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ECONOMIC PAPERS

Christopher Thiem

Cross-category Spillovers of Economic Policy Uncertainty

Imprint

Ruhr Economic Papers

Published by

RWI – Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

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

Ruhr Economic Papers #744

Responsible Editor: Volker Clausen

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ISSN 1864-4872 (online) – ISBN 978-3-86788-864-6

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Bibliografische Informationen der Deutschen Nationalbibliothek

The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available on the Internet at <http://dnb.dnb.de>

RWI is funded by the Federal Government and the federal state of North Rhine-Westphalia.

<http://dx.doi.org/10.4419/86788864>

ISSN 1864-4872 (online)

ISBN 978-3-86788-864-6

Christopher Thiem¹

Cross-category Spillovers of Economic Policy Uncertainty

Abstract

This paper analyses the interdependence of policy uncertainty from 1985 to 2017 across six different categories of US economic policy: Monetary, fiscal, healthcare, national security, regulatory, and trade policy. To this end, we apply the Diebold and Yilmaz (2012, 2014) connectedness index methodology to the newspaper-based uncertainty indices developed by Baker et al. (2016). We find that, in total, the category-specific uncertainties are indeed closely interrelated. However, some policy categories are strong net transmitters of uncertainty spillovers (e.g. fiscal policy), while others show only a low degree of average connectedness and are predominantly net receivers (e.g. trade policy). A modified rolling-window approach further reveals that the intensity and direction of spillovers change significantly over time. The total connectedness index not only shows strong bursts related to certain events, but also exhibits a positive long-run trend. The latter is particularly driven by an increasing average connectedness of both healthcare and regulatory policy uncertainty. Finally, we highlight the different characteristics of the uncertainty network across presidential administrations, as well as before and after the most recent election.

JEL Classification: C32, D80, E65, H00

Keywords: Economic policy uncertainty; network connectedness; spillovers; US presidents; variance decomposition; vector autoregression

February 2018

¹ Chair of International Economics, University of Duisburg-Essen, Universitaetsstr. 12, 45117 Essen, Germany.
E-Mail: christopher.thiem@vwl.uni-due.de

1. Introduction

During recent years, the United States experienced several episodes of extraordinary high economic policy uncertainty (EPU). First came the financial crisis of 2007/08 during which policymakers had to quickly implement many previously untested policies. Afterwards, the political landscape was shaped by recurring partisan conflict over the federal budget, a controversial overhaul of the US healthcare system, and, finally, the surprising victory of a political outsider in the 2016 presidential election. One by one, these events have reinvigorated academic interest in EPU, and by now there are scores of papers documenting its detrimental effects on various financial and macroeconomic variables.² However, only few empirical studies focus on the phenomenon itself.³ This is particularly unfortunate given that a better understanding of EPU's underlying nature is key to reducing its future level and impact.

In this paper, we contribute to this kind of knowledge by characterising the interaction of EPU across six different categories of US economic policy: Monetary, fiscal, healthcare, national security, regulatory, and trade policy. More specifically, we use the Diebold and Yilmaz (2012, 2014) connectedness index methodology and Baker et al.'s (2016) category-specific EPU indices to quantify and analyse the intensity and direction of uncertainty spillovers between the policy areas.⁴

Our empirical analysis is built around three main research questions. First, we ask whether cross-category EPU spillovers are in any way quantitatively important. Second, we analyse whether the different policy areas play distinct roles in the network of category-specific uncertainties. For example, do we find that certain categories are particularly strong transmitters of EPU shocks compared to other categories? Are some categories more closely interrelated than others? Third, we examine whether the properties of the different kinds of uncertainty are inherently static or whether they change over time.

To answer the first two questions, we compute bilateral, multilateral, and system-wide measures of EPU spillover intensity for our full sample period from January 1985 to March 2017. Following Diebold and Yilmaz (DY), these spillover indices are based on the estimation of a vector autoregression (VAR) and of corresponding generalised forecast error variance decompositions (GFEVD). Our results show that cross-category uncertainty spillovers are indeed substantial. On average across the EPU categories, spillovers account for more than fifty percent of the total forecast variation. Moreover, there are significant differences in the importance and characteristics of the EPU network's members. For example, we find that fiscal policy is an important net transmitter of uncertainty shocks, while trade policy is only relatively weakly integrated and a distinct net receiver.

After the analysis of the full-sample, i.e. unconditional or "fundamental", aspects of the EPU system, we devote a significant part of the paper to answering the third research question. We construct dynamic versions of our spillover measures via a rolling-window estimation approach and provide a detailed characterisation of their evolution. Our main results are as follows: The intensity and direction of spillovers are highly dynamic and show distinct patterns across the different types of EPU. Consequently, the categories' roles and influence change throughout the sample period. We also find different kinds of dynamics at different time horizons. In the short run, (total) EPU connectedness reacts significantly to many events in- and outside of the political sphere. Nevertheless, large movements in the level of policy-related uncertainty do not always trigger significant spillover effects

² See, for instance, the literature reviews in Baker et al. (2016) or Hassett and Sullivan (2016).

³ Notable exceptions are Baker et al. (2014), Funke et al. (2016), Hassett and Sullivan (2016), and Davis (2017).

⁴ As highlighted by Diebold and Yilmaz (2014, 2016), there is a close relationship between the concepts of spillover intensity and network connectedness (see also Section 3 below). We will, therefore, use these terms synonymously throughout the paper – see also Cotter et al. (2017).

and vice versa. In the medium term, our system-wide or total spillover index (SOI) goes through four different phases, caused by alternating trending behaviours in the category-specific spillover measures. We relate these trends to major policy initiatives and other important events that changed the political agenda. In general, we document a high degree of consistency between our results and political-economic history. Finally, over the long-run, total spillover intensity exhibits a positive trend. We show that this is mainly because healthcare and regulatory policy uncertainty tend to become more involved in the EPU spillover network.

The previous findings raise our interest in elections and changes in government, as these events hold the greatest likelihood of fundamentally changing the country's political direction. We, therefore, decide to look at these situations more closely in the form of a case study. Using simple regressions, we first identify a significant election effect in the SOI. While the effect is robust to the inclusion of various control variables, it is strictly limited to elections that led to a change in party control of the White House. In a second part, we study the EPU system's conditional structure for each of the five presidencies in our sample period. Among other things, our network graphs reveal a strong triangular relationship between fiscal, monetary, and security EPU during the 1990s Bush administration, a central position of healthcare policy uncertainty during the Clinton presidency, and an exceptional link between fiscal and healthcare policy EPU during the Obama administration. Finally, we compare the EPU network before and after the most recent election. We observe a jump in EPU spillovers originating from trade and regulatory policy, which likely reflects the more unorthodox and interventionist aspects of Trump's governing approach.

On the methodological side, our paper makes two contributions: First, we introduce a new index to the DY framework that measures the average intensity of all spillovers that an EPU category transmits and receives. "Average connectedness" therefore provides a clear representation of each category's overall importance in the EPU network. Second, instead of using a single rolling window for the construction of the dynamic connectedness indices as is common in the literature, we average our estimations over a range of window sizes at each point in time. This window averaging (WinAv) procedure preserves the simplicity and generality of DY's original approach, but at the same time addresses several of its main shortcomings.

To the best of our knowledge, this paper is the first attempt to systematically analyse the relationships between different types of policy area-related EPU. The studies closest to ours all focus on the international transmission of EPU shocks and typically do not distinguish between different policy categories. Yin and Han (2014), and Klößner and Sekkel (2014), for instance, use DY spillover measures based on Cholesky decompositions to quantify the degree of aggregate EPU spillovers across several developed economies and China. Gupta et al. (2016) study how uncertainty in developed and developing countries drives the EPU level in Canada using Bayesian Additive Regression Trees, while Husted et al. (2016) examine the transmission of monetary policy uncertainty with two-country VARs. Most recently, Balli et al. (2017) employ the DY framework to analyse spillover determinants across a panel of 16 economies. All five of these studies find substantial cross-country EPU spillovers. In addition, there is a growing literature on the effects of international EPU spillovers on macroeconomic variables. Although these papers have a different focus, they too document strong links between country-specific EPU indices. Examples include Colombo (2013), Belke and Osowski (2017), and Caggiano et al. (2017).

As a final point, it is worth noting that our concept of EPU captures various aspects of policy uncertainty (see also Baker et al. 2016, Azzimonti 2017). For one thing, it comprises uncertainty regarding the political process before new legislation is passed – i.e., the "if", "how", "which" and "when" of policy implementation. For another, it captures uncertainty about what happens after a new bill comes into effect – i.e., uncertainty about its economic and political consequences. This definition implies that there may be many different (political) mechanisms at work behind the high degree of EPU spillovers.

In this regard, our study can only scratch the surface, and we leave it to future research to analyse these mechanisms in full detail. Nonetheless, there are two particular triggers that frequently seem to play a role during episodes of heightened spillover intensity and therefore deserve a brief introduction:

The first one is political bargaining and the exhaustion of political capital.⁵ The former often involves making concessions to certain political groups or the opposing party in one policy area to achieve one's goals in another. Therefore, if the issue is important enough to potentially justify significant concessions, uncertainty may spread from one policy category to another, or even several others. Similarly, when a policy initiative falls through, this may create the perception that the group behind the initiative exhausted its political capital, which, in turn, puts the success of its other policy goals into question. In fact, even if the bargaining was successful, the same outcome may still arise if the group had to make too many concessions to reach the agreement.⁶

Another reason for EPU spillovers are issues of financing and the budget. Especially in the run-up to important elections, political parties and their candidates tend to make wide-ranging promises regarding future economic policies, but often fail to provide realistic accounts of how these proposals are going to be financed. This leads to uncertainty about future tax policy and borrowing, and, more importantly, about potential cutbacks in other policy areas. Likewise, the mounting public-sector debt itself can become a source of EPU spillovers – specifically when it limits the (perceived) flexibility of fiscal policy during recessions.

The remainder of the paper is structured as follows. Section 2 describes Baker et al.'s category-specific EPU indices and investigates some of their properties. Section 3 introduces the econometric framework, the DY spillover measures and our WinAv procedure. Section 4 contains the results of the static and dynamic analyses, as well as the presidential case study. Section 5 concludes by highlighting the implications of our findings for different groups of readers.

2. Category-specific Measures of Economic Policy Uncertainty

We use the main category-specific uncertainty indices constructed by Baker et al. (2016).⁷ These measures are based on the relative frequency of newspaper articles addressing EPU in the Access World News Newsbank (Newsbank) database, which covers approximately 1,500 newspapers in the United States.

For an article to count towards any of the category-specific EPU indices, it has to contain one or more keywords from each of four different term sets. The first three are common to all indices and refer to the economy, government policy, and uncertainty, respectively. The fourth keyword set is category-specific and contains a number of terms relevant to the particular type of policy.⁸ Overall, there are monthly uncertainty indices for eight different policy areas: The six mentioned in the introduction plus entitlement policy and sovereign debt & currency crisis. We retrieve the measures from www.policyuncertainty.com for the period from January 1985 until March 2017.

Baker et al. (2016) go through extensive efforts to ensure the validity and reliability of their uncertainty measures. Among other things, they conduct a human audit study of 12,000 newspaper articles and,

⁵ See also Hassett and Sullivan (2016) for a discussion of this mechanism in the context of tax policy.

⁶ Note that this also provides a theoretical justification for the existence of asymmetric EPU spillovers, i.e. situations in which uncertainty regarding one policy area decreases as a direct consequence of a political bargain, while, due to the same agreement, uncertainty with respect one or several other policy areas increases.

⁷ The authors also construct several different aggregate EPU indices as well as subindices for some of the policy categories.

⁸ For further details on the construction of the category-specific indices and on the relevant term sets see the online appendix to Baker et al. (2016).

based on the results, further refine the aforementioned keyword criteria.⁹ Nevertheless, we need to address one potential caveat to the use of their indices for our analysis: The boundaries between the different EPU categories may not be entirely clearly defined. In general, since uncertainty itself is a relatively fuzzy and imprecise concept, this can hardly be avoided. However, in the case at hand, there are also two potential technical reasons which require closer inspection.

The first reason Baker et al. (2016) mention is that one newspaper article may count towards more than one category-specific EPU index if it meets the necessary keyword criteria. It is very unlikely that this reduces the meaningfulness of our analysis. On the contrary, if two different kinds of policy uncertainty are frequently mentioned together and are useful for forecasting each other, this is exactly the type of EPU connectedness between two policy areas that we want to measure and analyse.

The second potential reason is that some keywords appear in more than one category-specific term set. Looking first at the scale of the intersections, however, we find that all commonalities are negligible in terms of quantity (Appendix Table A1). For the overwhelming majority of category pairs there are no shared keywords at all and for the remaining combinations the Jaccard index is below ten percent.¹⁰ Next, we examine the EPU indices' pairwise correlation coefficients over the sample period (Appendix Table A2).¹¹ In general, the coefficients lie in a very broad range, assuming values as low as 0.03 (Trade – Entitlement) and as high as 0.84 (Entitlement – Healthcare). This already speaks against any systematic influence from the way the EPU measures are constructed. Indeed, we also do not find any discernible relationship between the strength of correlation and keyword overlap. National security policy EPU, for instance, shows a lower correlation coefficient with fiscal policy EPU (0.58) than with monetary policy EPU (0.68), even though it shares a few keywords with the former, but not with the latter. As part of our sensitivity analysis in Appendix B, we also eliminate the keyword overlaps completely by using available subindices for some of the categories. Despite the narrower content of the subcategories, our main results described below change relatively little. Finally, Baker et al. (2016) show that stocks in sectors such as defence or healthcare are most susceptible to the corresponding category-specific EPU indices, which further highlights the measures' individual information value.

Nonetheless, we decide to proceed cautiously and exclude the entitlement EPU index from our analysis. While the keyword commonalities with fiscal and healthcare policy are still quantitatively insignificant, in this case, they do occur jointly with relatively high correlations.¹² The category is moreover only of secondary interest with respect to its content. For the same reason, we also omit the sovereign debt & currency crisis index.¹³

Figure 1 presents the remaining six uncertainty measures. Overall, given the detailed audit by Baker et al. (2016) and the results from our own investigation in this section, we conclude that the indices are informative and sufficiently accurate proxies for category-specific EPU in the US.

⁹ Other qualities of the indices are i) their availability at a monthly frequency, and for a long sample period and broad set of categories, ii) the consistent method of construction across categories, and iii) their market use validation through adoption by various groups of practitioners (see Baker et al. 2016).

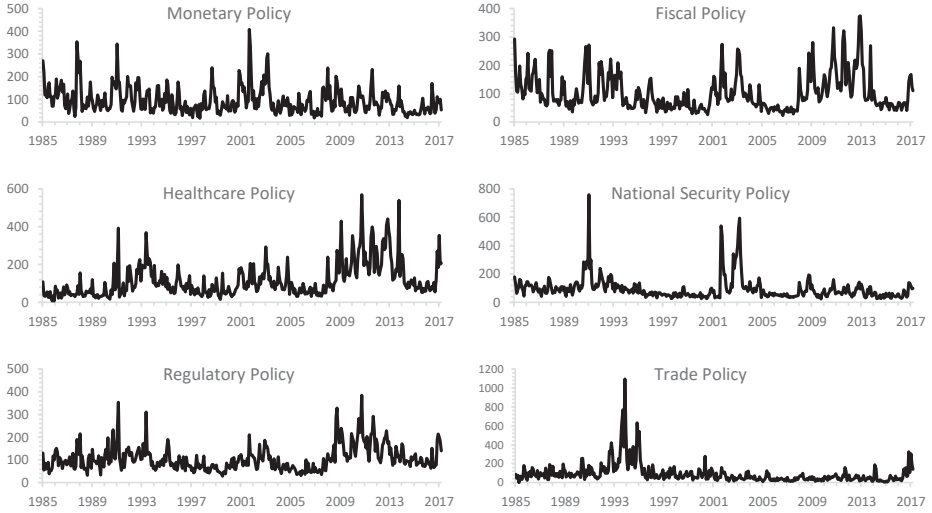
¹⁰ For each pair of policy categories, the Jaccard index is defined as the relative share of common keywords in the combined sets of unique category-specific keywords.

¹¹ Note that we have excluded sovereign debt & currency crisis from the table. We elaborate on the reasons further below.

¹² In a similar situation, DY (2015) exclude Canada from their analysis of G-7 business cycles because its industrial production growth correlates highly with that of the US (0.87). The correlation coefficients for the remaining six series lie between 0.47 and 0.69 – see their Table 8.A.1.

¹³ In this case, the category-specific keywords largely refer to events in emerging markets and Europe. In addition, a large number of zero values makes it difficult to work with the index. Trade policy EPU also exhibits a single zero value in April 1985. We replace this number by taking the average of the neighbouring two observations.

Figure 1: Category-specific EPU Indices



Data Source: Baker et al. (2016), www.policyuncertainty.com.

3. Empirical Methodology

To characterise the relationships between the different kinds of economic policy uncertainty, we utilise the connectedness measurement framework developed by DY (2009, 2012, 2014). The approach relies on the concept of variance decompositions and was first introduced by DY (2009, 2012) to measure return and volatility spillovers in financial markets. Subsequently, the authors pointed out that the derived variance decomposition matrix can also be interpreted as the adjacency matrix of a weighted directed network, which can be used to quantify the overall connectedness of the network's components (see DY 2014, 2016).

3.1 The Diebold-Yilmaz Framework

As an approximating model, the DY framework employs an N -variable VAR with p lags: $\mathbf{y}_t = \sum_{i=1}^p \Phi_i \mathbf{y}_{t-i} + \varepsilon_t$, where \mathbf{y}_t is an $N \times 1$ vector of endogenous variables, Φ_i are $N \times N$ matrices of coefficients, and $\varepsilon_t \sim (\mathbf{0}, \Sigma)$ is an $N \times 1$ vector of i.i.d. disturbances. If the $VAR(p)$ process is stationary,¹⁴ its (infinite) vector moving average representation, $VMA(\infty)$, exists and is given by $\mathbf{y}_t = \sum_{i=0}^{\infty} \mathbf{A}_i \varepsilon_{t-i}$. 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 $\mathbf{A}_{i<0} = \mathbf{0}$. The covariance matrix of the H -period ahead forecast error $\mathbf{e}_t(H)$ can then be calculated as $\text{var}[\mathbf{e}_t(H)] = \sum_{h=0}^{H-1} (\mathbf{A}_h \Sigma \mathbf{A}_h')$ (see, e.g., DY 2012, Klößner and Sekkel 2014).

The goal of the variance decomposition is to break down the total variance of the forecast error of each variable y_i – the i th element on the main diagonal of $\text{var}[\mathbf{e}_t(H)]$ – into fractions that can be traced back to shocks in variable y_j , i.e. $\varepsilon_{j,t+1}, \dots, \varepsilon_{j,t+H}$, with $i, j = 1, \dots, N$.¹⁵ To achieve this, one needs to take into account that the disturbances are usually contemporaneously correlated across

¹⁴ I.e., all roots of $|\Phi(z) = \mathbf{I}_N - \Phi_1 z - \dots - \Phi_p z^p|$ lie outside the unit circle – cf. Hamilton (1994).

