



# Multi–Scale Risk Connectedness Between Economic Policy Uncertainty of China and Global Oil Prices in Time–Frequency Domains

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## Abstract

With a sample of monthly data from January 2000 to July 2021, this paper investigates the risk connectedness relationship between different kinds of China’s EPU and global oil prices in both time and frequency domains. To achieve that, a research framework mainly consists of wavelet transform method and spillover index approach is established. The results show that EPU of China receives the risk spillover from global oil prices in most cases. Moreover, we find fiscal policy uncertainty and trade policy uncertainty are generally the recipients of risk spillover on most time scales, except that monetary policy uncertainty primarily serves as the risk transmitter. Lastly, the risk role of exchange rate policy uncertainty in China has the most frequent change among four kinds of EPU. This paper provides valuable policy implications for policymakers, investors and risk managers in the energy market.

**Keywords** Economic policy uncertainty · Global oil prices · Wavelet transform · Risk connectedness

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## 1 Introduction

In recent years, the linkage of economic policy uncertainty (EPU) and crude oil price has received an increasing attention of researchers. For one thing, most researches point out that EPU has a vital impact on economic activities (Adedoyin et al., 2021; Apergis et al., 2021; Herrera et al., 2019). For example, EPU can directly affect the investment decisions of investors and the production plans of enterprises, and then affect the demand and price of crude oil (Degiannakis et al., 2018). For another thing, crude oil, as a global strategic commodity, is essential for the stable development of the global economy and financial markets (Cheng & Cao, 2019; Dong et al., 2019; Jarrett et al., 2019; Zhang et al., 2017). Oil price could affect inflation (Chen et al., 2020), output (Nusair & Olson, 2021) and interest rate (Mohaddes & Pesaran, 2017), and lead to the fluctuation of EPU (Rehman, 2018). In view of such close connection between EPU and oil price, it is of great significance to examine the internal interaction and risk spillover between them in depth.

Starting with the pioneering work of Kang and Ratti (2013a), there is a growing body of literature focusing on the nexus between EPU and crude oil, but the conclusions remain no consensus. Some scholars find evidence that there exists a negative linkage between EPU and crude oil (Antonakakis et al., 2014; Zhang & Yan, 2020), while others believe their connection tends to be positive (Kang & Ratti, 2013b; Ma et al., 2019), also some consider that EPU and crude oil prices fluctuations can be asymmetrically associated (Hailemariam et al., 2019; Lei et al., 2019). Meanwhile, these researches provide corresponding explanations for their conclusions. For example, Zhang and Yan (2020) attribute the negative effect to the socio-economic impact, whereas Kang and Ratti (2013b) declare that the increased oil anticipation caused by EPU can push up global oil prices. Lei et al. (2019) indicate that their relationship changes after the global financial crisis.

On the basis of existing literature, this paper adopts a multi-scale perspective, mainly because of the following three reasons. First, since stakeholders in the market have different concerns on time scales, the frequency domain information could be important and should not be ignored. Specifically speaking, policymakers basically focus on the long-term trends to keep the entire market balanced and stable in the long run, manufactures mainly refer to the middle-term trends since they are highly dependent on the seasonal production cycle in single year, and speculators pay more attention to the short-term trends because of their interest in returns from transactions in a very short time (Huang et al., 2016). Second, analyzing global oil price from a multi-scale perspective can avoid the interaction of various macro and micro factors, meanwhile change the complexity to the simplicity (He et al., 2021). Third, different types of EPU have been proved to have diverse interactions with global oil prices from the short term to the long term (Qin et al., 2020). In this case, ignoring the information in different time scales might be important reason for the inconsistent conclusions of existing studies.

This research focuses on China, since China plays an increasing vital role in the global economic recovery, especially during the 2019-covid pandemic (Yu et al., 2020). In addition, China's rising demand for crude oil significantly is influencing the world energy market (Kang & Ratti, 2015). For your information, the oil dependence of

China on foreign countries has exceeded 70% since 2018, indicating China's economy tends to be more sensitive and vulnerable to global oil price shocks. To the best of our knowledge, only few studies explore the relationship between EPU of China and global oil prices from the perspective of time domain. For instance, Antonakakis et al. (2014) and Wang and Lee (2020a) examine the dynamic spillovers between global oil prices and EPU of oil-importing countries. While Kang and Ratti (2015) investigate the independence of them, Gao et al. (2020) distinguish the different spillover effect levels of EPU on crude oil and other markets. However, the multi-scale risk connectedness between different kinds of China's EPU and global oil prices has not been deeply explored.

In this case, our prime motivation is to investigate all the time–frequency information that is integrated as a whole in the original time series to reveal the multi-scale risk transmission between them. To achieve that, we firstly apply the wavelet transform to separate our time series into different time scales. Then we employ the DY spillover index approach to compute the multi-scale static net risk connectedness between different kinds of China's EPU and global oil prices. Finally, we examine their dynamic net risk spillover effects by utilizing a rolling window approach. This framework can not only help investigate the complex connection between oil prices and EPU of a certain country, but also can be extended to evaluate the intricate effects between other international commodity markets from multi-scale perspective.

Compared with the prior literature, this research makes at least the following three contributions. First, unlike existing research mainly discussed from the perspective of time domain (e.g., Lin & Bai, 2021; Zhang et al., 2019), we combine the wavelet transform, DY spillover index approach and rolling window approach to better investigate the linkage between EPU and oil prices from a multi-scale perspective. The existing research of DY spillover index in the frequency domain is mainly based on Baruník and Krehlík (2018), such as Lovcha and Perez-Laborda (2020). On this basis, our research decomposes the time series by wavelet transform before the DY spillover index approach in view of its advantages over other frequency decomposition methods. As an alternative to the Fourier transform, wavelet transform means decomposing the raw time series into various basis wavelets generated by the mother wavelet in time–frequency domains (Dong et al., 2019). The wavelet transform can ensure that as much information of the time series as possible is utilized, without satisfying some prerequisites. Meanwhile, it is data-driven, which distinguishes it from other models that rely on parameters (Vacha & Baruník, 2012). DY spillover index approach also has many advantages. It is simple and easy to operate (Awartani & Maghyreh, 2013), and it can calculate the direction and magnitude of spillover effects at the same time (Xu et al., 2019), and analyze the relative importance of each variable without relying on their sequences (He et al., 2020). In addition, the rolling window approach can avoid missing the crucial secular and cyclical movements of the spillover effects (Diebold & Yilmaz, 2012).

