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Which Uncertainty Measure is Most Informative? A Time-varying Connectedness Perspective

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ABSTRACT: We investigate the relationship between the three most popular uncertainty measures with the means of the state-of-the-art connectedness frameworks applied to the time-varying parameters vector autoregression model with stochastic volatility. We find marked increases in uncertainty connectedness during major economic turmoil and hostile events. VIX turns out to be the most forward-looking uncertainty measure that persistently transmits shocks to the remaining uncertainty proxies at lower frequencies. In turn, GPR, approximating specific information related to geopolitical risk, transmits shocks to other measures at short-term frequencies, while the EPU index is largely replicating unanticipated movements in the VIX or GPR. We also present implications of these findings for economic modelling.

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1 Introduction

The importance of uncertainty for the real economy and financial markets is well recognized in the literature. The theoretical framework on how the economy reacts to uncer-

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tainty shocks was already developed in the early 1980s (e.g., Bernanke, 1983). However, the voluminous empirical literature, which attempts to measure the magnitude and persistence of uncertainty shocks and their effects on the real economy and financial markets, started to emerge two decades later. There are two reasons behind this delay. First, during the Great Moderation period, which was characterized by a significant reduction in the volatility in business cycle fluctuations, the academic interest in the topic of how uncertainty transmits to the economy was low. This situation has changed with the critical events that sharply elevated uncertainty, such as the global financial and European sovereign debt crises, the outbreak of the Covid-19 pandemic, and the Russian invasion of Ukraine. Second, the advances in machine learning coupled with rising computational power and the dissemination of dedicated software have allowed researchers to easily examine, describe and interpret textual data by transforming it into a quantitative representation. This development in natural language processing gave rise to econometric analyses on the link between sentiment and key economic variables (for a survey on sentometrics see Algaba et al., 2020). In economics, this progress allowed researchers to develop news-based uncertainty measures, of which the most well-known ones are the Economic Policy Uncertainty (EPU) index by Baker et al. (2016) and the most recent Geopolitical Risk (GPR) index by Caldara and Iacoviello (2022). The high interest in both these indices is reflected, among others, by the fact that according to the Google Scholar database by the end of 2023 both articles had been cited well over 10 thousand and 1 thousand times, respectively.

Uncertainty is inherently a latent variable. Consequently, it cannot be precisely measured and must be approximated. In the literature, two broad methods of quantifying uncertainty are usually applied.[1] The first one is based on newspaper articles. It has gained high popularity in economics and finance, most likely due to the ubiquity of textual data for different geographic regions and the simplicity of computation once the database of news articles is at disposal. For instance, the EPU index proposed by Baker et al. (2016) is a weighted average of three components: (i) the frequency of major news discussing economic policy-related uncertainty in ten major US newspapers, (ii) a measure of expiring tax provisions and (iii) forecasters' disagreement about the economic outlook. In turn, the GPR index by Caldara and Iacoviello (2022) aims to proxy geopolitical tensions and is solely based on a tally of newspaper articles reporting on threats to peace (e.g., war, nuclear or terror threats and military buildups) or actual hostilities (wars, their escalation, and acts of terror) which affect the peaceful course of international relations. The second measure of uncertainty is based on the volatility of a given financial asset. It can be calculated as the conditional volatility from a GARCH or SV model or derived as implied volatility by inverting the valuation model of options for a given underlying instrument (see Poon and Granger, 2003, for a review of these methods in forecasting

[1] There are also other methods based on, among others, the level of disagreement by professional forecasters or survey-related confidence indicators. However, these kinds of measures usually relate to specific variables or markets, hence we do not discuss them in this paragraph.

volatility in financial markets or Smiech et al., 2021 for a survey on how these measures are applied to model the dynamics of the crude oil market). In the latter case, the Volatility Index (VIX), developed and maintained by the CBOE, is the best known example. It represents market expectations for the 30-day ahead S&P500 index volatility derived from the prices of options. As a result, given an efficient market, it should discount all backward and forward-looking information available to market participants. The above three uncertainty proxies (EPU, GPR and VIX) are the most commonly used variables in investigations on how uncertainty affects the economy and financial markets.

Regarding the economic consequences of uncertainty shocks, in the seminal paper, Baker et al. (2016) demonstrate that EPU innovations lead to declines in investment, output, and employment in the US and in other major economies. In the same vein, Caldara and Iacoviello (2022) find that the GPR shock induces persistent declines in investment, employment, and stock prices. Overall, uncertainty's negative impact on economic activity and ambiguous on inflation has been presented in a number of studies (e.g., Colombo, 2013; Caggiano et al., 2014; Leduc and Liu, 2016; Mumtaz and Surico, 2018; Nilavongse et al., 2021). The standard explanation is that high uncertainty causes a delay in the hiring and investment activity of firms due to non-zero firing costs and the permanent nature of investment. Moreover, the effects of uncertainty are contractionary due to the upward pressure on the cost of capital. A detailed review of the empirical literature on the business cycle effects of uncertainty shocks is provided by the recent survey paper by Castelnuovo (2023).

Another strand of the literature focuses on the relationship between uncertainty and financial asset prices. The theoretical framework of Pastor and Verones (2012) implies that spikes in economic uncertainty should lead to stock prices decline. A number of empirical investigations has subsequently confirmed the implications of this model. Kang and Ratti (2013) demonstrate that an increase in the EPU leads to lowering market returns in the US. Brogaard and Detzel (2015) show that the EPU helps forecast excess market returns in the US, both in time series and cross section. Within the asset pricing stochastic discount framework, the authors claim that a significant EPU risk premium can be identified. Similar to Kang and Ratti (2013), Arouri et al. (2016) conclude that an increase in policy uncertainty significantly reduces stock returns. The authors also show that this effect is more substantial and persistent during extreme volatility periods. In an out-of-sample setting, Phan et al. (2018) discover that the EPU helps forecast excess stock returns in 10 out of 16 investigated countries. Moreover, they show that the forecast accuracy is both country- and sector-dependent. Balcilar et al. (2018) point to the negative impact of the GPR on the return and volatility of the BRIC countries' stock markets. Das et al. (2019) compare the effects of the EPU and GPR on 24 emerging stock markets to find that the impact of the former is stronger than that of the latter. Xu et al. (2021) show that a high EPU level exerts a significant and negative impact on Chinese stock returns and has better out-of-sample predictability than a number of selected macroeconomic variables. Kwon (2022) show that EPU shocks lead to a decline in the returns on global stock markets. Huang and Liu (2022) examine the asymmetric effects of the EPU on G7 stock returns and observe that increases in the EPU have a greater influence on G7 stock returns than declines in the EPU. Overall, the literature provides ample evidence that increases in the EPU, and to a lesser in the GPR, lead to lower stock returns.

There are also empirical studies analyzing the relationship between uncertainty and commodity markets. Antonakakis et al. (2017) show that the GPR negatively affects oil prices and volatility. On the contrary, Bilgin et al. (2018) show that prices of gold increase after both VIX and global EPU shocks, which confirms the role of gold as a safe haven in times of high risk aversion and economic or political uncertainty. Uddin et al. (2018) explore the relationships between geopolitical and economic uncertainty, and the crude oil market to find that economic uncertainty shocks exert stronger effects on energy commodity prices than geopolitical ones. Within the time-varying parameter structural vector autoregression framework, Ozcelebi and Tokmakcioglu (2022) show that the GPR exerts a negative impact on oil prices and production. In turn, Sharif et al. (2020) show that the connectedness of oil prices, stock prices and the EPU is time-varying and depends on the horizon of the analysis. Gao et al. (2021) investigate spillovers between the EPU, oil, gold, and stock markets to find that the EPU is the main spillover receiver from all three markets and that the connectedness between these markets is time-varying. On the contrary, Li et al. (2022) claim that crude oil prices are not leading GPR changes. Finally, Gong and Xu (2022) find that time-varying connectedness among major commodity markets is affected by fluctuations in the GPR. Overall, the above studies point to time and frequency variation in the relationship between uncertainty and commodity prices and that commodity markets are usually leading news-based (EPU, GPR) measures of uncertainty.

The above list of selected studies accurately illustrates that measuring the effects of uncertainty shocks has become a widely explored topic in the literature, with the three variables (EPU, GPR and VIX) most commonly used as proxies for uncertainty. However, more is needed to know how these three measures are connected among themselves. Do they repeat the same information or instead convey different sources of uncertainty? For instance, Baker et al. (2016) only mention that the VIX and EPU often co-move (with correlation at 0.58), but also show distinct patterns during selected events. In turn, Caldara and Iacoviello (2022) present visual evidence on the independent development in these three indices. It also needs to be determined whether the relation between uncertainty measures stems from their short-term or long-term variation.

This article discusses the advantages and shortcomings of various uncertainty measures by investigating the time-varying connectedness of the EPU, GPR and VIX, both in the time and frequency domain. We do it in two steps. First, we estimate a time-varying parameters vector autoregression model with stochastic volatility á la Primiceri (2005, henceforth TVP-VAR-SV), which allows us to examine the evolving relationship between the three uncertainty proxies at each point in time. Next, we compute the Diebold and Yilmaz (2009, 2012, 2014, henceforth DY) and Barunik and Krehlík (2018, henceforth BK) spillover statistics to gauge how uncertainty measures are related to each other, both in time and at different frequencies. The frequency decomposition of connectedness is insightful since it allows us to understand better the varying degree of persistence stemming from shocks at various horizons. We complement the connectedness analysis by presenting the results of predictive regressions aimed to assessing how the three uncertainty measures affect the economy and financial markets, both when these indices are considered in isolation or together.

Our research question is related to several recent contributions that analyze links among various uncertainty indices. In the first study of this kind, Klosner and Sekkel (2014) calculate DY statistics for EPU indices in six developed countries to find that US and UK are net transmitters and that spillovers are significantly increasing in times of financial crises. Gabauer and Gupta (2018) apply the TVP-VAR framework and DY measures to analyze the connectedness of the EPU between the US and Japan. Using a similar approach, Antonakakis et al. (2018) focus on the transmission channel of the EPU among the US, EU, UK, Japan and Canada. The authors also investigate the dynamics of EPU components at various frequencies using wavelet models. Next, Kang and Yoon (2019) study the dynamic connectedness of the EPU across nine regions to find that the total spillover index amounts on average to almost 70%, indicating a high level of connectedness across the borders. Finally, Cui and Zou (2020) investigate connectedness among the EPU of G20 countries using the BK method to find that the level of connectedness is high, time-varying and that uncertainty spillover is mainly related to short term (up to 4 months) frequencies. Overall, while the above studies indicate that uncertainty proxies are often linked, they focus mainly on the connectedness between country-specific economic policy uncertainty measures.

