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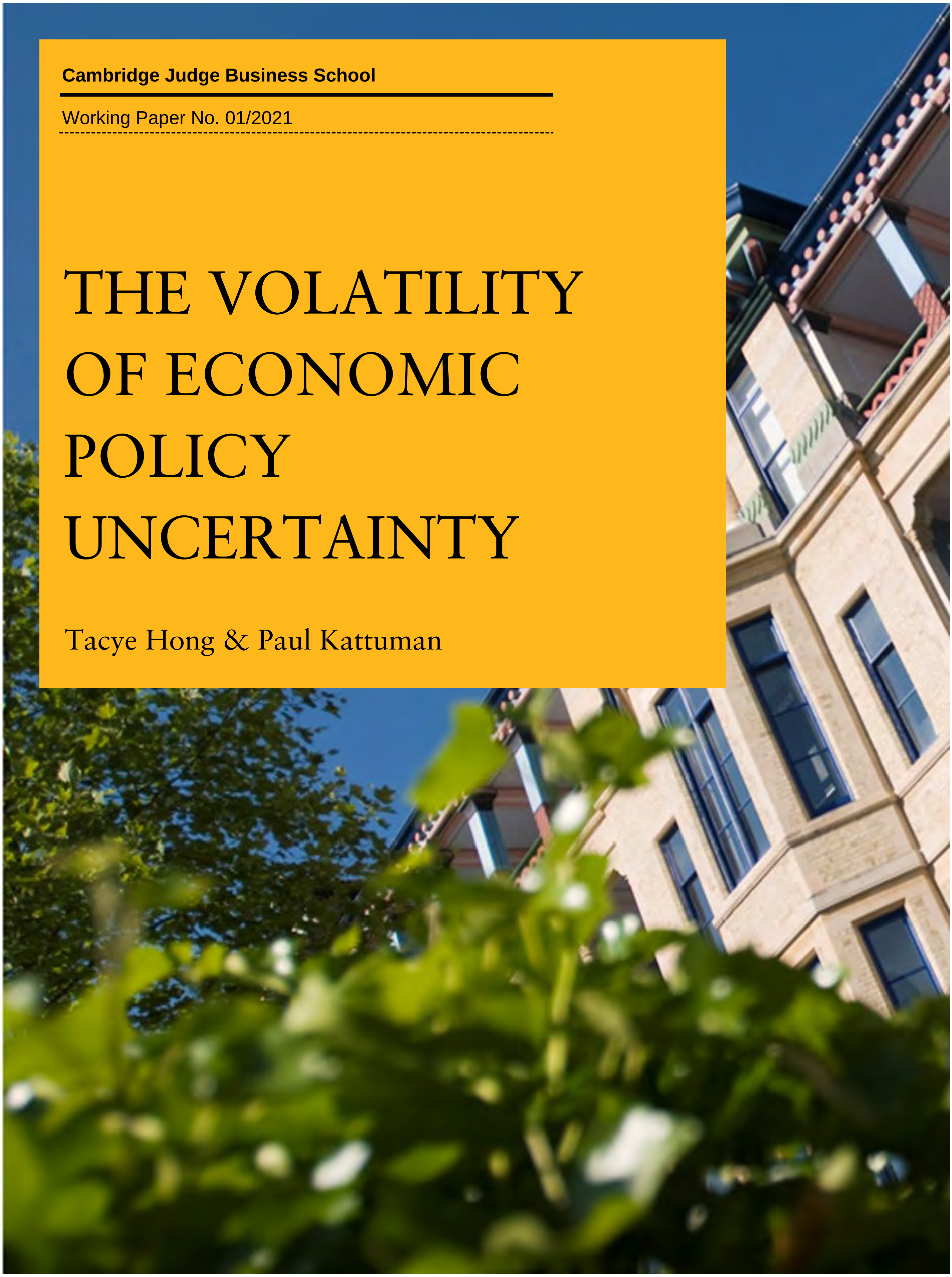

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The Volatility of Economic Policy Uncertainty

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Abstract

Theory as well as empirics suggest that both the level and the volatility of uncertainty impact important economic variables. There is a need to extend models of uncertainty to the volatility of uncertainty. We analyse the dynamics of the Economic Policy Uncertainty index developed by (Baker et al., 2016) and show that for four major economies in Europe – France, Germany, Italy and the UK – between 1997 and 2019, considerable portions of both the level and the volatility of economic policy uncertainty were generated by spillovers. Spillovers in the volatility of economic policy uncertainty was higher than spillovers in levels during major crises. These findings are relevant to the appraisal of economic policy uncertainty episodes in major trading partners.

Keywords: economic policy uncertainty, volatility clustering, GARCH estimation, spillovers

JEL codes: C22, C32, D80, F42

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1 Introduction

The effects of uncertainty, and the channels through which uncertainty impacts economic variables, are of great concern to researchers and policymakers. But obtaining precise measurements of uncertainty is difficult and the time series properties of uncertainty have not yet been studied very thoroughly. Researchers have tended to rely on surveys such as the Federal Reserve Bank of Philadelphia Survey for Professional Forecasters (SPF) and the European Central Bank (ECB) SPF for information about forecast uncertainty. These pure measures lack in frequency, and do not allow detailed examination of their dynamic properties.

Our focus in this paper is on policy uncertainty. The world constantly faces huge policy uncertainty; recent examples include the U.S. presidential election, the U.S.-China trade war, Brexit negotiations, and ongoing policies towards the COVID-19 pandemic. Our particular focus in this paper is on the nature and extent of spillovers of policy uncertainty between countries. The creation of the newspaper-based Economic Policy Uncertainty (EPU) index (Baker et al., 2016), which is available as frequently as daily, presents an opportunity to address the dynamic properties of policy uncertainty.

The EPU index measures aggregate uncertainty about economic policies by analyzing the frequency of policy-, uncertainty-, and economy-related keywords in newspaper articles. We study the monthly EPU index for 18 countries over a 22 year period to 2019 and find that there was significant asymmetry between the effects of increases and decreases in the level of economic policy uncertainty on its volatility. Building on this we analyse spillovers of both the level and the volatility of economic policy uncertainty, focusing on 4 major economies in Europe. We find that in the 1997 to 2019 period, on average about 20% of the forecast error variance of both the level and volatility was due to cross-border spillovers. During the financial crisis, and after the Brexit referendum, spillovers of volatility of uncertainty exceeded spillovers of the levels of uncertainty. This holds the of important message tha governmentsneed to take note of their spillover potential when evaluating episodes of economic policy uncertainty in major trading partners.

