.

[Insert Figure 4 around here]

[Insert Figure 5 around here]

A similar picture emerges when looking at the dynamic net directional connectedness plots as depicted in Figure 6. According to Figure 6, we see that Japan and the UK are mostly net receivers of monetary policy ~~shocks~~ spillovers during our sample period. EU is a net transmitter of monetary policy ~~shocks~~ spillovers since the introduction of Euro into circulation and up to the Great Recession, and from 2012 onward, while a net receiver of monetary policy ~~shocks~~spillovers in the remaining periods. Finally, the US is on the receiving ends of monetary policy transmission from 1995 to 2000 and from the period of the Great Recession onward, and on the receiving ends since the introduction of the Euro and up to the onset of the the Great Recession.

[Insert Figure 6 around here]

Finally, focusing on the net pairwise directional connectedness of monetary policy ~~shocks~~, i.e. monetary policy shocks spillovers across pairs of countries, which are presented in Figure 7, we observe the following empirical regularities. First, in net terms, monetary policy spillovers are of greater magnitude between pairs of European countries and between the Euro Area (UK) and the US, compared to pairs of countries where the Japan is one of them. The Euro Area seems to be the dominant net transmitter of monetary policy ~~shocks~~spillovers to the UK (since the introduction of the Euro) and to the US (from the inception of the Euro and up to the Great Recession), while the US is the dominant net transmitter of monetary policy ~~shocks~~spillovers to the UK, especially since the Great Recession.

[Insert Figure 7 around here]

In an attempt to examine whether the transmission of monetary policy spillovers differs between periods of conventional monetary policy and unconventional monetary policy (zero lower bound), we split the sample into two subperiods: (a) from January 2, 1995 to November 30, 2008 (conventional monetary policy sample of non-zero interest rate policy in the US) and (b) December 1, 2008 to September 22, 2017 (unconventional monetary policy sample of zero interest rate policy in the US, with the SSR turning negative for the first time on the starting date of the sub-sample).

The results of this analysis are reported in Table 3. According to these results, we observe that, despite that overall monetary policy spillovers do not change dramatically between the ZLB (unconventional) period and the non-ZLB (conventional) era, as indicated by the TCI in the lower right corner in panel a and panel b of Table 3, the US is the dominant transmitter of monetary policy spillovers during the ZLB era, while a net receiver of shocks in the pre- ZLB era. In other words, the introduction of unconventional monetary policy in the US since December 2008 was associated with a significant increase in international monetary policy spillovers originating from the US. In particular, monetary policy ~~shocks~~innovations??? in the US explain 9.1%, 2% and 6.9% of the forecast error variance of monetary policy ~~shocks~~innovations??? in the Euro Area, Japan and the UK, respectively, during the era of conventional monetary policy, while 13.2%, 2.3% and 17.6% of the forecast error variance of monetary policy ~~shocks~~innovations??? in the Euro Area, Japan and the UK, respectively, since the ZLB era. Before the introduction of unconventional policy measures in the US (i.e. until November 2008), Euro Area was the dominant transmitter of international monetary policy ~~shocks~~ followed by the US. However, with the introduction of unconventional monetary policy during the ZLB era, the US became the main transmitter of international monetary policy ~~shocks~~. This is line with the study of Cook and Devereux (2016) who find that spillovers, during the ZLB, can be larger compared to those during normal times.

[Insert Table 3 around here]

These results have important policy implications in the sense that, during episodes of severe crises adding international dimensions in a particular country's monetary policy design could reduce the impact of domestic policy failures or make it easier for policy makers to deviate from optimal domestic policy, and get one closer to the global optimal Engel (2016). In other words, there could be possible gains from coordinating monetary policy decisions, especially in the wake of extraordinary situations like those observed during the recent global financial and the European debt crises.

Note that in the introduction we indicated that our empirical hypothesis is that monetary policy spillovers are higher during episodes of crises compared to normal times. Based on our results, this is precisely what we observe, with the US, understandably, playing the dominant role as a transmitter during the "Great Recession", given that it was at the epicentre of the recent financial crisis. The Euro Area is shown to act as the dominant transmitter during the sovereign debt crisis. Hence, unlike the literature, which tends to point towards limited spillovers, we do find quite strong evidence of spillovers that are increasing in magnitude during episodes of crises. This could be due to the time-varying and hence, the nonlinear approach that we take, and also due to the usage of a common metric, i.e., the SSR, in measuring the monetary policy stance. Hence, irrespective of the complexity of cooperation due to differences at legal and institutional levels, monetary policy cooperation is shown to be quite high, in general, amongst the four developed economies considered. Our results thus tend to suggest that the central banks in developed economies do realize the welfare of cooperation in monetary policy decisions, especially during turbulent times.

4 Robustness Analysis

In an attempt to check the robustness of the main results obtained based on the TVP-VAR-based version of the connectedness index, we also conducted three different sensitivity analyses. In particular, we used different prior parameters for $\boldsymbol{\beta}_0$ and $\boldsymbol{S}_0$ in order to check whether the total connectedness index is sensitive to different priors. These results are reported in Figure 8. According to this figure, we observe that, apart from some divergence at the beginning of the sample, the total connectedness indices based on different priors are basically identical throughout the sample.

[Insert Figure 8 around here]

Next, we analysed the evolution of the total connectedness index based on different J-step-ahead GFEVDs, ranging from 5-step-ahead to 40-step-ahead ones. The results of this analysis, which are reported in Figure 9, indicate that the total connectedness indices based on different J-step-ahead GFEVDs are qualitatively very similar. That is, total connectedness indices evolve homogeneously over time, and those based on longer-step-ahead GFEVDs generally lie slightly above those based on shorter-step-ahead ones since late 2010. Put differently, uncertainty of forecasts are greater the greater the J-step-ahead GFEVDs are during the period of negative SSRs.

[Insert Figure 9 around here]

Finally, we compared the connectedness measures based on the TVP-VAR approach with the traditional connectedness measures developed by Diebold and Yılmaz (2012, 2014) based on rolling-windows. These results are presented in Figures B.1-B.5 in the Appendix. It can be observed that the connectedness measures based on the rolling-window approach over-react with a time delay to outliers (i.e. extreme economic events, such as the latest financial crisis), and remain above those based on the TVP-VAR approach for so long as the outlier lies within the rolling-window (see, for instance, Figure B.1). By contrast, the TVP-VAR based connectedness measures react immediately to outliers, a result which is also supported based on Monte Carlo simulations in Antonakakis and Gabauer (2017).

5 Conclusion

In this study we examined the international transmission of monetary policy ~~shocks~~ across the US, the Euro Area, UK and Japan over the period of 1995 to 2017 based on a TVP-VAR methodology. The results of our empirical analysis suggest that, the transmission of international monetary policy ~~shocks~~ is an important source of domestic monetary policy fluctuations. Moreover, the magnitude of international monetary policy spillovers behaves heterogeneously overtime, with peaks reached during the “Great Recession”. In addition, the dominant transmitters of international monetary policy ~~shocks~~ are the Euro Area and the US, while Japan and the UK are the dominant receivers of international monetary policy

~~shocks~~. Interestingly enough, international monetary policy ~~shocks~~spillovers originating from the US are the largest during the zero lower bound and the related unconventional monetary policy actions era, indicating potential gains from monetary policy coordination. Last but not least, our results remain firm to several robustness checks.

While we restricted ourselves to the analysis of monetary policy spillovers across four developed economies only, as part of future research, it would be interesting to analyze the spillovers across a larger set of developed and developing countries.