¹⁵ Note that using the same notation as DY implies that we condition on the information set Ω_t , whereas in the related literature it is often Ω_{t-1} . In case of the latter we would have $\text{var}[\mathbf{e}_t(H)] = \sum_{h=0}^{H-1} (\mathbf{A}_h \Sigma \mathbf{A}_h')$ and $\varepsilon_{j,t}, \varepsilon_{j,t+1}, \dots, \varepsilon_{j,t+H}$. Cf. Koop et al. (1996), Pesaran and Shin (1998), Pesaran (2015), and Lanne and Nyberg (2016).

equations. One way to do this, for example, would be to orthogonalize the elements of ε by means of a Cholesky decomposition of Σ . However, a serious drawback of this approach is that the variance decompositions – and, therefore, all connectedness measures derived from them – would become dependent on the variable ordering. Especially in the context of our analysis, where we do not have any credible information regarding a potential causal ranking of the category-specific uncertainties, making such strong a priori assumptions would be highly questionable.

A better alternative is to follow DY (2012) and use the GFEVD proposed by Pesaran and Shin (1998), which, in turn, are based on the generalised impulse response functions (GIRF) of Koop et al. (1996). The GFEVD are unique and invariant to the variable ordering. They have a conclusive theoretical foundation and account appropriately for the correlation of the error terms observed in the data (cf. Pesaran and Shin 1998). Formally, the elements of the $N \times N$ generalised variance decomposition matrix θ^g can be written as¹⁶

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (s_i' A_h \Sigma s_j)^2}{\sum_{h=0}^{H-1} (s_i' A_h \Sigma A_h' s_i)}, \quad (1)$$

where σ_{jj} is the variance of ε_j and s_i, s_j are appropriate selection vectors.¹⁷ Each $\theta_{ij}^g(H)$ represents the relative contribution of variable j to the H -step ahead forecast error variance of variable i . Hence, for $i = j$, we obtain the share of the variable i 's own variance contribution, whereas for all $i \neq j$, we obtain the cross-variable variance shares, i.e. spillovers from other variables.

Due to the nature of the GFEVD, however, these shares do not necessarily sum to unity for each variable i ($\sum_{j=1}^N \theta_{ij}^g(H) \neq 1$). DY (2012) thus suggest normalising each entry of θ^g by the respective row sum $\sum_{j=1}^N \theta_{ij}^g(H)$. This yields

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

with $\sum_{j=1}^N \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H) = N$. We can easily show that the expression in (2) is equivalent to the new GFEVD proposed by Lanne and Nyberg (2016), i.e.

$$\tilde{\theta}_{ij}^g(H) = \frac{\sum_{h=0}^{H-1} [GIRF_{ij}(h+1)]^2}{\sum_{j=1}^N \sum_{h=0}^{H-1} [GIRF_{ij}(h+1)]^2}.^{18} \quad (3)$$

Therefore, $\tilde{\theta}_{ij}^g(H)$ can be interpreted as the share of i 's total variation – caused by repeated shocks to the N variables over the forecast horizon – that can be attributed to j .¹⁹ We will use this interpretation throughout the paper.

¹⁶ For a full derivation of the GFEVD see Pesaran (2015), pp. 593-595.

¹⁷ Note that it is a common mistake in the literature to refer to σ_{jj} as the standard deviation of ε_j .

¹⁸ With $GIRF_{ij}(h+1) = s_i' A_h \sigma_{jj}^{-1/2} \Sigma s_j$. Once again, the differences in notation follow from conditioning on Ω_t .

¹⁹ Note that $GIRF_{ij}(h+1) = E[y_{i,t+h+1} | \varepsilon_{j,t+1} = \sqrt{\sigma_{jj}}, \Omega_t] - E[y_{i,t+h+1} | \Omega_t] = E[y_{i,t+H} | \varepsilon_{j,t+H-h} = \sqrt{\sigma_{jj}}, \Omega_t] - E[y_{i,t+H} | \Omega_t]$. Hence, the sum of $GIRF_{ij}$ over the forecast horizon can either be interpreted as the cumulative impact of a single y_j shock in $t+1$ on y_i over H periods, or as the total impact of a series of consecutive y_j shocks on $y_{i,t+H}$.

3.2 Spillover Measures

Based on $\tilde{\theta}_{ij}^g(H)$, DY (2012, 2014) derive various measures of spillover intensity and network connectedness, respectively. Proceeding from the detailed to the aggregate level, we first have pairwise directional connectedness,

$$C_{i \leftarrow j} = \tilde{\theta}_{ij}^g(H) \cdot 100, \quad (4)$$

which is the share of variable i 's total variation explained by shocks to variable j in percentage points. The net uncertainty spillover of i towards j can then be computed as

$$C_{ij} = C_{j \leftarrow i} - C_{i \leftarrow j}. \quad (5)$$

Consequently, if $C_{ij} > 0$, i can be called a bilateral net transmitter of uncertainty spillovers, while j is a bilateral net receiver – and vice versa.

Summing $C_{j \leftarrow i}$ over all $j \neq i$, we obtain a measure of the spillovers transmitted from variable i to all other variables:

$$C_{\blacksquare \leftarrow i} = \sum_{j=1, j \neq i}^N C_{j \leftarrow i} = 100 \cdot \sum_{j=1, j \neq i}^N \tilde{\theta}_{ji}^g(H). \quad (6)$$

Hereafter, we will also refer to $C_{\blacksquare \leftarrow i}$ as *To Others* or *transmitted*.

Similarly, the intensity of the EPU spillovers that i receives from all other policy categories is given by

$$C_{i \leftarrow \blacksquare} = \sum_{j=1, j \neq i}^N C_{i \leftarrow j} = 100 \cdot \sum_{j=1, j \neq i}^N \tilde{\theta}_{ij}^g(H).^{20} \quad (7)$$

$C_{i \leftarrow \blacksquare}$ will be referred to as *From Others* or *received*. It gives the percent share of i 's total variation over the forecast horizon that can be explained by spillovers.

The variable's net total uncertainty spillover then follows logically from the preceding equations as

$$C_i = C_{\blacksquare \leftarrow i} - C_{i \leftarrow \blacksquare}. \quad (8)$$

Furthermore, we introduce a new spillover measure which we call the *average connectedness* of variable i . It is defined as

$$\bar{C}_i = \frac{C_{\blacksquare \leftarrow i} + C_{i \leftarrow \blacksquare}}{2(N-1)} = 100 \cdot \frac{\sum_{j=1, j \neq i}^N [\tilde{\theta}_{ji}^g(H) + \tilde{\theta}_{ij}^g(H)]}{2(N-1)}. \quad (9)$$

\bar{C}_i measures the average intensity of all spillovers that variable i either receives or transmits. So far, this indicator has not been utilised within the DY framework. It is, however, known in network theory as the total weighted degree of a node – see, e.g., Da F. Costa et al. (2007) or Squartini et al. (2013).²¹

²⁰ Note that, with respect to the generalised variance decomposition matrix $\tilde{\theta}^g$, $C_{\blacksquare \leftarrow i}$ is the i th column sum minus the element on the main diagonal, while $C_{i \leftarrow \blacksquare}$ is the i th row sum minus the same element.

²¹ To be more precise, \bar{C}_i is the total weighted degree – also known as total node strength – scaled by $\frac{1}{2(N-1)}$. Note further that DY (2014, p. 123) discuss the concept of node degree, but – consistent with their previous work

Throughout the paper, we will use network graphs to visualise and compare the system of category-specific uncertainties (nodes) and their spillovers (edges). In these cases, the average connectedness of a node (inversely) reflects its mean distance to all other nodes. Consequently, the higher i 's average connectedness, the closer the policy category moves to the centre of the network diagram.²² \bar{C}_i therefore summarises i 's total level of involvement in the system (cf. Opsahl et al. 2010). Moreover, compared to the To Others and From Others indicators, average connectedness gives us a clearer picture of how important a variable is with respect to the total connectedness in the EPU network.²³

To quantify the latter, DY (2012, 2014) introduce the total spillover (or connectedness) index:

$$C = \frac{1}{N} \sum_{i,j=1, i \neq j}^N C_{i \leftarrow j} = 100 \cdot \left[\frac{1}{N} \sum_{i,j=1, i \neq j}^N \bar{\theta}_{ij}^g(H) \right]. \quad (10)$$

The SOI is the system's average spillover intensity per variable. Put differently, it represents the average share of each variable's total variation that is due to "foreign" shocks. We could also rewrite Eq. (10) as $C = \frac{1}{N} \sum_{i=1}^N C_{\bullet \leftarrow i}$, $C = \frac{1}{N} \sum_{i=1}^N C_{i \leftarrow \bullet}$, or $C = \frac{N-1}{N} \sum_{i=1}^N \bar{C}_i$. Hence, the SOI can either be viewed from a transmitter perspective, a receiver perspective, or a combination of both.

3.3 Rolling-window Approach & Window Averaging

The spillover measures described in the previous section are based on the one-time estimation of a VAR model with fixed parameters and for a given sample. Thus, they are clearly static in nature. There exist, however, a multitude of potential reasons for why the relationships between the category-specific uncertainties may in fact be dynamic and change – either fast or slowly – over time; e.g., global or domestic events of various kinds, changes in the structure of the political process, transitions in government, progress in information technology, etc. To capture any such time-variation in direction and intensity of spillovers, we employ an improved version of the widely-used rolling-window estimation approach.

The rolling-window approach is a simple way to allow for time-varying VAR parameters and, according to DY (2014, 2015), is consistent with many possible data-generating processes. Nonetheless, the procedure requires the choice of a window width w , which is associated with an important trade-off between the precision and stability of the estimates on the one hand, and the appropriate weight of new information on the other (cf. Alter and Beyer 2014): If too small a w is chosen, the estimation results are subject to undersmoothing. The estimated VAR coefficients may then be imprecise and show erratic behaviour. In addition, if the number of model parameters is too large relative to the window size, the estimates often imply a non-stationary VAR process. In that case, the VMA representation of the process is undefined and so are all variance decompositions and connectedness measures derived from it. This leads to "missing" observations in the spillover measures and to corresponding gaps in their time series plots.²⁴ If too large a w is chosen, in contrast, there is a risk of

– only use the weighted in-degree ($C_{i \leftarrow \bullet}$) and out-degree ($C_{\bullet \leftarrow i}$) as node-specific connectedness measures. Similarly, DY (2016) mention "average pairwise directional connectedness" in conjunction with network graphs, but neither define nor quantify it as a spillover measure.

²² This is based on the fact that in our network all nodes are linked – albeit to a varying degree.

²³ This can be illustrated with a simple example: Assume that, due to a sudden event, the amount of uncertainty spillovers that policy category i transmits to all other variables increases very sharply. At the same time, however, the effect is exactly offset by a decline in the amount of spillovers that i receives from all other categories. Consequently, if we were to look at $C_{\bullet \leftarrow i}$ ($C_{i \leftarrow \bullet}$) only, we would grossly overestimate (underestimate) i 's importance after the event, when, in fact, the total amount of spillovers associated with i (transmitted plus received), its average connectedness, and also the total connectedness in the system remain unchanged.

²⁴ See, for example, the figures in DY (2009), and Klößner and Sekkel (2014).

oversmoothing. The parameters may then be too inflexible to capture relevant structural changes, which undermines the main purpose of the rolling window. Also, since $w + p$ initial observations are needed to calculate the first estimation, the larger the window size, the more potentially interesting episodes at the beginning of the sample are excluded from the analysis.

The difficulty in applied work is that there is no well-established criterion to choose an “optimal” w with respect to this trade-off. Specifically for the situation at hand, there is not even a clear target function in terms of which optimality can be defined.²⁵ As a consequence, the vast majority of studies in the literature pays little attention to the issue.²⁶ It is common practice, for instance, to use an arbitrarily chosen window size in the main analysis and afterwards redo the estimation with only two or three alternative values of w to investigate robustness. This can be criticised on the grounds that the alternative window widths are no less arbitrary than the original w , and also that, in this regard, the corresponding estimation results are still “point estimates”.

Similar to most studies, we find that our aggregate spillover index is indeed robust to reasonable alterations of the window size. However, we also find that the more disaggregated measures sometimes show w -specific outliers. The more disaggregate the measures are, the more relevant the phenomenon becomes. To mitigate this problem, we modify the rolling-window procedure: Instead of conducting the VAR estimation with only a single window size w , we will calculate the spillover indices for a whole range of window sizes at each period, i.e. $w = [w_{Min}, w_{Max}]$, and then average the results.

This WinAv procedure preserves the two most compelling advantages of the single rolling-window approach – its simplicity and generality (see DY 2015). At the same time, however, it improves the original version in several ways:

First of all, WinAv generally leads to more robust conclusions. This is not only because it averages out w -specific outliers, but also because it reduces the risk of both under- and oversmoothing, as well as the impact of large variations at the end of the observation range.²⁷ Second, as a pragmatic solution, the procedure is easy to implement and requires only minimal assumptions. For example, we are able to effectively sidestep the issue of having to find an optimal w in this setting and the related task of evaluating multiple selection methods. Third, we can, at least partially, draw on supporting evidence from the forecasting literature. Simulation studies and comparisons with real-world data by Pesaran and Timmermann (2007), Pesaran and Pick (2011), and Inoue et al. (2017), for instance, show that in almost all situations WinAv produces better out-of-sample forecasts than the single-window alternative. What is more, in many circumstances it also performs better than various window selection techniques. Fourth, the choice of w_{min} and w_{max} is still arbitrary, but much less impactful than before and easier to make. Fifth, by starting the computation at the period implied by the minimum window size, we can reduce the number of observations lost at the sample beginning. As we then progressively add more observations and window sizes, the results quickly become more robust. Likewise, we can reduce the likelihood of missing observations by simply ignoring non-stationary VAR estimations when taking the average. Finally, the WinAv approach allows us to illustrate the sensitivity

²⁵ Analogous to the work of Ivanov and Kilian (2005) on impulse-response functions, the geometric mean of the relative mean squared error for each element in the GFEVD matrix may be a potential candidate for a target function. Nonetheless, the criterion would still require some adjustment for the rolling-window case. Among other things, it is not obvious how the loss of observations at the sample beginning, as well as any missing observations due to instability in the VAR, should be treated. We leave it to future research to further explore these questions.

²⁶ We are only aware of one attempt by Alter and Beyer (2014) to find an optimal window size within a comparable setting. The authors try to solve the problem by balancing two ad hoc criteria. However, both criteria are only weakly substantiated, and their overall properties remain unclear.

²⁷ Appendix C discusses these and some of the following points in further detail.

of all connectedness measures in a concise manner by highlighting their distribution with respect to w directly in the spillover plots.

4. Results

Before we proceed with the discussion of our results, we need to determine a few more parameters of our econometric framework:

With respect to their time series properties, the EPU indices have much in common with realised volatilities derived from financial return series. In particular, they are also asymmetrically distributed with a substantial right skew. As is common in the literature, we therefore take natural logarithms to obtain approximate normality – see, e.g., DY (2014, 2016), Diebold et al. (2017). To ensure stationarity, the series are further linearly detrended.²⁸ Figure A1 in the appendix shows the empirical distribution of the uncertainty indicators before (first and third column) and after the data is transformed (second and fourth column).

For the VAR model, the Akaike and the Hannan-Quinn information criteria both indicate an optimal lag order of $p = 2$. We accept this recommendation. Furthermore, it is necessary to specify the forecast horizon for the calculation of the GFEVD. We decide to analyse the spillover intensity over a period of one year, i.e. $H = 12$ months. For the dynamic analysis via WinAv, we set $w_{Min} = 36$ months and $w_{Max} = 60$ months. We believe that the former is close to the lower bound of the number of observations with which the VAR can still be estimated reliably, while the latter is high enough to capture regularly occurring political events.^{29, 30} Appendix B presents several robustness checks with respect to these choices.

4.1 Static, Full-sample Analysis

We begin our analysis with the characterisation of the static, unconditional relationships between the different kinds of EPU. After estimating the VAR model for the full sample from 1985:01 to 2017:03, the GFEVD and the corresponding connectedness measures can be presented in an easy-to-read spillover table (Table 1).

The entries of the $\tilde{\theta}^g$ matrix (times 100) are depicted in the form of a lightly blue-coloured heatmap in the centre. The row labels indicate the respective policy category receiving uncertainty spillovers (variable i), while the column labels identify the source of each spillover (variable j). Consequently, on the main diagonal, where $i = j$, we find the own-effect shares for each policy area. The very first entry in the matrix gives us this share for monetary policy with a value of 46.4. In other words, 46.4 percent of MPU's total forecast variation can be attributed to its own shocks.³¹ Conversely, an even larger share of the variation must be due to spillovers from other policy categories.

²⁸ Even beforehand, the common unit root- / stationarity tests often indicated stationary behaviour. Nevertheless, the overall picture was not entirely unambiguous. This being said, the transformation has hardly any influence on our findings. Results without the detrending are available upon request.

²⁹ This maximum window size ensures that each computation accounts for at least one midterm and presidential election – usually with a sufficient number of observations before and after the events.

³⁰ Alternatively, one may also experiment with different single-window sizes and look for clear signs of under- and oversmoothing to determine the boundaries. In this case, we would choose $w = [24, 72]$ (Appendix Figure B3).

³¹ For the sake of readability and brevity, we will hereafter sometimes use the following abbreviations: Monetary policy uncertainty (MPU), fiscal policy uncertainty (FPU), healthcare policy uncertainty (HPU), national security policy uncertainty (SPU), regulatory policy uncertainty (RPU), and trade policy uncertainty (TPU). Similarly, we will use the indices $i, j = M, F, H, S, R, T$ to denote the categories' spillover measures.

Table 1: Full-sample EPU Spillover Table

To \ From	Monetary	Fiscal	Healthcare	Security	Regulation	Trade	From Others
Monetary	46.4	17.7	7.3	15.4	10.8	2.4	53.6
Fiscal	12.4	38.9	14.3	14.3	19.4	0.8	61.1
Healthcare	8.4	24.1	38.4	10.8	15.8	2.4	61.6
Security	12.5	17.1	6.1	47.6	15.2	1.5	52.4
Regulation	9.4	22.6	11.7	10.4	44.3	1.6	55.7
Trade	5.8	5.4	11.0	4.4	7.9	65.6	34.4
To Others	48.5	86.9	50.3	55.3	69.1	8.7	53.1%
Net	-5.1	25.8	-11.3	2.9	13.4	-25.7	
Avg. Conn.	10.2	14.8	11.2	10.8	12.5	4.3	

We can rank the latter in terms of intensity by looking at the remaining entries in the first row. Fiscal policy is found to have the strongest influence. Across the whole sample period, spillovers from this category explain 17.7 percent of MPU's total variation. Interestingly, with $C_{M \leftarrow S} = 15.4$, the degree of uncertainty spillovers from national security policy is almost as high. Shocks to TPU, in contrast, have by far the weakest impact on MPU. They only explain 2.4 percent of the total effect.