Second, some literature has demonstrated the significant relationship between monetary policy uncertainty (MPU) or fiscal policy uncertainty (FPU) and global oil prices (Pieschacon, 2012; Razmi et al., 2020). But trade policy uncertainty (TPU) and exchange rate policy uncertainty (ERPU) should also be taken into account, especially in the context of the COVID-19, Sino-U.S. trade war and anti-globalization.

Although Chen et al. (2019) and Sun et al. (2020) consider both of the time and frequency domains, they fail to further investigate the multi-scale interaction between different kinds of EPU and global oil prices. Which kind of policy uncertainty is the most relevant to global oil market, how do the fluctuations of global oil prices affect the EPU and what is the difference in the impact of oil prices on different types of policy uncertainty? These questions can be answered by investigating the linkage among MPU, FPU, TPU, ERPU and global oil prices from the perspective of different time horizons. However, to our best knowledge, there are few studies that investigate the above questions, our paper is a pioneering effort to study their static and dynamic risk connectedness in time–frequency domains.

Third, we get some novel findings. (1) EPU of China remains as the recipient of risk from global oil prices on most of the time scales. (2) While FPU always receives the risk on different time scales, TPU and MPU are mainly the risk receiver and transmitter, respectively. (3) Among four kinds of China's EPU, ERPU's changes in the direction of risk spillover fluctuate the most dramatically. These findings can give insights to Chinese policy-makers to adjust macroeconomic policy with the trend of oil prices at different time horizons, then take measures to avoid potential risk at home and abroad.

The remainder of our paper is structured as follows. Section 2 reviews the relative literature. Section 3 describes our sample data and outlines the basic methodology used in this paper. Section 4 presents the static and dynamic results of multi-scale risk connectedness between China's EPU and global oil prices in time–frequency domains. Section 5 concludes this paper and provides corresponding policy implications.

## 2 Literature review

Since the 2008 Global Financial Crisis, EPU has gained more and more attentions from policymakers, investors and other market participants. In this case, Baker et al., (2011, 2016) develop the widely-acknowledged EPU index based on the newspapers, which inspires many scholars to study the relationship between EPU and other economic variables (e. g., Kurov & Stan, 2018). Among them, the early research of Kang and Ratti (2013a) focuses on the relationship between EPU and global oil prices, which find that aggregate oil demand shocks, oil supply-side shocks and oil market-specific demand shocks separately have negative, insignificant and positive impacts on EPU. Since then, more and more scholars began to study the nexus between EPU and oil prices, mainly including the following three strands.

The first strand of literature verifies that global oil prices can influence EPU. For example, Kang and Ratti (2013b) prove that oil-market specific demand shock has a positive impact on EPU. Kang et al. (2017) discuss the dynamic impacts of US and non-US oil production shocks on EPU and detect that US oil production shocks positively influence EPU while the effect is not significant for non-US oil production shocks. Hailemariam et al. (2019) apply a nonparametric panel data method to investigate the time-varying effect of global oil prices on EPU and prove that global oil prices negatively influence EPU when there is a surge in global aggregate oil demand. Kang et al. (2019) discover that the response of EPU to global oil prices is asymmetrical,

while it is concluded that different global oil prices shocks have diverse impacts on different faces of EPU (Degiannakis et al., 2018) and diverse countries' EPU (Rehman, 2018). However, Yang (2019) states that the impact of oil price shocks on EPU is insignificant.

The second strand of literature explores the impact of EPU on global oil prices. In terms of the global oil prices shocks, Yao and Sun (2018) find that higher global oil price is connected with higher EPU, but Reboredo and Uddin (2016) conclude there is no co-movement and Granger causality between EPU and global oil prices. In terms of the global oil prices returns, Aloui et al. (2016) adopt the copula estimation and get the conclusion that EPU has a positive effect on oil returns during the financial crisis and Great Recession, but the impact changes to be negative over the entire sample period. Zhang and Yan (2020) support that EPU negatively influence oil prices returns and the effect is asymmetric (Ji et al., 2018), whereas Bonaccolto et al. (2018) implement a non-parametric method and quantiles forecasts to reveal that EPU separately has a negative and positive effect on the lower and upper quantiles of global oil prices returns. Mei et al. (2019) find that EPU has a mixed impact on oil prices volatility based on the chosen models, while Hu et al. (2020) reveal that EPU has a time-varying influence on the realized volatility of global oil price by using high-frequency data.

The third strand of studies investigates the interaction between EPU and global oil prices. Antonakakis et al. (2014) test the dynamic bidirectional relationship between them in net oil-exporting and net oil-importing countries and consider that there exists negative interaction between them. Kang and Ratti (2015) prove that EPU of China has negatively influence on global oil prices and oil market-specific demand shocks have a positive impact on EPU of China. Sun et al. (2020) employ the wavelet coherence approach and certify that the mutual influence between them is weak in the short term, but turns to negative in the medium term and positive in the long term. Qin et al. (2020) study the time-varying interaction between global oil prices and different kinds of EPU in time–frequency domains and find that EPU can positively and negatively influence global oil price, but global oil price has a positive impact on EPU. But Andreasson et al. (2016) examine the interaction between oil prices returns and EPU through linear and nonlinear causality tests, and show strong evidence of unidirectional relationship from EPU to oil prices returns.

From the existing studies, it can be found that there are still some deficiencies. Firstly, most of the studies are mainly focused on the developed countries, but there are relatively few literatures investigating EPU of China and global oil prices alone. Secondly, the causality and correlativity between EPU and global oil prices are mostly discussed. Although some scholars begin to investigate the linkage between EPU and global oil prices, there is almost no investigation about their risk connectedness from a multi-scale perspective. Finally, comprehensive EPU index developed by Baker et al. (2016) is often applied to discuss its relationships with global oil prices, but few scholars study the nexus among different kinds of China's EPU and global oil prices. Therefore, in order to fill the gaps in the existing literature about the multi-scale risk connectedness between different types of China's EPU and global oil prices, our paper uses the wavelet transform and DY spillover index approach raised by Diebold and Yilmaz (2012) with structured Lasso Penalties to investigate their risk transmission relationship in time–frequency domains.

## 3 Data and Methodology

### 3.1 Data Description

Two monthly indices are mainly used to measure the EPU of China, which are separately established by Baker et al. (2016) and Huang and Luk (2020), and both of them are based on the Chinese newspapers' coverage frequency. By contrast, the former only refers to one Hong Kong's newspaper in consideration of the media censorship, while the latter chooses ten newspapers in mainland China. To better quantify the policy-specific EPU of China, we use the index from Huang and Luk (2020). To be specific, following the basic compilation strategy of Baker et al. (2016), the index of Huang and Luk (2020) collect the number of articles containing at least one of four keywords (namely Economy, Uncertainty, Policy and four kinds of economic policy terms). Then the number is scaled, standardized and normalized to describe the average monthly policy-specific EPU of China, including FPU, MPU, TPU and ERPU. As for global oil prices, we apply WTI and Brent crude oil future prices at the same time. While WTI primarily reflects the domestic crude oil price in the United States, Brent represents the benchmark prices for crude oil in countries and regions such as the North Sea, the Mediterranean and Africa. All data of oil prices (Dollars per Barrel) are collected from the U.S. Energy Information Administration (EIA). Furthermore, our chosen sample period runs from January 2000 to July 2021.