The rest of the paper is organised as follows. Section 2 reviews the substantive work on policy uncertainty as well as the literature on estimation methods. Section 3 details the model, with an illustration of the implementation for the United Kingdom. Section 4 studies the spillovers of shocks to the level and volatility of uncertainty in Europe and Section 5 concludes.

2 Literature

The EPU index has been used in a number of studies to investigate the effects of policy uncertainty, and its basic statistical properties have been documented.[1] Yu et al. (2017), Phan et al. (2018), and Fang et al. (2018) note that the EPU index displays volatility clustering. Bijsterbosch and Guérin (2013) noted that episodes of high EPU and episodes of high volatility in EPU often coincided with each other. Hall and Bentley (2017) studied volatility clustering in the US EPU index and found that marked yet temporary increases in volatility were associated with rare and significant events in the US. Gaps remain in our understanding of the dynamics of policy uncertainty. To the best of our knowledge this paper is the first to study the volatility of economic policy uncertainty along with its level with reference to international spillovers.

The gap in the modelling literature is critical as both theoretical and empirical work have shown that in general terms the volatility of uncertainty has an important role in determining the impact of uncertainty shocks on real variables. Using three "workhorse" macroeconomic models (an endowment asset pricing model, a real business cycle model, and a New-Keynesian model), de Groot (2019) showed that the volatility of uncertainty affects the risk premium and increases welfare costs.[2] Bachmann and Bayer (2009) considered different characterisations of volatility of uncertainty and showed that there was an almost linear relationship between the volatility of uncertainty and the volatilities of macroeconomic variables. Studying the EPU index Antonakakis et al. (2013) showed that increases in it volatility leads to increased uncertainty and reduced stock market returns. Similarly, Yin and Han (2014) showed that it would lead to increased price and volatility in the commodity markets. In a different vein Fendel et al. (2020) proxied for uncertainty using comprehensive survey data on levels of confidence, and studied the first four moments of this measure. They found that shocks to any of the first three moments of uncertainty could lead to a reduction in GDP, with the third moment generating a smaller impact, and the inclusion of the second moment improving the accuracy of GDP growth forecast.

In general, Volatility is often been used as a proxy for uncertainty. The literature on the volatility of volatility provides useful insights for the study of volatility of policy uncertainty.[3] The fact the Chicago Board Options Exchange (CBOE) began to publish the Volatility of Volatility Index (VVIX) in 2012 is a testament to the increased importance of the second order of volatility.[4] The ensuing literature constructed realized volatility measures and modelled them using fractionally integrated autoregressive moving average (ARFIMA) models and heterogeneous autoregressive (HAR) models. However, the Gaussian assumption on the residuals does not align with the right skewness and fat tails that residuals display empirically. Hence, Corsi et al. (2008) applied a standardized normal inverse Gaussian (NIG) distribution to a HAR-GARCH specification. This provided more accurate realized volatility density forecasts. A similar methodology was applied by Bubák et al. (2011) to the volatility of exchange rate volatility. The VVIX index has been shown by Park (2015) to be a better "tail risk indicator" than existing measures as the VIX options have greater market liquidity. It may be that the volatility of economic policy uncertainty can help improve impact analysis when used along with the level of economic policy uncertainty, or that it can be an even better indicator than the level itself. Careful modelling will be the first step to answering this question.

The final strand in the literature relevant to this paper relates to spillovers. The first measurement of spillover using an index is due to Diebold and Yilmaz (2008), who measured the financial asset returns and volatility spillover in the global equity market. This index was adopted by Klößner and Sekkel (2014) to study international spillovers of EPU. In a similar vein, Thiem (2018) used the spillover index to investigate the spillovers among different categories of EPU indices, also developed by Baker et al. (2016). These papers abstracted from the theory of spillover channels but Klößner and Sekkel (2014) suggested that international spillovers were caused by policies such as the unconventional monetary policy from the Federal Reserve affecting capital flows in other countries. Thiem (2018) proposed that political bargaining between different parties, as well as constraints due to financing and budget, lead to the spillovers across EPU categories. Studies such as Biljanovska et al. (2017) and Bhattarai et al. (2020) have shown both empirically and theoretically that uncertainty can spill over to other countries' real variables and interest rate spreads.

3 Asymmetric behaviour of the volatility of policy uncertainty

In order to examine asymmetry in the response of volatility of uncertainty to its level, we fit a univariate Threshold Generalized Autoregressive Conditional Heteroskedasticity (TGARCH) specification, with the conditional mean of the uncertainty series following an Autoregressive Integrated Moving Average (ARIMA) process.

Formally, we posit that the uncertainty series y_t follows an ARIMA(p, d, q) specification:

$$\Phi(L)(1-L)^d(y_t-\mu_t)=\Theta(L)\varepsilon_t, \tag{1}$$

where $\Phi(L) = 1 - \phi_1 L - \phi_2 L^2 - ... - \phi_p L^p$ and $\Theta(L) = 1 + \theta_1 L + \theta_2 L^2 + ... + \theta_q L^q$ are polynomials for the lag operator L, with p and q being the orders of the AR and MA processes, respectively. $d \in \mathbb{Z}_+$ indicates the number of times the series is being differenced. In the specification, feedback arises from volatility σ_t entering the equation for the mean of the series:

$$\mu_t = \mu + \gamma \sigma_t, \tag{2}$$

where μ is a constant and γ is the coefficient for the ARCH-in-mean (M) effects.