The final column of the table sums all the off-diagonal elements in each row (*From Others*, $C_{i \leftarrow \blacksquare}$). For monetary policy, the total effect share of EPU spillovers is 53.6 percent, which is in line with our previous statement. Nonetheless, as the colour scheme clearly indicates (from green – weakest, over yellow, to red – strongest), it is still not the strongest receiver of spillovers in the system. In the cases of FPU and HPU, the measure is yet another 7.5 ($C_{F \leftarrow \blacksquare} = 61.1$) and 8.0 ($C_{H \leftarrow \blacksquare} = 61.6$) percentage points higher, respectively. The category least affected by uncertainty shocks in other areas is trade policy with an intensity of spillovers received of 34.4 percent. Accordingly, it is also the category with the highest own-effect share (65.6 percent).

The last entry in the *From Others* column contains the value for the total spillover index using the full-sample information.³² To answer our first research question, with $C = 53.1$ percent, we find that the magnitude of spillovers in the system is indeed substantial. On average, more than half of the total variation of each variable over the forecast horizon is caused by cross-category spillovers of EPU.

Thus far, we have only analysed the relationships of the category-specific EPU indices from the receiver perspective. To change this, we can now look at the *To Others* row in Table 1, which contains the off-diagonal column sums ($C_{\blacksquare \leftarrow j}$). Of all categories, fiscal policy contributes the most to the total variation of other uncertainties (86.9 points), followed by regulatory policy (69.1 points), national security policy (55.3 points) and healthcare policy (50.3 points) at a certain distance. In comparison, the relative influence of monetary policy is surprisingly weak (48.5 points). Nevertheless, it still exceeds the total impact of spillovers from trade policy (8.7 points) by a wide margin. Overall, from the transmitter perspective, we can see pronounced differences between the six EPU categories.

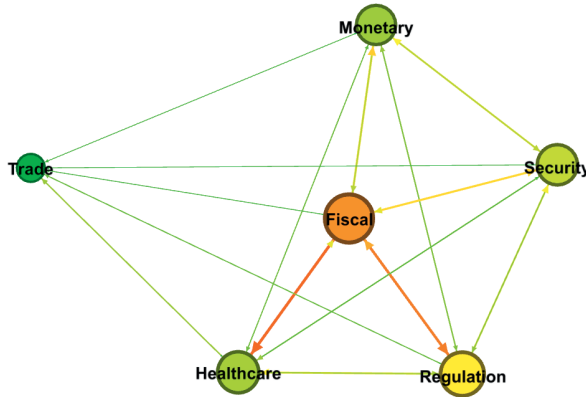
This impression is also confirmed by the net uncertainty spillover measures (C_i) in the following row. While the amount of spillovers that fiscal policy receives from all other variables is already high, the intensity of spillovers that it transmits still exceeds that by $C_F = 25.8$ points. Consequently, it is the system's largest net transmitter of uncertainty spillovers. In the case of trade policy, in contrast, the connectedness is relatively low from both viewing angles, but the spillovers received are nonetheless

³² Note that the colour scheme for the shading of the cell containing the SOI value (light blue – lowest, dark blue – highest) is comparable across all spillover tables in the main text and appendix. The other colouring, however, is individual by table and by connectedness measure.

significantly larger than the spillovers transmitted ($C_T = -25.7$). Therefore, it lies once again at the other end of the spectrum as the system's largest net receiver. The remaining categories are equally split: Regulatory (13.4 points) and national security policy (2.9 points) are (moderate) net transmitters, whereas monetary (-5.1 points) and healthcare policy (-11.3 points) are (moderate) net receivers.

At this point, it is useful to introduce Figure 2 as a visualisation of the unconditional relationships discussed so far. The figure condenses all information from Table 1 into a single network graph.³³ Edge thickness and colour mirror the intensity of bilateral spillovers; node colour reflects each category's relative strength as a transmitter of spillovers (To Others); node size and overall position in the network indicate a category's average connectedness.³⁴

Figure 2: Full-sample EPU Spillover Network (SOI = 53.1%)



The latter is also the last spillover measure that still needs to be discussed. From Figure 2, we can immediately see that fiscal policy has the highest average connectedness in the EPU network. Its node lies directly in the centre of the graph. At the same time, trade policy shows the lowest total level of involvement. Its node is located at the outer edge. The entries in the last row of Table 1 simply confirm this result ($\bar{C}_F = 14.8$, $\bar{C}_T = 4.3$). The network graph also makes other information from the spillover table easier to recognise. It is now straightforward to see, for instance, that there are relatively strong connections between FPU, HPU and RPU.

By now, the spillover table and network graph's answer to the second research question is clear: In terms of EPU spillovers, the different policy categories have very different characteristics. On the one hand, there are categories that are strong net transmitters with a high average connectedness. On the other, there are strong net receivers with a low average connectedness. Over the entire sample period, fiscal policy is the most important category in the EPU network. This may not only be the case because questions related to the financing of new policy proposals are ubiquitous in all policy areas, but also because budgetary issues are repeatedly a trigger of partisan conflict and government dysfunction – see, e.g., Azzimonti (2017) – and because government spending and taxation are often also forms of

³³ Following DY (2016) and others, all network diagrams in this article are produced with the open-source software Gephi (gephi.org), and node locations are determined by Jacomy et al.'s (2014) ForceAtlas algorithm.

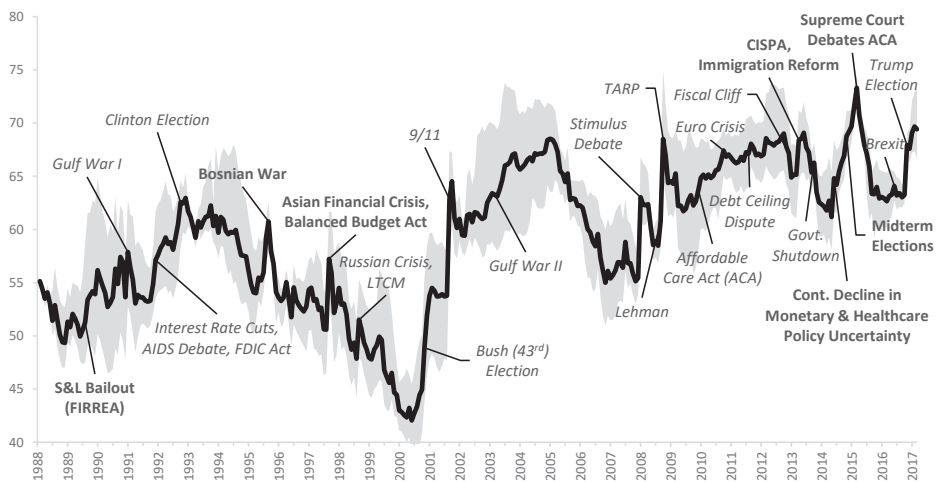
³⁴ We take several steps to maximise comparability across all network graphs in the paper: First, since the outcome of ForceAtlas is not unique and – as far as the underlying network structure allows it – depends on the initial locations of the nodes (see also Demirer et al. 2017), we arrange all EPU networks in a similar way before running the programme. Second, for the same reason, we run the algorithm simultaneously for all networks. Third, we impose that, across all diagrams, nodes and edges share the same scales for their sizes and colours (deep green – weakest, yellow, deep red – strongest).

subsidies (e.g. Medicaid) or regulation (e.g. environmental taxes). Trade policy, in contrast, is presumably the least important category in terms of total EPU connectedness because of its typically outward-looking nature. Also, throughout our sample period, the US has entered into several important trade agreements.³⁵ It is reasonable to assume that these permanent commitments have not only exerted downward pressure on the level of TPU in the long-run, but have also limited the category's importance as an EPU transmitter and receiver (cf. Handley 2014, Handley and Limao 2017a).

4.2 Dynamic, Rolling-sample Analysis

In the previous section, we have found several important relationships and distinctive properties among the category-specific uncertainties. However, given that our sample covers over three decades of policy making and many significant events, it is possible that these linkages and characteristics change over time. We will now investigate this using the WinAv procedure introduced in Section 3.3. We begin by analysing whether there have been any changes in the total intensity of spillovers. Afterwards, we turn to the directional, average and net connectedness measures.

Figure 3: Dynamic Total EPU Spillover Index



Notes: Rolling-window estimation with window averaging, $w = [36, 60]$. The grey shaded area indicates the 90% interval of the distribution across window sizes. See Appendix Table A3 for abbreviations and label sources.

4.2.1 Total Spillover Index

Figure 3 illustrates the dynamic behaviour of the total spillover index. Total connectedness in the EPU system is clearly not static but varies significantly over time. The SOI does not only show strong short-term bursts in relation to important events, but also exhibits different types of trending behaviour in the medium and longer term. In general, the figure reveals the following important results.

First, with respect to their short-run behaviour, the differences between the total spillover index and the original overall EPU index seem to outweigh their commonalities. The italicised labels in Figure 3 indicate events that are associated with large spikes in the US EPU level index computed by Baker et al. (2016). We have adopted most of the markers from Figure I in their paper.³⁶ As can be seen, many

³⁵ Among other things, the US has joined the North American Free Trade Agreement (NAFTA), reduced trade barriers in conjunction with the Uruguay Round, and granted permanent Most-favored-nation status in the course of China's accession to the World Trade Organisation (WTO).

³⁶ We have also reproduced the figure with more recent data from policyuncertainty.com (Newsbank version, April 2017) – see Figure A2 in the appendix.

of the most far-reaching events do also cause sudden jumps in the amount of spillovers in the system. The Bush election in 2000, 9/11 and the events during the financial crisis (Stimulus Debate, Lehman, TARP) are very good examples of this. Nevertheless, there are also just as many EPU shocks that only lead to less than proportional or almost no visible increases in total spillover intensity. Consider, for example, the beginning of the US intervention in Kuwait in January 1991. During this episode, the EPU level index jumps quite significantly, while the EPU spillover index shows only a moderate increase. Other events for which the SOI's short-run reaction is relatively muted include the Russian Financial Crisis and the fall of LTCM, the Debt Ceiling Dispute of 2011, the Government Shutdown in 2013, as well as Brexit. Likewise, there are multiple cases of intensifying spillovers without noticeable rises in the original EPU index (labels printed in bold). These periods are usually associated with either mixed up- and downward, or predominantly negative movements of the category-specific EPU indices. During the height of the Bosnian War between March and September 1995, for instance, SPU fluctuates significantly up and down. With a short delay, these movements also become partially visible in other uncertainty categories. However, since the changes are skewed to the downside, the EPU level index and SOI ultimately move in opposite directions. In a similar manner, the SOI's first increase on the way to the highest value of spillover intensity in the sample period is caused by persistent declines in MPU and HPU prior to June 2014. The connectedness index then continues to climb before and after the 2014 midterm elections. We will see later that, during this time, it is mostly driven by intensifying spillovers from healthcare policy. Eventually, the spillover index reaches its maximum value of 73.3 percent in March 2015 – despite the aggregate EPU level staying largely flat throughout the preceding nine months.

Second, we can roughly identify four different phases in the SOI's medium-run behaviour. The first phase begins in late 1988 with an index value of approximately 49 percent and continues until shortly after the Clinton election. Overall, it is a phase of moderate rises in spillover intensity. After December 1992, the underlying structural forces seem to change entirely, and the SOI begins to fall for a prolonged period of time. Between 1992 and mid-2000 it drops from 63.0 to 42.0 percentage points – its lowest value during the entire sample period. The third phase then begins with a rapid increase in the amount of spillovers in conjunction with the Bush election. Shortly after that, 9/11 hits the system in the form of a second abrupt rise in total connectedness and the SOI climbs to 64.5 percent. This is followed by a more moderate positive trend between 2002 and 2005, and another noticeable decline until November 2006. Nonetheless, at the end of this cycle, the index remains highly elevated (SOI = 55.0 percent) compared to its levels during the pre-Bush era. The fourth and final phase from 2007 onwards is again best characterised as a moderate, but continuous increase of spillover intensity – albeit with a slightly higher variance than during the first cycle in the early 1990s. At the end of our sample, the index indicates that on average almost 70 percent of the total variation of each variable over a 12-month horizon is caused by cross-category uncertainty spillovers.

Finally, over the very long run, uncertainty spillovers between the different policy areas are becoming continuously more important. The medium-term structural changes are predominantly positive and, when taken together, cause an upward trending behaviour in the total spillover index between 1985 and 2017. This can be illustrated by fitting a linear trend to the spillover plot (see Figure A3 in the appendix). The estimated trend coefficient is highly significant and indicates that total connectedness in the EPU network rises by an average $12 \times 0.044 \approx 0.53$ percentage points per year. In other words, it is increasing considerably in the longer term. Additionally, this positive tendency further distinguishes the SOI from the EPU level index.³⁷ In case of the latter, the same regression has only very low explanatory power ($R^2 = 0.03$ compared to $R^2 = 0.42$).

³⁷ Altogether, the two indices' correlation over the sample period is 0.23.

4.2.2 Directional Spillovers – To Others

We can learn more about the different roles of the EPU categories regarding the short- and medium-term behaviour of the total spillover index by breaking it down into dynamic versions of the To Others and From Others measures.

Figure 4 illustrates how the spillovers transmitted by each category change over time. From a bird's-eye perspective, the relative importance of the policy categories implied by the WinAv procedure is almost identical to the one implied by the previous unconditional estimation. The only exception is monetary policy, which turns out to be on average a more important spillover transmitter when allowing for time-varying parameters. However, one can also immediately see that the To Others measures vary significantly over time and across categories. Multiple short-run jumps are discernible in each diagram, and we have highlighted the most important category-specific events related to them. In the medium-term, the series exhibit trending patterns that look very similar to the cycles we have identified in the previous section. However, it becomes apparent that not each policy area contributes equally to each phase or spike in the total connectedness index. Their relative importance therefore varies significantly throughout the sample period.

First Cycle (1988-1992)

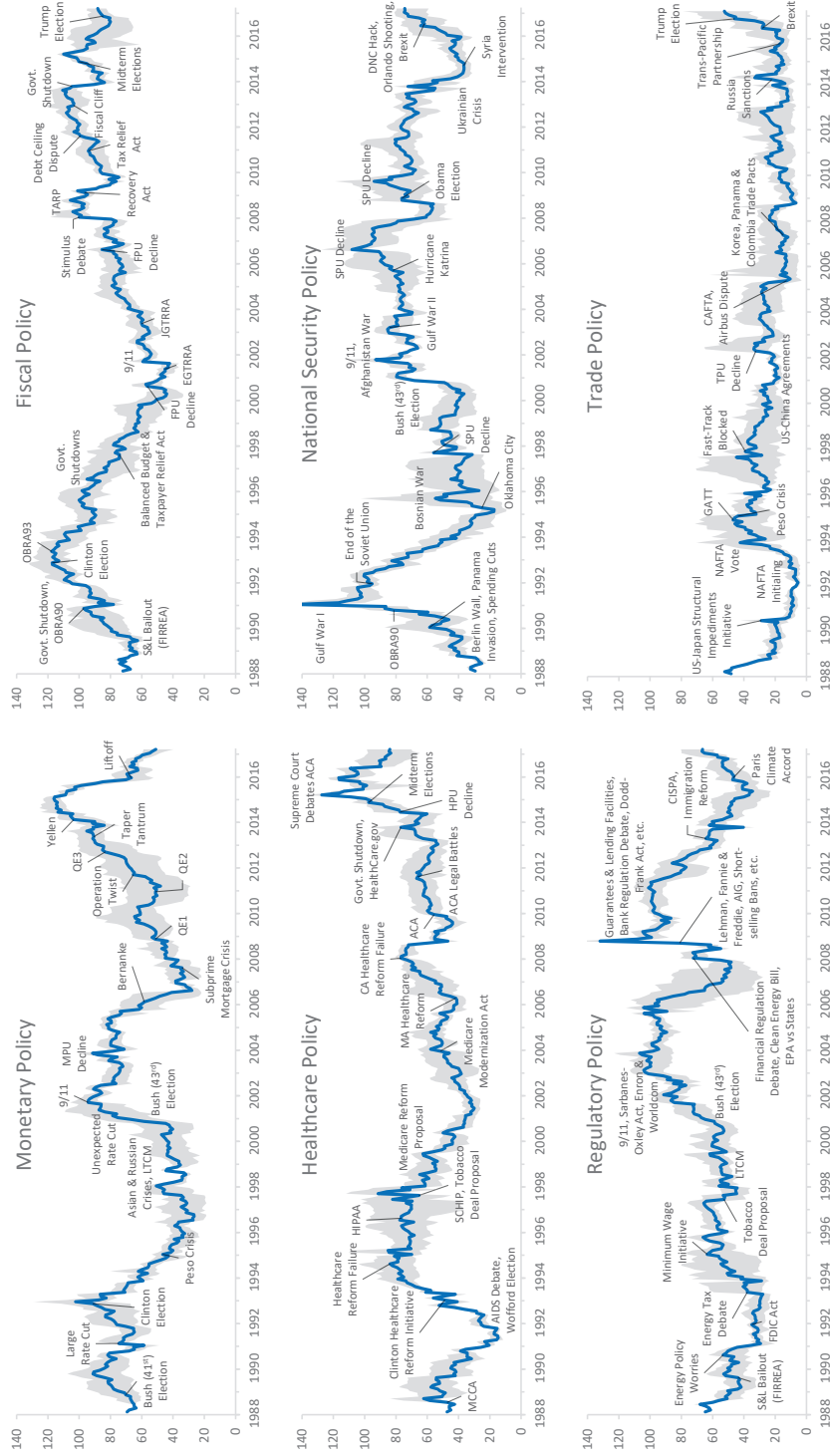
The SOL's first medium-run cycle is mostly driven by increasing spillovers from national security and fiscal policy EPU. After the Savings & Loan (S&L) bailout of August 1989, the FPU spillover measure sets out on a continuous three-year rise. While surely not the only reason for this development, it is likely that the bailout acted as some sort of catalyst for it. During the Reagan administration total public debt had already risen from 30 percent of GDP to over 48 percent,³⁸ and the new law was expected to draw another 166 bn. USD from public funds. Moreover, there was uncertainty about the economic implications of the plan. While the additional government borrowing necessary to finance the rescue was expected to put upward pressure on market interest rates, for instance, it was possible that, by reducing risk premia, the bailout itself would work in the opposite direction (cf. Kurtzman 1989).

Following the S&L rescue, $C_{\square \leftarrow F}$ seems to be growing alongside actual and projected budget deficits, and by mid-1990 fiscal policy supersedes monetary policy as the most important source of EPU spillovers. Against this backdrop, it is also not surprising that the Omnibus Budget Reconciliation Act of 1990 (OBRA90) did not stop the overall trend in the spillover measure. Even after the act's passing, budget deficit forecasts remained on a downward trajectory as the proposed spending cuts were insufficient to compensate for the mounting costs of the S&L bailout and generally weakening economic conditions (see, e.g., Elmendorf et al. 2002).