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Figure 1: Shadow short rates

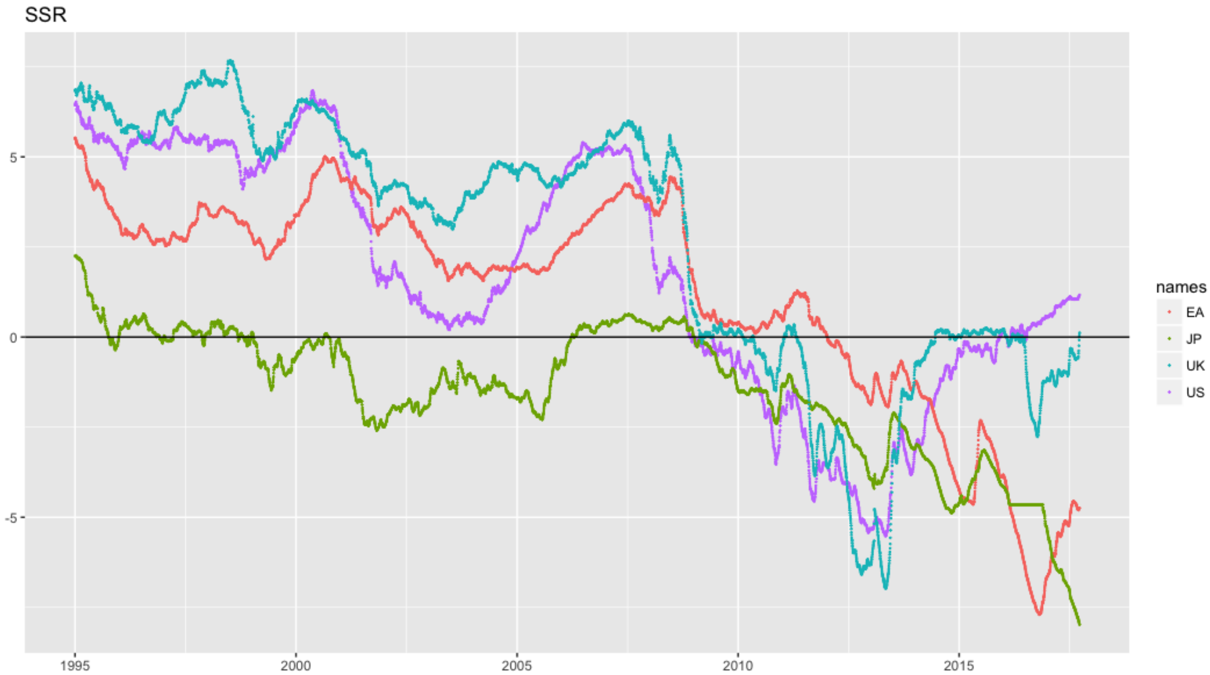


Figure 2: First difference of shadow short rates

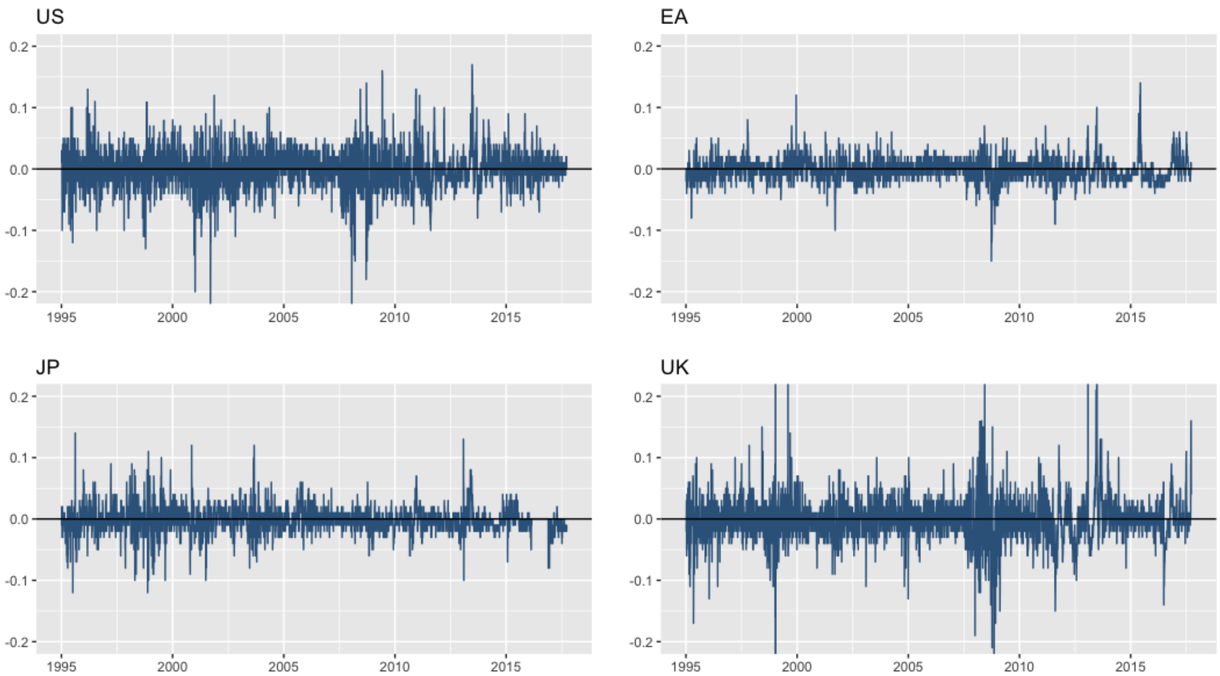


Figure 3: Total connectedness

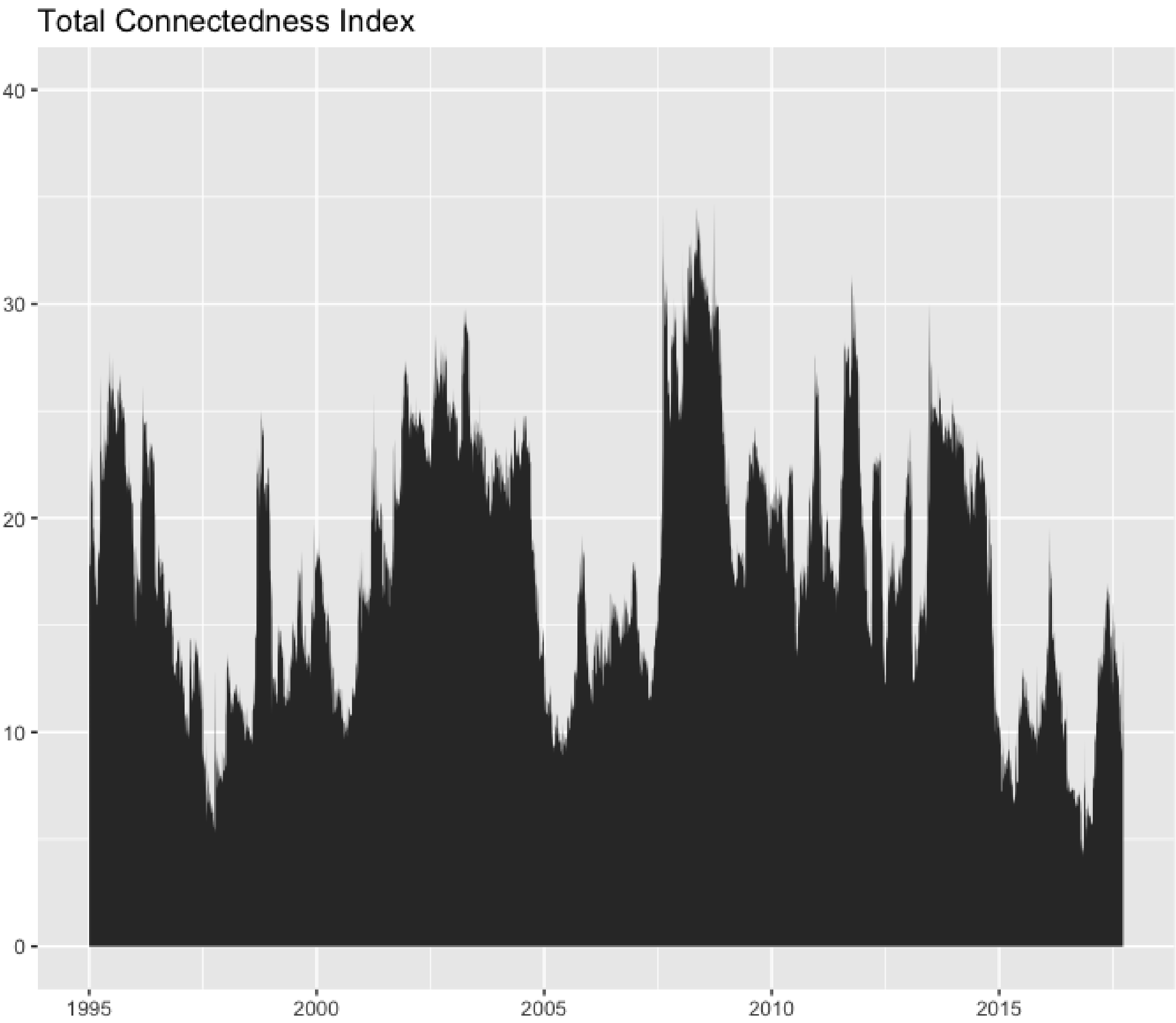


Figure 4: Directional connectedness *from* country i to others

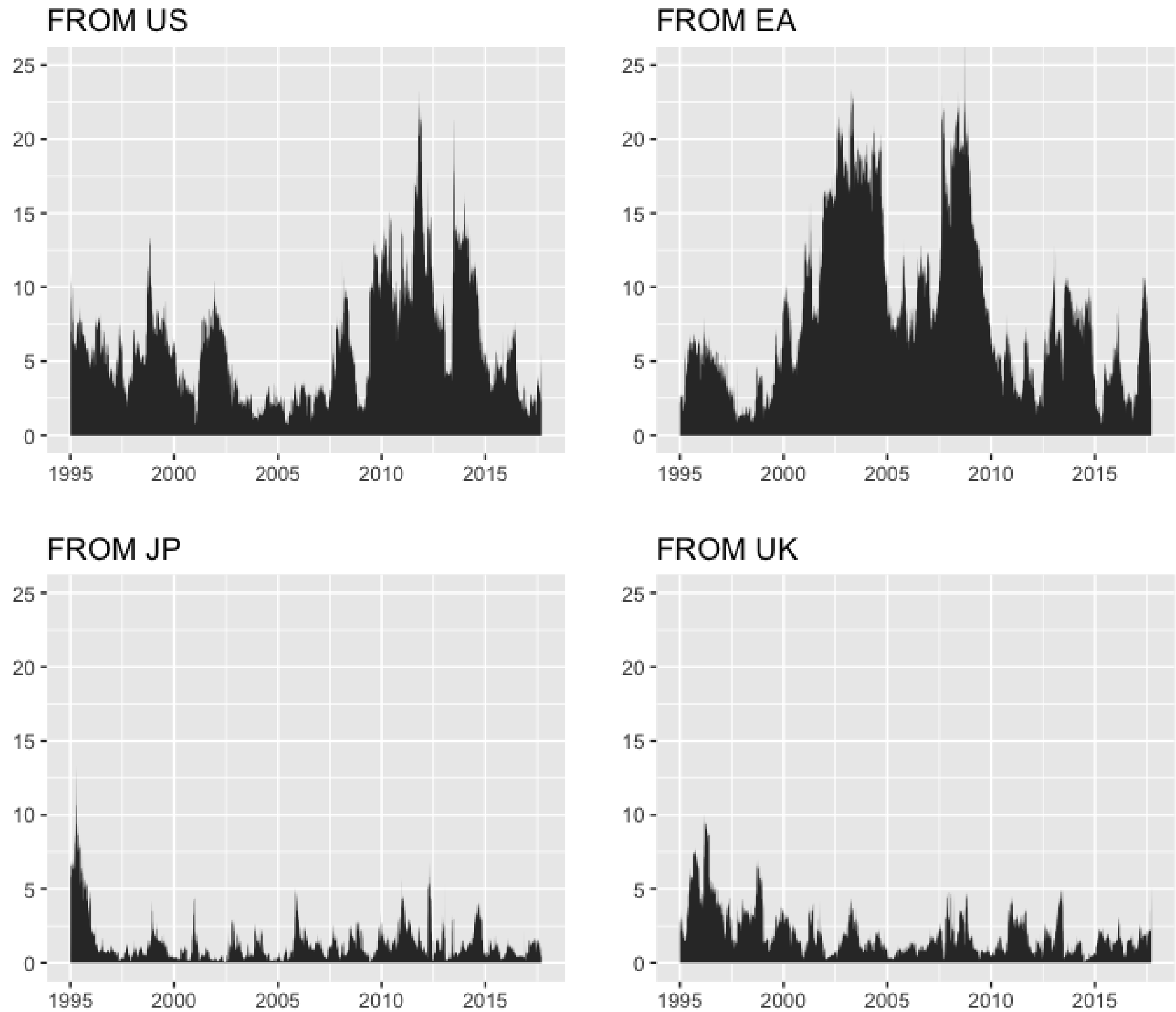


Figure 5: Directional connectedness *to* country i from others

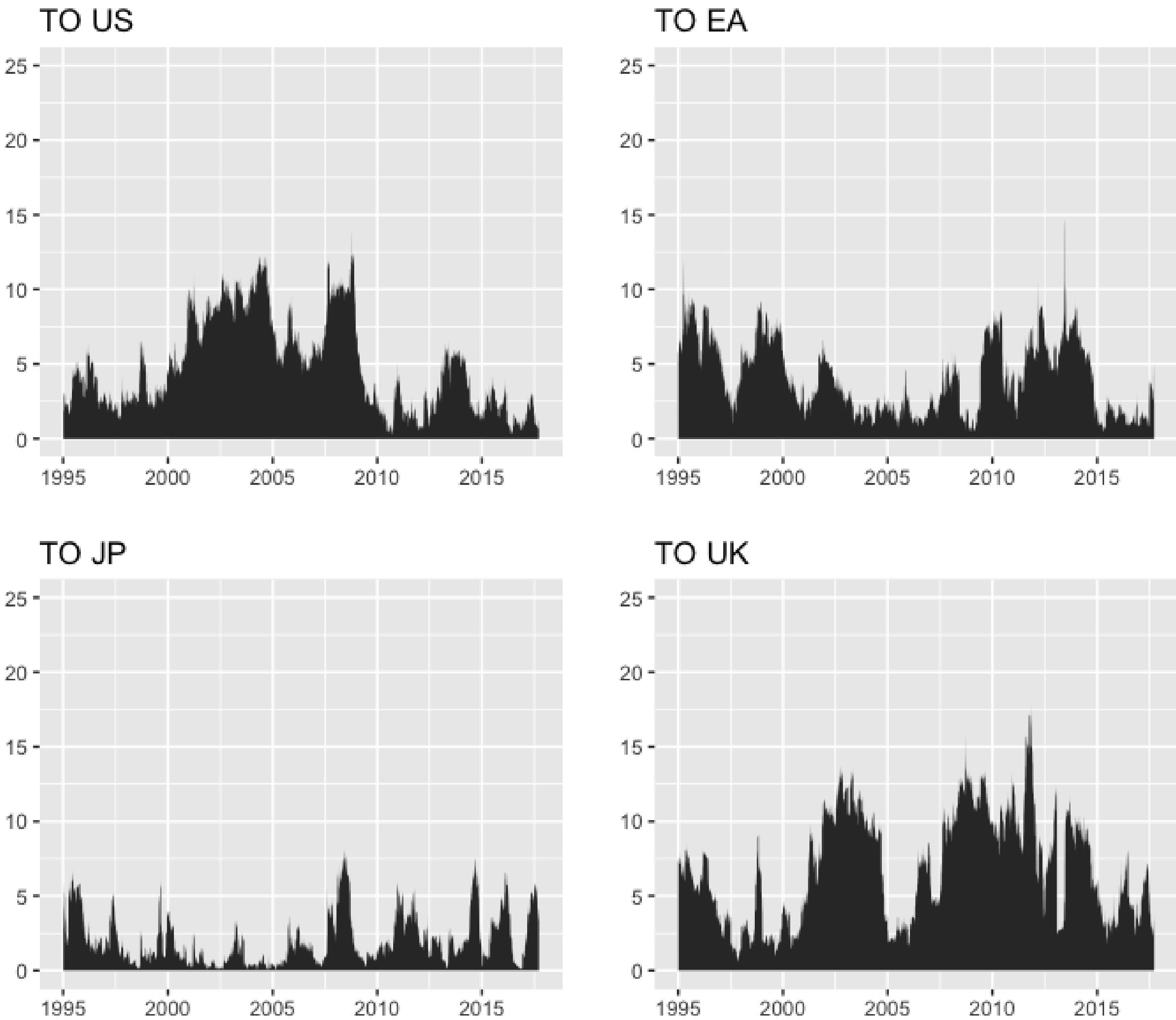


Figure 6: Net directional connectedness

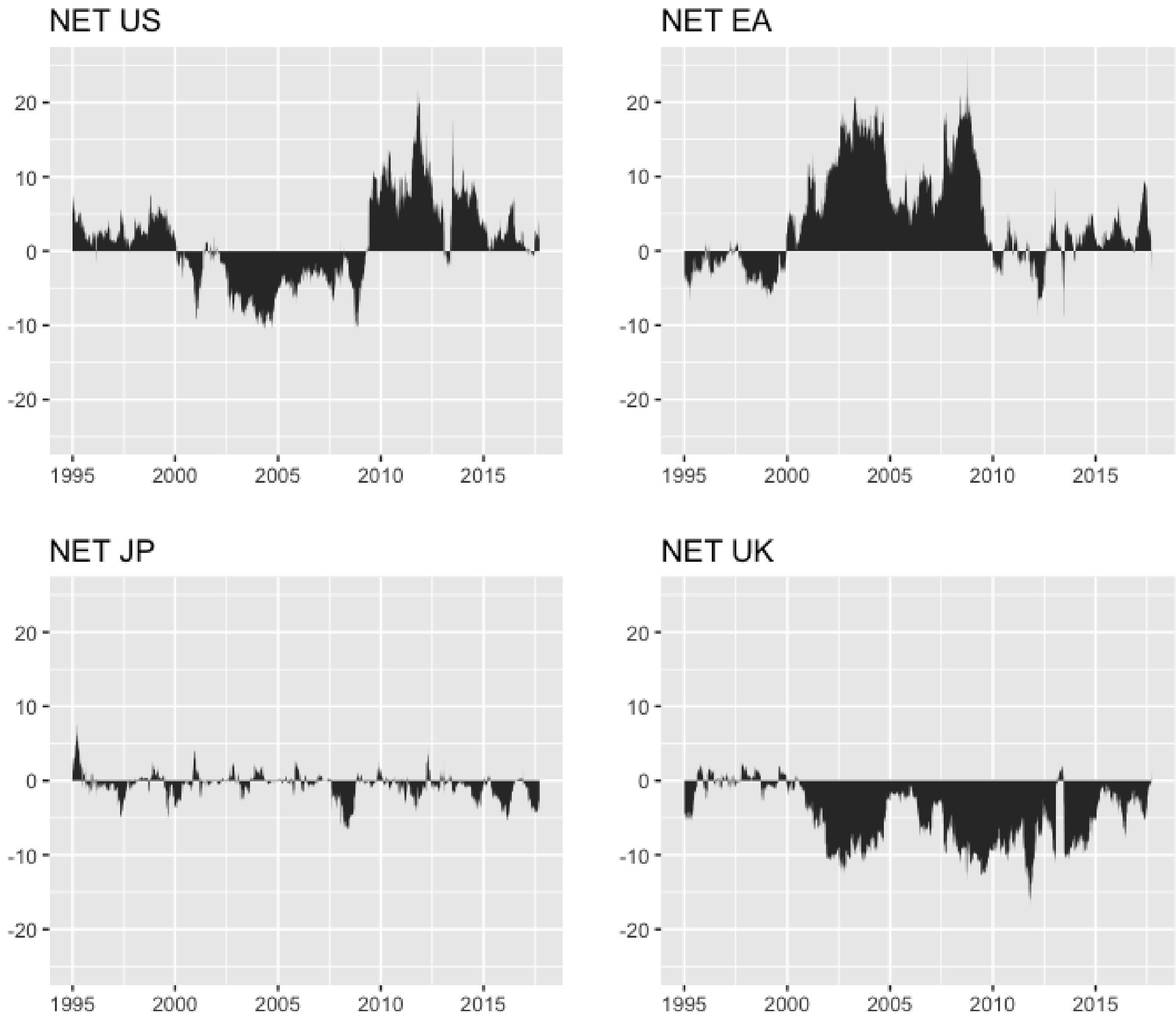