Table 1 displays the descriptive statistics of China's EPU and global oil prices, which indicates that TPU and global oil price separately exhibit the highest and least mean and standard error. The skewness of all variables is bigger than zero and their Kurtosis is more than 3. According to the Jarque–Bera (J-B) test, all variables all reject the normal distribution hypothesis. And the Augmented Dicky Fuller (ADF) and Phillips–Perron (PP) tests all confirm that all EPU and global oil prices are stationary when the significance is at 1% level.

Following Diebold and Yilmaz (2009) and BenSaïda et al. (2018), we use the volatility spillover to represent the risk transfer between different variables. Our measure of volatility is in line with Giles (2008), which points out that volatility expressed by the square of returns can implicitly estimate the actually unobserved volatility. Following Guhathakurta et al. (2020), we estimate the returns of variables as  $R(X_{it}) = \ln X_{it} - \ln X_{it-1}$ . And the volatilities of variables are computed as squared of their returns as  $V(X_{it}) = (\ln X_{it} - \ln X_{it-1})^2$ .

### 3.2 Methodology

The methodology utilized in this paper is threefold. First, using the wavelet transform with MODWT algorithm, we decompose the time series into several frequency bands to represent different time scales. Second, the DY spillover index approach raised by Diebold and Yilmaz (2012) with structured Lasso Penalties is adopted. Specifically speaking, we first employ the VAR model to extract the mutual residuals between variables, then put those residuals to the DY spillover index model to analyze their static net risk spillover effects between China's EPU and global oil prices in time–frequency

**Table 1** Descriptive statistics of variables

	Obs	Mean	Std	Min	Max	Skew	Kurt	J-B	ADF	PP
FPU	258	0.20	0.34	0.00	2.67	3.55	16.47	3518.60***	-4.90***	-182.55***
MPU	258	0.11	0.21	0.00	2.32	5.93	50.60	29,514.00***	-5.65***	-218.43***
TPU	258	0.31	0.51	0.00	3.87	3.27	13.86	2569.30***	-4.90***	-227.87***
ERPU	258	0.17	0.28	0.00	2.07	3.65	17.39	3889.00***	-6.45***	-170.23***
WTI	258	0.01	0.05	0.00	0.61	10.26	116.42	152,627.00***	-5.28***	-320.90***
Brent	258	0.01	0.04	0.00	0.64	12.70	181.01	364,838.00***	-5.82***	-270.19***

\*\*\* indicates significance at 1% level

domains. It is noteworthy that the wavelet transform uncovers the complete information from the short term to the long term, while DY spillover index takes a picture of risk connectedness between EPU and global oil prices in the whole-time domain. Hence, an organic combination of the wavelet transform method and DY spillover index makes it possible to analyze the risk spillover relationship in both time and frequency domains. Third, using a rolling window approach, their dynamic net risk connectedness is calculated.

### 3.2.1 Wavelet Transform

There are two principal segments in the discrete wavelet transform, wavelet filter  $W_l$  and scaling filter  $S_l$ , which satisfy the following conditions (Percival & Walden, 2000):

$$\sum_0^{L-1} W_l = 0, \sum_0^{L-1} W_l^2 = 1, \sum_0^{L-1} W_l, W_{l+2n} = 0 \tag{1}$$

$$\sum_0^{L-1} S_l = \sqrt{2}, \sum_0^{L-1} S_l^2 = 1, \sum_0^{L-1} S_l, S_{l+2n} = 0 \tag{2}$$

where  $n$  is an integer and  $L$  represents the length of the filter. We mainly employ a wavelet transform by applying the MODWT algorithm. By doing so, our chosen series are decomposed to coefficients connected with variations over multiple different time scales. Using the MODWT, the readjusted  $j$ th level wavelet filter  $W_{j,l}^*$  and scaling filter  $S_{j,l}^*$  can be expressed as:

$$W_{j,l}^* = \frac{W_{j,l}}{a}, S_{j,l}^* = \frac{S_{j,l}}{a} \tag{3}$$

where  $a = j/2$  and  $j$  is the totality of the decomposition levels. Likewise, the readjusted filters also need to meet some requirements as:

$$\sum_0^{L-1} W_l^* = 0, \sum_0^{L-1} W_l^{*2} = \frac{1}{2^l} \tag{4}$$

$$\sum_0^{L-1} S_l^* = 1, \sum_0^{L-1} S_l^{*2} = \frac{1}{2^l} \tag{5}$$

$$\sum_{-\infty}^{+\infty} W_l^* W_{l+2n}^* = \sum_{-\infty}^{+\infty} S_l^* S_{l+2n}^* \tag{6}$$

The time-dependent coefficients of the filters are indicated as:

$$w_{j,t} = \sum_0^{L-1} \left( \frac{W_{j,l} X_{t-1}}{2^a} \right) \text{ mod } N \tag{7}$$

$$s_{j,t} = \sum_0^{L-1} \left( \frac{S_{j,l} X_{t-1}}{2^a} \right) \text{ mod } N \tag{8}$$



### 3.2.2 DY Spillover Index Approach with Structured Lasso Penalties

After decomposing the time series into several frequency bands, we then utilize the DY spillover index approach raised by Diebold and Yilmaz (2012), which can quantitatively compute the total and dynamical directional spillovers based on the forecast error variance decomposition (FEVD). At first, to extract the mutual residuals between variables, we use the VAR model as:

$$X_t = \sum_{i=1}^P C_i X_{t-i} + \varepsilon_i \quad (9)$$

where  $X_t$  is a vector of  $N \times 1$  endogenous variable,  $P$  is the lag length,  $C_i$  represents the matrix of estimated coefficients and  $\varepsilon_i$  is a vector of disturbance. To conduct the FEVD and measure the contribution of the shock of  $x_j$  to the forecast error of  $x_i$ , we transform the VAR model into a moving average representation as:

$$X_t = \sum_{i=1}^{\infty} M_i \varepsilon_i \quad (10)$$

where  $M_0$  is an  $N \times N$  identity matrix and  $M_i$  can be represented as:

$$M_i = \sum_{j=1}^P C_{i-j} M_j \quad (11)$$

To reduce the heavy parameter of the VAR model that causes an arbitrary specification of decreased series subset, we bring in the structured Lasso Penalties as:

$$\min \sum_{t=1}^T \|X_t - \sum_{i=1}^P C_i X_{t-i}\|_2^2 + \lambda P_y(C_i) \quad (12)$$

where  $\lambda$  means the non-negative penalty parameter and  $P_y(C_i)$  shows the group penalty structure on endogenous coefficient. Considering the VAR model does not include the non-modeled exogenous variables, we mainly employ the Basic Penalty, which is widely used to divide variables to their own groups and can greatly deal with larger optimization problems. Afterwards, we put the extracted residuals into the DY spillover index model. Following Pesaran and Shin (1998), shares of the generalized FEVD can be computed by:

$$\theta_{i,j}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' M_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' M_h \sum M_h' e_i)^2} \quad (13)$$

where  $H$  means the forecast step,  $\sigma_{jj}$  shows the standard deviation of error term of the  $j$ th equation.  $e_i$  is a selection column vector, whose value is one for the  $i$ th portion, but zero for others. Considering the non-orthogonality of variables shocks, shares of

FEVD should be normalized as:

$$\bar{\theta}_{i,j}(H) = \frac{\theta_{i,j}(H)}{\sum_{j=1}^n \theta_{i,j}(H)}, \text{ with } \sum_{j=1}^n \bar{\theta}_{i,j}(H) = 1 \text{ and } \sum_{i,j=1}^n \bar{\theta}_{i,j}(H) = N \quad (14)$$

Accordingly, the total risk spillover can be measured as:

$$S(H) = \frac{\sum_{i,j=1,i \neq j}^N \bar{\theta}_{i,j}(H)}{\sum_{i,j=1}^N \bar{\theta}_{i,j}(H)} = \frac{\sum_{i,j=1,i \neq j}^N \bar{\theta}_{i,j}(H)}{N} \quad (15)$$

Also, the directional risk spillover can be counted as:

$$S_{i \rightarrow \bullet}(H) = \frac{\sum_{j=1,i \neq j}^N \bar{\theta}_{i,j}(H)}{\sum_{i,j=1}^N \bar{\theta}_{i,j}(H)} = \frac{\sum_{j=1,i \neq j}^N \bar{\theta}_{i,j}(H)}{N} \quad (16)$$

$$S_{i \leftarrow \bullet}(H) = \frac{\sum_{i=1,i \neq j}^N \bar{\theta}_{i,j}(H)}{\sum_{i,j=1}^N \bar{\theta}_{i,j}(H)} = \frac{\sum_{i=1,i \neq j}^N \bar{\theta}_{i,j}(H)}{N} \quad (17)$$

Therefore, net directional risk spillover from each variable to all other variables can be captured as:

$$S_i(H) = S_{i \rightarrow \bullet}(H) - S_{i \leftarrow \bullet}(H) = \frac{\sum_{j=1,i \neq j}^N \bar{\theta}_{i,j}(H) - \sum_{i=1,i \neq j}^N \bar{\theta}_{i,j}(H)}{N} \quad (18)$$

### 3.3 Theoretical Background of Empirical Analysis

In the abstract and literature review section, we state that China is still extremely dependent on crude oil imports and China's policy adjustment faces the risk of global oil prices shocks. As Cheng et al. (2019) point out that China mainly serves as an acceptor and responder to global oil price shocks, so it is reasonable to assume that global oil prices tend to transmit risks to China's EPU. In addition, the relationship between global oil prices and EPU is diverse in different studies, it can be unidirectional (Kang et al., 2017), mutual (Jiang & Cheng, 2021), positive (Kang & Ratti, 2013b), negative (Zhang & Yan, 2020), asymmetric (Jiang et al., 2021) and insignificant (Yang, 2019). As mentioned before, the risk connectedness in different time scale might be various, and the ignorance of the frequency domain information might lead to this inconsistency of this conclusion. To solve that, the multi-scale analysis is adopted.

According to the related research of Liu et al. (2020), monetary policy is the uncertainty giver, while fiscal policy, trade policy, exchange rate policy are all net uncertainty receivers. Therefore, we assume that MPU mainly serves as the risk transmitter, while FPU, TPU and ERPU basically receive the risk spillover. The possible transmission channels can be divided into three parts. First, the interest rate parity theory indicates

that the difference in interest rates between the two economies can directly influence the exchange rates of their currencies. Therefore, interest rates may change with monetary policy, thereby further affecting the exchange rate and trade (Liu et al., 2020). Second, global oil prices can affect the inflation and production output (Ji et al., 2018), thereby putting pressure on policymakers to choose proper strategies and leading to further EPU. Third, global oil prices may have an impact on government size (El Anshasy & Bradley, 2012) and the efficient operation of the government (Antonakakis et al., 2014), eventually driving EPU to fluctuate (Degiannakis et al., 2018).

## 4 Empirical Results

### 4.1 Results of Wavelet Transform

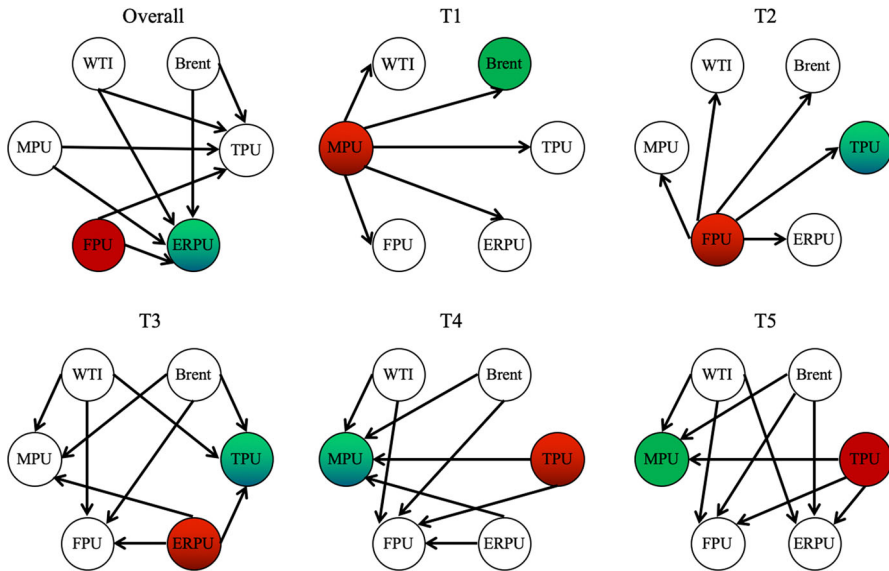
To investigate the risk transmission relationship between China's EPU and global oil prices in frequency domain, we first adopt the wavelet transform using MODWT algorithm. According to the results of wavelet transform, the totality of decomposition levels  $j$  is five, and the corresponding time scales range from 2 to  $2^{j+1}$  (Boubaker & Raza, 2017; Gupta et al., 2018). Hence, our raw series are divided into five frequency bands, including T1 (approximately 2–4 months), T2 (approximately 4–8 months), T3 (approximately 8–16 months), T4 (approximately 16–32 months) and T5 (approximately over 32 months). Among them, the short term is associated with the highest frequency fluctuation and the risk lover trader while the risk aversion trader may concentrate more on the long term (Boubaker & Raza, 2017). Therefore, the empirical results of risk connectedness at diverse time scales can give a reference to different market participants when making their own strategic decision.