Indeed, the 1990/91 recession is most likely another crucial factor behind the high levels of FPU spillovers during this time. Due to the mounting debt pile, the Bush administration had little room left for expansionary fiscal measures, and the president increasingly tried to pressure the Federal Open Market Committee (FOMC) and its chairman Alan Greenspan into cutting interest rates. As a result, monetary policy was perceived as becoming increasingly politicised, which undermined the FOMC's credibility and raised uncertainty regarding future policy decisions (cf. Todd 2011).

³⁸ See <https://fred.stlouisfed.org/series/GFDEGDQ188S>.

Figure 4: Dynamic Total Directional EPU Spillovers – To Other Categories



Notes: Rolling-window estimation with window averaging, $w = [36, 60]$. Grey shaded areas indicate the 90% intervals of the distributions across window sizes. See Appendix Table A3 for abbreviations and label sources.

Turning to national security policy, our results show an increasing contribution to others' total variation during the late 1980s, coinciding with events such as the invasion of Panama, growing unrest in the Soviet Union and the fall of the Berlin Wall. However, these movements are all dwarfed by a large jump in the category's spillover index due to the Persian Gulf War. With the beginning of Operation Desert Storm in January 1991, $C_{\blacksquare \leftarrow S}$ rises to its sample maximum of 145.6 points – a 68% increase from its previous month's value of 86.5. Afterwards it subsides quickly, but the decline is only partial, and national security policy remains an important transmitter of uncertainty shocks for another one and a half years. One of SPU's channels of influence during this time were likely the contradictory implications of the potential end of the Soviet Union and the Gulf War regarding future fiscal policy. As discussed in contemporary newspaper articles (e.g. Niskanen 1990), the prospective dissolution of the USSR reduced the expected future financing needs of the military and caused speculation about spending cuts, while the US intervention in the Middle East had precisely the opposite effect.

Second Cycle (1993-2000)

Throughout the early 1990s and prior to the second phase in the SOI, MPU also shows an elevated degree of directional connectedness. Due to the recession and the strained relationship between the Fed and the White House, it seems probable that uncertainty shocks were transmitted in both directions between monetary and fiscal policy. Instead of immediately bowing to the political pressure, for instance, the Fed lowered interest rates only gradually in 1990, which in turn worsened the Bush administration's dilemma. In addition, Greenspan conditioned further rate cuts on a budget agreement between the White House and Congress – an unusual linkage between these two types of economic policy. By 1992, the Fed's potential actions were viewed as a decisive factor regarding the upcoming presidential election (cf. Todd 2011). After the election, however, the relationship between the White House and the central bank began to normalise.³⁹ Now contributing to the SOI's second medium-run cycle, we see a long-lasting decline in MPU's To Others measure. Presumably, this movement is facilitated further by the Clinton administration's resolute fiscal discipline. According to Mankiw (2002), the latter made monetary policy decisions easier. It is likely that it also made them more predictable.

A key element of this new fiscal policy framework was OBRA93. This massive package of new tax legislation and spending cuts reduced the projected 10-year budget deficit by 1,500 bn. USD. Moreover, by lowering market interest rates and fostering private investment, it contributed significantly to the mid-1990s economic expansion (cf. Elmendorf et al. 2002). According to our results, OBRA93 also marks an important turning point in the intensity of FPU spillovers. Following the 1992 presidential election, FPU's to-connectedness measure slows down markedly and reaches a peak in May 1993 – the month OBRA93 passed the House. Afterwards, the underlying trend in $C_{\blacksquare \leftarrow F}$ reverses completely, and the measure falls in a largely uninterrupted manner for the next seven and a half years. Similar to $C_{\blacksquare \leftarrow M}$, $C_{\blacksquare \leftarrow F}$ thus facilitates the SOI's structural decline during this period.

A third, even more rapid decrease can be found in $C_{\blacksquare \leftarrow S}$. After the official dissolution of the Soviet Union, SPU spillovers fall from 100.1 points in May 1992 to 17.2 points in March 1995. At this point, national security policy has become the least influential EPU transmitter in the network – a position usually assumed by trade policy.

In sharp contrast, $C_{\blacksquare \leftarrow H}$ more than triples between 1992 and 1994, and, relative to the other categories, HPU becomes considerably more important. Almost undoubtedly, this is a consequence of Clinton's healthcare reform initiative and its eventual failure – the latter being “the most important health policy event of the 1990s” (Fuchs 2002, p. 875). Healthcare issues already took a prominent position during the 1992 presidential campaign. After taking office, Clinton then mandated a

³⁹ For instance, in contrast to the previous administration, the Clinton administration largely refrained from making public comments on monetary policy (Mankiw 2002).

specialised task force to work out the details of the envisaged Healthcare Security Act (HSA). Many observers agree that this task force was not very effective. On top of insufficient internal debate and multiple delays, information was often only released in small drops, sparking a considerable amount of uncertainty along the way (cf. Cutler and Gruber 2002). The healthcare plan eventually failed to gather enough political support and was pronounced dead in August 1994 (see, e.g., Clymer et al. 1994). After the end of the HSA, healthcare policy's to-spillover measure continues to hover at an elevated level for a little more than three years. It then begins to follow a downward trend similar to the ones observed in $C_{\blacksquare \leftarrow F}$, $C_{\blacksquare \leftarrow M}$ and $C_{\blacksquare \leftarrow S}$.

Third Cycle (2000-2006)

The SOI's third phase between November 2000 and November 2006 is more event-driven than the previous two cycles and less shaped by major political projects. As discussed in Section 4.2.1, two events largely stand out: The election of George W. Bush and the 9/11 terrorist attacks. Figure 4 now additionally reveals that the reactions of the category-specific spillover indices to these episodes are quite heterogeneous. In case of the Bush-Gore election, our results suggest that the uncertainty shock caused by the close voting outcome is mainly transmitted through SPU and MPU. From October to November 2000, $C_{\blacksquare \leftarrow S}$ jumps by 39% (from 49.0 to 68.1 points) and $C_{\blacksquare \leftarrow M}$ increases by 31% (from 44.7 to 58.5 points).⁴⁰ The to-connectedness indices for the remaining categories stay mostly flat. The tragic events of September 2001, in contrast, raise the spillover measures for all types of EPU in the system. The index associated with fiscal policy exhibits the strongest reaction – a 17.1 point (41%) increase. It is followed by $C_{\blacksquare \leftarrow R}$ (12.9, 18%), $C_{\blacksquare \leftarrow S}$ (12.6, 17%), $C_{\blacksquare \leftarrow M}$ (8.3, 10%), $C_{\blacksquare \leftarrow T}$ (1.83, 10%), and, finally, $C_{\blacksquare \leftarrow H}$ (1.6, 5%).⁴¹

The paths of the spillover measures in the aftermath of the two events also differ across categories. There are three types of relevant movements. First, $C_{\blacksquare \leftarrow M}$ and $C_{\blacksquare \leftarrow S}$ continue to move within relatively narrow bands around their newly elevated levels. Monetary policy and national security policy therefore remain important sources of EPU spillovers. This largely fits the historical narrative. Post-9/11, the Fed gradually cut down the target rate until it reached a historically low level of one percent in June 2003. Throughout the process, the policy meetings were often surrounded by uncertainty regarding the FOMC's willingness and ability to respond to the mixed economic outlook – see, for instance, Andrews (2003). Moreover, the low rate itself became a reason for concern. As acknowledged by Bernanke (2003), there was the possibility that the Fed would have to push the target rate even closer towards the zero bound, which would have meant entering previously uncharted policy territory. Likewise, it can be assumed that there is a link between the high level of $C_{\blacksquare \leftarrow S}$ and the US involvement in Afghanistan and Iraq. Both military operations lasted longer and were costlier than originally expected and, therefore, continued to be prominent issues in the political debate. With respect to the two policy areas, it is indeed somewhat surprising that the described events merely seem to support the high levels of $C_{\blacksquare \leftarrow S}$ and $C_{\blacksquare \leftarrow M}$ already reached after the Bush election – instead of causing them to rise even further.

Second, following 9/11, the contribution of regulatory policy to others' total variation continues to trend upwards until reaching a local peak slightly above 100 points in February 2003. Throughout this

⁴⁰ Of course, we cannot rule out that the bursting of the dotcom bubble also contributed to the increase in $C_{\blacksquare \leftarrow M}$. However, since the bulk of the stock market collapse had already taken place, and since we are not able to identify any other events of comparable importance to monetary policy that took place in November 2000 (see also Goodfriend 2002), the timing of the spillover measure's rise remains quite telling.

⁴¹ When we look at average connectedness, FPU and SPU switch positions in the 9/11 response ranking. \bar{C}_S increases by 2.6 points (21%), \bar{C}_F by 2.2 points (19%). In other words, national security policy becomes generally more important in the spillover network, while fiscal policy becomes specifically more influential as an EPU transmitter.

period, the ongoing collapse of the dotcom bubble and the Enron and WorldCom accounting scandals revealed marked deficiencies in the US regulatory framework. Congress reacted to this by passing the Sarbanes-Oxley Act in July 2002. In the same month, $C_{\blacksquare \leftarrow R}$ surpasses $C_{\blacksquare \leftarrow S}$ and $C_{\blacksquare \leftarrow M}$. After 2003, the spillover index ceases to move further upward, but nonetheless stays above all other measures shown in Figure 4 until mid-2006.

Third, the FPU to-connectedness index displays another reversal of its structural trend. In September 2001, the long decline in $C_{\blacksquare \leftarrow F}$ suddenly ends and, from then onwards, the measure rises continuously. This increase once again coincides with a deterioration of public finances. Together with the costs of two major wars, the sizeable tax cuts enacted by the Bush administration in the early 2000s fostered a substantial rebound in public debt relative to GDP (cf. Gale and Orszag 2004).⁴² The tax abatements were also all temporary in nature, which, according to Davis (2017), made fiscal policy more unpredictable. Indeed, the question about their future extension still raised uncertainty in December 2010 and 2012 when policymakers clashed over the Tax Relief Act and the Fiscal Cliff, respectively. This may explain why the new trend in $C_{\blacksquare \leftarrow F}$ ultimately lasts for more than eleven years and well into the SOI's fourth cycle.

Fourth Cycle (2007-2017)

Apart from this, the final phase in the total spillover index is pre-eminently shaped by the global financial crisis. Parallel to the many events that – sometimes rapidly – unfolded in 2008, we see large jumps in the intensity of EPU spillovers transmitted by fiscal and regulatory policy. $C_{\blacksquare \leftarrow F}$ first increases by 20.4 points (26%) in January 2008 – the same month Congress passed a 150 bn. USD stimulus package (see, e.g., Herszenhorn and Stout 2008). We then find a 19.8 point (32%) increase in $C_{\blacksquare \leftarrow R}$ in September of the same year, likely due to events like the failure of Lehman Brothers and the introduction of short-selling bans. Nevertheless, as the debate on future financial regulation further intensified during October 2008, the contribution of RPU shocks to others' total variation rises by an even larger magnitude of 50.9 points (63%). Leaving behind a temporary slump between 2006 and 2008, regulatory policy once again becomes the most dominant source of EPU spillovers in the network. It remains in this position until the beginning of a new round of fiscal policy battles in late 2011.

Perhaps surprisingly, $C_{\blacksquare \leftarrow M}$ does not show any similarly large spikes as $C_{\blacksquare \leftarrow F}$ and $C_{\blacksquare \leftarrow R}$ during the height of the financial crisis. While its increase in January 2008 is still significant in relative terms (23%), it is comparatively small in absolute ones (8.3 points). The rise appears even more modest given the fact that, during the same month, the FOMC surprised markets with an unprecedented single rate cut of 0.75 percentage points, followed by another 0.5 point cut just a week later (cf. DY 2016). Likewise, against the backdrop of the first quantitative easing (QE) announcement, $C_{\blacksquare \leftarrow M}$'s increase in November 2008 (18%, 7.8 points) is somewhat weaker than expected.⁴³ Still, despite the lack of strong jumps, the degree of uncertainty spillovers transmitted by monetary policy increases substantially before, during, and after the global crisis. Roughly coinciding with the first signs of stress in the subprime mortgage market in February/March 2007 (see, e.g., DY 2016), $C_{\blacksquare \leftarrow M}$ begins to move upwards at a slow, but steady pace. It continues to follow that path during the years of acute crisis and for an even longer period afterwards. Along the way, each announcement of new unorthodox monetary policy instruments – e.g., zero interest rates, the various rounds of QE, Operation Twist – seems to further extend $C_{\blacksquare \leftarrow M}$'s upward momentum. After the resolution of the 2013 Government Shutdown and a corresponding drop in $C_{\blacksquare \leftarrow F}$, the influence of MPU shocks on the other category-specific EPU indices again exceeds that of shocks to FPU. Nonetheless, monetary policy's to-

⁴² Interestingly, we find that $C_{\blacksquare \leftarrow F}$ and total public debt as percent of GDP are positively correlated in the medium-run (quarterly data). For the first two thirds of our sample, we have $\rho = 0.6$. Only after 2008, the relationship becomes weaker as total debt outpaces our directional spillover measure ($\rho = 0.3$).

⁴³ Note that the September and October 2008 changes of $C_{\blacksquare \leftarrow M}$ are also negligible.

connectedness index surges even further after the beginning of the Fed's QE tapering process in January 2014. This time, however, the move in $C_{\blacksquare \leftarrow M}$ is specifically driven by a decline in MPU, as the latter falls back to a level last seen in 2006. The spillover measure finally reaches its sample maximum of 116.2 points in January 2015. It then drops strongly before the interest rate lift-off in December 2015, suggesting that the uncertainty surrounding the actual timing of the move was hardly transmitted to the other categories.

Finally, in a very similar manner, HPU moves to the centre stage over the 2014/15 period. As can be seen in the mid-left panel of Figure 4, $C_{\blacksquare \leftarrow H}$ reaches an all-time high of 127.4 points in March 2015. Before getting there, however, the to-spillover index goes through three different stages of development, all of which are apparently shaped by the introduction of the Affordable Care Act (ACA) and its political consequences: First, with the ACA's passage through the Senate, $C_{\blacksquare \leftarrow H}$ increases from 47.4 in November to 55.6 points in December 2009. The index then fluctuates around 60 points between 2010 and 2012, as the new law faced numerous political attacks and legal challenges.⁴⁴ Second, HPU spillover intensity reaches a local peak of 76.8 points in October 2013, coinciding with the government shutdown. The latter occurred because Republicans initially conditioned their agreement to a new spending bill on a delay or defunding of the ACA, which in turn was unacceptable to Democrats (see, e.g., Davis and Jackson 2013). The same month also saw the launch of the government's online health insurance exchanges, which were plagued by many technical glitches. Altogether, both events are prime examples of politically-manufactured uncertainty (cf. Davis 2017). Third, $C_{\blacksquare \leftarrow H}$'s strongest surge begins in June 2014. This overlaps with the Supreme Court's 5-4 ruling against the ACA's contraceptive mandate (*Burwell v. Hobby Lobby*). Interestingly, despite the narrow decision, the level of HPU declines during that month. Nonetheless, $C_{\blacksquare \leftarrow H}$ jumps from 60.1 points to 77.3 points and continues to rise afterwards. The measure reaches a value of 97.4 near the 2014 midterm elections and then climbs further to its aforementioned sample maximum. In March 2015, the Supreme Court looked divided over *King v. Burwell* – a case with potentially important consequences for Obama's healthcare legislation (see, e.g., Barnes 2015). With the court's decision to uphold the constitutionality of the ACA three months later, $C_{\blacksquare \leftarrow H}$ returns to the vicinity of 100 points. However, it partially bounces back afterwards, and healthcare policy remains one of the most important EPU transmitters until the end of our sample period.

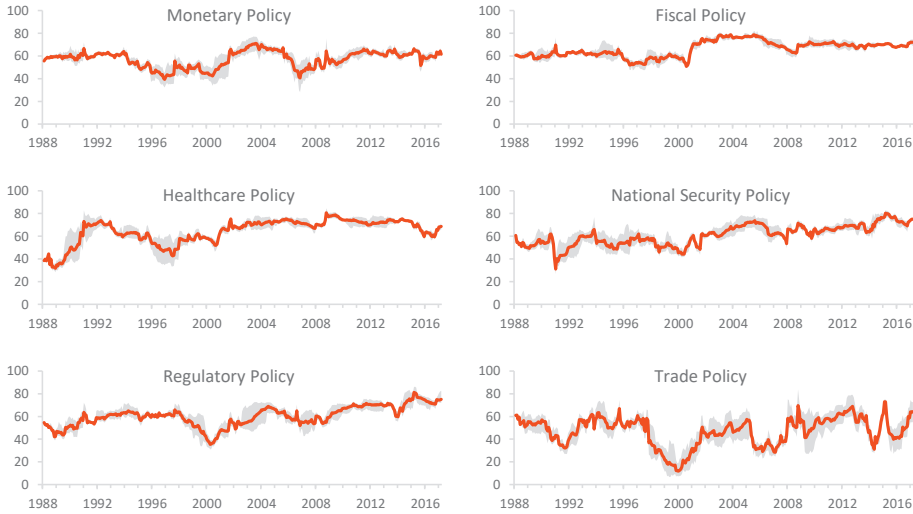
4.2.3 Directional Spillovers – From Others

Like the to-connectedness indices, the from-connectedness indices shown in Figure 5 tend to change over time and show a different behaviour across the EPU categories. Apart from that, however, the two kinds of spillover measures bear little resemblance to each other. Except for trade policy's index, the from-spillover indices are smoother and exhibit a much lower variance. There are hardly any short-term spikes. The measures exhibit some degree of variation in the medium-run, but most of the changes are either driven by the series' long-run trending behaviour or by one-time structural shifts.

As it turns out, one of the latter is particularly striking. In conjunction with the election of George W. Bush, several policy areas seem to become permanently more susceptible to EPU spillovers from other categories. The structural change is most obvious for fiscal policy. There is a clear upward shift in $C_{F \leftarrow \blacksquare}$ between August 2000 and March 2001 and afterwards the indicator stays at an elevated level for the remainder of the sample period. The break is also visible in the indices related to healthcare and national security policy – even though, in the latter case, the timing is more ambiguous.

⁴⁴ In August 2011, for instance, the 11th Circuit Court of Appeals ruled parts of the ACA unconstitutional, which led to a subsequent Supreme Court hearing of the matter in March 2012, and a very close 5-4 vote in favour of the healthcare law in June (see, e.g., Cooper 2011 and Liptak 2012).

Figure 5: Dynamic Total Directional EPU Spillovers – From Other Categories



Notes: Rolling-window estimation with window averaging, $w = [36, 60]$. Grey shaded areas indicate the 90% intervals of the distributions across window sizes.

However, none of these shifts lead to any substantial changes regarding the categories' relative importance as spillover receivers. In general, the latter changes only infrequently because of the otherwise relatively small variation in the from-connectedness indices. For most of the sample period, fiscal and healthcare policy act as the strongest recipients of EPU shocks, while trade policy is usually the weakest.