The debate on how to incorporate information about uncertainty in the macro and finance modeling is ongoing and remains vivid. The reason is that academics and policymakers need to make a number of choices, related among others to the most appropriate measure of uncertainty or how to include uncertainty in model specification. This study contributes to the above debate as it provides several guidelines. Specifically, we are the first to investigate the connectedness and spillovers among the three most popular uncertainty indices using the TVP-VAR-SV methodology augmented for DY and BK connectedness statistics, which allows us to make few new observations. First, we provide robust evidence that the three indices convey different information on uncertainty. This is well reflected in the fluctuation of the total spillover, which elevates to 40% during extreme market events, but develops otherwise on a much lower level. Second, we show that the VIX leads the EPU, whereas the GPR is broadly independent. This is intuitive as implied volatility can be considered to be a forward-looking measure of uncertainty, whereas article news tend to be backward-looking. Third, we show that total connectedness is driven mainly by lower frequencies. Finally, we find that the GPR transmits shocks in times of major hostile events and this transmission goes through higher frequencies. In general, these results imply that while measuring the impact of uncertainty on the economy or financial markets, different uncertainty measures should be considered in the model specification depending on the research question.

The remainder of the article is structured as follows. In section 2 we characterize the data used in the study. Section 3 describes the methodology. The main results are reported in section 4. Section 5 grants conclusions and policy implications.

2 Data

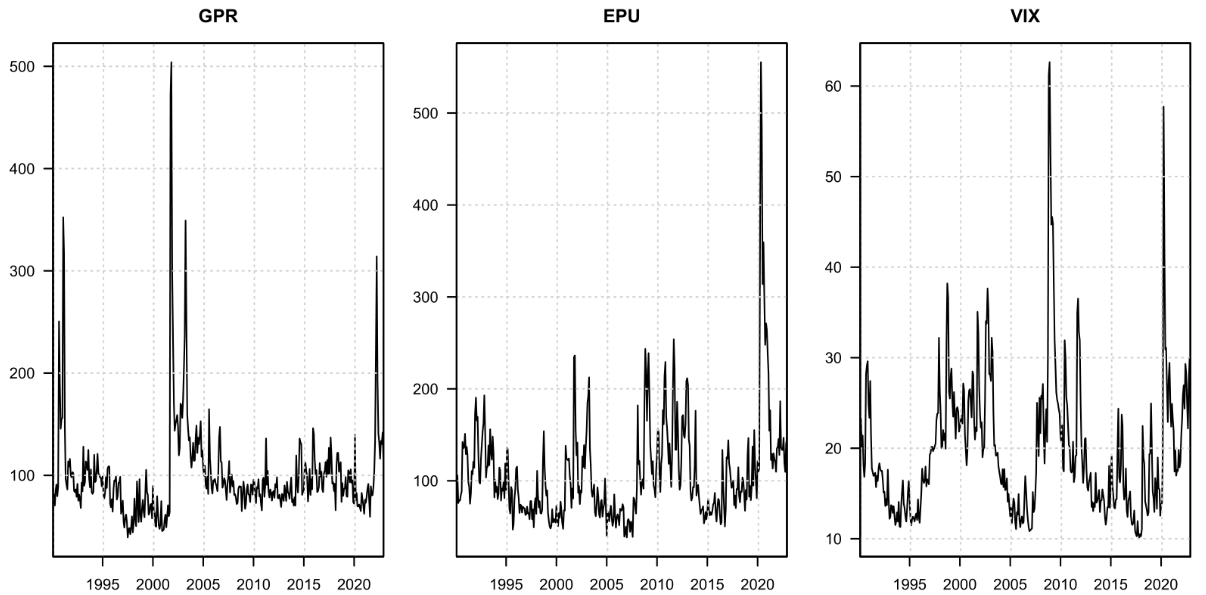
Our analysis is based on monthly data for the three uncertainty measures described in the introduction: the GPR, EPU and VIX. We cover the period from Jan. 1990 to Nov. 2022, where the starting point is determined by data availability for the VIX. It can be noted that observations from 1990-1999 are used for technical purposes, i.e., as a pre-sample to calibrate prior information for the TVP-VAR-SV model, whereas all connectedness measures are computed for the period 2000-2022, during which major uncertainty spikes related to geopolitic tensions and economic risk were observed.

All series are presented in Figure 1. It shows that major spikes in the three measures occur both jointly and independently. For instance, the GPR increases were most pronounced during September 11 terrorist attacks, the beginning of the Iraq war and the Russian invasion of Ukraine. These three events also raised the EPU and VIX, but the increases were much less pronounced than in March 2020, i.e., following the panic related to the worldwide spread of the Covid-19. Moreover, a visual comparison of EPU and VIX dynamics indicates that both measures behaved somewhat differently during the global financial crisis. The figure also illustrates that all series experience periods of higher and lower variability, which would suggest that a robust model describing these variables should take into account that the volatility of shocks is time-varying.

The visual characteristics of the data presented in Figure 1 are complemented by descriptive statistics in Table 1. It shows that the EPU is slightly more volatile that the remaining series, which is reflected by the highest ratio of standard deviation or max-min range relative to the average value of the index. In line with the intuition, all variables are positively skewed, which means that their increases are more intensive than declines. The value of kurtosis points to fat tails, whereas the results of the ADF test strongly indicate stationarity of all uncertainty indices. The last columns of the table show that the EPU and VIX are highly correlated, with the correlation coefficient amounting to 0.51, whereas the GPR is only loosely linked to the remaining two indices.

The correlation analysis from Table 1 is extended in Figure 2, which presents cross-correlation (CCF) for the three variables in levels (upper panel) and simple differences

Figure 1: Time series for uncertainty measures



Notes: The figure presents the development in the studied uncertainty measures over the pre-sample and main sample.

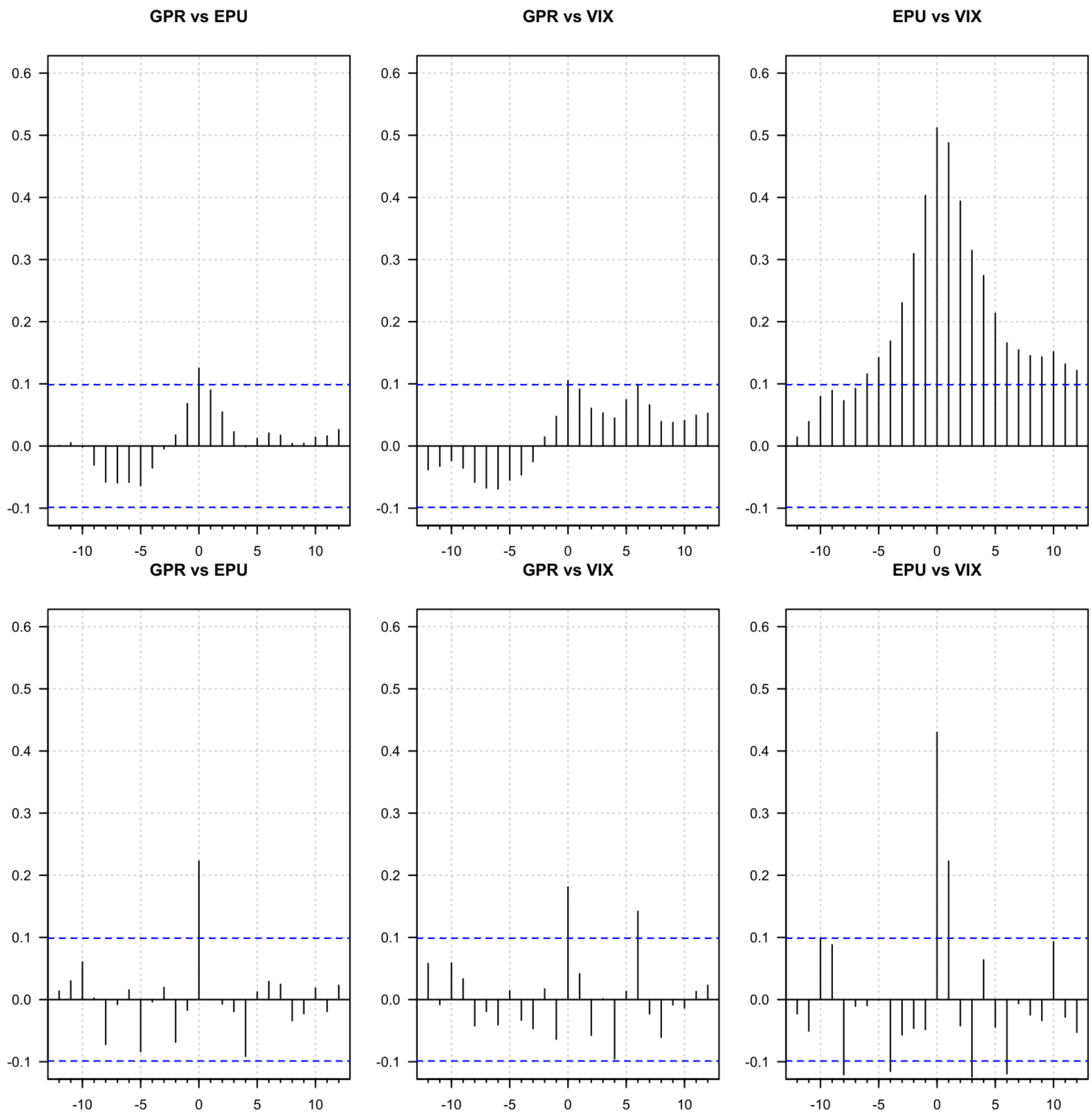
Table 1: Descriptive statistics for uncertainty measures

	Moments							Correlation with		
	Mean	Std. dev.	Skew.	Kurt.	Min.	Max.	ADF	GPR	EPU	VIX
GPR	100.2	49.1	4.1	27.1	39.1	504.1	−8.42	1.00	0.13	0.11
EPU	109.5	58.5	2.8	16.9	38.2	555.3	−6.41	0.13	1.00	0.51
VIX	19.7	7.6	2.0	9.4	10.1	62.6	−5.93	0.11	0.51	1.00

Notes: The table presents descriptive statistics for the level of GPR, EPU and VIX. The specification of the Augmented Dickey-Fuller (ADF) test includes a constant and one lag. The 1% and 5% critical values are -3.44 and -2.87, respectively.

(lower panel). It confirms the strong correlation between the EPU and VIX, but also illustrates that the VIX is leading the EPU. In particular, it can be seen that the current values of the EPU are strongly correlated with the past values of the VIX. This is even more vivid after inspecting differences in uncertainty proxies. The figure also indicates that the development in the GPR is neither strongly related to past nor present values of the EPU and VIX. Interestingly, the contemporaneous link is stronger for the EPU, suggesting that changes in geopolitical tensions propagate very quickly to uncertainty related to economic policy, whereas market participants may perceive these risks in advance. It should be noted, however, that the CCF analysis does not take into account the time variation in the relationship among variables or a complex relationship structure. For that reason, in the next subsection we present a robust and reliable analysis based on the DY and BK connectedness methodology applied on estimates from a TVP-VAR-SV model.

Figure 2: Cross-correlation of uncertainty measures in levels and differences



Notes: The figure presents the cross-correlogram for the three measures of uncertainty in levels (upper panel) and differences (lower panel). The dashed lines present 95% confidence interval for zero. Significant CCF on the left from zero means that the first variable is leading the second one, whereas significant CCF on the right from zero implies the opposite.