Figure 7: Net pairwise directional connectedness

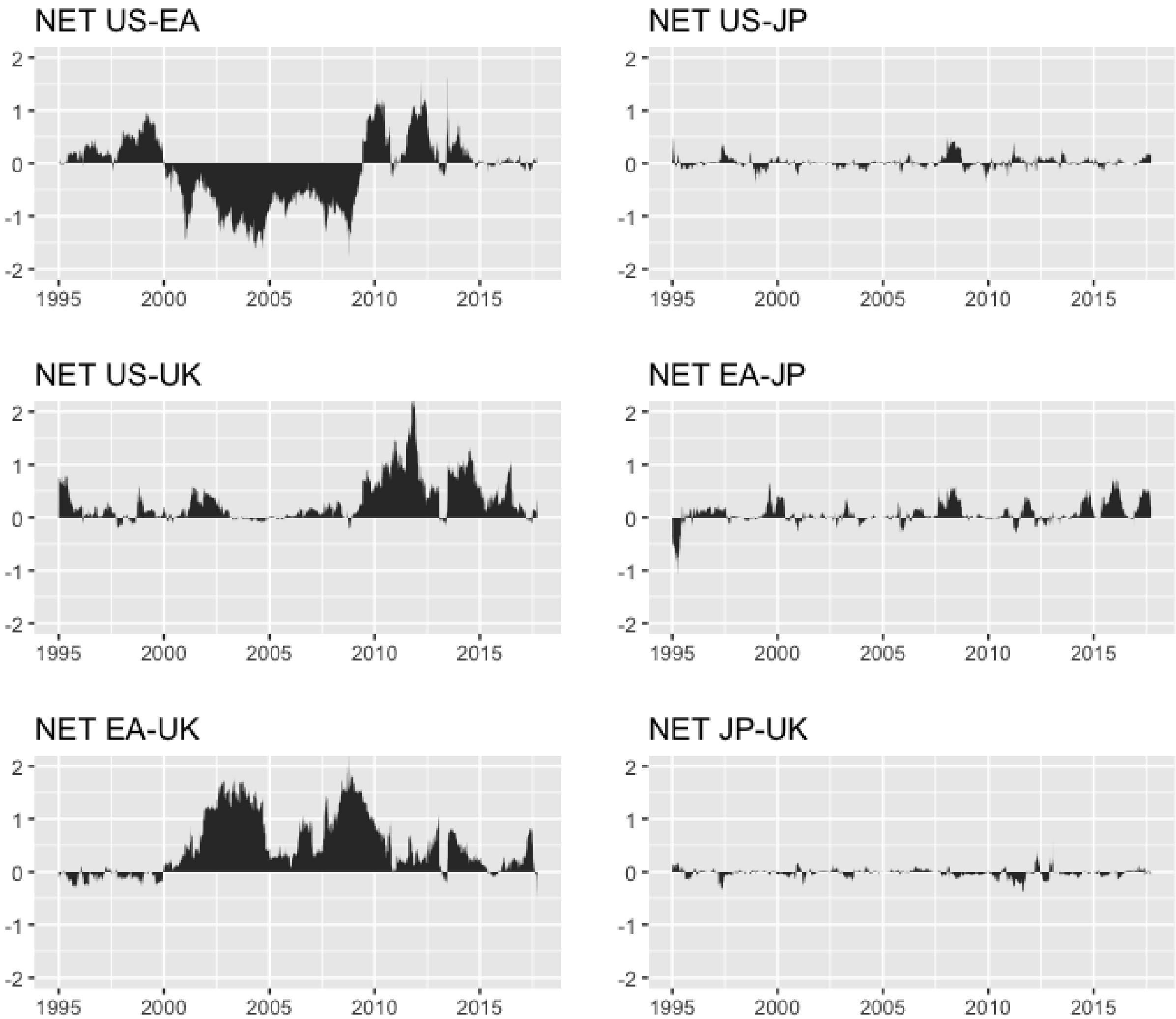


Figure 8: Prior Sensitivity Analysis

Notes: (dark green) $\boldsymbol{\beta}_0 = \mathbf{0}$ and $\mathbf{S}_0 = \mathbf{I}$, (brown) $\boldsymbol{\beta}_0 = \mathbf{0}$ and $\mathbf{S}_0 = 0.01\mathbf{I}$, (light green) $\boldsymbol{\beta}_0 = \boldsymbol{\beta}_{1:200}$ and $\mathbf{S}_0 = \mathbf{S}_{1:200}$, (dark blue) $\boldsymbol{\beta}_0 = \boldsymbol{\beta}_{1:100}$ and $\mathbf{S}_0 = \mathbf{S}_{1:100}$, (light blue) $\boldsymbol{\beta}_0 = \boldsymbol{\beta}_{1:50}$ and $\mathbf{S}_0 = \mathbf{S}_{1:50}$ and (black) mean of TVP.