Finally, we observe a few instances where the from-connectedness indices diverge from their usual patterns and change significantly in the short- or medium-term. Among these episodes, the ones during which the to- and from-spillover indices of a category move in opposite directions are especially noteworthy. Throughout the 1998-2000 period, for example, regulatory policy becomes a slightly stronger transmitter of uncertainty shocks, but, simultaneously, receives much less EPU spillovers from others. Likewise, between 1989 and 1991, $C_{\blacksquare \leftarrow H}$ and $C_{H \leftarrow \blacksquare}$ move inversely to each other. Yet, the most prominent example is given by the SPU connectedness measures. $C_{S \leftarrow \blacksquare}$ drops sharply between September 1990 and January 1991, while $C_{\blacksquare \leftarrow S}$ jumps strongly upwards. Furthermore, after the First Gulf War, the two indices' movements continue to mirror each other until 1993.

In sum, when we look in isolation at either the to-connectedness indices in Figure 4 or the from-connectedness measures in Figure 5 during these episodes, it is very difficult to assess whether the category in question has become more or less integrated in the EPU spillover network. Moreover, the two types of spillover measures send contradictory signals about whether the total spillover index has increased or decreased because of the changes related to a particular policy area. Fortunately, our average connectedness measures can help us solve this conundrum.

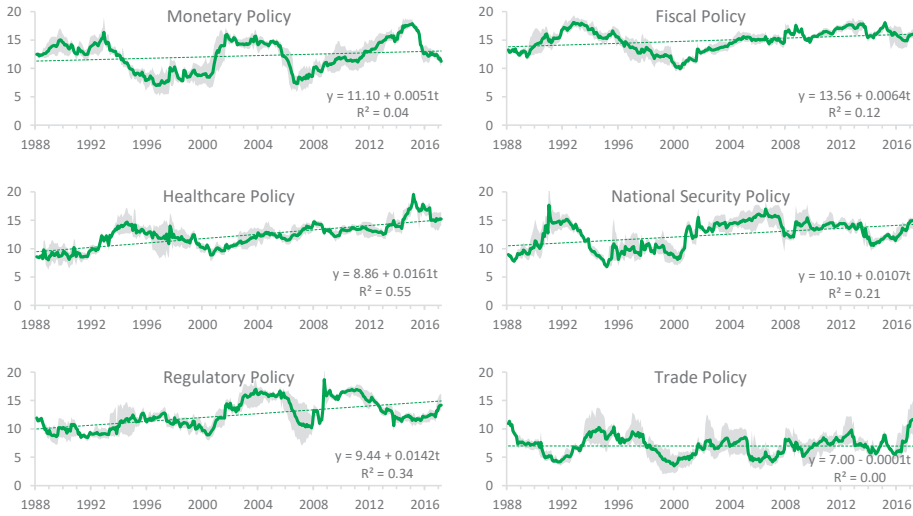
4.2.4 Average Connectedness

As noted earlier, when it comes to analysing the categories' total involvement in the EPU network, average connectedness is potentially the most informative spillover measure as it accounts for each category's contribution as a transmitter as well as a receiver of spillovers. It is therefore useful to also

introduce dynamic versions of the average connectedness measures. Figure 6 plots the respective series for each type of policy-related uncertainty.

Due to the low variation in the From Others indices, the average connectedness measures turn out to be predominantly shaped by the movements in the To Others indices over the short- and medium run.⁴⁵ In other words, during the various episodes discussed in the previous section, each policy category's overall importance in relation to the other variables is consistent with its relative importance as an EPU transmitter. Nonetheless, there are several cases in which average connectedness provides us with a more reliable assessment of which changes in the SOI can be attributed to a certain kind of policy uncertainty. To illustrate this, we can once again use the First Gulf War and the associated changes in the SPU connectedness indices as an example:

Figure 6: Dynamic Average EPU Connectedness



Notes: Rolling-window estimation with window averaging, $w = [36, 60]$. Grey shaded areas indicate the 90% intervals of the distributions across window sizes.

From December 1990 to January 1991, $C_{\blacksquare \leftarrow S}$ rises by 59.1 points. Taken by itself, this should lead to a 9.8-point increase in the SOI, but effectively the index rises only by 4.2 percentage points. As described in the previous section, this is because SPU simultaneously becomes less important as a spillover receiver. The two developments were triggered by the same policy event, but only average connectedness accounts for both of them. Accordingly, \bar{C}_S rises by 4.9 points, which implies a more realistic 4.1-point contribution of SPU to the aggregate index.⁴⁶ In contrast to the directional spillover measures, average connectedness can neither under- nor overstate an uncertainty category's impact on the SOI.⁴⁷

⁴⁵ For the discussion in this section, it is useful to remember that $\bar{C}_i = \frac{C_{\blacksquare \leftarrow i} + C_{i \leftarrow \blacksquare}}{2(N-1)}$ and $C = \frac{N-1}{N} \sum_{i=1}^N \bar{C}_i$.

⁴⁶ Note that the overall importance of the other uncertainty categories changes relatively little. On the one hand, they transmit fewer spillovers to national security policy, but, on the other hand, they receive more.

⁴⁷ Other examples of cases in which the relevant to-spillover (from-spillover) measure slightly overestimates (underestimates) an EPU category's overall contribution include the impacts of MPU and SPU in the course of the Bush election, the influence of RPU in late 2008, and the contribution of HPU in early 2015. Similarly, the

Due to this property, the average connectedness measures can also help us learn more about the factors behind the SOI's long-run increase. Figure 6 reveals that for five of the six policy areas there is a positive trend in \bar{C}_t . Therefore, the majority of EPU categories tend to become more closely connected over the sample period. Among those, HPU's average connectedness exhibits the highest trend coefficient. It also shows little variation around the trend, which results in a relatively high R^2 of 0.55. Altogether, this category alone is responsible for more than 30% (0.16 percentage points yearly) of the average long-term increase in total EPU spillovers.⁴⁸ \bar{C}_R shows the second most distinct trending behaviour, albeit with larger fluctuations. It accounts for another 0.14 percentage points (27%) of the aggregate trend. In the cases of \bar{C}_S , \bar{C}_F and \bar{C}_M , the trend is less pronounced, but still positive. Trade policy, on the other hand, is the only category where average EPU connectedness does not show a positive long-run tendency. Consequently, while healthcare and regulatory policy tend to become more important relative to the other categories, trade policy becomes less relevant in terms of EPU spillovers.

Overall, the series' observed trending behaviour is in line with political-economic history. Healthcare reform, for instance, has been on the public agenda for decades, but policymakers have nonetheless failed to deliver any fundamental changes over a long period of time (see, e.g., Cutler and Gruber 2002). As a result, US healthcare expenditure as a percentage of GDP has grown steadily since the 1960s, while the number of uninsured remained unusually high by international standards.⁴⁹ The long-run trend in \bar{C}_H likely reflects the combination of the issue's growing political urgency and the constantly rising financing needs of the healthcare system.⁵⁰ Likewise, the increasing influence of RPU matches the long-term expansion of the regulatory state. As highlighted by Baker et al. (2014) and Davis (2017), the latter has grown immensely in terms of scale and complexity during the previous decades. This has generally made the economic environment more uncertain.⁵¹ Finally, the absence of a positive trend in \bar{C}_T can also be explained by the likely spillover-limiting effects of the major trade agreements implemented since 1985 (see Section 4.1).

4.2.5 Net Directional Spillovers

After analysing the categories' overall importance in the EPU spillover network, we finally focus on the relative importance of their dual roles as transmitters and receivers of uncertainty shocks. At each point in time, the dynamic net directional spillover measures tell us which of the two functions characterises the categories' behaviour more strongly.

Figure 7 presents the total net spillover indices. The most important observation we can make is that for each policy area there are periods during which it is a net transmitter of uncertainty shocks as well as phases when it is a net receiver. Across all categories, fiscal and trade policy exhibit the most distinct

respective to-spillover (from-spillover) indices underestimate (overestimate) the 1989-1991 impact of HPU, as well as MPU's total involvement in late 2015.

⁴⁸ The relative contribution of the trend in \bar{C}_H to the average yearly change in the SOI is calculated as $\frac{\frac{6-1}{6} \cdot 12 \cdot 0.0161}{0.53} = 0.304$.

⁴⁹ For data on national health expenditure see the website of the Centers for Medicare & Medicaid Services (www.cms.gov). Data on insurance coverage is provided by the Centers for Disease Control and Prevention (www.cdc.gov).

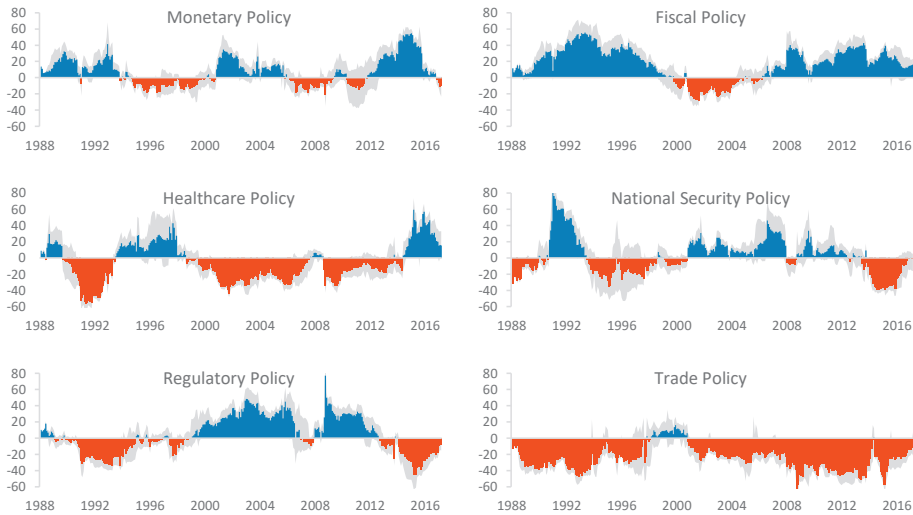
⁵⁰ Indeed, we find a strong positive trend in the pairwise average connectedness between HPU and FPU.

⁵¹ The interpretation of statutes and their enforcement by regulatory agencies, for instance, have become increasingly discretionary and unpredictable (Davis 2017). As this injects uncertainty into the economy, it also makes it more difficult, for example, to assess the potential economic effects of new policy initiatives. Similarly, uncertainty shocks related to other policy areas may increasingly cause regulatory uncertainty, as it has become less clear which regulators need to respond to any legislative changes and in which way they will do so.

profiles as net EPU transmitter and receiver, respectively. However, even in these two cases, there are several years in the late 1990s / early 2000s during which the categories diverge from their usual roles.

When looking at the other policy areas, we find that the net connectedness measures switch direction even more frequently. Regulatory policy, for instance, becomes a strong net EPU transmitter after the burst of the dotcom bubble and during the financial crisis but is a net receiver during the most recent years. Similarly, national security policy turns into a pronounced net transmitter of uncertainty in the presence of military conflict – e.g., during the First Gulf War and in the 2000s – but is evidently a net receiver during other times. In general, whether a category is a net EPU transmitter or receiver at any given time appears to be determined mainly by a combination of three factors: Its fundamental, or long-term, role in the system, the prevailing political agenda, and, finally, any major events with the potential to change this agenda.

Figure 7: Dynamic Net Directional EPU Spillovers – Total



Notes: Rolling-window estimation with window averaging, $w = [36, 60]$. Grey shaded areas indicate the 90% intervals of the distributions across window sizes.

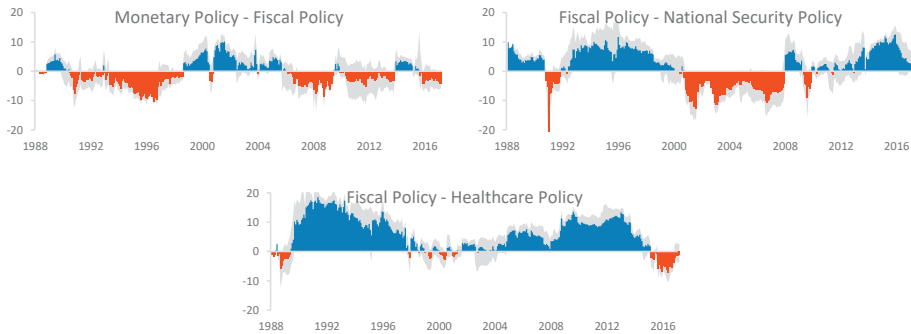
The DY framework further allows us to calculate bilateral net directional spillover measures for each pair of EPU indices. However, since there are $\frac{N(N-1)}{2} = 15$ combinations, it is impractical to discuss all of them in detail. We therefore select and shortly investigate only the three pairs which we consider to be the most interesting and informative.⁵²

The upper-left panel of Figure 8 displays the degree of net EPU spillovers from monetary to fiscal policy. Throughout the sample period, their bilateral spillover index frequently takes on relatively small positive and negative values – without a clear tendency in either direction. As already suspected in Section 4.2.2, monetary policy develops into a net receiver of EPU spillovers vis-à-vis fiscal policy after the election of George H.W. Bush.⁵³ Interestingly, the category also acts as a net receiver during most of the financial crisis and its aftermath.

⁵² The remaining pairwise spillover indices are depicted in Figure A4 in the appendix.

⁵³ Note that the net spillover measure declines further after the 1992 election. In this case, this is simply because $C_{F \leftarrow M}$ falls more quickly than $C_{M \leftarrow F}$.

Figure 8: Dynamic Net Directional EPU Spillovers – Selected Pairwise



Notes: Rolling-window estimation with window averaging, $w = [36, 60]$. Grey shaded areas indicate the 90% intervals of the distributions across window sizes.

Next, we have the FPU and SPU net index. This measure exhibits quite different characteristics compared to the previous one. There are medium-sized net spillovers, again in both directions, but now with a noticeable pattern: National security policy acts a bilateral net transmitter of uncertainty spillovers during, or close to, major armed conflicts and as a net receiver during other times.

Figure 8's last panel depicts the dynamic net connectedness of FPU and HPU. We find large net spillovers that predominantly go in the direction from the former to the latter EPU category.

These results have several interesting implications for investors: First, market participants should pay attention to the fact that the FPU-MPU net spillover index is mostly balanced over the long run. Uncertainty shocks spill over in both directions. For example, even during the financial crisis, it would have been a mistake to focus one's attention solely on the central bank's possible reaction and to disregard the uncertainty surrounding potential fiscal policy actions. Second, specifically in the absence of active military conflict, FPU tends to spill over to national security policy. Recent evidence in the empirical literature suggests that this in turn may raise the volatility of defence-related stocks and depress capital investment in the sector (see Baker et al. 2016, Hassan et al. 2016). Third, the same argument carries over to stocks in the healthcare sector. In this case, however, FPU's net influence is found to be even larger and is present for most of the sample period.

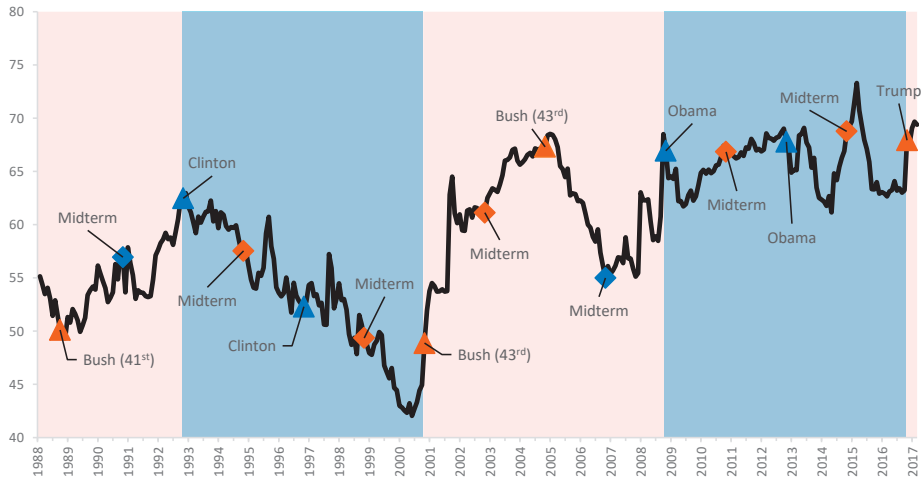
Our third research question asked whether the properties of the EPU spillover network as a whole and the roles of its members change over time. By now, we have obtained more than enough evidence to confirm that this is the case. We have found that the SOI exhibits different kinds of dynamic behaviour over the short-, medium- and long-run. The more disaggregated spillover measures additionally show distinct dynamics for each policy area. As a consequence, all types of policy-related uncertainty exhibit phases during which they are important contributors to the SOI and phases during which they are not. Our detailed analysis of the dynamic to-connectedness indices further suggests that the EPU system's behaviour is not only shaped by important events in- and outside of the political sphere, but also that decisive legislative actions and changes to the political agenda can have a long-lasting impact.

4.3 Case Study: US Presidencies and the Trump Election

National elections are recurring events with a high likelihood of altering the political agenda as they may lead to changes in political majorities and even the government. Indeed, in the previous sections, we have already identified a few instances in which our connectedness measures have reacted to these types of events. In this section, we investigate more systematically if and how elections and changes in government alter the structure of the EPU spillover network. We begin by re-examining the total

spillover index with a special emphasis on potential election effects. Afterwards, we characterise the EPU system during the different presidential administrations covered by our sample period. Finally, we analyse the impact of the most recent presidential election.

Figure 9: Dynamic Total EPU Spillover Index (Election Focus)



Notes: Rolling-window estimation with window averaging, $w = [36, 60]$. Triangles mark presidential elections, squares midterm elections. Marker's colours refer to the winning party of the respective election – Republican (Red), Democrat (Blue). Background shading indicates party control of the White House.

4.3.1 Total Connectedness and Elections

Previous studies like Baker et al. (2016) or Hassett and Sullivan (2016) highlight the existence of a distinct election effect with respect to the overall level of EPU. A visual inspection of Figure 9, however, yields only rather mixed evidence regarding the influence of national elections on the total degree of EPU spillovers. In addition to the 2000 Bush-Gore election, we can discern substantial increases of spillover intensity around the 1992 and 2008 presidential elections as well as in proximity to the most recent Trump-Clinton election. The SOI also seems to be elevated close to the 1990 and 2014 midterms. Still, for all other major elections, we do not observe any particularly strong increases. We therefore have to refute the idea that elections in general cause uncertainty to spill over across different policy areas. Note, however, that all four presidential elections for which we find substantial increases in the SOI are associated with a change in party control of the White House. Hence, there may be a less general election effect instead.

We run a few basic regressions to verify this notion (Appendix Table A4). While controlling for the SOI's own dynamics, we first find that the index is on average 0.4 percentage points higher during the months before and of a national election. However, the respective coefficient is not significant at any of the common statistical thresholds. The general election effect also disappears when we add another dummy variable to differentiate between the two types of national elections. It is replaced by a significant presidential election effect with a magnitude of 0.9 percentage points. Nevertheless, this effect too vanishes when we finally allow for a specific impact of elections that resulted in a change of the presidential party. The coefficient of 2.5 on the new dummy variable is relatively large and highly

significant. Moreover, it is robust to the inclusion of various control variables.⁵⁴ We thus confirm the existence of a specific “White House” effect.