3 Methodology

Our investigation on the relationship among the uncertainty measures is based on the TVP-VAR-SV model for a trivariate ($N = 3$) vector $y_t = [GPR_t \ EPU_t \ VIX_t]'$ and two state-of-the-art connectedness measures: Diebold and Yilmaz (2012, 2014) in the time domain and Barunik and Krehlík (2018) in the frequency domain. We start by describing the model. Next, we outline the DY and BK connectedness methodologies.

3.1 TVP-VAR-SV model

In this time-varying framework the dynamics of the dependent variable y_t is given by a VAR process of order P according to the following rule of motion:

$$y_t = B_{0,t} + B_{1,t}y_{t-1} + ... + B_{P,t}y_{t-P} + u_t \qquad t = 1, ..., T \tag{1}$$

We allow all model parameters to vary over time. This concerns the vector of constant terms, $B_{0,t}$, the coefficients in the autoregressive matrices, $\{B_{p,t}\}_{p=1}^{P}$, and the variance-covariance matrix Ω_t of model residuals u_t, as we assume that u_t follows a Gaussian process, i.e., $u_t \sim \mathcal{N}(0, \Omega_t)$. The time variation in the lagged coefficients is designed to capture possible nonlinearities and time variation in the lag structure of the model, whereas the variability in the error term describes the heteroscedastic structure of innovations in the system (Granger, 2008; Ng and Wright, 2013; Lubik and Matthes, 2015). Moreover, Cogley and Sargent (2005) claim that overlooking stochastic volatility leads to spurious dynamics in random coefficients.

These advantages of the TVP-VAR-SV model come at the cost of heavy parametrization and non-trivial estimation. Nonetheless, time-varying parameters models have become increasingly popular in various investigations, in particular related to the evolution and interplay of key macroeconomic variables (e.g., Primiceri, 2005; Lubik et al., 2016; Bjørnland et al., 2019; Corsello and Nispi Landi, 2020) or the developments and interconnectedness in financial markets, exchange rates, commodity markets and uncertainty (e.g., Baumeister and Peersman, 2013; Wiggins and Etienne, 2017; Antonakakis et al., 2018; Czudaj, 2019; Liu and Gong, 2020; Lin and Chen, 2021; Anand and Paul, 2021; Ding et al., 2021; Lyu et al., 2021; Shang and Hamori, 2021; Papież et al., 2022; Szafranek et al., 2023).

Following Primiceri (2005), to estimate the model efficiently we assume that Ω_t can be decomposed as follows: $A_t\Omega_t A_t' = \Sigma_t\Sigma_t'$, where A_t is a lower triangular matrix that models the contemporaneous relations between endogenous variables, while Σ_t is the diagonal matrix of standard deviations. In our case, i.e., for the trivariate system, their specification is:

$$A_t = \begin{bmatrix} 1 & 0 & 0 \\ a_{21,t} & 1 & 0 \\ a_{31,t} & a_{32,t} & 1 \end{bmatrix}, \quad \Sigma_t = \begin{bmatrix} \sigma_{1t} & 0 & 0 \\ 0 & \sigma_{2t} & 0 \\ 0 & 0 & \sigma_{3t} \end{bmatrix} \tag{2}$$

Given the above decomposition, we perform common VAR analysis in the time-varying framework by drawing from the posterior distribution. For that purpose we write down model (1) as:

$$y_t = X_t'\beta_t + A_t^{-1}\Sigma_t\eta_t, \tag{3}$$

where β_t is a vector that collects all parameters from $\{B_{p,t}\}_{p=0}^{P}$ and $X_t' = I_3 \otimes [1, y_{t-1}', ..., y_{t-P}']$, with $\otimes$ being the Kronecker product. Regarding the error term, in the above specification $\eta_t \sim \mathcal{N}(0, I_3)$ so that $u_t = A_t^{-1}\Sigma_t\eta_t$.

Following Primiceri (2005), the time-varying parameters from vector β_t and the free elements of matrix A_t, which are stacked into $\alpha_t = [a_{21,t}, a_{31,t}, a_{32,t}]'$, are governed by the standard random walk. In turn, the vector of standard deviations $\sigma_t = [\sigma_{1t}, \sigma_{2t}, \sigma_{3t}]'$ follows the geometric random walk. Consequently, they are specified as follows:

$$\beta_t = \beta_{t-1} + \nu_t, \tag{4}$$

$$\alpha_t = \alpha_{t-1} + \zeta_t, \tag{5}$$

$$\log\sigma_t = \log\sigma_{t-1} + \epsilon_t. \tag{6}$$

All innovations in the system are assumed to be mutually independent and normally distributed with the variance-covariance matrix:

$$Var\left(\begin{bmatrix}\eta_t \\ \nu_t \\ \zeta_t \\ \epsilon_t\end{bmatrix}\right) = \begin{bmatrix} I_3 & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix}, \tag{7}$$

where Q, S and W are positive definite, time-invariant matrices.

To estimate the model we rely on Bayesian methods, in particular the Markov Chain Monte Carlo (MCMC) approach and the Gibbs sampler proposed by Del Negro and Primiceri (2015). As regards the prior, we follow the procedure as well as choices described by Primiceri (2005), which is a standard approach in the literature (e.g., Lubik et al., 2016; Bjørnland et al., 2019; Czudaj, 2019; Anand and Paul, 2021; Chatziantoniou et al., 2021; Lyu et al., 2021). In the first step, we need to set the prior for the initial value of model parameters, i.e. β_0, α_0 and $\log\sigma_0$. We do it by estimating the (constant parameters) VAR model using pre-sample observations. The point estimates ($\hat{\beta}$, $\hat{\alpha}$ and $\hat{\sigma}$) as well as the respective variance matrices ($\hat{V}_{\hat{\beta}}$ and $\hat{V}_{\hat{\alpha}}$) are taken as parameters of the prior distribution, namely:

$$\beta_0 \sim \mathcal{N}(\hat{\beta}, k_\beta \cdot \hat{V}_{\hat{\beta}}) \tag{8}$$

$$\alpha_0 \sim \mathcal{N}(\hat{\alpha}, k_\alpha \cdot \hat{V}_{\hat{\alpha}}) \tag{9}$$

$$\log\sigma_0 \sim \mathcal{N}(\log\hat{\sigma}, k_\sigma \cdot I_3) \tag{10}$$

As regards the hyperparameters specifying the tightness of the prior, we set them to the standard values from the literature, i.e. $k_\beta = 4$, $k_\alpha = 4$, $k_\sigma = 1$.

In the second step, we impose a prior on matrices Q, S and W by assuming that:

$$Q \sim \mathcal{IW}(k_Q^2 \cdot p_Q \cdot \hat{V}_{\hat{\beta}}, p_Q) \tag{11}$$

$$W \sim \mathcal{IW}(k_W^2 \cdot p_W \cdot I_3, p_W) \tag{12}$$

$$S_j \sim \mathcal{IW}(k_S^2 \cdot p_{S_j} \cdot \hat{V}_{\hat{\alpha}_j}, p_{S_j}) \text{ for } j \in \{1, 2\} \tag{13}$$

where $\mathcal{IW}$ stands for the inverse Wishart distribution. In equation (13) S_1 and S_2 denote two blocks of matrix S, sized 1×1 and 2×2, and corresponding to parameters belonging to separate equations of the TVP-VAR-SV model (for details see Primiceri, 2005). As regards the hyperparameters, we use the standard values of $k_Q = 0.01$, $k_W = 0.01$ and $k_S = 0.10$, which are also chosen in most studies quoted at the beginning of this section. Next, we set $p_Q = 120$ to accounts for the number of observations in the pre-sample and choose $p_W = N + 1$ and $p_{S_j} = j + 1$, as is usually done in the empirical literature. We fix the number of MCMC draws to initialize the sampler at 5×10^3 and the number of MCMC draws at 5×10^4. Since we employ a thinning factor of 10, in the end we retain 5×10^3 draws. Finally, we set $P = 1$ for our TVP-VAR-SV as indicated by the BIC for the constant coefficient VAR estimated via OLS on the main sample. In presenting our results we report the mean estimates along with 68% credible sets. For the detailed and critical description of the TVP-VAR-SV model, including estimation issues, we refer the reader to Lubik and Matthes (2015).

3.2 Time domain interconnectedness and spillovers

To establish how the three uncertainty measures are connected in the time domain we use the well-established methodology developed by Diebold and Yilmaz (2009, 2012, 2014). The authors propose a method to quantify connectedness and spillovers between variables using the decomposition of the forecast error variances in a vector autoregression. Specifically, this approach quantifies the fraction of the H-step-ahead error variance in forecasting variable k that is due to the shock in variable j.

We apply the approach by Diebold and Yilmaz (2012, 2014), who employ the KPPS generalized IRF method (Koop et al., 1996; Pesaran and Shin, 1998), rather than the initial framework of Diebold and Yilmaz (2009), which is based on Cholesky factorization of the variance-covariance matrix. In the refined approach, at the expense of shocks being correlated – but still accounted for appropriately using the historical observed distribution of the errors – the forecast error variance decomposition is invariant to the ordering of variables. Consequently, this framework enables the researcher to quantify both the total spillovers between variables and to measure various directional spillovers, which substantially enriches the analysis. Therefore, it is a suitable econometric tool to capture the connectedness and spillovers between uncertainty measures and to establish which variable transmits or receives signals from the remaining ones.

We integrate the DY framework with the TVP-VAR-SV model as we consider this kind of approach extremely practical and elegant to derive time-varying connectedness measure. It should be noted that since the work by Diebold and Yilmaz (2012), in order to obtain dynamic measures of connectedness the dominant approach in the literature consists in performing a fixed-length rolling window estimation (e.g., Diebold and Yilmaz, 2012; Hałka and Szafranek, 2016; Yarovaya et al., 2016; Collet and Ielpo, 2018; Elsayed et al., 2021; Albrecht and Kočenda, 2023). However, as argued by Korobilis and Yilmaz (2018) such approach has serious shortcomings. Firstly, the results come at a cost of selecting in a completely arbitrary manner the length of the window T^* that commonly is far smaller than the sample size T (i.e. $T^* \ll T$), which limits the degrees of freedom in the estimated VAR model that may already be quite heavily parametrized. Hence, valuable information from the sample is sacrificed while the efficiency of estimation decreases, an especially problematic aspect when dealing with data of relatively low frequency. Moreover, the choice of the size of the window leads to the lack of information on the connectedness for the first $T^* - 1$ observations. Secondly and more importantly, employing model re-estimation of fixed-length rolling window introduces spurious, excessive persistence into the connectedness measures, as they may elevate at an inadequately high level as long as data pertaining to the large shock remain within the fixed-length rolling-sample window of analysis. Third, TVP-VAR-SV models are commonly estimated via a Kalman filter, which is less sensitive to outliers than the traditional OLS approach used to estimate time-invariant VAR. Hence, we use this robust model to quantify connectedness measures and spillovers.