The TGARCH specification for the motion of the volatility is:

$$\sigma_t = \omega + \sum_{j=1}^{P} \alpha_j \sigma_{t-j}(|z_{t-j}| - \eta_j z_{t-j}) + \sum_{j=1}^{Q} \beta_j \sigma_{t-j}, \tag{3}$$

where ω is a constant, P is the order of the ARCH terms and Q is the order of the GARCH terms. z_{t-j} are the standardized innovations and η_j govern the rotation in the news impact curve, with $|\eta_j| \leq 1$. Interpretation for η_j is as follows: For each j, if η_j is positive (and significant), then for $z_{t-j} > 0$, the effect of z_{t-j} on σ_t is lowered, with the extreme of no impact if $\eta_j = 1$; and for $z_{t-j} < 0$, the effect of z_{t-j} on σ_t is magnified, to potentially doubling the effect if $\eta_j = 1$. On the other hand, if η_j is negative (and significant), then its impact on the effect of z_{t-j} is reversed. Hence, for $z_{t-j} > 0$, the effect of z_{t-j} on σ_t is magnified; and for $z_{t-j} < 0$, the effect of z_{t-j} on σ_t will be lowered. Hence, there is an asymmetry in the effects of positive and negative innovations on the volatility.

The error z_t is assumed to follow a normal inverse Gaussian (NIG) distribution (Barndorff-Nielsen, 1997), which falls within the class of Generalized Hyperbolic distributions. It is widely used in finance for modelling the realized volatility in financial markets (Corsi et al., 2008).[5] The NIG distribution family is flexible in accommodating a range of symmetric and asymmetric distributions, and has the advantage over the Gaussian distribution in that it captures any skewness in the error. It can also improve the accuracy of realized volatility density forecast (See Corsi et al. (2008)).

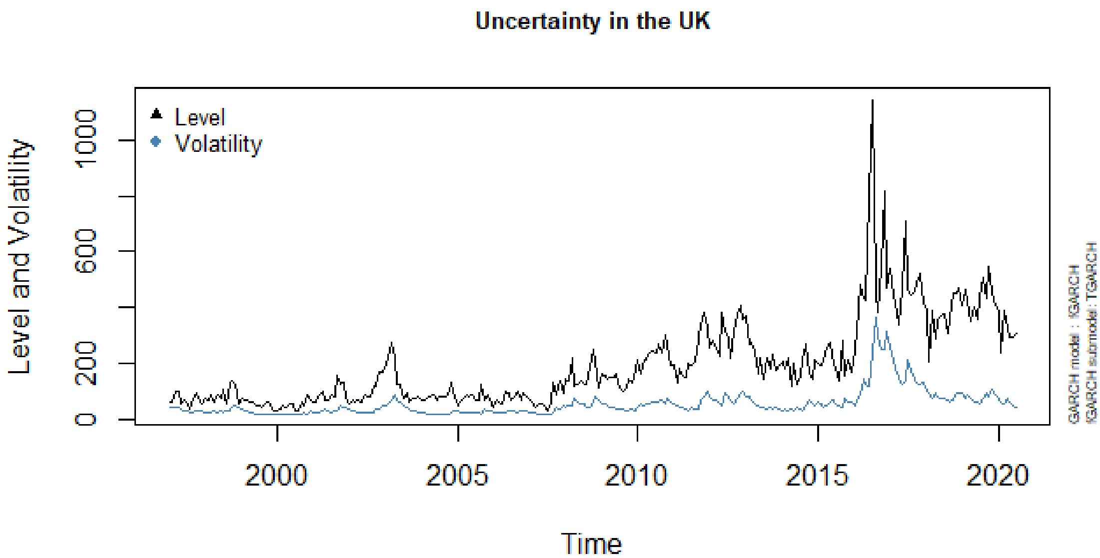
We follow the Box-Jenkins approach to decide on suitable time-series models for the EPU index. We begin with the analysis of the UK EPU index, and extend the analysis to 18 other countries' EPU indices. The model specification was based on several diagnostics: the Bayes Information Criterion; the weighted Ljung-Box and the weighted ARCH Lagrange Multiplier tests to check for autocorrelation in the residuals; the Nyblom stability test to check for any structural changes in the time series; the Engle and Ng sign bias tests to check for the effects of positive and negative shocks on volatility not predicted by the model; and the adjusted Pearson goodness-of-fit tests to check if the empirical distribution of the residuals follows the theoretical distribution assumed. Upon confirming the need to account for time-dependent conditional heteroskedasticity we proceed to fit the TGARCH-M-NIG specification as described in Equations (1), (2), (3), and (5).

Table 1: TGARCH-M-NIG Model Parameters for the UK EPU Index

Parameter	Coefficient	Parameter	Coefficient
μ	50.42***	γ	0.76**
	(12.57)		(0.30)
ϕ_1	1.32***	ω	1.69***
	(0.00)		(0.75)
ϕ_2	-0.16***	α_1	0.17***
	(0.02)		(0.05)
ϕ_3	-0.16***	β_1	0.82***
	(0.02)		(0.05)
θ_1	-0.85***	η_1	-1***
	(0.04)		(0.17)
Model Diagnostics			
Bayes Info. Criterion (BIC)			10.51
ARCH Lagrange Multiplier p-value			0.69
(Joint) Sign Bias p-value			0.82
Adjusted Pearson p-value			0.40

Note: The estimates for a TGARCH-M-NIG model fitted for the UK Economic Policy Uncertainty index from January 1997 to July 2020. The EPU index is taken from *policyuncertainty.com*. See equations (1), (2), (3), and (5) for the full specification of the model. The model passes all the diagnostic tests.

Figure 1: Level and Volatility of the UK EPU Index



Note: The figure shows the level and volatility of uncertainty in the UK from January 1997 to July 2020. The level of uncertainty is measured by the Economic Policy Uncertainty index created by Baker et al. (2016), available on *policyuncertainty.com*. The volatility is extracted from the TGARCH-M-NIG model specification explained in Table 1.

The estimated coefficients as well as the diagnostic test results for the TGARCH-M-NIG model fitted to the UK EPU index are shown in Table 1. Figure 1 plots the EPU index with its volatility as extracted from the model. It is apparent that the two series' trends are similar, justifying the ARCH-M specification considered. The most striking epoch when both the level and the volatility of uncertainty were high occurred in 2016, when the United Kingdom was grappling with Brexit-related events and issues. From 2018, the level of economic policy uncertainty in the UK has been higher than pre-2014 years, but the volatility of uncertainty has stabilised. Figure A1 in Appendix A displays the quantile-quantile (Q-Q) plot and the news impact curve. The news impact curve shows that there is extreme asymmetry between the effects of positive and negative innovations: an unexpected increase in economic policy uncertainty increases its volatility; whereas an unexpected decrease in uncertainty does not affect its volatility. This shows that the empirical distribution of the residuals in the TGARCH-M-NIG model indeed follows the theoretical distribution specified, i.e. the NIG distribution.