As a second important point, Figure 9 suggests that changes in government also matter considerably for the development of the SOI after Inauguration Day. As we can see, the SOI’s four medium-run cycles largely coincide with the different presidencies over the last thirty years.

The idea that economic variables vary systematically across presidents and even across presidential parties is not new. In a recent study, Blinder and Watson (2016) draw attention to the phenomenon that Democratic presidents have beaten Republican presidents on a wide range of economic performance measures. While the authors are able to relate a large share of the performance gap to factors independent of domestic policy, some parts of it still remain unexplained. This inspired us to test whether there is also a systematic difference between Democrats and Republicans in terms of EPU spillovers. Using our previous regression framework, we find that the SOI is indeed on average 0.4 percentage points lower during Democratic presidencies.⁵⁵ Of course, despite its strong significance, this result has to be taken with a grain of salt as our sample period only includes five different presidencies. Nonetheless, it leads to two interesting conclusions: First, it may be worthwhile to investigate the relationship between the SOI and measures of economic activity, which we will leave to future research, and, second, it may be interesting to compare the EPU network across the different presidencies, which we will turn to now.

4.3.2 The EPU Spillover Network across Presidencies

Figure 10 presents snapshots of the EPU system for each of the five different presidencies between 1985 and 2017.⁵⁶ The depicted network diagrams replicate many of the findings from the rolling window analysis in a more condensed form. For the second term of the Reagan administration, for instance, the conditional SOI is relatively low (48.8 percent). Accordingly, we see that the different nodes are scattered rather loosely and with near equal distance around fiscal policy, which lies at the centre of the EPU spillover network. As spillover intensity then increases over time, five of the six categories show a tendency to move closer to each other. The remaining one, trade policy, in contrast, moves further away from the others and towards the outer edge of the network.

Apart from that, however, the diagrams also reveal many interesting new details about the EPU network – especially regarding the fundamental relationships of the category-specific uncertainties during the five administrations. In the following, let us briefly highlight the most important of these connections for each presidency.⁵⁷

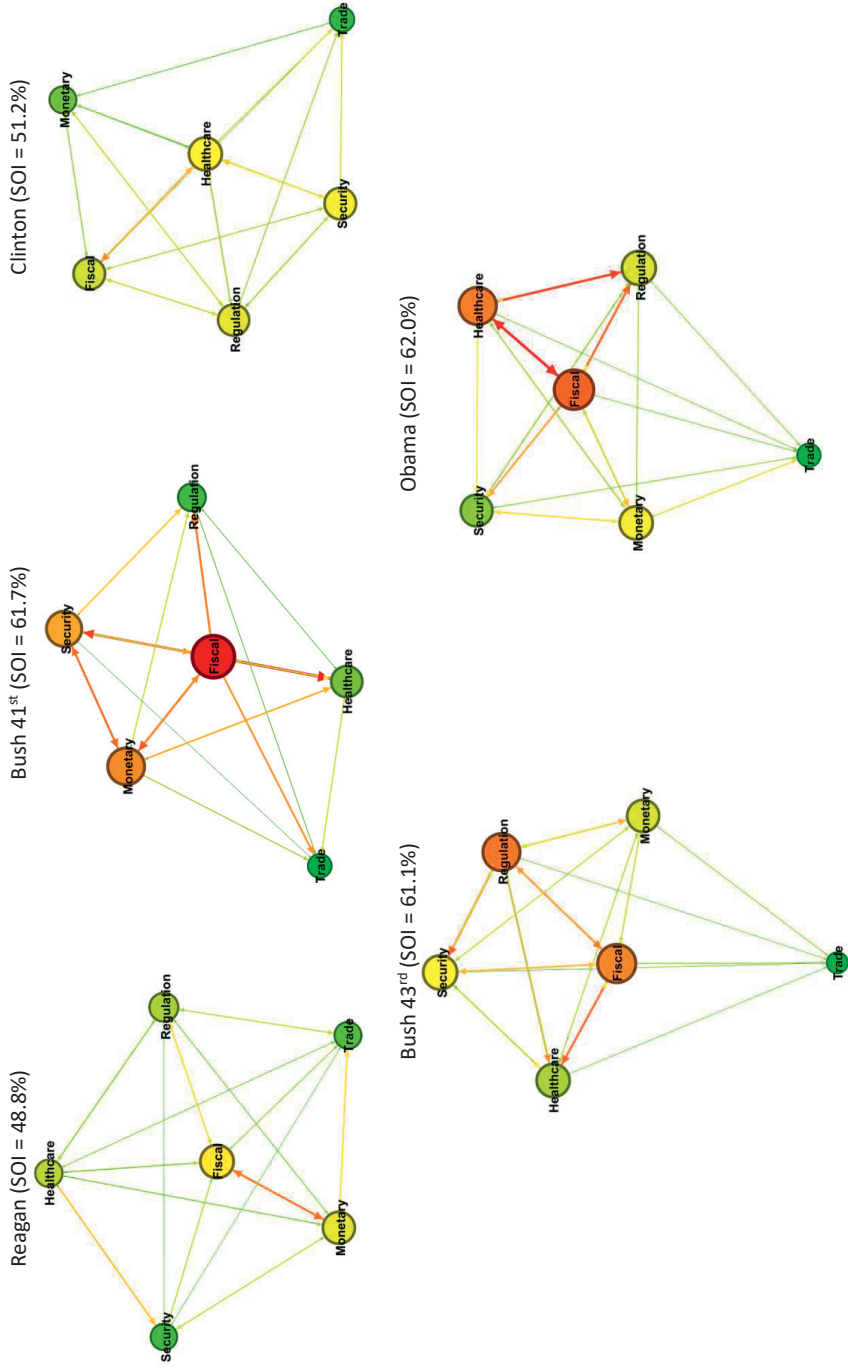
⁵⁴ Among others, we add the NBER recession indicator, Azzimonti’s (2017) partisan conflict index, and the aggregate EPU level index. While the main purpose of these estimations is to complement the analysis of Figure 9, they can also be viewed as a first attempt to identify the determinants of the observed EPU spillovers. However, the fact that most of our explanatory variables – which are inspired by the related literature – turn out to be insignificant, highlights the need for more in-depth future research into this area.

⁵⁵ Note that Blinder and Watson find that shocks to the *level* of EPU, in contrast, favoured Republican presidents.

⁵⁶ In this section, our goal is to characterise the fundamental structure of the EPU network during the five administrations. To this end, we estimate the VAR model for separate subsamples corresponding to each presidency. In other words, we momentarily return to a static, but now also conditional analysis. To avoid any potential bias from the previously found election effect, we exclude the months close to presidential elections after which a change in office took place from our estimations. In each case, the effective sample therefore begins in March after the respective president took office, and ends in September before he either lost an election or his presidency ended due to the 22nd Amendment.

⁵⁷ The corresponding spillover tables can be found in the appendix.

Figure 10: EPU Spillover Network Across Different Presidential Administrations



Notes: Static, conditional estimations. Effective samples begin in March after each president's inauguration and end in September before he was replaced (except for Reagan, 1985:03–1988:09).

In the first graph, we find a relatively close link between MPU and FPU. We conjecture that this due to at least three different factors present during Reagan's time in office. First, his administration followed an ambitious new economic policy framework, also known as Reaganomics – see, e.g., Feldstein (1994). However, simultaneously reforming the tax system, combating inflation and reducing the budget deficit was not a trivial task and at times resulted in a complex interplay of (potential) causes and effects between monetary policy, fiscal policy, and the economy (cf. Mussa 1994). While the most considerable policy changes were already implemented before 1985, there were also numerous examples of these kinds of interactions during Reagan's second term – see, e.g., Crudele (1985) or Nash (1986). Second, the 1987 stock market crash triggered much speculation about its potential causes and the resulting theories often involved the two policy types in question (see, e.g., Crichton 1987). Furthermore, despite the Fed's immediate reaction to the crash, Black Monday left many market participants more uncertain about the future paths of the central bank's and the White House's economic policy (cf. Kilborn 1987, Mussa 1994). Finally, a third link between MPU and FPU was established via the budget deficit's twin brother, the trade deficit.⁵⁸ Even though many economists saw the fundamental reasons for the large current account gap on the fiscal policy side, there was mounting political pressure to solve the problem via currency devaluation. It is very likely that the conflict between these two viewpoints and the associated solution approaches acted as a strong source of EPU. Moreover, the Plaza and Louvre meetings later made the Fed's policy indeed appear to have become more interventionist and therefore less predictable – even though actual monetary policy did not change very much initially (cf. Modigliani 1987, Feldstein 1994).⁵⁹

During the presidency of George H.W. Bush, the conditional SOI is substantially higher than during his predecessor's administration (61.7 percent). This increase is mainly due to fiscal policy, which turns out to be an exceptionally strong transmitter of uncertainty spillovers throughout this period. The category is particularly strongly connected to MPU and SPU, both being important sources of spillovers on their own. Together the three types of EPU form a close triangle in the network, with substantial spillovers going in each direction. This constitutes a significant finding because i) it confirms our previous assessment that the economic and political situation in the early-1990s also caused EPU spillovers to go from monetary to fiscal policy, ii) it further supports the notion that the Soviet Union's dissolution and the First Gulf War influenced FPU, and iii) it newly reveals a strong connection between MPU and SPU, with the 1990/91 recession and the prospect of war in the middle-east being once again the most likely interconnecting factors.⁶⁰

The next diagram plots the underlying EPU network for the Clinton administration. The main result here is that this presidency represents somewhat of an outlier in terms of the network's overall structure. Evidently, it is the only subperiod where conditional total spillover intensity decreases in comparison to the preceding administration (51.2 percent). Likely reflecting the White House's success with OBRA93 and the normalisation of its relationship with the Fed, fiscal and monetary policy are both largely neutralised as sources of EPU spillovers. The former even moves away from the network's centre, which is another result unique to this presidency. Equally consistent with political-economic history, the central position is instead assumed by HPU.

⁵⁸ Remember that, by construction, the GFEVD and thus our bilateral connectedness measures also account for any third-, fourth-, or fifth-round, etc. influences – e.g., a shock in MPU leading an increase in TPU, which, in turn, raises FPU.

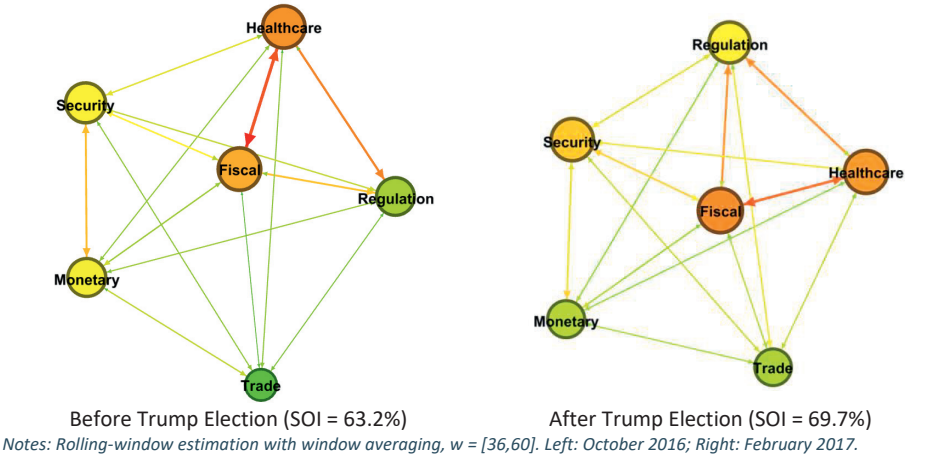
⁵⁹ Note that this interpretation is further corroborated by the unusually high connectedness between MPU and TPU that we find during the 1985-88 period.

⁶⁰ The Iraqi invasion of Kuwait, for example, caused the 1990s' largest oil price uncertainty and inflation shocks, and prompted speculation about the Fed's potential reaction to the developing recessionary and inflationary pressures (see, e.g., Silk 1990, Mankiw 2002, Thiem 2018).

When estimating the VAR for George W. Bush’s eight years in office, we not only find that FPU returns to its original location, but also that RPU becomes significantly more important. Both types of uncertainty exert a strong influence on all other variables in the system, except for TPU. As a result, total connectedness rises to 61.1 percent. Regarding the network’s edges, the relatively strong link from FPU to HPU is now particularly noteworthy. Taking the 2003 Medicare Modernization Act (MMA) as an example, it seems plausible that the connection is caused by the reinvigorated downward trend in public finances in combination with the healthcare system’s growing funding needs during that time. From the beginning, the MMA’s political process was difficult because of fears that the programme would further accelerate the deficit growth triggered by the Bush administration’s earlier tax cuts. The act was passed only after Republican leaders assured their colleagues that its costs would not exceed 400 bn. USD. However, shortly after the MMA’s signing, the White House surprisingly disclosed calculated expenses of more than 530 bn. USD, causing a considerable bipartisan outcry (see, e.g., Pear 2004).

Finally, the network graph for the Obama administration shows an even stronger EPU link between fiscal and healthcare policy. With substantial uncertainty spillovers in both directions, the two categories’ degree of connectedness turns out to be the highest across all diagrams depicted in Figure 10. In fact, the same also applies to the conditional SOI which rises to 62.0 percent for this presidency. Furthermore, the roles and the relationship of HPU and RPU have fundamentally changed. The former has replaced the latter as the EPU network’s second most important member. Moreover, healthcare policy now transmits large uncertainty spillovers towards regulatory policy, which seems to be a consequence of the ACA’s difficult implementation. In general, the conditional structure of the EPU network is clearly shaped by Obama’s most important political project.

Figure 11: EPU Spillover Network Before and After the Trump Election



4.3.3 The Trump Election

The result of the most recent election in November 2016 caught many journalists, politicians and investors by surprise. It was widely unexpected that Donald Trump – a Washington outsider with many extreme political views – would triumph over his more moderate and experienced rival, Hillary Clinton. Due to the president-elect’s plans to bring about major changes of existing legislation and institutions, the election outcome has created substantial uncertainty regarding future economic policy (see also Bown 2017). As we have seen above, it has also caused a significant jump in cross-category EPU spillovers.

Regarding the EPU spillover network's structure, we can get a first impression of Trump's presidency by looking at the near-term changes that have occurred since the election. Figure 11 shows the network before the election on the left-hand side (October 2016) and after the election on the right (February 2017). Also, Table 2 quantifies the differences between the two.⁶¹

Table 2: Differences Between the EPU Spillover Measures Before and After the Trump Election

To \ From	Monetary	Fiscal	Healthcare	Security	Regulation	Trade	From Others
Monetary	-5.9	0.4	0.1	-0.6	2.7	3.3	5.9
Fiscal	-1.3	-3.7	-4.7	2.9	2.2	4.6	3.7
Healthcare	-1.5	-2.1	-6.9	2.6	2.7	5.2	6.9
Security	-3.9	2.3	0.9	-5.9	3.5	3.1	5.9
Regulation	-2.1	2.7	-0.6	1.3	-3.7	2.5	3.7
Trade	-1.7	4.0	2.1	2.8	5.4	-12.6	12.6
To Others	-10.6	7.3	-2.2	8.9	16.5	18.7	6.4%
Net	-16.5	3.7	-9.1	3.0	12.8	6.1	
Avg. Conn.	-0.5	1.1	0.5	1.5	2.0	3.1	

Notes: Rolling-window estimation with window averaging, $w = [36, 60]$. Difference February 2017 / October 2016.

Between October 2016 and February 2017, the SOI rises by 6.4 percentage points, with TPU being the main contributor to this increase. The category's average connectedness measure surges by 3.1 percentage points and the corresponding node in the network graph moves much closer to the centre. This, in turn, is both attributable to trade policy receiving more uncertainty spillovers from other policy areas ($\Delta C_{T \leftarrow \blacksquare} = 12.6$), as well as transmitting more spillovers ($\Delta C_{\blacksquare \leftarrow T} = 18.7$), with an emphasis on the latter. Consequently, the policy area becomes more of a net EPU transmitter ($\Delta C_T = 6.1$).⁶²

Three of the remaining EPU categories exhibit similar changes: For regulatory policy EPU, we find a 12.8-point increase in the net spillover index. With \bar{C}_R rising by 2.0 percentage points, the category is also the second largest contributor to the SOI's increase. FPU and SPU display smaller changes with respect to their net connectedness indices – +3.7 and +3.0 points, respectively – but their total involvement nonetheless rises significantly as well ($\Delta \bar{C}_F = 1.1$, $\Delta \bar{C}_S = 1.5$). Post-election, only healthcare and monetary policy do not transmit more uncertainty spillovers to the rest of the system. On the contrary, both categories' aggregate to-spillover measures decline ($\Delta C_{\blacksquare \leftarrow H} = -2.2$, $\Delta C_{\blacksquare \leftarrow M} = -10.6$), while their from-spillover measures increase ($\Delta C_{H \leftarrow \blacksquare} = 6.9$, $\Delta C_{M \leftarrow \blacksquare} = 5.9$), ultimately leading to strongly negative net spillover effects ($\Delta C_H = -9.1$, $\Delta C_M = -16.5$) as well as relatively small changes in average connectedness ($\Delta \bar{C}_H = 0.5$, $\Delta \bar{C}_M = -0.5$). In summary, the election of Donald Trump has affected all parts of the EPU spillover network in profound, but also very different ways.

This variation in our results can be explained by the nature of Trump's political agenda. According to Bown (2017), in certain policy areas such as healthcare, taxation, and financial regulation, reforms at least similar to those now proposed by the Trump administration were to be expected sooner or later and also under any other president. However, in other policy areas such as trade policy, immigration

⁶¹ Using February 2017 as a point of reference for the election effect allows us to maximise the visual difference between the two network graphs in Figure 11, as the SOI also reaches its post-election maximum during that month. Nevertheless, the results are qualitatively similar when we use other months after October 2016 as benchmark.

⁶² Note that we are analysing the spillover measures' changes. In absolute terms, trade policy is a net receiver of uncertainty shocks both before and after the election. See also Tables A9-A10 in the appendix.

regulations, and international (security) cooperation, Trump’s approach to policymaking is considerably more unorthodox, unpredictable, and potentially damaging.⁶³

With respect to trade policy, for instance, Trump’s protectionist philosophy is unusual among the leaders of developed countries and almost certainly harmful. He has not only withdrawn the US from the Trans-Pacific Partnership, but also threatened to leave long-established trade agreements such as NAFTA or the WTO (see, e.g., Handley and Limao 2017b). As we explained earlier, up until now, the credible US commitment to these treaties has most likely limited the influence of TPU in the network. Moreover, Handley and Limao (2017b) argue that Trump’s actions have initiated a “trade cold war”, which generates enough uncertainty to significantly hurt the economy in the long-run. This may explain why the increase of $C_{\blacksquare \leftarrow T}$ is not only substantial, but also broadly spread across the other categories.