### 4.2 Static Analysis of Risk Connectedness

To investigate the static net risk connectedness of EPU and global oil prices in time–frequency domains, we employ the DY spillover index approach raised by Diebold and Yilmaz (2012) with structured Lasso Penalties. The results are revealed in Fig. 1 and Table 2. Overall, WTI, Brent, MPU and FPU can transmit risk to TPU and ERPU, among which FPU and ERPU are the most influential risk transmitter and receiver, respectively.

In different terms, we obtain some different findings. From the perspective of the short term, in scale T1, global oil prices and FPU act as the risk receivers, and Brent is the biggest risk receiver. While MPU is the biggest risk transmitter, TPU and ERPU remain as the risk receivers. In T2, global oil prices, TPU and ERPU are still the risk receivers, while MPU begins to act as the risk receiver and TPU is the most influential risk receiver. Meanwhile and interestingly, FPU becomes the source of risk and the biggest risk transmitter throughout the full terms. And ERPU keeps serving as the risk receiver in the whole short term.

From the perspective of the medium term, in T3, only the risk roles of TPU and MPU remain as the same as in T2. Furthermore, global oil prices and ERPU change to the risk



**Fig. 1** Static risk connectedness on different time scales

**Table 2** Results of net spillover on different time scales

	WTI	FPU	MPU	TPU	ERPU	Brent
Overall	0.0781	0.1588	0.1497	-0.0118	-0.4126	0.0378
T1	-0.2842	-0.0036	1.1045	-0.1980	-0.2946	-0.3241
T2	-0.0213	2.7835	-0.2139	-2.0419	-0.4640	-0.0425
T3	0.0923	-0.4650	-0.3300	-0.5781	1.2605	0.0202
T4	0.8213	-1.1137	-2.1742	0.9729	0.7353	0.7583
T5	0.3240	-0.2156	-4.0482	3.9786	-0.3596	0.3208

transmitters. While TPU is still the biggest risk receiver, the biggest risk transmitter changes to ERPU. In T4, global oil prices and ERPU are still the risk transmitters, while TPU changes from the risk receiver to the risk transmitter. Meanwhile, FPU and MPU are still the risk receivers. Moreover, the most influential risk transmitter and receiver are TPU and MPU, respectively. From the perspective of the long term, in T5, only ERPU becomes the risk receiver, while the risk roles of other variables and the biggest risk transmitter and receiver remain the same as in T4.

Our static results of risk connectedness can be summarized into three parts. First, on the whole, the biggest risk transmitter and receiver are separately FPU and ERPU. But in different periods, the biggest risk transmitter and receiver are totally diverse. We find that four kinds of EPU mutually serve as the most influential risk transmitter and receiver at five different time scales. This is in line with the research of Liu et al. (2020),

which claim that from the short term to the long term, the main uncertainty transmitter among China's EPU is diverse. Second, though acting as the risk transmitters on the whole, global oil prices play different risk roles in different time scales. Specifically speaking, they are risk receivers in the short term, but change to risk transmitters in the medium term and long term. Similarly, Yin (2016) concludes that there exists unidirectional spillover from uncertainty to oil returns in the short term. Last, as for four kinds of EPU, FPU is always the risk receiver except in T2, when it serves as the only risk transmitter. This finding echoes with the conclusion of Cheng et al. (2019) that global oil price volatility contributes to expansionary fiscal policy. MPU changes from risk transmitter to risk receiver, while TPU changes from risk receiver to risk transmitter, echoing with Wei (2019) that different kinds of global oil prices shocks and EPU all influence China's trade. As the time scale increases, trade policy may affect the supply and demand side of crude oil to affect its price. Moreover, ERPU is the risk receiver in the short term and the long term, but it changes to the risk transmitter in the medium term. A possible reason is that ERPU has the most direct and close connection with oil prices (Wang & Lee, 2020a, 2020b), thus are much more sensitive to the global oil prices volatility.

### 4.3 Dynamic Analysis of Risk Connectedness

To compute the dynamic net risk connectedness between EPU of China and global oil prices, we apply a rolling window of 50 observations (about 20% of the sample size) as suggested in Kang et al. (2019) and Plakandaras et al. (2020). The results on the whole are displayed in Fig. 2, and that of different time scales are presented in the appendices (Figs. 3, 4, 5, 6 and 7). Overall, in the sample periods, global oil prices are the risk transmitters, and FPU is the risk receiver. Meanwhile, MPU transforms from the risk receiver to the risk transmitter, but TPU and ERPU change from the risk

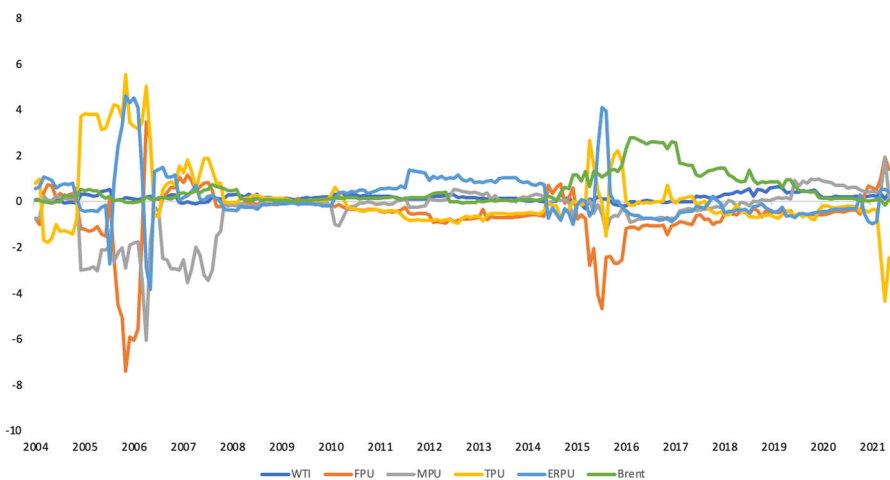


Fig. 2 Dynamic risk connectedness on the whole

transmitters to the risk receivers. And interestingly, FPU and MPU basically maintain the same trend of change, which is attributed to the fact that the two policies are often implemented at the same time. Moreover, the directions of risk transmission of TPU and ERPU are opposite in most cases, but keep in sync in certain specific periods, such as after the outbreak of COVID-19.