The starting point for integrating the DY framework and TVP-VAR-SV model consists in writing down the forecast error at horizon H formulated at time t in the moving average representation:

$$y_{t+H} - E_t(y_{t+H}) = \sum_{s=0}^{H-1} \Lambda_{s,t} u_{t+H-s}. \tag{14}$$

Matrices $\Lambda_{s,t}$ obey the recursion:

$$\Lambda_{s,t} = B_{1,t}\Lambda_{s-1,t} + B_{2,t}\Lambda_{s-2,t} + \cdots + B_{P,t}\Lambda_{s-P,t} \quad \text{for} \quad s > 0, \tag{15}$$

$\Lambda_{0,t} = I_3$ and $\Lambda_{s,t} = 0$ for $s < 0$. This representation is key to understanding the dynamics of the system.

Following DY, we denote by $\theta^g_{kj,t}(H)$ the contribution of shock j to forecast error variance of variable k at horizon H. The superscript g emphasizes the fact that the contribution is calculated with the KPPS generalized IRF method. In turn, the subscript t emphasizes that this statistic is time-varying. The formula is:

$$\theta^g_{kj,t}(H) = \frac{\sigma^{-1}_{jj,t} \sum_{h=0}^{H-1} (e'_k \Lambda_{h,t} \Omega_t e_j)^2}{\sum_{h=0}^{H-1} (e'_k \Lambda_{h,t} \Omega_t \Lambda'_{h,t} e_k)} \tag{16}$$

where Ω_t is the variance-covariance matrix for the error vector u_t, $\sigma_{jj,t}$ is the j element of the diagonal of the matrix Ω_t at time t and e_k is the selection vector with 1 as the kth element and 0 otherwise.

As shocks to each variable are not orthogonalized, the sum of contributions to the variance of the forecast error may not necessarily equal 1. Therefore, DY normalize each entry of the variance decomposition matrix by the row sum, which we follow in our time-varying setting:

$$\tilde{\theta}^g_{kj,t}(H) = \frac{\theta^g_{kj,t}(H)}{\sum_{j=1}^N \theta^g_{kj,t}(H)}. \tag{17}$$

Consequently, in each period t the conditions $\sum_{j=1}^N \tilde{\theta}^g_{kj,t}(H) = 1$ is satisfied, which implies that $\sum_{k,j=1}^N \tilde{\theta}^g_{kj,t}(H) = N$.

Following DY, we calculate the overall connectedness as the *total spillover index*, using the normalized forecast-error variance contributions from the KPPS variance decomposition. In our case this measure is time-varying by construction and amounts to:

$$S^g_t(H) = \frac{\sum_{\substack{k,j=1\\k\neq j}}^N \tilde{\theta}^g_{kj,t}(H)}{\sum_{k,j=1}^N \tilde{\theta}^g_{kj,t}(H)} \times 100 = \frac{\sum_{\substack{k,j=1\\k\neq j}}^N \tilde{\theta}^g_{kj,t}(H)}{N} \times 100 \tag{18}$$

Employing the generalized VAR framework enables us to learn about the direction of the spillovers. Therefore, we can exploit additional information from further connectedness measures introduced by Diebold and Yilmaz (2012) and refined in Diebold and Yilmaz (2014).

We also focus on three additional measures. They are also time-varying and include: Gross directional spillovers received by variable k from all other variables j:

$$S^g_{k\leftarrow\bullet,t}(H) = \sum_{\substack{j=1\\j\neq k}}^N \tilde{\theta}^g_{kj,t}(H) \times 100 \tag{19}$$

We interpret this statistic as an indicator of uncertainty shock absorption.
Gross directional spillovers transmitted by variable k to all other variables j:

$$S^g_{\bullet\leftarrow k,t}(H) = \sum_{\substack{j=1\\j\neq k}}^N \tilde{\theta}^g_{jk,t}(H) \times 100 \tag{20}$$

We interpret this measure as an indicator for the uncertainty shock transmission.
Net spillovers for variable k:

$$S^g_{k,t}(H) = S^g_{\bullet\leftarrow k,t}(H) - S^g_{k\leftarrow\bullet,t}(H) \tag{21}$$

This statistic allows us to assess whether the given uncertainty measure is leading or lagging in the transmission of uncertainty.

It can be noted that Diebold and Yilmaz (2012, 2014) define also net pairwise spillovers but to save space we do not report them in the paper. These results are available upon reasonable request. Given that we work with monthly data we set the horizon for our analysis to 36 periods, i.e., $H = 36$, which corresponds to three years. It can be noted that we have checked that at this horizon IRF coefficients are almost negligible.

3.3 Frequency domain connectedness and spillovers

To further investigate the connectedness between our three chosen uncertainty measures we employ the Barunik and Krehlík (2018) methodology. The key appealing feature of this approach is that it allows a researcher to decompose the DY connectedness measures and quantify the spillovers between variables arising from heterogeneous responses to shocks at different frequencies. Thus, it helps to better understand the development in the spillover measures estimated in the time domain as it identifies the contribution of selected frequency components. Below we outline how the BK framework is applied in our setting.

We start by defining, for each frequency $\omega \in (-\pi, \pi)$ and period t, the Fourier transform of the moving average representation coefficients Λ_t from equation (14):

$$\Lambda_{H,t}(exp\{-i\omega\}) = \sum_{s=0}^{H-1} exp\{-i\omega s\}\Lambda_{s,t}, \tag{22}$$

and the spectrum of forecast error at horizon H:

$$S_{y,t}(\omega, H) = \Lambda_{H,t}(exp\{-i\omega\})\Omega_t \Lambda'_{H,t}(exp\{i\omega\}), \tag{23}$$

so that the total forecast error variance amounts to $\frac{1}{2\pi}\int_{-\pi}^{\pi} S_{y,t}(\omega, H)d\omega$.

Next, we notice that the contribution of shocks j to the spectrum of forecast error of variable k is:

$$\theta^g_{kj,t}(\omega, H) = \frac{\sigma^{-1}_{jj,t}|e'_k\Lambda_{H,t}(exp\{-i\omega\})\Omega_t)e_j|^2}{e'_k\Lambda_{H,t}(exp\{-i\omega\})\Omega_t\Lambda'_{H,t}(exp\{i\omega\})e_k},$$

which is the frequency equivalent of equation (16).

In our investigation we are interested in decomposing the value of $\theta^g_{kj,t}(H)$ defined in equation (16) into selected bands of frequencies. For that purpose, we need to weight $\theta^g_{kj,t}(\omega, H)$ by the share of frequency ω in the total variance of forecast for variable k:

$$\Gamma_{k,t}(\omega, H) = \frac{e'_k\Lambda_{H,t}(exp\{-i\omega\})\Omega_t\Lambda'_{H,t}(exp\{i\omega\})e_k}{\frac{1}{2\pi}\int_{-\pi}^{\pi} e'_k\Lambda_{H,t}(exp\{-i\lambda\})\Omega_t\Lambda'_{H,t}(exp\{i\lambda\})e_k d\lambda}. \tag{24}$$

Consequently, the contribution of frequencies within band $d = (a, b) : a, b \in (-\pi, \pi), a < b$ to the value of $\theta^g_{kj,t}(H)$ amounts to:

$$\theta^g_{kj,t}(d, H) = \frac{1}{2\pi}\int_d \Gamma_{k,t}(\omega, H)\theta^g_{kj,t}(\omega, H)d\omega, \tag{25}$$

so that $\theta^g_{kj,t}(D, H) = \theta^g_{kj,t}(H)$ for $D = (-\pi, \pi)$. In turn, the contribution of frequencies within band d to the normalized value $\tilde{\theta}^g_{kj,t}(H)$ defined in equation (17) can be easily calculated as:

$$\tilde{\theta}^g_{kj,t}(d,H) = \theta^g_{kj,t}(d,H) \times \frac{\tilde{\theta}^g_{kj,t}(H)}{\theta^g_{kj,t}(H)}. \tag{26}$$

Finally, the values of $\tilde{\theta}^g_{kj,t}(d,H)$ can be inserted to the nominator of equation (18) and equations (19)-(21) to compute the contribution of frequencies in the band d to DY spillover measures. The exact formulas are:

$$S^g_t(d,H) = \frac{1}{N} \sum_{\substack{k,j=1 \\ k \neq j}}^{N} \tilde{\theta}^g_{kj,t}(H) \times 100 \tag{27}$$

$$S^g_{k\leftarrow\bullet,t}(d,H) = \sum_{\substack{j=1 \\ j \neq k}}^{N} \tilde{\theta}^g_{kj,t}(d,H) \times 100 \tag{28}$$

$$S^g_{\bullet\leftarrow k,t}(d,H) = \sum_{\substack{j=1 \\ j \neq k}}^{N} \tilde{\theta}^g_{jk,t}(d,H) \times 100 \tag{29}$$

$$S^g_{k,t}(d,H) = S^g_{\bullet\leftarrow k,t}(d,H) - S^g_{k\leftarrow\bullet,t}(d,H) \tag{30}$$

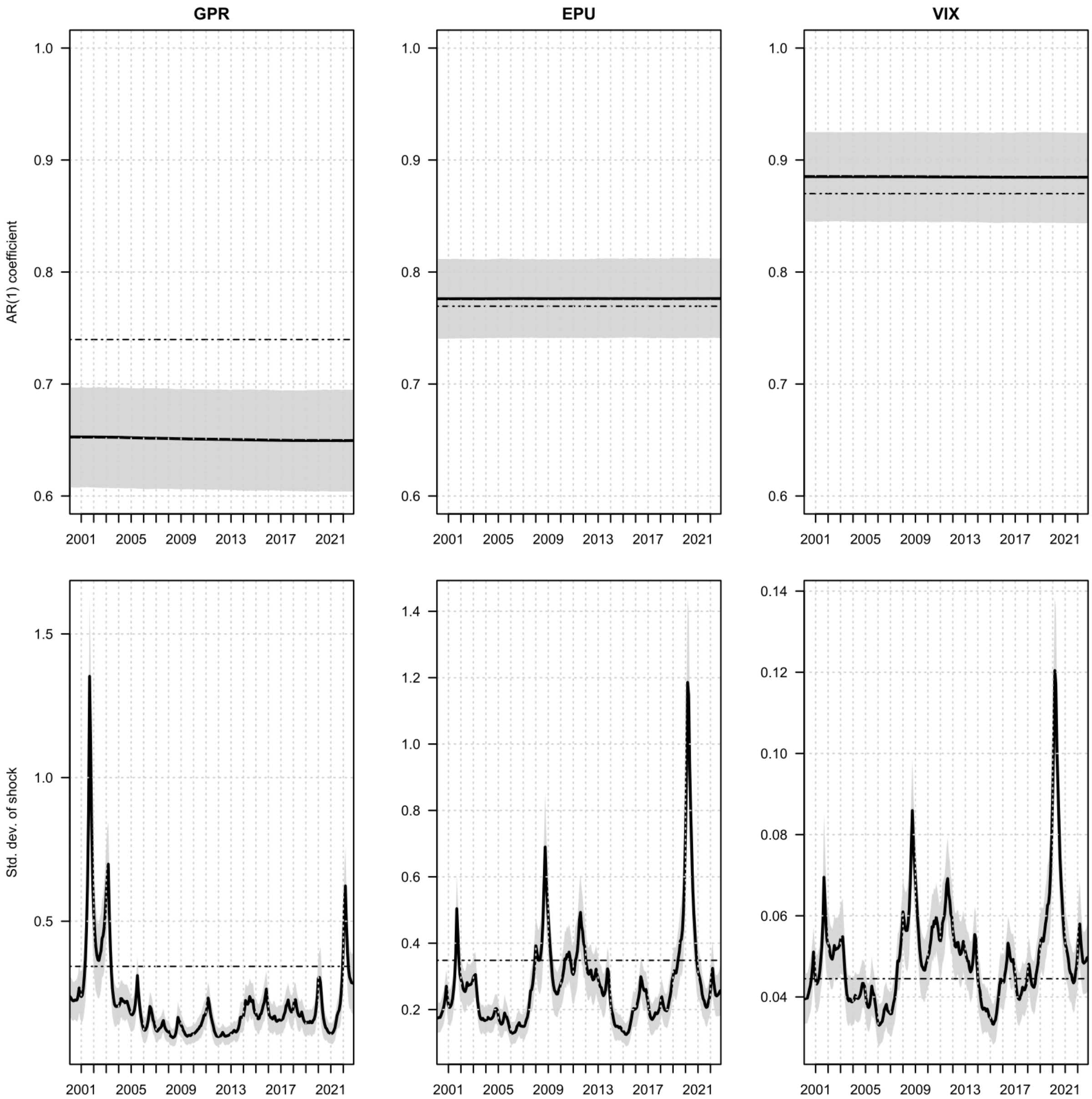
In the empirical application we use two bands d to differentiate between short-term (up to 1 year) and long-term (above 1 year) frequencies.