Similarly, Trump’s anti-immigrant campaign rhetoric and executive orders have revealed the most extreme and interventionist aspects of his approach to governing. Apart from the message that these measures conveyed about the potential long-term economic effects of Trump’s immigration policy (see, e.g., Mayda and Peri 2017), the ensuing legal challenges also showed that he tends to overstep the conventional boundaries of presidential authority (Bown 2017). Naturally, this causes uncertainty to spill over from regulatory policy to other policy areas.⁶⁴

All this being said, we have to keep in mind that this large increase in EPU spillovers is not without precedent. As we have seen in Section 4.3.1., there have been strong reactions of the SOI to changes in the Oval Office before. However, in some cases, total connectedness has continued to increase under the new government, while in others it has consistently fallen. In addition, our results in 4.3.2 suggest that the EPU categories’ relationships during each presidency are heavily influenced by the president’s key policy initiatives, especially when these affect the government’s financial outlook. In the case of Trump, the promised major tax reform was just recently enacted. If, in the medium to long run, this important project turns out to be more or less politically and economically successful than currently expected, the underlying direction and intensity of EPU spillovers may again change considerably. For these reasons, it is yet too early to reach a final verdict on how Donald Trump’s presidency will ultimately shape the EPU system.

5. Conclusions

We investigate spillovers of economic policy uncertainty across different policy areas in the United States. Using an augmented version of the Diebold-Yilmaz (2012, 2014) connectedness measurement framework and the category-specific EPU indices of Baker et al. (2016), we show that such spillovers are significant, heterogeneous across policy areas, and highly dynamic. We are able to match the time-varying behaviour of system-wide and category-specific connectedness with various important episodes in political-economic history. In particular, events leading to changes in the general political agenda, such as the election of a new president, seem to have a long-lasting influence on the EPU network.

Our study has important implications for different groups of readers. From an academic perspective,

⁶³ Bown (2017) also mentions potential reform of central bank independence as one of the disruptive policies unique to the Trump administration. However, we do not see much, if any, influence of this topic on the EPU network. The substantial drop in the category’s to-spillover measure, for instance, is likely caused by Yellen’s timely assurance that monetary policy would not be affected by the election outcome and the subsequent continuation of rate rises (cf. Appelbaum 2016).

⁶⁴ Two additional findings further support this interpretation: First, the largest jump in C_R occurs in January 2017, the month Trump issued three immigration-related executive orders, including the controversial “Muslim” travel ban. Second, when we use the financial regulation subindex, instead of the overall regulation EPU index, the strong increase in the category’s net spillover index disappears (see Appendix Figure B5).

our findings provide grounds for various types of future research. It would be interesting, for example, to conduct a more systematic investigation of the spillovers' (political) determinants. Likewise, further studies may compare EPU networks across countries or examine cross-country cross-category EPU spillovers. However, there are also two important lessons regarding econometric procedure: First, when analysing the impact of a *specific* type of EPU on economic variables, it is necessary to control for the influence of other EPU categories. Otherwise, spillovers are likely to cause an upward bias in the estimated effects. Second, using only an aggregate EPU index in empirical research may potentially lead to imprecise and unstable regressions as different policy categories dominate the EPU network at different points in time. The more specific the object of interest (e.g. aggregate vs sector-specific real activity), the more relevant this issue becomes.

Furthermore, being aware of cross-category EPU spillovers and of the EPU system's fundamental structure can help investors avoid EPU-induced return fluctuations. As a case in point, we identify a distinct pattern in the relationship between fiscal and healthcare (national security) policy uncertainty. This regularity may be useful, for instance, to anticipate share price volatility in the healthcare (defence) sector, when there is a looming partisan conflict over fiscal policy.

Finally, this paper's findings suggest that, to the extent that policymakers can influence the design and success of their major political projects, they can also influence the structure of the EPU network. Consequently, there is an additional incentive for them to manage communication better and to formulate more realistic policy proposals. Focussing on issues of government spending and taxation is probably most effective in this regard. As illustrated by our results for the Clinton era, neutralising fiscal policy as the central transmitter and receiver of uncertainty spillovers can significantly reduce EPU system's overall connectedness and hence its complexity.

Appendix A: Additional Figures & Tables

Table A1: Percentage of Shared Keywords in Combined Category-specific Term Sets

	Monetary	Fiscal	Healthcare	Security	Entitlement	Sovereign Debt	Regulation	Trade
Monetary	100%							
Fiscal	0%	100%						
Healthcare	0%	0%	100%					
Security	0%	6%	0%	100%				
Entitlement	0%	2%	8%	0%	100%			
Sovereign Debt	0%	0%	0%	0%	0%	100%		
Regulation	0%	0%	1%	0%	0%	0%	100%	
Trade	0%	0%	0%	0%	0%	0%	0%	100%

Notes: For further details on the category-specific terms see the online appendix to Baker et al. (2016).

Table A2: Correlations of the Category-specific EPU Indices

	Monetary	Fiscal	Healthcare	Security	Entitlement	Regulation	Trade
Monetary	1.00						
Fiscal	0.61	1.00					
Healthcare	0.24	0.73	1.00				
Security	0.68	0.53	0.22	1.00			
Entitlement	0.39	0.78	0.84	0.32	1.00		
Regulation	0.40	0.70	0.71	0.37	0.62	1.00	
Trade	0.14	0.08	0.10	0.12	0.03	0.11	1.00

Notes: Correlations are calculated for the full-sample period from January 1985 to March 2017.

Figure A1: Distributions of the Category-specific EPU Indices Before and After the Data Transformation

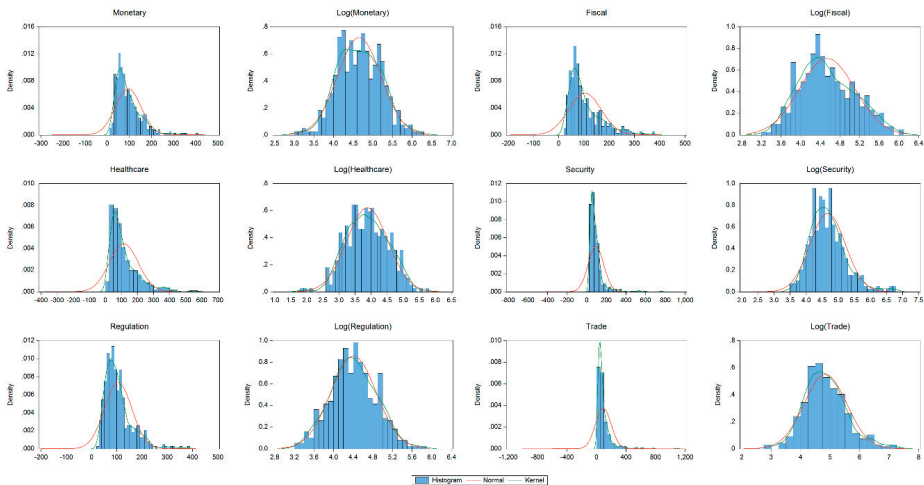
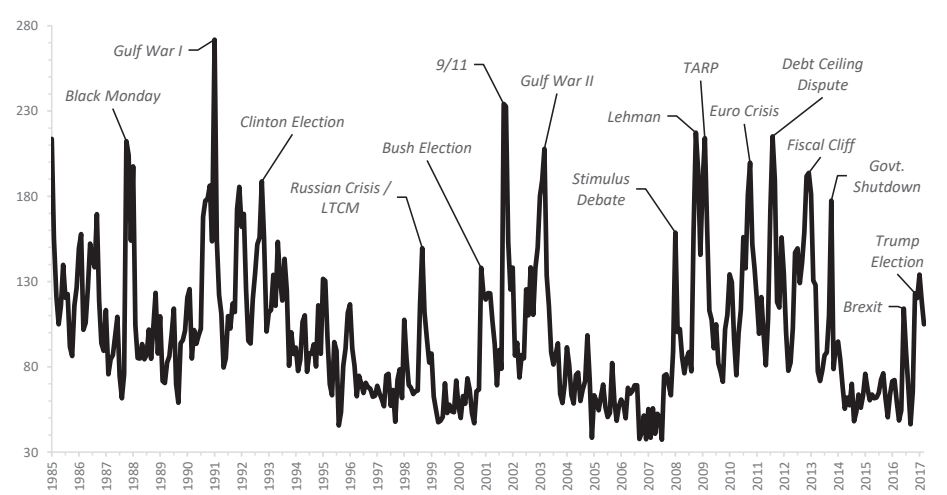


Table A3: List of Abbreviations & Label Sources

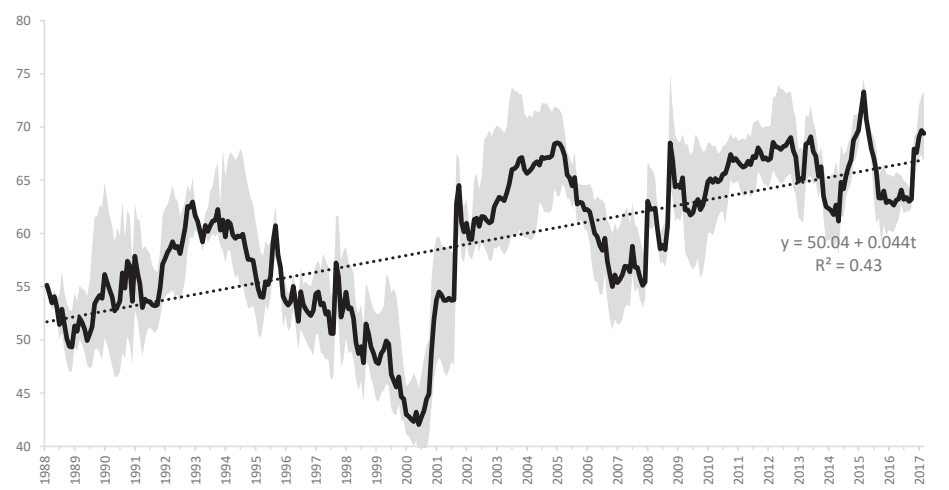
List of Abbreviations			
ACA	Affordable Care Act	JGTRRA	Jobs and Growth Tax Relief Reconciliation Act of 2003
AIG	American International Group	LTCM	Long-Term Capital Management
CA	California	MA	Massachusetts
CAFTA	Central America Free Trade Agreement	MCCA	Medicare Catastrophic Coverage Act of 1988
CISPA	Cyber Intelligence Sharing and Protection Act	NAFTA	North American Free Trade Agreement
DNC	Democratic National Committee	OBRA90	Omnibus Budget Reconciliation Act of 1990
EGTRRA	Economic Growth and Tax Relief Reconciliation Act of 2001	OBRA93	Omnibus Budget Reconciliation Act of 1993
EPA	Environmental Protection Agency	QE	Quantitative Easing
FDIC Act	Federal Deposit Insurance Corporation Improvement Act of 1991	SCHIP	State Children's Health Insurance Program
FIRREA	Financial Institutions Reform, Recovery, and Enforcement Act of 1989	S&L	Savings & Loan
GATT	General Agreement on Tariffs and Trade	TARP	Troubled Asset Relief Program
HIPAA	Health Insurance Portability and Accountability Act		
Label Sources: Baker et al. (2016), Davis (2017), Cutler and Gruber (2002), Elmendorf et al. (2001), Gale and Orszag (2004), Goodfriend (2002), Husted et al. (2016), Lawrence (2002), NY Times Digital Archive (www.nytimes.com), Todd (2011)			

Figure A2: EPU Index for the United States



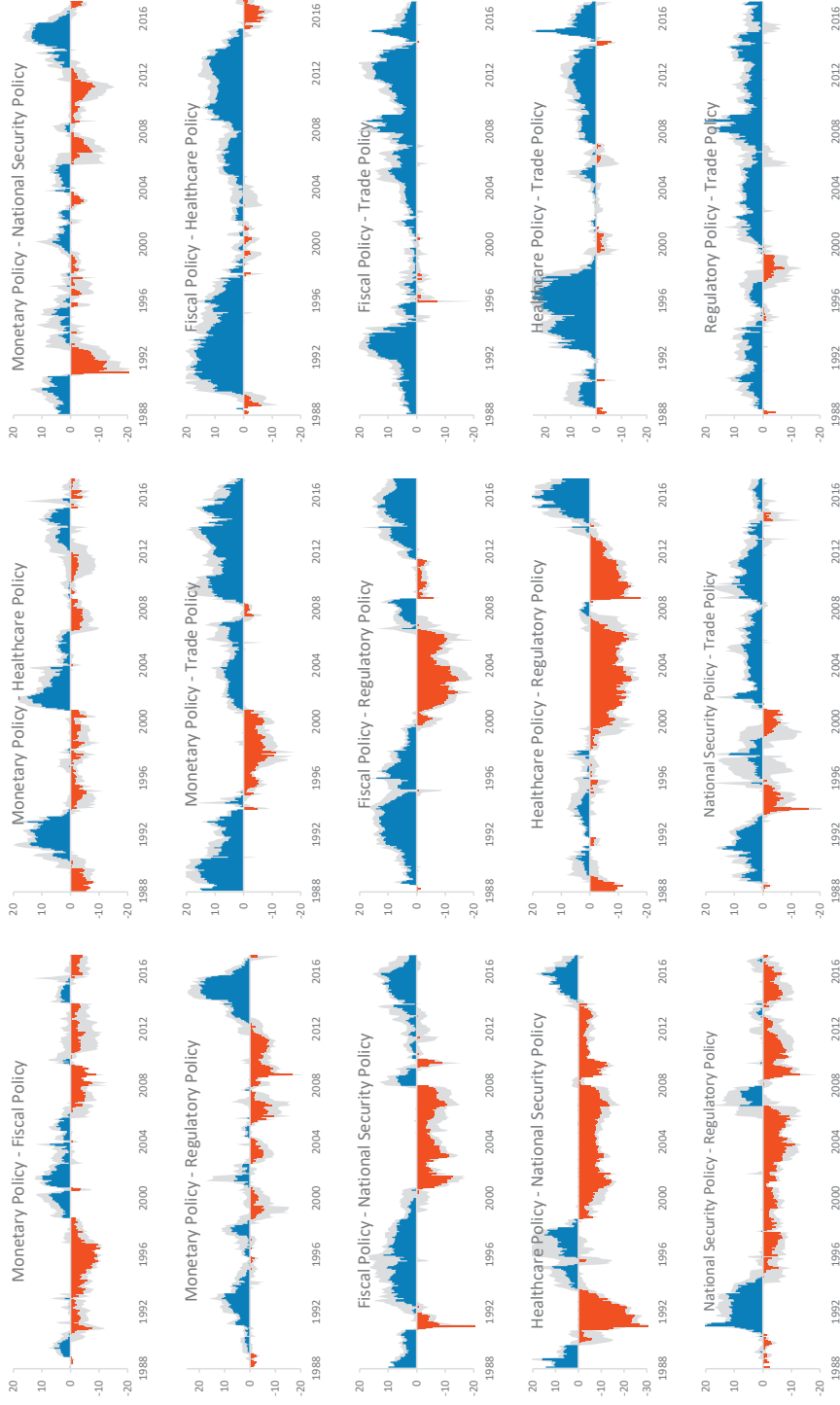
Data & Label Source: Baker et al. (2016), www.policyuncertainty.com (Newsbank version, April 2017). See Table A3 for abbreviations.

Figure A3: Dynamic Total EPU Spillover Index (linear trend, no event labels)



Notes: Rolling-window estimation with window averaging, $w = [36,60]$. The grey shaded area indicates the 90% interval of the distribution across window sizes.

Figure A4: Dynamic Net Directional EPU Spillovers – Pairwise



Notes: Rolling-window estimation with window averaging, $w = [36, 60]$. Grey shaded areas indicate the 90% intervals of the distributions across window sizes.

Table A4: Determinants of the Total EPU Spillover Index

Dep. Variable: SOI_t	(1)	(2)	(3)	(4)	(5)
<i>Constant</i>	2.111 (0.009)	2.097 (0.009)	1.932 (0.015)	-0.150 (0.894)	0.193 (0.864)
SOI_{t-1}	0.957 (0.000)	0.957 (0.000)	0.961 (0.000)	0.942 (0.000)	0.931 (0.000)
<i>Trend_t</i>	0.002 (0.036)	0.002 (0.036)	0.002 (0.068)	0.002 (0.046)	0.003 (0.011)
<i>Election_t</i>	0.443 (0.114)	-0.049 (0.902)	-0.050 (0.899)	-0.161 (0.682)	-0.170 (0.662)
<i>PresElection_t</i>		0.924 (0.085)	-0.308 (0.629)	-0.127 (0.899)	-0.354 (0.724)
<i>PresPartyChg_t</i>			2.466 (0.001)	2.187 (0.005)	1.998 (0.009)
<i>Recession_t</i>				0.050 (0.865)	-0.082 (0.786)
<i>PartisanC_t</i>				-0.001 (0.874)	0.001 (0.664)
<i>PresCloseness_t</i>				0.024 (0.864)	-0.012 (0.930)
<i>GovDivided_t</i>				0.148 (0.499)	0.138 (0.527)
<i>EPU_t</i>				0.677 (0.007)	0.710 (0.005)
<i>Democrat_t</i>					-0.404 (0.024)
\bar{R}^2	0.952	0.953	0.954	0.955	0.955
Observations	349	349	349	348	348

Notes: Linear regressions. Sample period: 1988:02–2017:03. *p*-values in parentheses. Test statistics significant at the 5% level are printed in bold. *Election_t* – October & November election dummy; *PresElection_t* – October & November presidential election dummy; *PresPartyChg_t* – October & November presidential election dummy with change in party control of the White House; *Recession_t* – NBER recession indicator; *PartisanC_t* – Azzimonti (2017) partisan conflict index; *PresCloseness_t* – popular vote margins of presidential elections in percentage points times -1 for October & November of election years, 0 otherwise; *GovDivided_t* – dummy for months with different party control of White House and Congress; *EPU_t* – Baker et al. (2016) aggregate EPU index; *Democrat_t* – dummy for months with Democratic control of the White House.

Table A5: EPU Spillover Table – Reagan Presidency

To \ From	Monetary	Fiscal	Healthcare	Security	Regulation	Trade	From Others
Monetary	43.3	23.8	9.9	8.8	7.9	6.3	56.7
Fiscal	22.9	42.9	12.1	4.6	12.9	4.6	57.1
Healthcare	1.5	6.9	69.1	4.3	13.0	5.2	30.9
Security	12.8	12.2	18.5	47.9	4.3	4.3	52.1
Regulation	6.8	17.2	6.2	4.4	55.0	10.5	45.0
Trade	17.1	9.5	7.5	4.2	12.9	48.8	51.2
To Others	61.1	69.6	54.2	26.3	51.0	30.9	48.8%
Net	4.4	12.5	23.3	-25.8	5.9	-20.3	
Avg. Conn.	11.8	12.7	8.5	7.8	9.6	8.2	

Notes: Static, conditional estimation. Effective sample: 1985:03 – 1988:09.