In T1, global oil prices and MPU are the risk transmitters, while FPU is the risk receiver. TPU converts from the risk transmitter to the risk receiver, but ERPU alters from the risk receiver to the risk transmitter. In T2, except that MPU becomes the risk receiver, other variables play the same risk roles as in T1. In T3, global oil prices and ERPU are the risk transmitters, while FPU is the risk receiver. MPU changes from the risk receiver to the risk transmitter, but TPU convert from the risk transmitter to the risk receiver. In T4, FPU remains as the risk receiver. Global oil prices and TPU transform from the risk receivers to the risk transmitters, but MPU and ERPU change in the opposite direction. In T5, global oil prices and ERPU are the risk transmitters, while FPU and MPU are the risk receivers, and TPU changes from the risk transmitter to the risk receiver.

Specially, Akhtaruzzaman et al. (2021a) indicate that during the COVID-19 period, financial contagion transmission appears through financial and nonfinancial firms, the oil price risk exposure of them seems to be moderated (Akhtaruzzaman et al., 2020), and gold is proved to be a safe-haven asset between December 31, 2019 and March 16, 2020 (Akhtaruzzaman et al., 2021b). Hence, we compare the appearances of dynamic results of risk connectedness before and after the COVID-19 outbreak. The results show that after the outbreak, global oil prices experience a sharp decline but still act as the risk transmitters. As for FPU, the risk receiver, changes from a relatively stable state to a constant increase. Other risk receivers, ERPU and TPU alter from the decline to the incline, while the transformation process of MPU, the risk transmitter is just the opposite.

Similar to the static results of risk connectedness, our dynamic results also can be summarized into three aspects. First, on the whole, global oil prices and FPU separately serve as risk transmitters and risk receiver. Other three kinds of China's EPU all experience the change of risk roles. Among them, TPU and ERPU are in the same process, but the change of MPU is the opposite. Second, from the perspective of five different time scales, global oil prices are basically risk transmitter, except in T4, when it changes from risk receiver to transmitter. Third, as for four kinds of China's EPU, FPU serves as risk receiver from the short term to the long term. In most of time scales, MPU is mainly risk transmitter, although it changes to risk receiver in T2 and T5. TPU changes from risk transmitter to risk receiver except in T4, when it changes oppositely. ERPU experience the opposite transformation of risk roles to TPU in the short term and T4, but it keeps as risk transmitter in T3 and T5.

Furthermore, three main findings can be acquired after comparing the static and dynamic results of risk connectedness. First and overall, global oil prices transmit the risk to EPU, while different EPU appear differently in static and dynamic cases. Second, as for global oil prices on different time scales, even though the static result shows that they serve as risk receiver in short term, they are mainly risk transmitter on most time scales, combining the static and dynamic results. Third, changes in risk roles of four kinds of China's EPU occur on different time scales, but in most cases

their risk roles appear basically the same. FPU is always risk receiver except in T2 as depicted in static results, MPU mainly serves as risk transmitter, while TPU and ERPU receive the risk spillover.

#### 4.4 Robustness Check

Following Maitra et al. (2021), we then assess the sensitivity of risk connectedness results by changing the rolling windows and horizons of FEVD. There are two main steps in our robustness tests: first, we remain the rolling windows at 50 months and then change the horizons of FEVD as  $H = 5, 10$  and  $15$ ; and second, we keep the horizons of FEVD at 10 and then change the rolling windows as  $W = 40, 50$  and  $60$  months. The robustness tests results are shown in Figs. 8 and 9, which are mostly consistent with our initial results and guarantee the robustness of our findings.

### 5 Conclusion and Policy Implications

Using the monthly data from January 2000 to July 2021, this paper investigates the multi-scale risk connectedness between different kinds of China's EPU and global oil prices in time–frequency domains. First, the wavelet transform approach is employed to separate the raw series into different time scales represents different frequency bands. By doing so, important information in the frequency domain from the short term to the long term can be fully recognized. Then, our paper uses the spillover index approach raised by Diebold and Yilmaz (2012) with structured Lasso Penalties to analyze their static net risk spillover effects under the condition of different time scales. DY spillover index is able to characterize the risk connectedness between different variables from the overall time dimension. And the organic combination of wavelet transform method and DY spillover index provides a comprehensive analysis of risk spillover relationship between economic variables or financial markets in both time and frequency domains. Finally, a rolling window approach is utilized to examine their dynamic net risk connectedness. So, the case when the crucial secular and cyclical movements of spillover effects is missed can be avoided (Diebold & Yilmaz, 2012).

Several main conclusions can be obtained from on the basis of the empirical results. Firstly, global oil prices transmit the risk to China's EPU on most time scales. This result further testifies the conclusion of Gao et al. (2020) that China's EPU is the receiver of oil fluctuation spillover. Secondly, FPU of China always shows as the risk receiver on different time scales. But on some of time scales, it also serves as the most influential risk transmitter. This conclusion can be attributed to the expansionary fiscal policy caused by global oil price shocks (Cheng et al., 2019). Thirdly, the risk role of ERPU has the most frequent changes, indicating that ERPU's risk spillover is volatile in China. This finding echoes with Wang and Lee (2020a, b) that comparing to other EPU, ERPU has the strongest correlation with global oil prices, so it fluctuates more sensitively to changes in global oil prices. Fourthly, China's TPU mainly appears as the risk receiver, although its risk role is also constantly changing on different time scales. Fifthly, unlike other kinds of China's EPU, MPU primarily transmits the risk

from the short term to the long term. This is in line with Liu et al. (2020) which find that monetary policy is the main uncertainty giver, while fiscal policy, trade policy, exchange rate policy are all net uncertainty receivers.