4 Results

The evolution in model parameters. We start by presenting the estimation results for the TVP-VAR-SV model. We do it by inspecting the evolution of model parameters over time. The top row of Figure 3 presents the posterior mean for autoregressive coefficients along with the 68% credible sets. The overwhelming impression is that these parameters vary very little in time. Moreover, it can be noted that the GPR is characterized by the lowest persistence throughout the sample, while the autoregressive parameter is higher for the EPU and the largest for the VIX. The bottom row of the figure points to high variation in stochastic volatility parameters. This kind of outcome is typical for studies applying the TVP-VAR-SV framework (e.g. Primiceri, 2005; Cogley and Sargent, 2005; Koop and Korobilis, 2013; Lubik et al., 2016; Amir-Ahmadi et al., 2016; Wiggins and Etienne, 2017; Corsello and Nispi Landi, 2020; Anand and Paul, 2021; Szafranek and Rubaszek, 2023).

The time-stability of the lag coefficients combined with large movements in stochastic volatility means that the propagation of shocks remains relatively constant, while the strength of the impulse varies over time. In our case, there are several, occasional and short-lived increases in the time-varying standard deviation of shocks. In the case of the GPR, the most pronounced spikes in stochastic volatility occurred after the September 11 terrorist attacks, directly before the 2003 US invasion of Iraq and most recently following

Figure 3: The evolution of selected coefficients in the TVP-VAR-SV model



Note: The black solid line represents the posterior mean, whereas the shaded area denotes the 68 percent posterior credible sets. The dashed line denotes the constant parameter VAR estimates.

the Russian invasion of Ukraine. For the EPU and VIX, the fluctuation in stochastic volatility resembles major economic and financial turmoil, such as the onset of the great financial crisis, the European sovereign debt crisis, and the outburst of the Covid-19 pandemics. In general, it can be observed that the series of stochastic volatility for the EPU and VIX are more tightly linked to each other, which is not the case for the GPR.

The evolution of connectedness measures and uncertainty spillovers. Table 2 presents the DY and BK connectedness measures at the beginning (February 2000) and the end

(November 2022) of the main sample. It shows that the connectedness structure has changed negligibly between these two periods. First, the total spillover index (TSI), defined by equation (18), has slightly decreased from 16.4% to 14.9%. The decomposition of the TSI for these two periods into frequencies below and above one year indicates that roughly one third of the TSI can be attributed to short-term fluctuations, whereas the remaining two thirds to the long-term ones. Next, the table shows that the VIX is an important transmitter of shocks to the EPU, accounting for around a quarter of its generalized forecast error variance. At the same time, the VIX is hardly affected by EPU or GPR shocks. This result might be related to the fact that the VIX is a forward-looking measure of uncertainty, as it is based on market expectation of future volatility. In contrast, the EPU and GPR are rather backward-looking uncertainty proxies since they are constructed using published news articles. In other words, today's news is yesterday's event. The last interesting result from the table is that the GPR was very loosely linked to the two remaining uncertainty indices in these two specific months. This corroborates our suspicion that the GPR conveys different information about uncertainty than the VIX and EPU, in line with the discussion by Caldara and Iacoviello (2022).

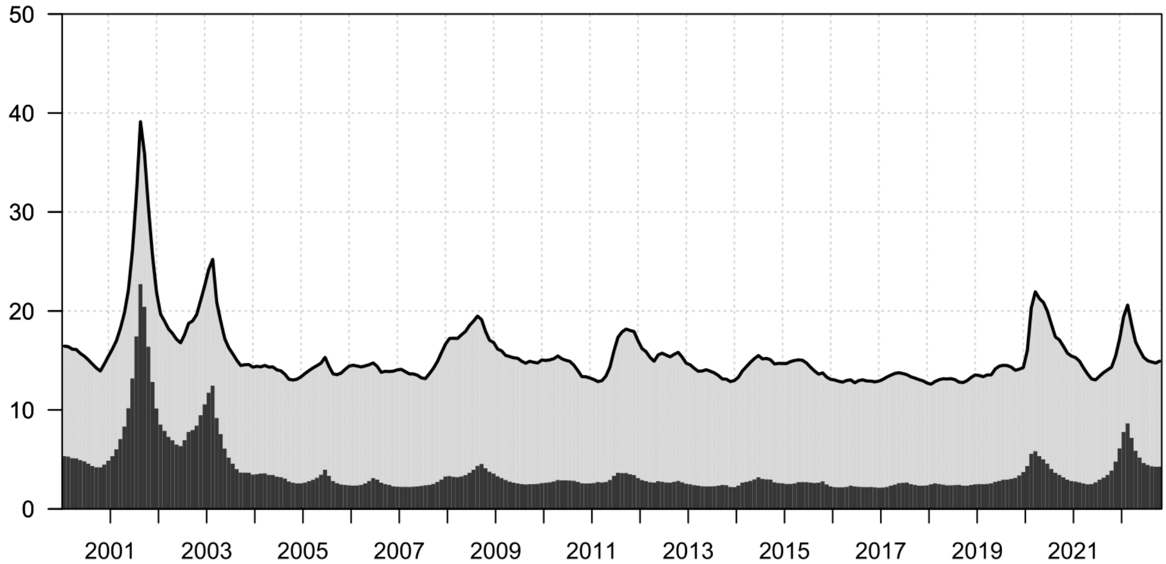
Table 2: DY and BK connectedness measures for the beginning and end of the sample

	Feb. 2000					Nov. 2022				
	All frequencies: DY connectedness									
	GPR	EPU	VIX	From	Net	GPR	EPU	VIX	From	Net
GPR	88.2	8.8	3.0	11.8	−4.4	90.6	5.9	3.6	9.4	−3.2
EPU	5.8	67.3	26.9	32.7	−20.8	4.4	70.7	24.9	29.3	−19.3
VIX	1.6	3.2	95.2	4.8	25.1	1.9	4.2	94.0	6.0	22.5
To others	7.4	11.9	30.0	**16.4**		6.3	10.0	28.5	**14.9**	
	Short term: BK connectedness for frequencies up to 1 year									
	GPR	EPU	VIX	From	Net	GPR	EPU	VIX	From	Net
GPR	56.4	6.1	1.5	7.5	−3.0	57.9	3.9	1.3	5.2	−2.1
EPU	3.8	31.6	2.6	6.4	1.1	2.5	32.4	2.8	5.3	0.4
VIX	0.7	1.4	27.4	2.2	1.9	0.6	1.7	27.2	2.4	1.7
To others	4.5	7.5	4.0	**5.4**		3.1	5.6	4.1	**4.3**	
	Long term: BK connectedness for frequencies over 1 year									
	GPR	EPU	VIX	From	Net	GPR	EPU	VIX	From	Net
GPR	31.8	2.7	1.6	4.3	−1.3	32.6	1.9	2.3	4.2	−1.1
EPU	2.0	35.7	24.3	26.4	−21.9	1.9	38.3	22.2	24.1	−19.7
VIX	0.9	1.8	67.8	2.7	23.3	1.2	2.4	66.8	3.7	20.8
To others	2.9	4.4	25.9	**11.1**		3.1	4.4	24.4	**10.7**	

Notes: For the DY connectedness the kj-th entry of the spillover matrix denotes the estimated contributions to the forecast error variance of variable k from variable j. The off-diagonal column sums ('To others') and row sums ('From others') are the gross directional spillovers transmitted and received, respectively. Taking their differences provides net spillovers. The total spillover index (in bold) can be calculated as the sum of the off-diagonal elements of the spillover matrix divided by the number of the variables in the system (or equivalently as the average of the 'From others' or 'To others' statistics). The sum of the respective BK connectedness measures at different frequencies is equal to the DY values.

The limitation of Table 2 is that it presents the result only for two specific months from the sample. We surpass it by presenting the development of selected connectedness measures throughout the main sample on the graphs. In particular, we focus on the evolution of the TSI (Figure 4) and the transmission and absorption of shocks by the three uncertainty indices in gross and net terms (Figures 5-7). In all cases we report the decomposition of the DY connectedness measures into short- and long-term frequencies obtained with the BK method.