To assess the validity of the model, in particular the normal inverse Gaussian distribution specified, we consider 12-month horizon out-of-sample forecasts for 2018 and 2019 using the original TGARCH-M-NIG specification and a TGARCH-M-Gaussian specification. As shown in Table 2, the TGARCH-M-NIG specification produces lower mean absolute percentage errors (MAPE) in both years compared to the TGARCH-M-Gaussian specification, indicating that the NIG distribution can improve forecast accuracy for the UK EPU index. As the daily data for the EPU index is not readily available on *policyuncertainty.com*, we are unable to construct a realized volatility measure to test the forecast accuracy of the TGARCH-M-NIG model for the volatility of uncertainty.

Table 2: UK EPU Forecast Accuracy Test

Specification	2018 MAPE	2019 MAPE
TGARCH-M-NIG	23.12	13.55
TGARCH-M-Gaussian	25.44	20.97

Note: The TGARCH-M-NIG specification is able to produce a lower Mean Absolute Percentage Error (MAPE) than the TGARCH-M-Gaussian specification, when forecasting the UK Economic Policy Uncertainty index for both the 2018 and the 2019 12-month horizons.

The method described for the UK EPU index was applied to EPU indices for other countries. Details of the EPU series analysed are in Table B1 in Appendix B. The results for selected European countries (explored further in the next section) are presented in Table C2, whilst the remaining results are summarized in Tables C1 and C3 in Appendix C. With the estimated $\hat{\eta}_1$ being around -1 and significant for most series, it is apparent that strong asymmetric effects characterise all the series. Among the five emerging market economies considered in this paper, four display no significant "in-mean" effects, suggesting that the level of uncertainty in developing markets does not depend on the volatility of uncertainty.

4 Spillovers of Uncertainty in Europe

We now turn to the examination of international connectedness and spillovers of both the level and volatility of economic policy uncertainty, focusing on four major economies in Europe. Klößner and Sekkel (2014) used VAR modelling to study the international spillover of policy uncertainty among 6 major economies around the world, with attention limited to the level of uncertainty. We introduce volatility estimated using the TGARCH-M-NIG models into the analysis to extend understanding to spillovers in the volatility of uncertainty. Using monthly data from France, Germany, Italy and the United Kingdom from January 1997 to December 2019, we estimate a Vector Autoregressive (VAR) model with a lag order of 2 and a forecast horizon of 3.[6] The correlation matrices for the level and the uncertainty series are presented in Table B2 and Table B3 respectively. We follow Klößner and Sekkel (2014)'s methodology and construct an uncertainty level spillover index and an uncertainty volatility spillover index.

Essentially, the spillover index defined by Diebold and Yilmaz (2008) (SOI) condenses forecast error variance decomposition into a single value. SOI is constructed by first rewriting the VAR model with p lags from $Y_t = \Phi_1 Y_{t-1} + \cdots + \Phi_p Y_{t-p} + \varepsilon_t$ in a moving average representation, i.e. $Y_t = \varepsilon_t + A_1\,\varepsilon_{t-1} + A_2\,\varepsilon_{t-2} + \ldots$. The SOI is then calculated as:

$$SOI = 100 \times \frac{1}{N} \sum_{i=1}^{N} \frac{\sum_{i \neq j} \sum_{h=0}^{H-1} (A_h \mathcal{L})_{ij}^2}{\sum_{h=0}^{H-1} (A_h \Sigma_\varepsilon A_h')_{ii}}, \tag{4}$$

where $\mathcal{L}$ is the lower-triangular Cholesky factor such that $\mathcal{L}\mathcal{L}' = \Sigma_\varepsilon$ and Σ_ε is the covariance matrix of ε. By this property, the forecast error variance of variable i, i.e. $(A_h \Sigma_\varepsilon A_h')_{ii}$, can then be written as $\sum_{j=1}^{N} (A_h \mathcal{L})_{ij}^2$. As the Cholesky decomposition depends on the ordering of the VAR model, we follow Klößner and Wagner (2013) and average across all possible permutations, that is, in our case, $4! = 24$ permutations.

The results are summarized in Table 3, where the (i, j)-th entry shows the percentage of forecast error variance in country i's level (volatility) of uncertainty that comes from innovations to the level (volatility) of uncertainty in country j. For example, 9.21% of the forecast error variance in the UK's economic policy uncertainty level comes from innovations to the economic policy uncertainty level in Germany. Net flow of spillover for each country is the difference between the outflow, i.e. the total spillovers exported, and the inflows, i.e. the total spillovers imported. Thus the UK exported 18.33% and imported 20.14% of the spillovers in the level of economic policy uncertainty, leading to a small net flow of -1.81%. For both the level and the volatility of uncertainty from 1997 to 2019, almost 20% of the forecast error variance in these four major economies in Europe is generated by spillovers. Italy has the smallest extents of spillovers, both level and volatility, to and from the other countries. In particular, there is only a small amount of uncertainty flowing between Italy and United Kingdom, which is consistent with the fact that Italy is only a minor trading partner of the United Kingdom.

Table 3: Spillover Tables for the Level and Volatility of Uncertainty

Level of Uncertainty					
	France	Germany	Italy	UK	*Inflow*
France	75.19	10.44	5.21	9.15	24.81
Germany	12.12	71.78	4.87	11.23	28.22
Italy	3.98	5.87	88.66	1.50	11.34
UK	12.01	9.80	1.96	76.22	23.78
Outflow	28.11	26.11	12.04	21.88	
Net Flow	3.31	-2.11	0.69	-1.89	$SOI = 22.04$

Volatility of Uncertainty					
	France	Germany	Italy	UK	*Inflow*
France	73.75	16.17	4.73	5.35	26.25
Germany	12.03	73.44	5.28	9.25	26.56
Italy	2.76	3.94	91.55	1.75	8.45
UK	4.79	14.52	2.61	78.08	21.92
Outflow	19.59	34.63	12.63	16.34	
Net Flow	-6.67	8.07	4.18	-5.58	$SOI = 20.80$

Note: The (i, j)-th entry is the percentage of forecast error variance in country i's level (or volatility) of uncertainty from innovations to the level (or volatility) of uncertainty in country j. *Net flow* is the difference between the *Outflow* (off-diagonal column sum) and the *Inflow* (off-diagonal row sum). The spillover index *SOI* is calculated by averaging across all off-diagonal entries.