According to our empirical results, several significant policy implications can be obtained. First, given that global oil prices tend to transmit risk to China's EPU, Chinese policymakers should fully evaluate the oil shock and take proper policy adjustment when facing violent oil price volatility. Second, for investors and managers in the energy market, the risk connectedness between EPU and global oil prices from the short to the long term is diverse, so they should incorporate different kinds of EPU and time scales into their risk forecasting models, and timely adjust their strategies to avoid the foreseeable risk. Third, economy that are highly dependent on crude oil is likely to face the dilemma of high EPU and severe oil price fluctuation at the same time. Therefore, government should support the technological development of clean energy and other renewable energy, and strengthen the global oil cooperation. Our further study may focus more on specific regions, such as the Asia–Pacific region and the European Union. And the following research can take the possible stylized facts that different types of assets may have into consideration, for instance, the multi-scale asymmetric risk connectedness between different kinds of EPU and global oil price.

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**Author contributions** SC: Methodology, contributed to the development of this empirical work, in terms of literature reading and empirical results and writing. WL: Methodology, Writing-original draft, Writing-review & editing, Visualization. QJ: Conceptualization, Writing-review & editing, Supervision. YC: Methodology, Writing-review & editing.

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**Data Availability** All data used during the study are available from Huang and Luk (2020) and the U.S. Energy Information Administration (EIA).

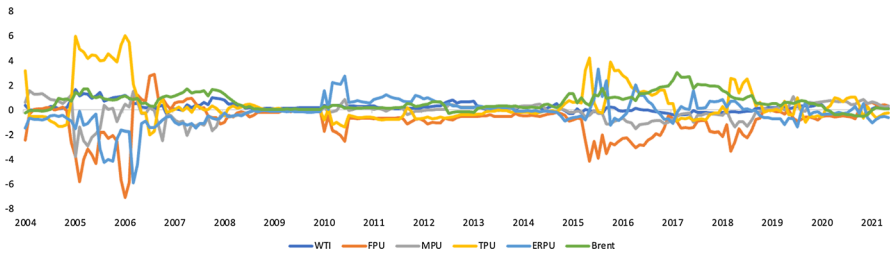
## Declarations

**Conflict of interest** The authors have no relevant financial or non-financial interests to disclose.

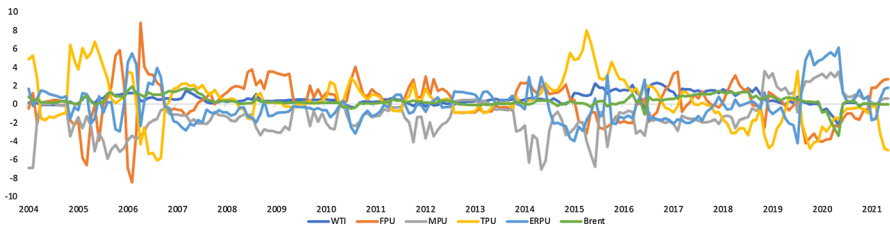


## Appendix

See Figures 3, 4, 5, 6, 7, 8 and 9.