Figure 4: The dynamic connectedness between uncertainty measures – the total spillover index

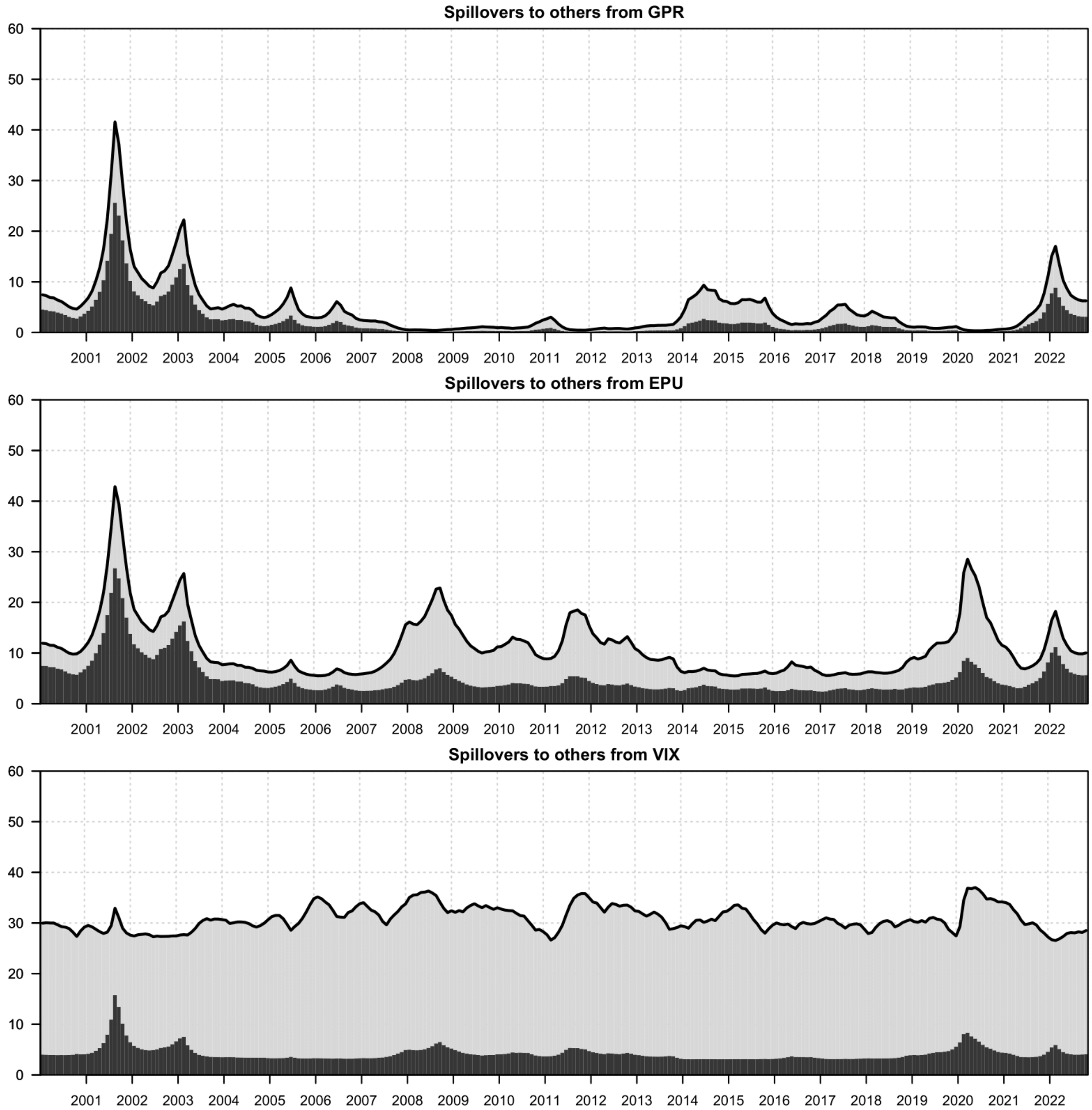


Notes: The solid line represents the total spillover index, $S_t^g(H)$. It is decomposed using the BK approach into short-term (up to 1 year, dark grey area) and long-term frequencies (over 1 year, light grey area).

Let us start by analyzing the evolution of the total spillover index, $S_t^g(H)$. Figure 4 illustrates that for the dominant part of the sample the TSI fluctuated between 15% and 20%, which can be labeled as a moderate level of connectedness. Moreover, in these "calm" periods the dominant part of the TSI is related to longer-term frequencies. The figure also reveals that there are four periods of elevated connectedness, during which the value of the TSI exceeds 20%. Specifically, the TSI spikes most visibly following the September 11 terrorist attacks and the Gulf war. For these two events the increase is driven by spillovers at short-term frequencies, which signifies their transitory character (this is especially vivid in the first case). In turn, during the outburst of the Covid-19 pandemic and the Russian invasion of Ukraine the TSI increased to a smaller extent, with the change driven rather by the long-term frequencies for the latter and short-term ones for the former. This kind of result summarizes the differences in perceived uncertainty related to geopolitical tensions and future macroeconomic development.

Next, Figures 5 and 6 allow us to better understand the drivers of this TSI development. The bottom panel of Figure 5 shows that the VIX persistently transmits shocks to

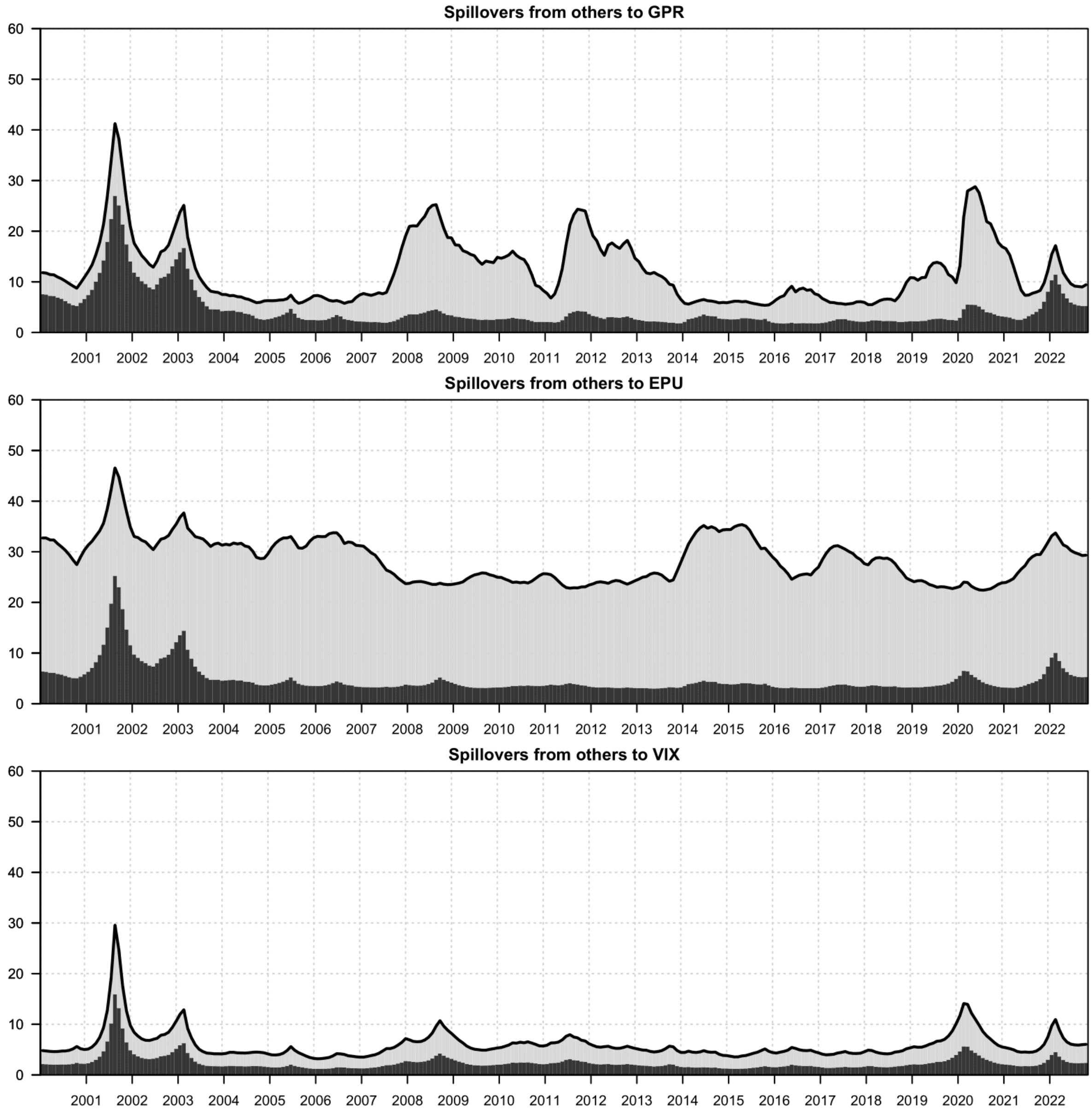
Figure 5: Transmission of shocks – directional spillovers to others



Notes: The solid line represents the gross directional spillovers to others, $S^g_{\bullet\leftarrow k,t}(H)$. Using the BK approach, they are decomposed into short-term (up to 1 year, dark grey area) and long-term frequencies (over 1 year, light grey area).

other uncertainty measures in the system. At the same time, it absorbs other uncertainty shocks to a limited extent. In net terms, Figure 7 nicely illustrates that apart from the period of terrorist attacks in September 2001 this measure is the most forward-looking one. In turn, the transmission of shocks from the EPU is far lower. This measure absorbs other uncertainty shocks, mostly from the VIX. Further investigation of the net pairwise spillovers (available upon request) validates that the EPU is strongly linked to the VIX, especially at lower frequencies (over 1 year). In fact, only during the outbreak of the Covid-19 pandemic the EPU transmitted uncertainty shocks to other measures in net