Figure 9: Forecast Horizon Sensitivity Analysis

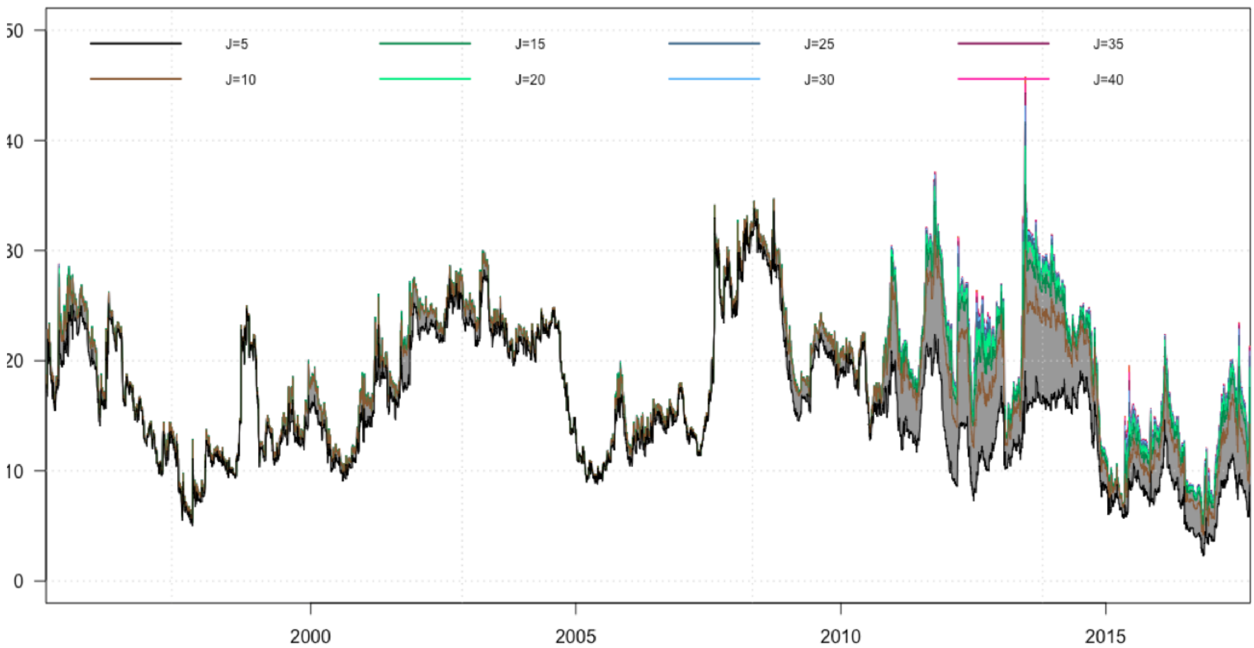


Table 1: Descriptive statistics

	US	EU	JP	UK
Mean	-0.001	-0.002	-0.002	-0.001
Variance	0.001	0.0003	0.0004	0.001
Skewness	-0.183***	0.405***	0.374***	0.861***
Kurtosis	7.194***	8.914***	7.792***	23.563***
JB	4, 377.7***	8, 799.2***	5, 809.1***	105, 151.7***
ERS	-22.071***	-16.339***	-22.306***	-20.649***
$Q(10)$	4, 359.604***	12, 296.500***	6, 850.743***	5, 442.093***
$Q^2(10)$	2, 559.140***	8, 567.538***	3, 513.103***	2, 397.681***

Note: Q and Q^2 are Ljung-Box statistics. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 2: Dynamic connectedness table

	From *(j)*				
To *(i)*	US	EU	JP	UK	FROM
US	80.3	14.3	1.7	3.7	19.7
EU	10.7	83.6	2.6	3.2	16.4
JP	2.1	4.4	91.9	1.7	8.1
UK	11.0	15.3	1.0	72.7	27.3
Contribution TO others	23.8	33.9	5.3	8.5	71.5
Contribution including own	104.1	117.5	97.2	81.2	**TCI**
Net spillovers	4.1	17.5	-2.8	-18.8	17.9

Notes: Values reported are variance decompositions for estimated TVP-VAR model. Variance decompositions are based on 10-step-ahead forecasts. A TVP-VAR lag length of order 1 was selected by the Bayesian information criterion.