As evident from TGARCH-M-NIG estimates, the volatility of uncertainty feeds into the level of uncertainty for all developed countries. The above result suggests that the spillovers in level are driven to a large extent by the spillovers in volatility. It is especially worth-noting that the spillovers in level are of a comparable magnitude to the spillovers in volatility. This should inform governments to be prudent when evaluating uncertainty from major trading partners.

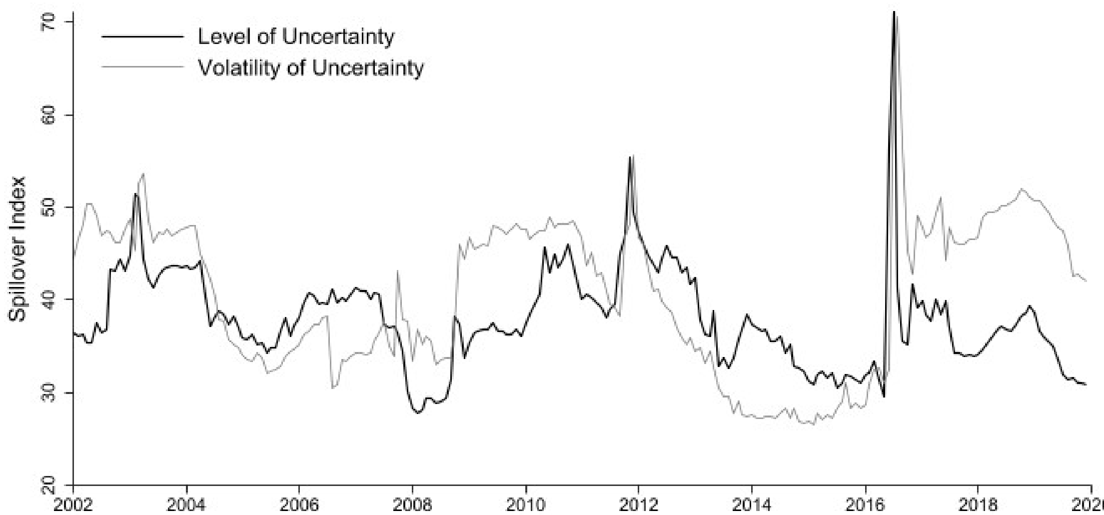
4.1 Dynamics of spillovers

We now turn our attention to the evolution of spillovers over time. The structure of the dynamic spillover index follows the one presented in the above section, but with a rolling window of 60 months. Figure 2 shows the spillover indices for both the level and volatility of uncertainty from 2002 to 2019, which demonstrates that the two indices move closely together for the majority of the period. During the financial crisis, the spillover in the volatility was higher than the spillover in the level of uncertainty. This was likely caused by the countries experiencing drastic differences in uncertainty from month to month. In late 2016, both indices experienced a huge spike, which was likely due to Brexit negotiations. However, afterwards, the magnitude of spillover in the volatility of uncertainty was again consistently higher than the spillover in the level.

To identify if the role of each country as an exporter or importer of uncertainty has changed across time, we now study the dynamic net spillover indices for each country. A positive value indicates that the country is exporting while a negative indicates the country is importing. Figure C2 illustrates that the patterns differ for across countries. The UK was suffering from a stagnant economy in 2002 and spilling out considerable uncertainty to the other countries. Among the four countries in our sample, Italy suffered the biggest slump due to the eurozone crisis. At the height of the crisis around 2011, Italy was exporting high levels of economic policy uncertainty. Between 2016 and 2017, there was a clear positive spike in UK's net spillover index, which can be attributed to Brexit. However, since the beginning of 2018, countries switched their roles and Italy once again became an exporter of uncertainty. Being the euro-zone's third largest economy, Italy's election struggle led to a slump in the global equity markets and posed a threat even to the U.S. rates hike, especially as Italy had substantial debt and was yet to recover from the crisis. While it was not very likely that Italy would also leave the European Union, the prospect will have been enough to cause huge spillover of uncertainty to the other countries.

The patterns for the spillover in the volatility of uncertainty are much sharper – each country only changes its role as an exporter/importer around once throughout the research horizon. According to Figure C3, the net spillover indices for France and Germany have similar magnitude but opposite signs. The two economies account for around half of the GDP in the euro area, but they diverged significantly after the economic crisis. Germany's stronger but more volatile economy compared to France (Cléaud et al., 2019) underpins these patterns. Germany's growth had been due to its substantial export share, while France relied on domestic demand and a slightly stronger import share. This is consistent with Germany exporting considerable volatility of uncertainty to the other economies, and France, with a negative trade balance vis-a-vis Germany, is likely to have absorbed a significant portion.

Figure 2: Dynamic Spillover Index



Note: The figure shows the dynamic spillover indices for the level and volatility of uncertainty using monthly data from January 1997 to December 2019. The level is measured by the Economic Policy Uncertainty index created by Baker et al. (2016), available on *policyuncertainty.com*; while the volatility is extracted from a TGARCH-M-NIG model specification. The spillover index shows the percentage of total variance in the forecast errors that is explained by spillovers of shocks across countries.

5 Discussions and Conclusions

The significant impact that volatility of economic uncertainty is known to have on welfare, risk premia and commodity prices highlights the importance of filling in gaps in our knowledge of the laws of motion of economic policy uncertainty and its volatility. This paper takes a useful first step by fitting a suitable empirical specification (TGARCH-M-NIG) to the Economic Policy Uncertainty index (Baker et al., 2016) and showing that (i) there is significant asymmetry in the effects of positive and negative innovations in economic policy uncertainty on its volatility; and (ii) the NIG distribution improves forecast accuracy for the EPU index. Building on this, we explore cross-border spillovers and find that both the level and the volatility of economic policy uncertainty spills across countries to significant extents. The spillovers in volatility of uncertainty were found to be greater during the financial crisis, and after the Brexit referendum. The dynamic patterns in spillovers map to economic conditions prevailing in the different countries.