Figure 6: Absorption of shocks – directional spillovers from others

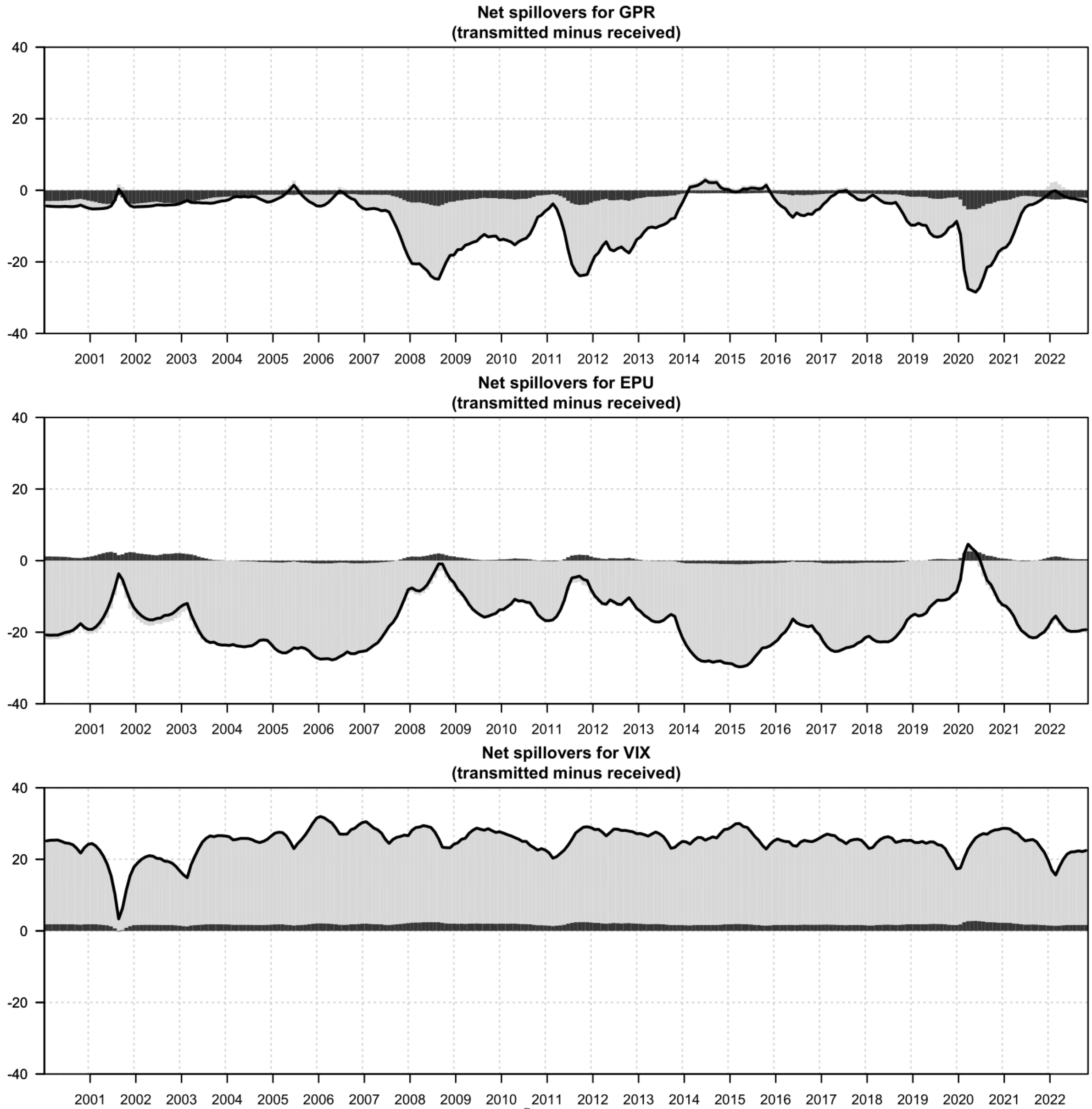


Notes: The solid line represents the gross directional spillovers from others, $S^g_{k\leftarrow\bullet,t}(H)$. Using the BK approach, they are decomposed into short-term (up to 1 year, dark grey area) and long-term frequencies (over 1 year, light grey area).

terms (Figure 7), which resulted from exceptional unpredictability of the policy measures to be implemented following the immediate shutdown of the global economy.

The figures also reveal that the GPR hardly transmits shocks to the EPU or VIX throughout the sample, except during major hostile events like the September 11 attacks. This result validates the necessity of constructing and quantifying the geopolitical risk separately as the index develops independently of other measures and picks up uncertainty related to threats to peace or hostile acts.

Figure 7: Uncertainty transmitters and absorbers - net spillovers



Notes: The solid line represents net spillovers, $S^g_{k,t}(H)$. Using the BK approach, they are decomposed into short-term (up to 1 year, dark grey area) and long-term frequencies (over 1 year, light grey area).

Empirical implications. In the Introduction we have reviewed the literature that investigates the relationship between the three uncertainty measures and economic activity, equity prices or the dynamics of commodity markets. In general, the surveyed studies usually analyze if a given measure of uncertainty exerts impact on the selected variable of interest. By focusing on one uncertainty proxy (VIX, EPU or GPR), there is an implicit assumption that the three measures relate to different areas of uncertainty (market, economy, and geopolitics), hence their impact on the economy or financial markets can be investigated independently. In this section we illustrate that this implicit assumption might lead to misleading results, given that dependencies described in the previous section explain why one can expect the risk of omitted variable bias. We do it by conducting a set of predictive regressions, in which changes in stock prices, crude oil prices or economic activity are explained by past changes in the three uncertainty measures.

The specification of the predictive regression including all uncertainty measures is:

$$\Delta \ln Y_{t+1} = \alpha_0 + \sum_{k=0}^{K} (\beta_k^{VIX} \Delta VIX_{t-k} + \beta_k^{GPR} \Delta GPR_{t-k} + \beta_k^{EPU} \Delta EPU_{t-k}) + \epsilon_{t+1} \quad (31)$$

where we consider three variants of the dependent variable Y_t. First, we explain the dynamics of the most commonly analyzed equity index (S&P500), the values of which are sourced from stooq.pl (ticker: `SPX`). Second, we include log growth rates in WTI prices, which are downloaded from the FRED database (ticker: `WTISPLC`). In both cases we take monthly averages. Finally, we estimate the model for global economic activity, which is proxied by the log monthly change in the World Industrial Production (WIP) constructed by Baumeister and Hamilton (2019).

For each of the three dependent variables model (31) is estimated in four specifications. There are three restricted versions, in which we consider only one uncertainty proxy (as it is usually done in the literature). The fourth specification is the unrestricted model, hence it includes all tree uncertainty proxies. All these models are estimated using exactly the same sample as before, which covers monthly data over the period Jan. 1990 - Nov. 2022. As regards the maximum lag K, it is set to two months as further lags turned out to be insignificant.

The results of all regressions are presented in Table 3. Its left panel shows that VIX is the only significant predictor of SP500 index changes, and this results does not depend on the whether one considers restricted or unrestricted version of the model. The results for WTI crude oil prices, which are presented in the middle panel of the table, are more interesting. They show that if EPU is considered in isolation, changes in uncertainty related to economic policy significantly leads oil prices dynamics. However, in the full model this effect becomes insignificant, as the relevant information contained in EPU is already accounted for in the market measure of uncertainty, namely VIX. In would imply that in specification (iii) of the predictive regression for WTI there is omitted variable problem, leading to endogeneity bias. The same kind of problem is seen in regressions for global economic activity, which are presented in the right panel of the table. It shows that GPR and EPU are significant determinants of WIP if analyzed in isolation, but not if considered together with VIX.

Overall, the above results illustrate that the findings from the connectedness analysis have meaningful implications for modeling the impact of uncertainty on the economy and financial markets. In particular, the fact that VIX leads EPU and GPR in terms of shock transmissions also implies that there is risk of omitted variable bias in regressions considering only one proxy of uncertainty.

Table 3: Predictive content of uncertainty measures

	Dependent variable											
	SP500 index: $y_t = \Delta \ln SP500_t$				WTI oil prices: $y_t = \Delta \ln WTI_t$				Global activity: $y_t = \Delta \ln WIP_t$			
Specification	(i)	(ii)	(iii)	(iv)	(i)	(ii)	(ii)	(iv)	(i)	(ii)	(ii)	(iv)
ΔVIX_{t-1}	-0.179^{**}			-0.187^{***}	-0.750^{**}			-0.710^{*}	-0.081^{**}			-0.068^{**}
	(0.071)			(0.064)	(0.366)			(0.362)	(0.038)			(0.032)
ΔVIX_{t-2}	0.041			0.054	−0.120			−0.206	-0.043^{***}			-0.039^{**}
	(0.041)			(0.056)	(0.251)			(0.220)	(0.014)			(0.018)
ΔGPR_{t-1}		0.006		0.011^{*}		−0.011		0.007		-0.002^{***}		0.000
		(0.006)		(0.006)		(0.017)		(0.017)		(0.001)		(0.002)
ΔGPR_{t-2}		−0.001		−0.003		−0.015		−0.025		−0.001		−0.001
		(0.006)		(0.006)		(0.011)		(0.016)		(0.001)		(0.001)
ΔEPU_{t-1}			−0.009	−0.003			-0.055^{***}	−0.014			-0.008^{*}	−0.004
			(0.009)	(0.009)			(0.018)	(0.018)			(0.005)	(0.002)
ΔEPU_{t-2}			0.002	−0.002			0.031	0.042			−0.000	0.001
			(0.007)	(0.006)			(0.043)	(0.026)			(0.003)	(0.002)
Nobs	392	392	392	392	392	392	392	392	392	392	392	392
R^2	0.042	0.004	0.007	0.054	0.103	0.005	0.044	0.126	0.212	0.009	0.115	0.232

Notes: Robust standard errors are reported in parentheses. ***, ** and * represent 1, 5 and 10% significance level.

5 Conclusion and discussion

This paper uses time and frequency domain perspectives to investigate time-varying connectedness among the three most essential measures of uncertainty, i.e., the EPU, GPR and VIX. For this purpose, we have estimated the TVP-VAR-SV model and applied the novel frequency connectedness method proposed by Barunik and Krehlík (2018), which is an extended version of the spillover index methodology by Diebold and Yilmaz (2012). We have also estimated a series of predictive regressions to assess if changes in uncertainty lead financial and commodity markets as well as the real sector of the global economy.

Our main findings are as follows. First, we provide new evidence that the three uncertainty indices cover different aspects of uncertainty: the total spillover index fluctuates between 10 and 40%, which might be classified as a moderate link. Second, we show that the VIX is leading the EPU, especially at lower frequencies (above one year). In turn, the GPR is broadly independent of the other two indices. Third, we find that the GPR transmits shocks during major hostile events, with the transmission going through higher frequencies (up to one year). Forth, our results indicate that the relationship between uncertainty indices varies in time and depends on frequency, providing insights for modeling the impact of uncertainty on the economy, financial, and commodity markets.

The results convey a key message for economists and investors. They predominantly imply that while measuring the impact of uncertainty on the economy or financial markets, the three indices deliver complementary information on uncertainty. In normal times, the VIX usually leads the EPU and to some extent the GPR. This can be attributed to the fact that it is a forward-looking measure of uncertainty, based on financial markets expectations. However, in turmoil periods the GPR and EPU transmit shocks to the VIX, especially at higher frequencies. This information is beneficial not only for academics who attempt to evaluate the impact of uncertainty on the economy or financial markets, but can also be exploited by investors whose portfolios depend on market volatility and the VIX.

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References

Albrecht, P. and Kočenda, E. (2023). Volatility Connectedness on the Central European Forex Markets. CESifo Working Paper 10728.

Algaba, A., Ardia, D., Bluteau, K., Borms, S., and Boudt, K. (2020). Econometrics meets sentiment: An overview of methodology and applications. *Journal of Economic Surveys*, 34(3):512–547.

Amir-Ahmadi, P., Matthes, C., and Wang, M.-C. (2016). Drifts and volatilities under measurement error: Assessing monetary policy shocks over the last century. *Quantitative Economics*, 7(2):591–611.

Anand, B. and Paul, S. (2021). Oil shocks and stock market: Revisiting the dynamics. *Energy Economics*, 96:105111.

Antonakakis, N., Gabauer, D., Gupta, R., and Plakandaras, V. (2018). Dynamic connectedness of uncertainty across developed economies: A time-varying approach. *Economics Letters*, 166(C):63–75.

Antonakakis, N., Gupta, R., Kollias, C., and Papadamou, S. (2017). Geopolitical risks and the oil-stock nexus over 1899–2016. *Finance Research Letters*, 23:165–173.

Arouri, M., Estay, C., Rault, C., and Roubaud, D. (2016). Economic policy uncertainty and stock markets: Long-run evidence from the US. *Finance Research Letters*, 18:136–141.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring Economic Policy Uncertainty. *Quarterly Journal of Economics*, 131(4):1593–1636.