Table 3: Connectedness table - Conventional versus unconventional monetary policy

Panel A: Conventional monetary policy era (02.01.1995-30.11.2008)					
	From *(j)*				
To *(i)*	US	EU	JP	UK	FROM
US	74.4	19.2	1.6	4.7	25.6
EU	9.1	84.0	2.8	4.1	16.0
JP	2.0	3.8	92.9	1.3	7.1
UK	6.9	16.9	0.8	75.4	24.6
Contribution TO others	17.9	39.9	5.2	10.1	73.2
Contribution including own	92.4	124.0	98.2	85.5	**TCI**
Net spillovers	-7.6	24.0	-1.8	-14.5	18.3
Panel B: Unconventional monetary policy era (01.12.2008-22.09.2017)					
	From *(j)*				
To *(i)*	US	EU	JP	UK	FROM
US	89.6	6.6	1.9	1.9	10.4
EU	13.2	82.9	2.3	1.7	17.1
JP	2.3	5.2	90.3	2.2	9.7
UK	17.6	12.7	1.3	68.5	31.5
Contribution TO others	33.0	24.5	5.4	5.9	68.8
Contribution including own	122.6	107.3	95.7	74.3	**TCI**
Net spillovers	22.6	7.3	-4.3	-25.7	17.2

Notes: Values reported are variance decompositions for estimated TVP-VAR models. Variance decompositions are based on 10-step-ahead forecasts. In both periods, a TVP-VAR lag length of order 1 was selected by the Bayesian information criterion.

A Technical Appendix

The TVP-VAR is represented as follows,

$$\begin{aligned} \boldsymbol{Y}_t =& \boldsymbol{\beta}_t \boldsymbol{Y}_{t-1} + \boldsymbol{\epsilon}_t & \boldsymbol{\epsilon}_t | \boldsymbol{F}_{t-1} \sim N(\mathbf{0}, \boldsymbol{S}_t) \\ \boldsymbol{\beta}_t =& \boldsymbol{\beta}_{t-1} + \boldsymbol{\nu}_t & \boldsymbol{\nu}_t | \boldsymbol{F}_{t-1} \sim N(\mathbf{0}, \boldsymbol{R}_t) \end{aligned}$$

where $\boldsymbol{Y}_t$ represents an $Nx1$ conditional volatilities vector, $\boldsymbol{Y}_{t-1}$ is an $Np \times 1$ lagged conditional vector, $\boldsymbol{\beta}_t$ 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, $\boldsymbol{S}_t$. The parameters $\boldsymbol{\beta}_t$ depend on their own values $\boldsymbol{\beta}_t$ and on an $N \times Np$ dimensional error matrix with an $Np \times Np$ variance-covariance matrix.

We are using empirical Bayes prior parameters, $\boldsymbol{\beta}_0$ and $\boldsymbol{S}_0$, where the priors are equal to the estimation results of a VAR estimation based on the first 200 days.

$$\begin{aligned} \boldsymbol{\beta}_0 \sim& N(\boldsymbol{\beta}_{OLS}, \Sigma^{\beta}_{OLS}) \\ \boldsymbol{S}_0 =& \boldsymbol{S}_{OLS}. \end{aligned}$$

The Kalman Filter estimation relies on forgetting factors ($0 \leq \kappa_i \leq 1$) which regulates how fast the estimated coefficients vary over time. If the forgetting factor is set equal to 1 we collapse to a constant parameter VAR. Since we do not assume that parameters are changeing dramatically from one to the other day, we set κ_2 equal to 0.99 and start with

$$\begin{aligned}
\boldsymbol{\beta}_t|\boldsymbol{Y}_{1:t-1} \sim& N(\boldsymbol{\beta}_{t|t-1}, \boldsymbol{\Sigma}^{\beta}_{t|t-1}) \\
\boldsymbol{\beta}_{t|t-1} =& \boldsymbol{\beta}_{t-1|t-1} \\
\hat{\boldsymbol{R}}_t =& (1-\kappa_2^{-1})\boldsymbol{\Sigma}^{\beta}_{t-1|t-1} \\
\boldsymbol{\Sigma}^{\beta}_{t|t-1} =& \boldsymbol{\Sigma}^{\beta}_{t-1|t-1} + \hat{\boldsymbol{R}}_t
\end{aligned}$$

The multivariate EWMA procedure for $\boldsymbol{S}_t$ is updated in every step, while κ_1 is set equal to 0.99. If we would assume constant variances we would set this parameter to unity.

$$\begin{aligned}
\hat{\boldsymbol{\epsilon}}_t =& \boldsymbol{Y}_t - \boldsymbol{Y}_{t-1}\boldsymbol{\beta}_{t|t-1} \\
\hat{\boldsymbol{S}}_t =& \kappa_1 \boldsymbol{S}_{t-1|t-1} + (1-\kappa_1)\hat{\boldsymbol{\epsilon}}_t'\hat{\boldsymbol{\epsilon}}_t
\end{aligned}$$