This paper is a first step in generating a dialogue on the volatility of economic policy uncertainty, mirroring the analogous concept of the volatility of volatility which has gained attention in the literature. The theory behind international spillovers of both the level and the volatility of policy uncertainty is an important issue for further research.

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Notes

1. See, among others, Stock and Watson (2012), Bachmann et al. (2013), Colombo (2013), and Caldara et al. (2016).

2. As a result, de Groot (2019) suggested that theoretical models featuring uncertainty should be solved using a fourth-order perturbation to take into the account the volatility of uncertainty, as opposed to the third-order used in the current literature.

3. Baker et al. (2016) showed that the EPU index had a correlation coefficient of 0.58 with the VIX over the period 1990 to 2012. Moreover, a newspaper-based index that featured search terms relating to equity prices had a correlation coefficient of 0.73 with the VIX.

4. The VVIX is created by applying the VIX methodology to a cross section of VIX options.

5. The NIG distribution has four parameters: μ which governs the location, α which governs the heaviness of the tail, β the asymmetry parameter, and δ the scale parameter. The probability density function is:

$$f(z;\alpha,\beta,\mu,\delta) = \frac{\alpha}{\pi}\frac{K_1\alpha\delta\sqrt{1+(\frac{z-\mu}{\delta})^2}}{\sqrt{1+(\frac{z-\mu}{\delta})^2}}\exp\left\{\delta\left(\sqrt{\alpha^2-\beta^2}+\beta\frac{z-\mu}{\delta}\right)\right\}, \tag{5}$$

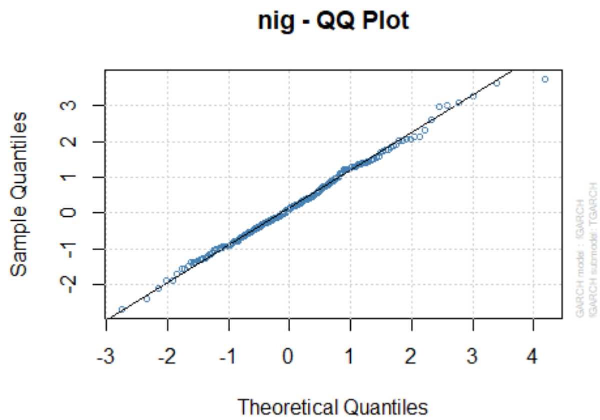
where K_1 is the modified Bessel function of the third kind of order 1.

The `rugarch` package in R Studio instead estimates $\zeta = \delta\sqrt{\alpha^2-\beta^2}$, and $\rho = \beta/\alpha$.

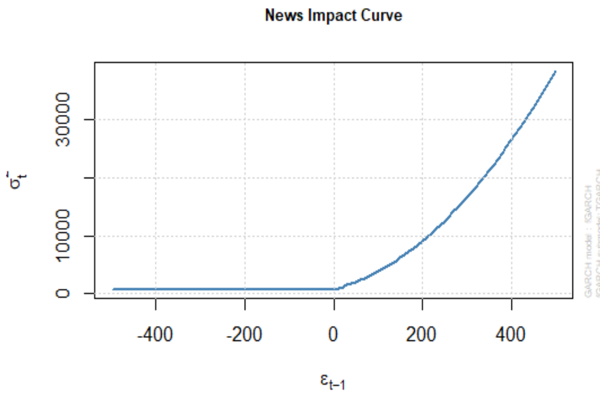
6. While a multivariate GARCH model might be more suitable given that uncertainty indices follow a GARCH structure as shown in the previous section, we keep the analysis here simple as it is not the main focus of this paper.

A Diagnostic Tests

Figure A1: Diagnostic Tests for the UK TGARCH-M-NIG Model



(a) Quantile-Quantile Plot



(b) News Impact Curve

Note: The quantile-quantile plot indicates that the empirical distribution of the residuals of the UK EPU index from the TGARCH model is close to the theoretical distribution (normal inverse Gaussian). The news impact curve shows that there is an asymmetry in the effects, i.e. only an unexpected increase in uncertainty will increase the volatility of uncertainty. Sample period: January 1997 to July 2020.

B Summary Statistics

Table B1: Summary of the EPU indices

Country	Adv. Econ.	Stationary	Source	Availability
Australia	✓	✓	Baker et al. (2016)	1997
Canada	✓		Baker et al. (2016)	1985
Chile			Cerda et al. (2017)	1993
China			Baker et al. (2013)	1995
France	✓	✓	Baker et al. (2016)	1987
Germany	✓	✓	Baker et al. (2016)	1993
Greece	✓	✓	Hardouvelis et al. (2018)	1997
India		✓	Baker et al. (2016)	1997
Italy	✓	✓	Baker et al. (2016)	1997
Japan	✓	✓	Arbatli et al. (2017)	1987
Korea	✓	✓	Baker et al. (2016)	1990
Mexico		✓	Baker et al. (2016)	1996
Netherlands	✓		Kroese et al. (2015)	1997
Russia			Baker et al. (2016)	1994
Spain	✓		Ghirelli et al. (2019)	1997
Sweden	✓		Armelius et al. (2017)	1985
United Kingdom	✓	✓	Baker et al. (2016)	1997
United States	✓		Baker et al. (2016)	1985

Note: Stationarity of the EPU series is tested using the Augmented Dickey-Fuller test. While all the series follow the methodology in Baker et al. (2016), some of these are created by different researchers. Monthly data starting from the earliest availability can be accessed via policyuncertainty.com.

Table B2: Correlation Matrix for the Level of Uncertainty

	France	Germany	Italy	UK
France	1			
Germany	0.73	1		
Italy	0.42	0.43	1	
UK	0.79	0.72	0.30	1

Note: The correlation matrix for the level of uncertainty among four major European economies from January 1997 to December 2019. The level of uncertainty is measured by the Economic Policy Uncertainty index, created by Baker et al. (2016) and available on *policyuncertainty.com*.

Table B3: Correlation Matrix for the Volatility of Uncertainty

	France	Germany	Italy	UK
France	1			
Germany	0.89	1		
Italy	0.04	0.08	1	
UK	0.71	0.74	0.12	1

Note: The correlation matrix for the volatility of uncertainty among four major European economies from January 1997 to December 2019. The volatility of uncertainty is extracted by estimating a TGARCH-M-NIG model for each country's Economic Policy Uncertainty index.