Balcilar, M., Bonato, M., Demirer, R., and Gupta, R. (2018). Geopolitical risks and stock market dynamics of the BRICS. *Economic Systems*, 42(2):295–306.

Barunik, J. and Krehlík, T. (2018). Measuring the Frequency Dynamics of Financial Connectedness and Systemic Risk. *Journal of Financial Econometrics*, 16(2):271–296.

Baumeister, C. and Hamilton, J. D. (2019). Structural Interpretation of Vector Autoregressions with Incomplete Identification: Revisiting the Role of Oil Supply and Demand Shocks. *American Economic Review*, 109(5):1873–1910.

Baumeister, C. and Peersman, G. (2013). Time-varying effects of oil supply shocks on the US economy. *American Economic Journal: Macroeconomics*, 5(4):1–28.

Bernanke, B. S. (1983). Irreversibility, Uncertainty, and Cyclical Investment. *Quarterly Journal of Economics*, 98(1):85–106.

Bilgin, M. H., Gozgor, G., Lau, C. K. M., and Sheng, X. (2018). The effects of uncertainty measures on the price of gold. *International Review of Financial Analysis*, 58:1–7.

Bjørnland, H. C., Thorsrud, L. A., and Torvik, R. (2019). Dutch disease dynamics reconsidered. *European Economic Review*, 119:411–433.

Brogaard, J. and Detzel, A. (2015). The Asset-Pricing Implications of Government Economic Policy Uncertainty. *Management Science*, 61(1):3–18.

Caggiano, G., Castelnuovo, E., and Groshenny, N. (2014). Uncertainty shocks and unemployment dynamics in U.S. recessions. *Journal of Monetary Economics*, 67:78–92.

Caldara, D. and Iacoviello, M. (2022). Measuring Geopolitical Risk. *American Economic Review*, 112(4):1194–1225.

Castelnuovo, E. (2023). Uncertainty before and during COVID-19: A survey. *Journal of Economic Surveys*, In Press.

Chatziantoniou, I., Filippidis, M., Filis, G., and Gabauer, D. (2021). A closer look into the global determinants of oil price volatility. *Energy Economics*, 95:105092.

Cogley, T. and Sargent, T. J. (2005). Drifts and volatilities: monetary policies and outcomes in the post WWII US. *Review of Economic Dynamics*, 8(2):262–302.

Collet, J. and Ielpo, F. (2018). Sector spillovers in credit markets. *Journal of Banking & Finance*, 94:267–278.

Colombo, V. (2013). Economic policy uncertainty in the US: Does it matter for the Euro area? *Economics Letters*, 121(1):39–42.

Corsello, F. and Nispi Landi, V. (2020). Labor Market and Financial Shocks: A Time-Varying Analysis. *Journal of Money, Credit and Banking*, 52(4):777–801.

Cui, J. and Zou, H. (2020). Connectedness Among Economic Policy Uncertainties: Evidence from the Time and Frequency Domain Perspectives. *Journal of Systems Science and Information*, 8(5):401–433.

Czudaj, R. L. (2019). Crude oil futures trading and uncertainty. *Energy Economics*, 80:793–811.

Das, D., Kannadhasan, M., and Bhattacharyya, M. (2019). Do the emerging stock markets react to international economic policy uncertainty, geopolitical risk and financial stress alike? *The North American Journal of Economics and Finance*, 48:1–19.

Del Negro, M. and Primiceri, G. E. (2015). Time Varying Structural Vector Autoregressions and Monetary Policy: A Corrigendum. *Review of Economic Studies*, 82(4):1342–1345.

Diebold, F. X. and Yilmaz, K. (2009). Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets*. *The Economic Journal*, 119(534):158–171.

Diebold, F. X. and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1):57–66.

Diebold, F. X. and Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1):119–134. Causality, Prediction, and Specification Analysis: Recent Advances and Future Directions.

Ding, Q., Huang, J., and Zhang, H. (2021). The time-varying effects of financial and geopolitical uncertainties on commodity market dynamics: A TVP-SVAR-SV analysis. *Resources Policy*, 72:102079.

Elsayed, A. H., Hammoudeh, S., and Sousa, R. M. (2021). Inflation synchronization among the G7 and China: The important role of oil inflation. *Energy Economics*, 100:105332.

Gabauer, D. and Gupta, R. (2018). On the transmission mechanism of country-specific and international economic uncertainty spillovers: Evidence from a TVP-VAR connectedness decomposition approach. *Economics Letters*, 171:63–71.

Gao, R., Zhao, Y., and Zhang, B. (2021). The spillover effects of economic policy uncertainty on the oil, gold, and stock markets: Evidence from China. *International Journal of Finance & Economics*, 26(2):2134–2141.

Gong, X. and Xu, J. (2022). Geopolitical risk and dynamic connectedness between commodity markets. *Energy Economics*, 110:106028.

Granger, C. (2008). Non-Linear Models: Where Do We Go Next - Time Varying Parameter Models? *Studies in Nonlinear Dynamics & Econometrics*, 12(3):1–11.

Hałka, A. and Szafranek, K. (2016). Whose Inflation Is It Anyway? Inflation Spillovers Between the Euro Area and Small Open Economies. *Eastern European Economics*, 54(2):109–132.

Huang, W.-Q. and Liu, P. (2022). Asymmetric effects of economic policy uncertainty on stock returns under different market conditions: Evidence from G7 stock markets. *Applied Economics Letters*, 29(9):780–784.

Kang, S. H. and Yoon, S.-M. (2019). Dynamic connectedness network in economic policy uncertainties. *Applied Economics Letters*, 26(1):74–78.

Kang, W. and Ratti, R. A. (2013). Oil shocks, policy uncertainty and stock market return. *Journal of International Financial Markets, Institutions and Money*, 26:305–318.

Klosner, S. and Sekkel, R. (2014). International spillovers of policy uncertainty. *Economics Letters*, 124(3):508–512.

Koop, G. and Korobilis, D. (2013). Large time-varying parameter VARs. *Journal of Econometrics*, 177(2):185–198.

Koop, G., Pesaran, M., and Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74(1):119 – 147.

Korobilis, D. and Yilmaz, K. (2018). Measuring Dynamic Connectedness with Large Bayesian VAR Models. Essex Finance Centre Working Papers 20937.

Kwon, D. (2022). The impacts of oil price shocks and United States economic uncertainty on global stock markets. *International Journal of Finance & Economics*, 27(2):1595–1607.

Leduc, S. and Liu, Z. (2016). Uncertainty shocks are aggregate demand shocks. *Journal of Monetary Economics*, 82:20–35.

Li, S., Tu, D., Zeng, Y., Gong, C., and Yuan, D. (2022). Does geopolitical risk matter in crude oil and stock markets? Evidence from disaggregated data. *Energy Economics*, 113:106191.

Lin, S. and Chen, S. (2021). Dynamic connectedness of major financial markets in China and America. *International Review of Economics & Finance*, 75:646–656.

Liu, T. and Gong, X. (2020). Analyzing time-varying volatility spillovers between the crude oil markets using a new method. *Energy Economics*, 87:104711.

Lubik, T. A. and Matthes, C. (2015). Time-Varying Parameter Vector Autoregressions: Specification, Estimation, and an Application. *Economic Quarterly*, (4Q):323–352.

Lubik, T. A., Matthes, C., and Owens, A. (2016). Beveridge Curve Shifts and Time-Varying Parameter VARs. *Economic Quarterly*, (3Q):197–226.

Lyu, Y., Tuo, S., Wei, Y., and Yang, M. (2021). Time-varying effects of global economic policy uncertainty shocks on crude oil price volatility: New evidence. *Resources Policy*, 70:101943.

Mumtaz, H. and Surico, P. (2018). Policy uncertainty and aggregate fluctuations. *Journal of Applied Econometrics*, 33(3):319–331.

Ng, S. and Wright, J. H. (2013). Facts and Challenges from the Great Recession for Forecasting and Macroeconomic Modeling. *Journal of Economic Literature*, 51(4):1120–54.

Nilavongse, R., Rubaszek, M., Staehr, K., and Uddin, G. S. (2021). Foreign and Domestic Uncertainty Shocks in Four Open Economies. *Open Economies Review*, 32(5):933–954.

Ozcelebi, O. and Tokmakcioglu, K. (2022). Assessment of the asymmetric impacts of the geopolitical risk on oil market dynamics. *International Journal of Finance & Economics*, 27(1):275–289.

Papież, M., Rubaszek, M., Szafranek, K., and Śmiech, S. (2022). Are European natural gas markets connected? A time-varying spillovers analysis. *Resources Policy*, 79:103029.

Pastor, L. and Verones, P. (2012). Uncertainty about Government Policy and Stock Prices. *Journal of Finance*, 67(4):1219–1264.

Pesaran, H. and Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58(1):17 – 29.

Phan, D. H. B., Sharma, S. S., and Tran, V. T. (2018). Can economic policy uncertainty predict stock returns? Global evidence. *Journal of International Financial Markets, Institutions and Money*, 55:134–150.

Poon, S.-H. and Granger, C. W. (2003). Forecasting Volatility in Financial Markets: A Review. *Journal of Economic Literature*, 41(2):478–539.

Primiceri, G. E. (2005). Time Varying Structural Vector Autoregressions and Monetary Policy. *Review of Economic Studies*, 72(3):821–852.

Shang, J. and Hamori, S. (2021). Do crude oil prices and the sentiment index influence foreign exchange rates differently in oil-importing and oil-exporting countries? A dynamic connectedness analysis. *Resources Policy*, 74:102400.

Sharif, A., Aloui, C., and Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis*, 70:101496.

Smiech, S., Papiez, M., Rubaszek, M., and Snarska, M. (2021). The role of oil price uncertainty shocks on oil-exporting countries. *Energy Economics*, 93:105028.

Szafranek, K., Papież, M., Rubaszek, M., and Śmiech, S. (2023). How immune is the connectedness of European natural gas markets to exceptional shocks? *Resources Policy*, 85:103917.

Szafranek, K. and Rubaszek, M. (2023). Have European natural gas prices decoupled from crude oil prices? Evidence from TVP-VAR analysis. *Studies in Nonlinear Dynamics & Econometrics*.

Uddin, G. S., Bekiros, S., and Ahmed, A. (2018). The nexus between geopolitical uncertainty and crude oil markets: An entropy-based wavelet analysis. *Physica A: Statistical Mechanics and its Applications*, 495:30–39.

Wiggins, S. and Etienne, X. L. (2017). Turbulent times: Uncovering the origins of US natural gas price fluctuations since deregulation. *Energy Economics*, 64(C):196–205.

Xu, Y., Wang, J., Chen, Z., and Liang, C. (2021). Economic policy uncertainty and stock market returns: New evidence. *North American Journal of Economics and Finance*, 58:101525.

Yarovaya, L., Brzeszczyński, J., and Lau, C. K. M. (2016). Intra- and inter-regional return and volatility spillovers across emerging and developed markets: Evidence from stock indices and stock index futures. *International Review of Financial Analysis*, 43:96–114.