$\boldsymbol{\beta}$ and Σ^{β} are updated by

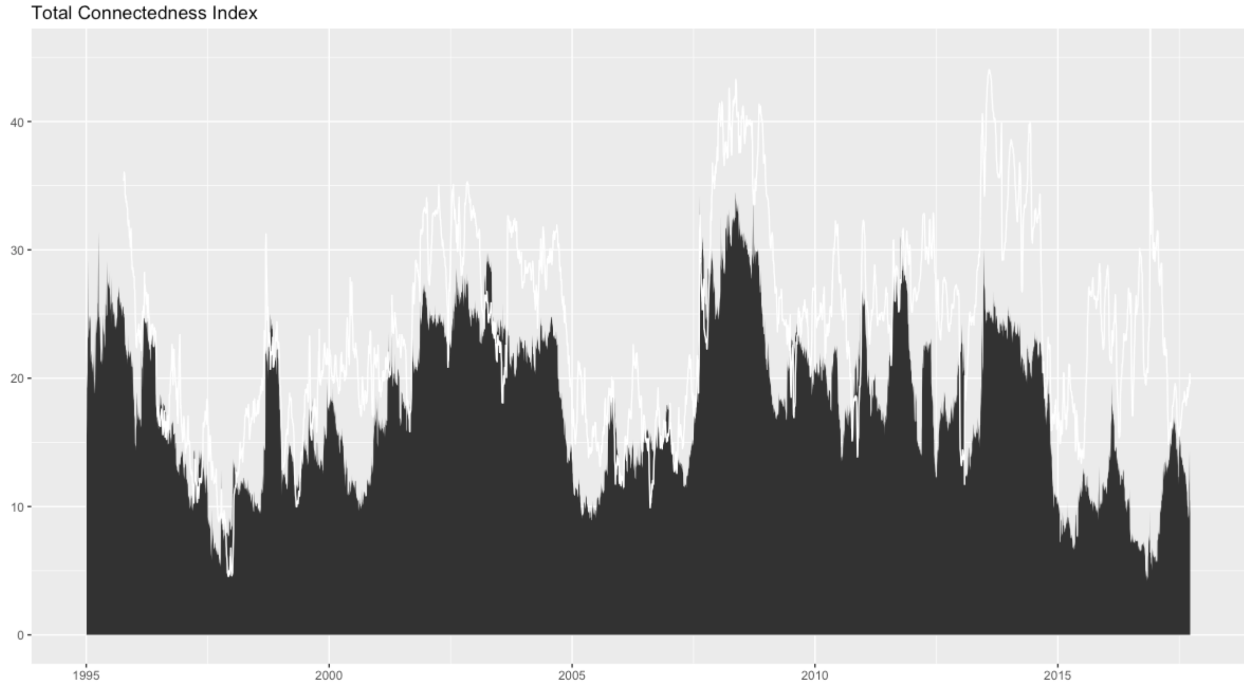
$$\begin{aligned}
\boldsymbol{\beta}|\boldsymbol{Y}_{1:t} \sim& N(\boldsymbol{\beta}_{t|t}, \boldsymbol{\Sigma}^{\beta}_{t|t}) \\
\boldsymbol{\beta}_{t|t} =& \boldsymbol{\beta}_{t|t-1} + \boldsymbol{\Sigma}^{\beta}_{t|t-1}\boldsymbol{Y}_{t-1}'(\hat{\boldsymbol{S}}_t + \boldsymbol{Y}_{t-1}\boldsymbol{\Sigma}^{\beta}_{t|t-1}\boldsymbol{Y}_{t-1}')^{-1}(\boldsymbol{Y}_t - \boldsymbol{Y}_{t-1}\hat{\boldsymbol{\beta}}_{t|t-1}) \\
\boldsymbol{\Sigma}^{\beta}_{t|t} =& \boldsymbol{\Sigma}^{\beta}_{t|t-1} + \boldsymbol{\Sigma}^{\beta}_{t|t-1}\boldsymbol{Y}_{t-1}'(\hat{\boldsymbol{S}}_t + \boldsymbol{Y}_{t-1}\boldsymbol{\Sigma}^{\beta}_{t|t-1}\boldsymbol{Y}_{t-1}')^{-1}(\boldsymbol{Y}_{t-1}\boldsymbol{\Sigma}^{\beta}_{t|t-1})
\end{aligned}$$

Then we update the variances, $\boldsymbol{S}_t$, by the EWMA procedure

$$\begin{aligned}
\hat{\boldsymbol{\epsilon}}_{t|t} =& \boldsymbol{Y}_t - \boldsymbol{Y}_{t-1}\boldsymbol{\beta}_{t|t} \\
\boldsymbol{S}_{t|t} =& \kappa_1 \boldsymbol{S}_{t-1|t-1} + (1-\kappa_1)\hat{\boldsymbol{\epsilon}}_{t|t}'\hat{\boldsymbol{\epsilon}}_{t|t}
\end{aligned}$$

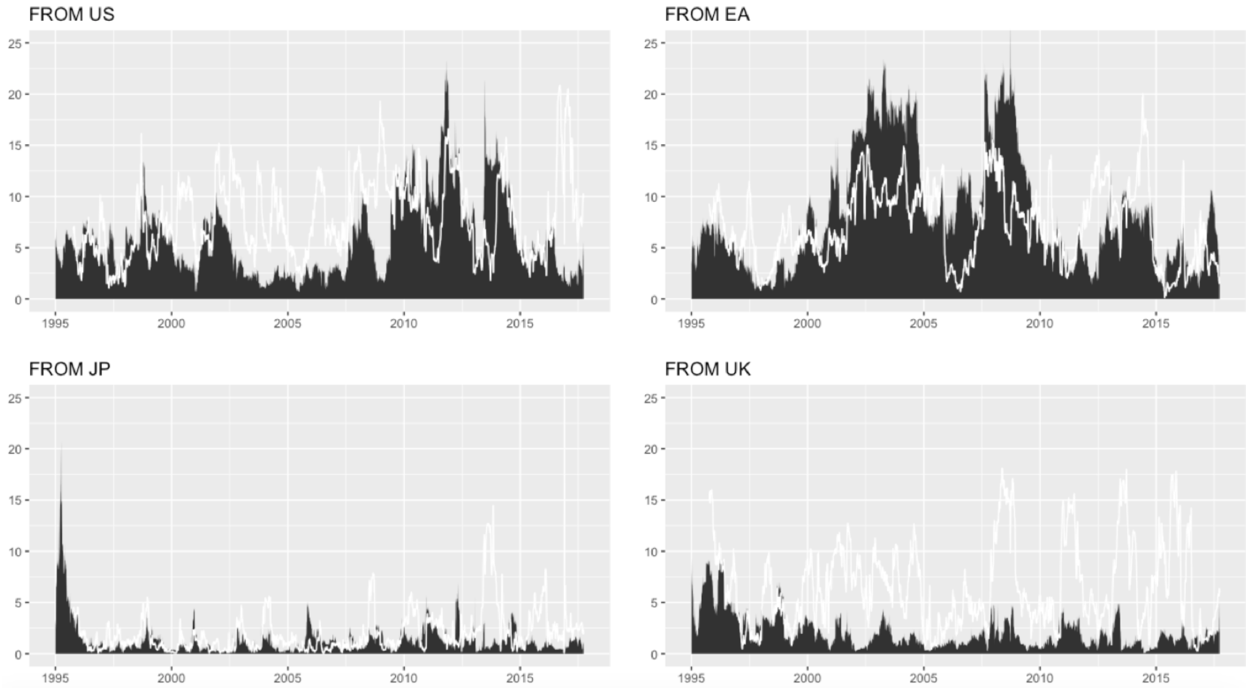
B TVP-VAR vs Rolling-Window-VAR Results

Figure B.1: TVP-VAR vs rolling-window-VAR: Total connectedness



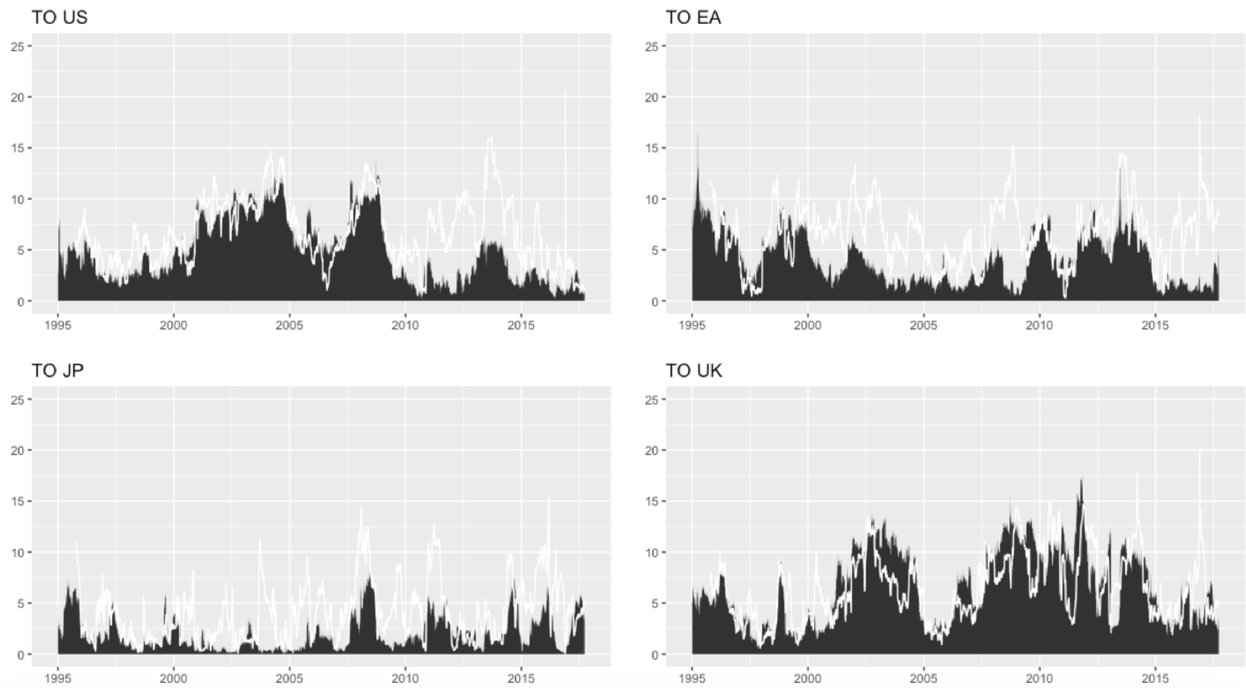
Note: Black line indicates TVP-VAR results; white line indicates rolling-window-VAR results.