C TGARCH-M-NIG Results

Table C1: Estimated Parameters for Emerging Market Economies

	Chile	China	India	Mexico	Russia
Specification	(3,1,0)(1,1)	(0,0,1)(1,1)	(1,1,2)(1,1)	(2,0,1)(1,2)	(3,1,1)(1,1)
μ	8.33***	2.00	104.93***	126.55***	1.03
	(0.45)	(1.47)	(14.19)	(12.64)	(0.73)
ϕ_1	-0.50***	-	0.94***	1.30***	0.27***
	(0.02)	-	(0.02)	(0.00)	(0.05)
ϕ_2	-0.35***	-	-	-0.30***	0.08
	(0.04)	-	-	(0.00)	(0.06)
ϕ_3	-0.22***	-	-	-	0.16***
	(0.05)	-	-	-	(0.05)
ϕ_4	-	-	-	-	-
	-	-	-	-	-
θ_1	-	-0.59***	-0.37***	-0.87***	-0.95***
	-	(0.05)	(0.09)	(0.02)	(0.00)
θ_2	-	-	-0.16***	-	-
	-	-	(0.06)	-	-
γ	-0.24***	-0.03	-0.30	0.48*	-0.01
	(0.02)	(0.04)	(0.42)	(0.27)	(0.02)
ω	3.22***	0.63	5.64***	1.03**	0.32***
	(0.30)	(0.51)	(1.75)	(0.51)	(0.02)
α_1	0.11***	0.08***	0.17***	0.12***	0.04***
	(0.02)	(0.03)	(0.05)	(0.04)	(0.01)
β_1	0.82***	0.92***	0.69***	0.15**	0.96***
	(0.02)	(0.03)	(0.07)	(0.08)	(0.00)
β_2	-	-	-	0.74***	-
	-	-	-	(0.08)	-
η_1	-1***	-0.89***	-1***	-1**	-1***
	(0.26)	(0.31)	(0.23)	(0.42)	(0.22)
BIC	9.76	10.29	9.56	9.92	11.08

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Each EPU index is fitted to a ARIMA(p, d, q)-TGARCH(P, Q)-M-NIG model. See Table B1 for data sources.

Table C2: Estimated Parameters for Selected European Economies

	France	Germany	Italy	UK
Specification	(4,0,0)(1,1)	(2,0,1)(1,1)	(4,0,0)(1,1)	(3,0,1)(1,1)
μ	158.89***	14.74**	-10.25	50.42***
	(27.80)	(7.48)	(14.80)	(12.57)
ϕ_1	0.57***	-0.01	0.12	1.32***
	(0.06)	(0.10)	(0.12)	(0.00)
ϕ_2	0.21***	0.29***	0.15***	-0.16***
	(0.04)	(0.06)	(0.05)	(0.02)
ϕ_3	0.07**	-	0.14**	-0.16***
	(0.03)	-	(0.07)	(0.02)
ϕ_4	0.12***	-	0.26***	-
	(0.03)	-	(0.06)	-
θ_1	-	0.32***	-	-0.85***
	-	(0.12)	-	(0.04)
γ	-1.91**	2.41***	4.12***	0.76**
	(0.80)	(0.19)	(0.46)	(0.30)
ω	0.86*	0.47***	19.39***	1.69***
	(0.48)	(0.16)	(2.06)	(0.75)
α_1	0.07**	0.04***	0.05***	0.17**
	(0.03)	(0.00)	(0.02)	(0.05)
β_1	0.93***	0.96***	0.30***	0.82***
	(0.02)	(0.01)	(0.08)	(0.05)
η_1	-1**	-1***	-1**	-1***
	(0.50)	(0.40)	(0.52)	(0.17)
BIC	10.35	10.37	9.70	10.51
ARCH LM p-value	0.75	0.85	0.74	0.69
Sign Bias p-value	0.50	0.21	0.91	0.82
Adj. Pearson p-value	0.49	0.55	0.25	0.40

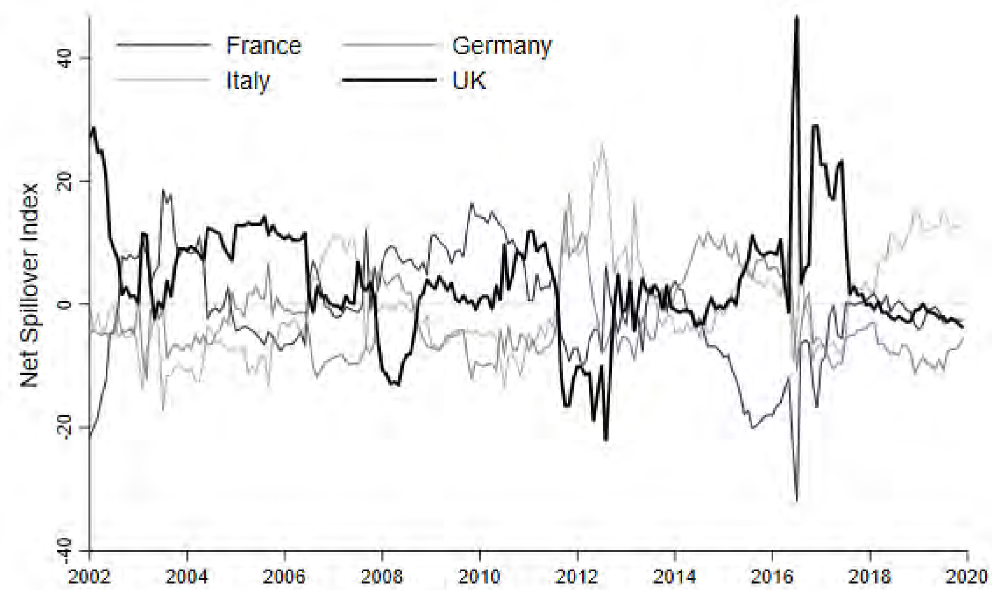
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Each EPU index is fitted to a ARIMA(p, d, q)-TGARCH(P, Q)-M-NIG model. See Table B1 for data sources.