Table A6: EPU Spillover Table – Bush (41st) Presidency

To \ From	Monetary	Fiscal	Healthcare	Security	Regulation	Trade	From Others
Monetary	37.9	25.3	7.8	23.9	4.0	1.1	62.1
Fiscal	21.2	39.6	11.5	20.1	7.4	0.2	60.4
Healthcare	19.2	31.3	28.6	16.9	3.5	0.5	71.4
Security	23.4	27.6	2.3	41.3	4.9	0.5	58.7
Regulation	13.4	22.7	5.2	17.8	38.6	2.4	61.4
Trade	11.5	20.8	13.4	3.0	7.4	44.0	56.0
To Others	88.6	127.8	40.2	81.7	27.1	4.6	61.7%
Net	26.5	67.4	-31.1	23.0	-34.3	-51.4	
Avg. Conn.	15.1	18.8	11.2	14.0	8.8	6.1	

Notes: Static, conditional estimation. Effective sample: 1989:03 – 1992:09.

Table A7: EPU Spillover Table – Clinton Presidency

To \ From	Monetary	Fiscal	Healthcare	Security	Regulation	Trade	From Others
Monetary	55.8	11.0	5.6	10.6	10.0	7.0	44.2
Fiscal	9.6	42.9	21.9	10.7	13.9	1.1	57.2
Healthcare	5.2	19.0	41.3	18.4	13.7	2.4	58.7
Security	6.9	11.4	14.7	48.5	12.9	5.6	51.5
Regulation	13.0	13.3	9.6	10.1	48.6	5.4	51.4
Trade	3.2	3.0	13.9	13.9	10.4	55.6	44.4
To Others	37.9	57.7	65.7	63.7	60.9	21.5	51.2%
Net	-6.3	0.5	7.1	12.2	9.5	-22.9	
Avg. Conn.	8.2	11.5	12.4	11.5	11.2	6.6	

Notes: Static, conditional estimation. Effective sample: 1993:03 – 2000:09.

Table A8: EPU Spillover Table – Bush (43rd) Presidency

To \ From	Monetary	Fiscal	Healthcare	Security	Regulation	Trade	From Others
Monetary	40.5	15.6	9.1	12.5	19.6	2.8	59.5
Fiscal	13.1	29.2	15.9	18.3	22.9	0.6	70.8
Healthcare	11.5	24.3	25.7	16.5	21.5	0.6	74.3
Security	12.8	18.9	9.4	32.9	24.6	1.4	67.1
Regulation	13.5	20.5	10.2	13.0	41.7	1.2	58.3
Trade	8.4	10.6	6.2	5.3	6.2	63.3	36.7
To Others	59.2	89.7	50.8	65.6	94.8	6.6	61.1%
Net	-0.3	18.9	-23.5	-1.6	36.5	-30.1	
Avg. Conn.	11.9	16.1	12.5	13.3	15.3	4.3	

Notes: Static, conditional estimation. Effective sample: 2001:03 – 2008:09.

Table A9: EPU Spillover Table – Obama Presidency

To \ From	Monetary	Fiscal	Healthcare	Security	Regulation	Trade	From Others
Monetary	39.6	19.0	13.3	14.8	10.4	2.9	60.4
Fiscal	12.3	34.0	29.9	8.6	14.2	1.0	66.0
Healthcare	9.8	29.6	39.9	6.1	13.2	1.4	60.1
Security	17.1	20.5	15.0	30.3	13.3	3.8	69.7
Regulation	10.1	24.7	27.3	5.9	30.2	1.8	69.8
Trade	14.6	7.2	7.3	8.9	8.0	54.1	45.9
To Others	63.9	100.9	92.9	44.3	59.2	10.8	62.0%
Net	3.5	34.8	32.8	-25.4	-10.6	-35.2	
Avg. Conn.	12.4	16.7	15.3	11.4	12.9	5.7	

Notes: Static, conditional estimation. Effective sample: 2009:03 – 2016:09.

Table A10: EPU Spillover Table – Before Trump Election

To \ From	Monetary	Fiscal	Healthcare	Security	Regulation	Trade	From Others
Monetary	41.4	13.5	10.5	18.7	9.3	6.7	58.6
Fiscal	10.9	31.7	29.6	12.3	10.5	5.1	68.4
Healthcare	10.6	25.7	38.7	10.7	8.8	5.6	61.3
Security	18.3	15.6	14.2	30.9	12.2	8.8	69.1
Regulation	11.3	18.0	21.8	13.0	29.0	6.9	71.0
Trade	12.8	7.6	10.4	10.6	9.6	49.0	51.0
To Others	63.9	80.3	86.5	65.2	50.3	33.1	63.2%
Net	5.3	12.0	25.2	-3.8	-20.7	-17.9	
Avg. Conn.	12.2	14.9	14.8	13.4	12.1	8.4	

Notes: Rolling-window estimation with window averaging, $w = [36, 60]$. October 2016.

Table A11: EPU Spillover Table – After Trump Election

To \ From	Monetary	Fiscal	Healthcare	Security	Regulation	Trade	From Others
Monetary	35.5	13.8	10.6	18.1	12.0	10.0	64.5
Fiscal	9.6	28.0	24.9	15.2	12.6	9.7	72.0
Healthcare	9.1	23.6	31.8	13.3	11.5	10.8	68.3
Security	14.4	17.8	15.1	25.1	15.7	11.9	74.9
Regulation	9.1	20.8	21.2	14.3	25.3	9.4	74.7
Trade	11.1	11.7	12.5	13.4	15.0	36.4	63.6
To Others	53.3	87.7	84.3	74.1	66.8	51.8	69.7%
Net	-11.2	15.6	16.1	-0.8	-8.0	-11.8	
Avg. Conn.	11.8	16.0	15.3	14.9	14.2	11.5	

Notes: Rolling-window estimation with window averaging, $w = [36, 60]$. February 2017.

Appendix B: Sensitivity Analysis

Model Parameters

Figure B1: Dynamic SOI – Different Lag Lengths

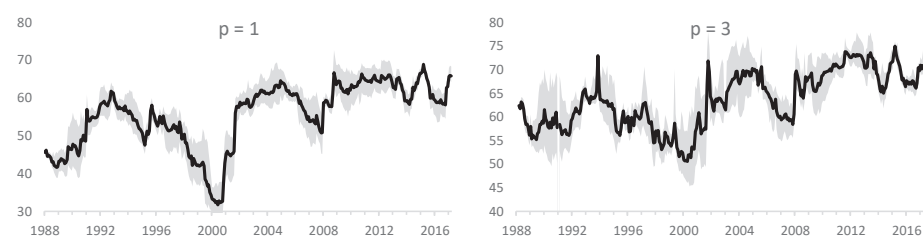


Figure B2: Dynamic SOI – Different Forecasting Horizons

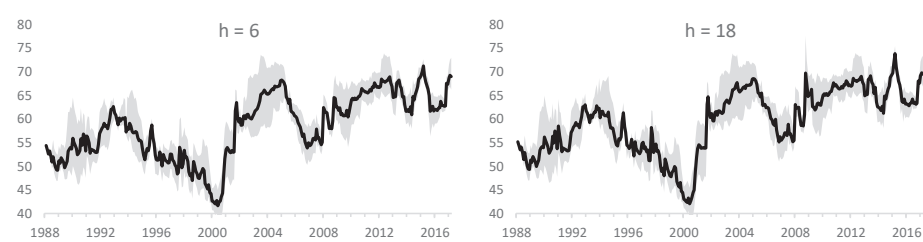
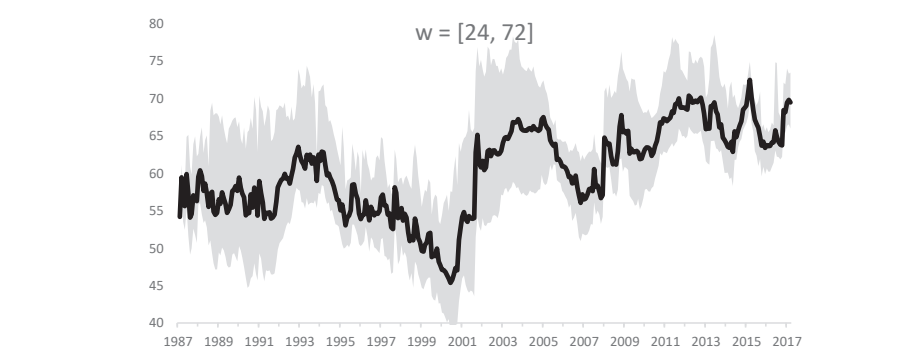
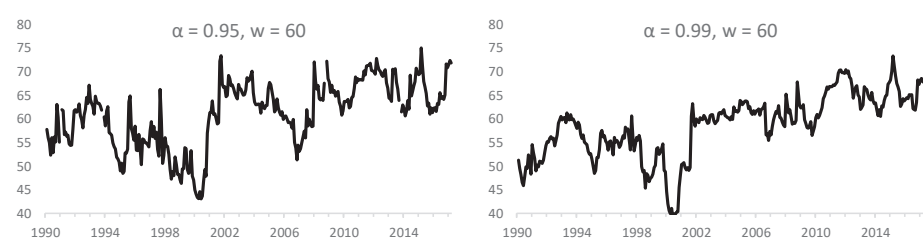


Figure B3: Dynamic SOI – Expanded Window Range



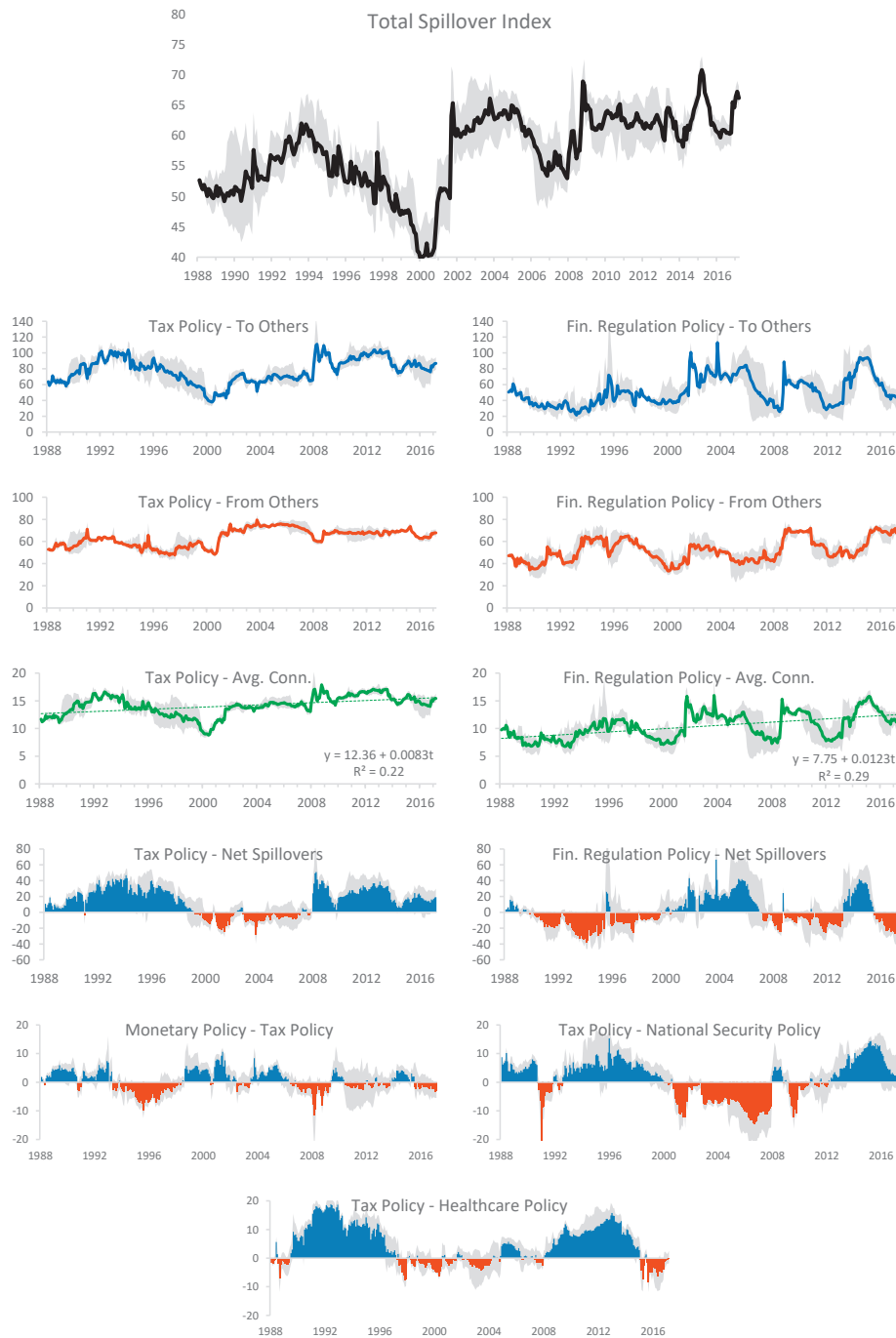
Exponential Smoothing Rolling Window

Figure B4: Dynamic SOI – Exponential Smoothing with Different Alpha



EPU Subindices: Tax Policy and Financial Regulation Uncertainty

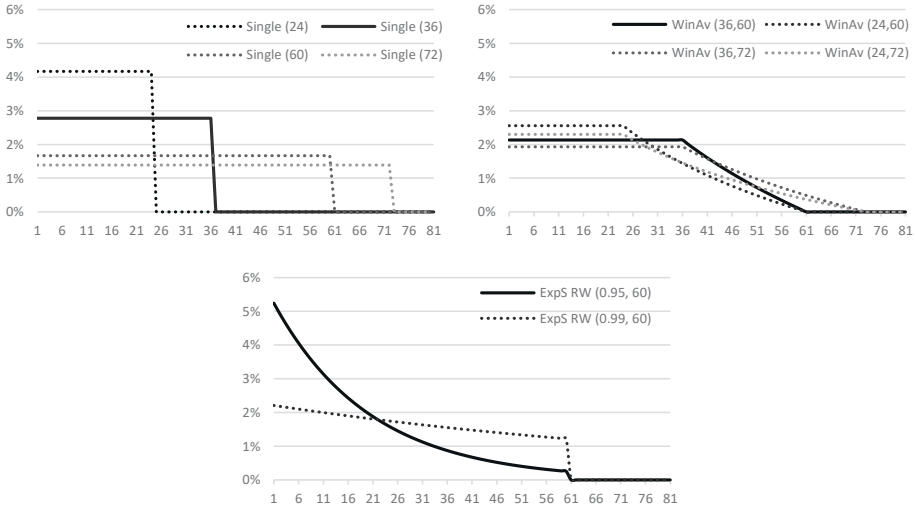
Figure B5: Dynamic Spillover Measures – Tax Policy and Financial Regulation Uncertainty in the EPU System



Appendix C: Advantages of the Window Averaging Procedure

In this appendix, we briefly illustrate some of the advantages of the WinAv procedure by comparing the (implicit) weights with which observations enter the VAR estimation in different rolling-window schemes. Figure C1 plots these weights for the traditional single-window approach, our WinAv procedure, and for an exponential smoothing (ExpS) rolling window – an alternative weighting scheme, where past observations receive continuously declining weights (see, e.g., Pesaran and Pick 2011, DY 2015, Tungsong et al. 2017).^{65, 66}

Figure C1: (Implicit) Observation Weights of Single, Window Averaging, and Exponential Smoothing Rolling Window Estimations



In the main text, one of the arguments that we mention in favour of WinAv is that the specific choices for the upper and lower boundaries of the window range, i.e. w_{Min} and w_{Max} , are less influential than the choice of a single w . From the depicted weight distributions, it now becomes clear why this is the case: With the single-window approach, each observation has either a weight of zero or the same weight as all other data points included in the window. For reasonable window sizes, any change in w

⁶⁵ It is important to note that in the WinAv case, the depicted weights materialise only indirectly. The WinAv procedure is first and foremost an averaging of estimation results and not an observation weighting scheme. Consequently, while the depicted weight distributions accurately reflect the procedure's behaviour in most cases, there are a few situations where the actual weights may differ from the ones depicted. This is the case, for example, when the results for a specific window size are excluded from the calculations because the estimated VAR was found to be non-stationary.

⁶⁶ The (implicit) observation weights ω can be calculated as $\omega_{Single}(y_j|w) = \begin{cases} \frac{1}{w}, & \text{for } 1 \leq j \leq w \\ 0, & \text{for } j > w \end{cases}$,

$$\omega_{WinAv}(y_j|w_{Min}, w_{Max}) = \frac{1}{w_{Max} - w_{Min} + 1} \sum_{w=w_{Min}}^{w_{Max}} \omega_{Single}(y_j|w), \text{ and}$$

$$\omega_{ExpS}(y_j|\alpha, w) = \begin{cases} \frac{1-\alpha}{1-\alpha^w} \alpha^{j-1}, & \text{for } 1 \leq j \leq w \\ 0, & \text{for } j > w \end{cases}, \text{ where } j = 1 \text{ represents the most recent observation and } \alpha \in [0,1] \text{ is the ExpS downweighting parameter (cf. Pesaran and Pick 2011).}$$

therefore implies a comparatively large redistribution of the relative weights of all included observations and, hence, a potentially large change of the estimation results.⁶⁷

When changing the upper boundary of the WinAv range, in contrast, there is only a relatively small redistribution effect because past observations are implicitly assigned lower weights than the most recent w_{Min} observations. Similarly, when changing the lower boundary, some of the data points receive a higher weight, while others receive a lower weight so that the change of any single observation's relative importance is again modest.

Because all observations have the same weight when a single window is used, once a past observation moves out of that window, its weight also drops to zero abruptly. As a consequence, important observations can have similarly large impacts on the estimation results when entering or leaving the simple rolling window. This is not the case with WinAv, where the ω_j 's decline continuously for $w_{Min} < j \leq w_{Max}$. As stated in the paper, our approach is therefore more robust to substantial variations at the end of the observation range.

Furthermore, the WinAv procedure reduces the risk of both over- and undersmoothing. While the former is another consequence of the relatively larger weights of more recent observations, the latter arises because WinAv typically uses a larger number of observations than the single window and because it tends to average out any erratic behaviour of the estimates present in small windows.

Finally, WinAv also has several advantages over ExpS. As can be seen from the lower panel of Figure C1, the downweighting parameter α has a considerable impact on the ExpS weight distribution and hence on the properties of the rolling window estimation.⁶⁸ The higher α , the more similar the distribution becomes to the one implied by the single-window approach, and therefore the more sensitive the estimation becomes to the choice of w and to any large variations in past observations. Only with a lower α , the estimates become more robust with respect to these two phenomena. In this case, however, the most recent observation also becomes increasingly overweight, which, in turn, makes the ExpS estimates more sensitive to outliers entering the window. Again, this problem does not arise with the WinAv approach, as its equal weighting of the recent w_{Min} observations provides a higher degree of stability.

⁶⁷ As w becomes larger, the specific choice of w becomes less relevant because the relative weights of individual observations become smaller. In that case, however, also the risk of oversmoothing increases as well as the loss of observations at the beginning of the sample period.

⁶⁸ ExpS, therefore, does not solve our main issue with the simple rolling window that a single parameter has a relatively strong impact on the estimation results. In fact, it may even worsen the problem, as there are situations in which both α and w are potentially important. The same can be said about explicitly time-varying parameter models because they are not only less general and more difficult to estimate, but also typically require a battery of assumptions and parameter choices that all influence the estimation outcome.

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