Figure B.2: TVP-VAR vs rolling-window-VAR: Directional connectedness *from* country i to others



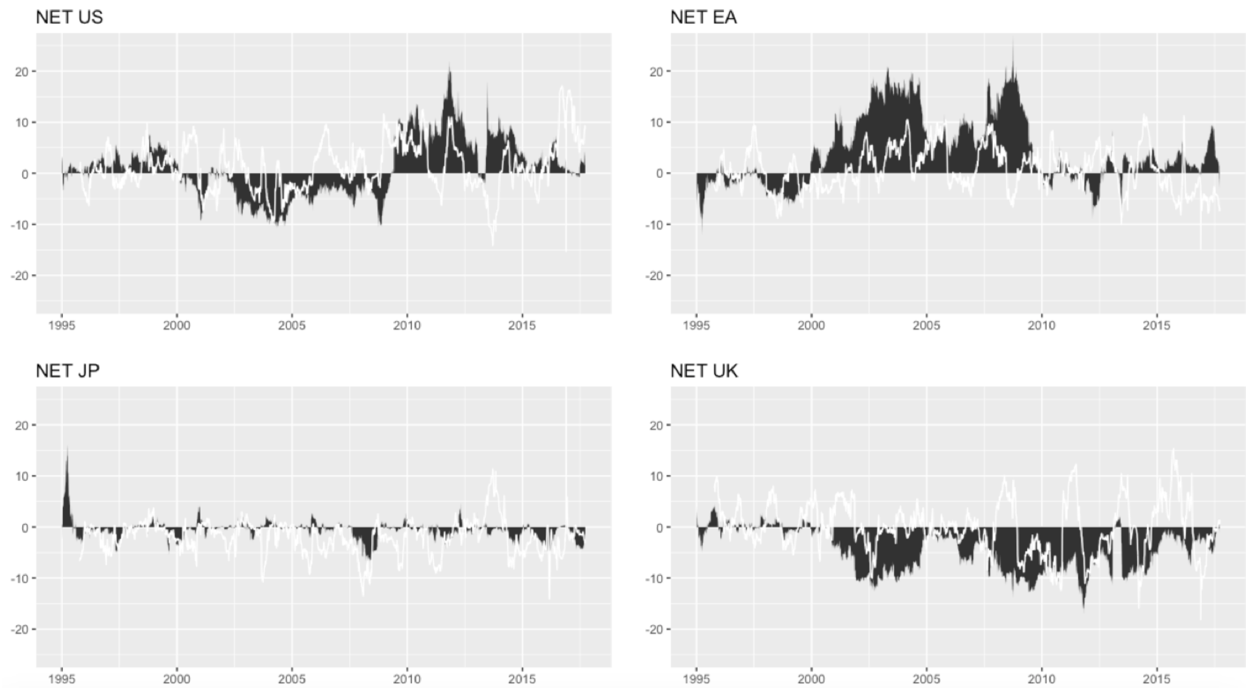
Note: Black lines indicate TVP-VAR results; white lines indicate rolling-window-VAR results.

Figure B.3: TVP-VAR vs rolling-window-VAR: Directional connectedness *to* country i from others



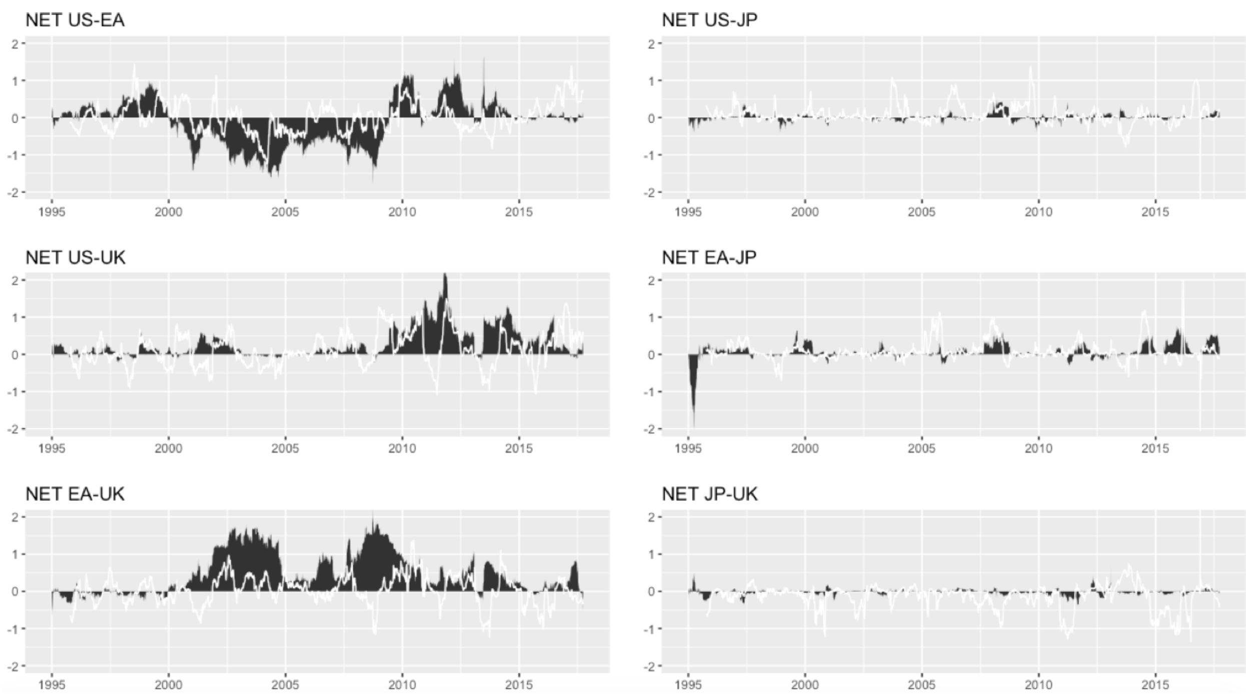
Note: Black lines indicate TVP-VAR results; white lines indicate rolling-window-VAR results.

Figure B.4: TVP-VAR vs rolling-window-VAR: Net directional connectedness



Note: Black lines indicate TVP-VAR results; white lines indicate rolling-window-VAR results.

Figure B.5: TVP-VAR vs rolling-window-VAR: Net pairwise directional connectedness



Note: Black lines indicate TVP-VAR results; white lines indicate rolling-window-VAR results.