**Fig. 3** Dynamic risk connectedness of volatilities in T1



**Fig. 4** Dynamic risk connectedness of volatilities in T2

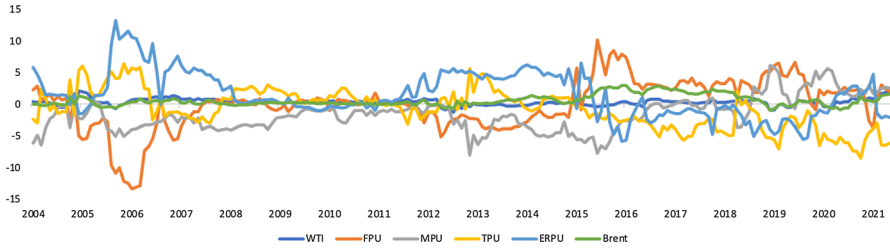


Fig. 5 Dynamic risk connectedness of volatilities in T3

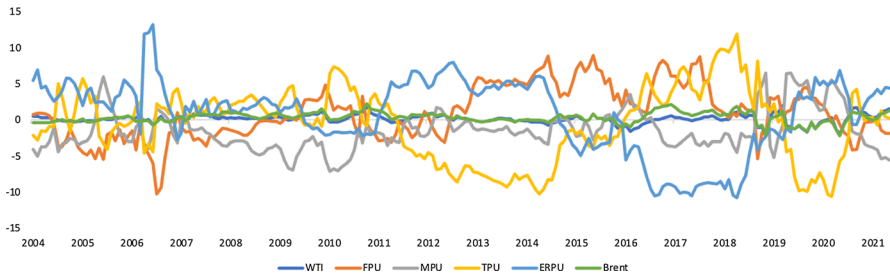


Fig. 6 Dynamic risk connectedness of volatilities in T4

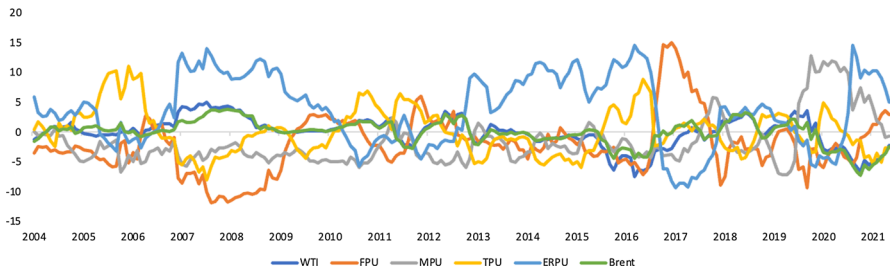


Fig. 7 Dynamic risk connectedness of volatilities in T5

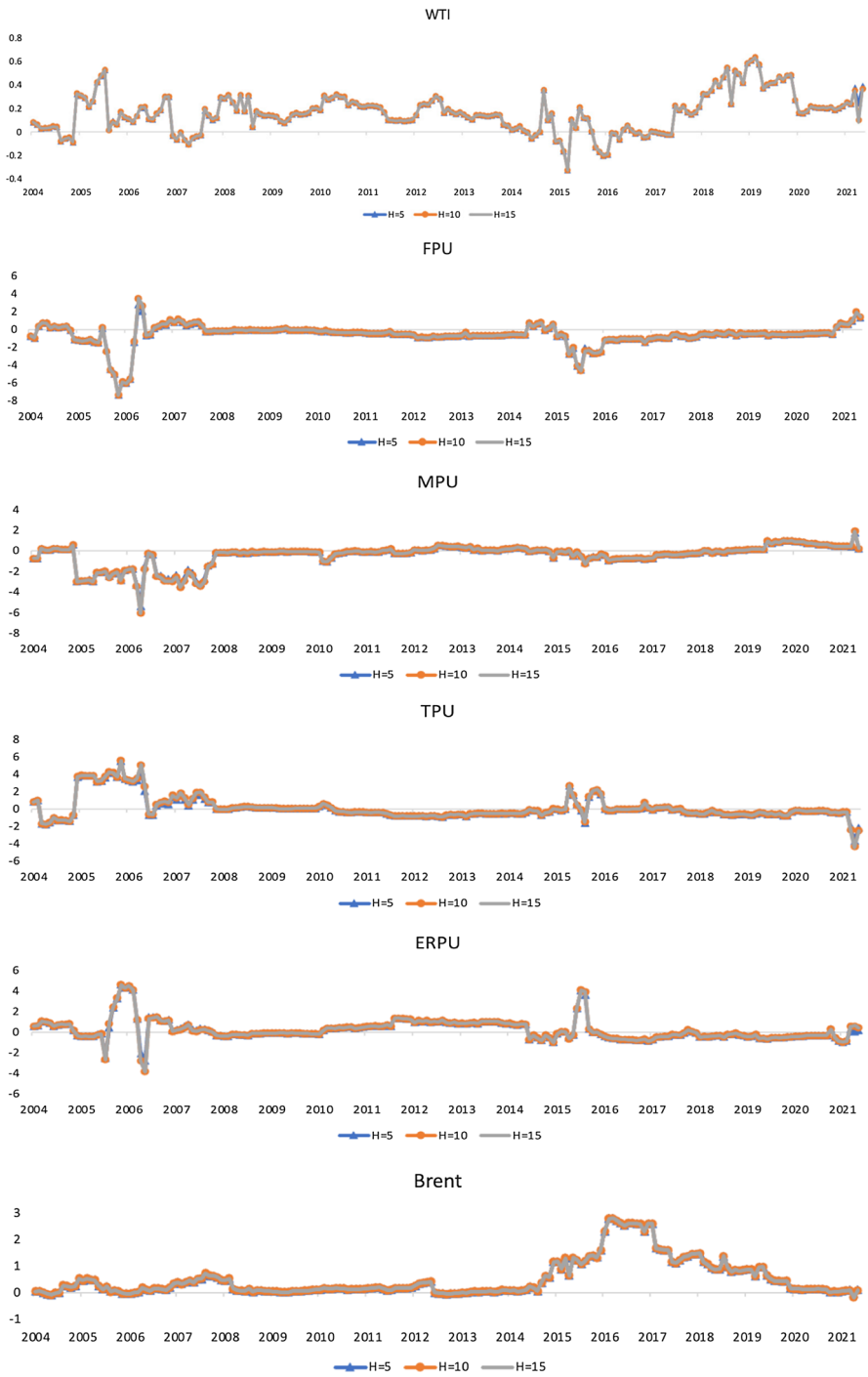


Fig. 8 Dynamic risk connectedness of volatilities at different horizons of FEVD

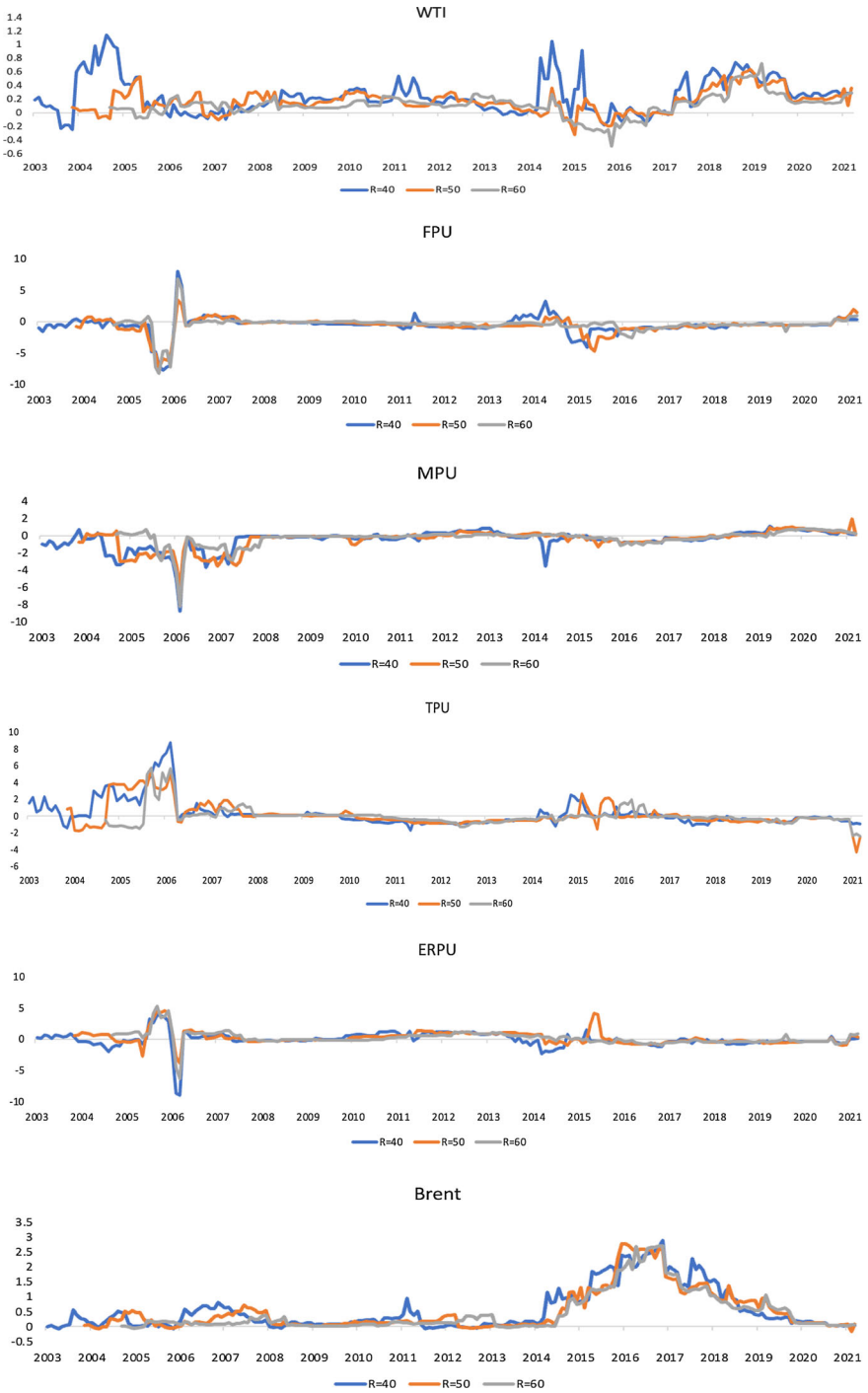


Fig. 9 Dynamic risk connectedness of volatilities at different rolling windows

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