Table C3: Estimated Parameters for Advanced Economies

	Australia	Canada	Greece	Japan	Korea	Netherlands	Spain	Sweden	US
Spec.	(2,0,0)(1,1)	(4,1,0)(1,1)	(4,0,0)(1,1)	(3,0,1)(1,2)	(3,0,1)(1,1)	(2,1,0)(1,1)	(3,1,0)(1,1)	(1,1,1)(1,1)	(1,1,1)(1,1)
μ	85.63***	10.27***	111.62***	100.43***	50.18***	9.31***	7.94***	-0.96***	1.62***
	(5.81)	(2.39)	(11.47)	(4.90)	(18.52)	(1.53)	(1.56)	(0.23)	(0.39)
ϕ_1	0.50***	-0.36***	0.73***	1.48***	1.27***	-0.52***	-0.31***	0.35***	0.44***
	(0.05)	(0.04)	(0.08)	(0.02)	(0.01)	(0.06)	(0.07)	(0.05)	(0.05)
ϕ_2	0.23***	-0.16***	-	-0.71***	-0.19***	-0.28***	-0.27***	-	-
	(0.04)	(0.05)	-	(0.04)	(0.03)	(0.06)	(0.09)	-	-
ϕ_3	-	-0.16***	-0.08**	0.17***	-0.09***	-	-0.15**	-	-
	-	(0.06)	(0.03)	(0.02)	-	(0.06)	-	-	
ϕ_4	-	-0.12**	0.11***	-	-	-	-	-	-
	-	(0.05)	(0.03)	-	-	-	(0.03)	-	-
θ_1	-	-	-	-0.63***	-0.90***	-	-	-0.91***	-0.86***
	-	-	-	(0.04)	(0.06)	-	-	(0.03)	(0.03)
γ	0.29***	-0.24**	-1.08*	-0.51**	1.28***	-0.34***	-0.42***	0.06***	-0.05***
	(0.11)	(0.06)	(0.63)	(0.20)	(0.47)	(0.07)	(0.09)	(0.02)	(0.01)
ω	8.76***	4.09***	4.92***	7.24***	6.24**	3.34***	2.97**	11.62	1.05
	(2.05)	(0.95)	(1.59)	(1.75)	(2.76)	(0.72)	(1.29)	(1.61)	(0.94)
α_1	0.22***	0.13***	0.11**	0.28***	0.14***	0.11***	0.09***	0.12***	0.07
	(0.06)	(0.03)	(0.05)	(0.07)	(0.04)	(0.03)	(0.03)	(0.05)	(0.05)
β_1	0.61***	0.80***	0.67***	0.22**	0.71***	0.79***	0.77***	0.09	0.92***
	(0.07)	(0.02)	(0.09)	(0.10)	(0.09)	(0.03)	(0.05)	(0.11)	(0.06)
β_2	-	-	-	0.15	-	-	-	-	-
	-	-	-	(0.11)	-	-	-	-	-
η_1	-1***	-1***	-1**	-1***	-1***	-1***	-1**	-1**	-1**
	(0.36)	(0.35)	(0.49)	(0.23)	(0.29)	(0.29)	(0.49)	(0.45)	(0.45)
BIC	9.95	10.02	8.91	8.64	10.08	9.41	8.47	8.23	9.45

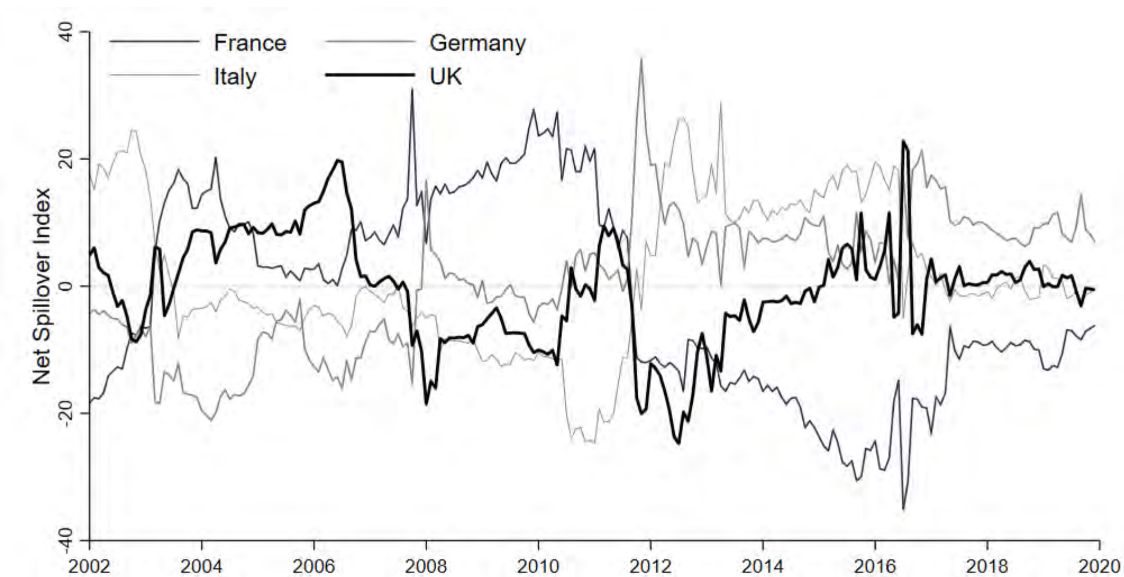
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Each EPU index is fitted to a ARIMA(p,d,q)-TGARCH(P,Q)-M-NIG model. See Table B1 for data sources.

Figure C2: Net Spillover Indices for the Level of Uncertainty



Note: The figure shows the dynamic spillover indices for the level and volatility of uncertainty using monthly data from January 1997 to December 2019. The level is measured by the Economic Policy Uncertainty index created by Baker et al. (2016), available on *policyuncertainty.com*. The net spillover index measures the outflow net of inflow. A positive value indicates that the country is an exporter of level of uncertainty while negative indicates an importer.

Figure C3: Net Spillover Indices for the Volatility of Uncertainty



Note: The figure shows the dynamic net spillover indices for the volatility of uncertainty using monthly data from January 1997 to December 2019. Volatility is extracted from a TGARCH-M-NIG model specification detailed in. A positive value indicates that the country is an exporter of volatility of uncertainty while negative indicates an importer.