4 ASYMMETRIC RISK SPILLOVER BETWEEN ENERGY MARKETS AND UNCERTAINTIES OF ECONOMIC POLICY, INFECTIOUS DISEASE AND GEOPOLITICAL RISK[1]

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Abstract

The paper studies the asymmetric risk spillover effect among crude oil, natural gas and uncertainties of economic policy, infectious disease as well as geopolitical risk. We utilize a time-frequency domain spillover framework and an asymmetric spillover method. We find a weak volatility connectedness between crude oil and natural gas on average over the sample period. The spillover effect within the network is found to be highly event-dependent, reaching peaks during major geopolitical and economic events including the Gulf war, the 2007-08 global financial crisis and COVID-19 epidemic. Asymmetric spillover analysis indicates that the risk connectedness under downside markets tends to be stronger, supporting the evidence of asymmetry in spillovers. From the frequency domain analysis, we observe that spillovers are dominated by the long-run components in most periods. Furthermore, of the three uncertainties, infectious disease uncertainty transmits the highest level of long-term risk to energy markets, especially during the COVID-19. The research will be valuable to investors for risk management and governments for policy making.

Keywords: Crude oil; Natural gas; Uncertainty; Asymmetric spillover; COVID-19

JEL Classification: C32, F30, G15, Q43

1. Introduction

The substitution of crude oil and natural gas leads to a long-standing price linkage between the two energy sources, referred to as oil indexation. From a supply perspective, conventional extraction techniques tend to make the extraction of oil accompanied by the output of natural gas. This results in a consistent supply of oil and gas and therefore has a similar impact on the price of both. From a demand perspective, higher oil prices drive consumers towards natural gas consumption, pushing up gas prices and vice versa. Therefore the prices of gas and oil demonstrate a linkage for a long time (Asche, Osmundsen and Sandsmark, 2006). Indeed, even now, oil indexation is still used to determine the price of natural gas in Europe and Asia. However, dramatic changes in global energy markets have been leading to oil indexation losing its foundation (Stern, 2014) and a decline in oil-gas substitutability (Hartley and Medlock III, 2014).

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Some recent studies in the literature have challenged the equilibrium relationship between the prices of crude oil and natural gas, arguing that the cointegration is weakening or has even been lost (Erdős, 2012).

A natural extension question is whether crude oil and natural gas exhibit a close linkage in terms of volatility? Only a limited amount of studies in the literature have explored this issue (Gong, Liu and Wang, 2021). To contribute to this research topic, we study the realized volatility connectedness between crude oil and natural gas. As pointed out in Barndorff-Nielsen, Kinnebrock and Shephard (2008), the realized volatility can be decomposed into positive (good) and negative (bad) realized semi-variances constructed based on positive and negative returns of assets, respectively. In this way, volatility spillovers between oil and gas may differ with asymmetric price movements because changes in asset prices have different sensitivities to good and bad news. In fact, volatility behaves in an asymmetric manner and tends to react more significantly to negative returns of assets (Ederington and Guan, 2010). This motivates us to further consider the asymmetric volatility spillover of crude oil and natural gas on the basis of their good and bad realized semi-variances.

The pattern of the global political economy has been profoundly restructured in recent years, with the global economy facing a high degree of uncertainty due to the frequent occurrence of extensive emergencies such as the trade conflict, the COVID-19 outbreak, and the Russia-Ukraine war. For energy markets, which feature both financial and geopolitical attributes, uncertainty risks represented by economic policy uncertainty (EPU) and geopolitical risk (GPR) have been emerging as important drivers of energy prices and volatility. On the one hand, energy and financial markets are deeply integrating (Zhang, 2017), as energy markets are increasingly utilized by financial investors for risk management and asset portfolios (Yang, Pu and Su, 2020). With the increased financialisation of energy markets, energy prices contain more information from economic policies and financial markets. Economic policy uncertainty arising from changes in economic policy affects energy prices by influencing energy demand in real industries and capital flows between financial markets (Liu et al., 2023). On the other hand, many major energy producers worldwide are situated in areas of high geopolitical instability, and geopolitical risks directly affect global energy supply. Dramatic fluctuations in energy prices are often associated with tense geopolitical situations (Zhang et al., 2022). Historically, there have been several energy crises caused by geopolitical events between major energy-producing countries. For example, the Russia-Ukraine war resulted in violent shocks in the international oil and gas markets.

The COVID-19 epidemic in 2020 has had an unprecedented blow on global energy markets (Akyildirim et al., 2022). As COVID-19 spread globally, crude oil and natural gas prices fluctuated dramatically, with WTI oil futures even witnessing a historic moment of negative price in April 2020. This has sparked a greater interest among academics in exploring uncertainty due to infectious diseases (e.g., H5N1, SARS, MERS, Ebola, COVID-19). The current research in the literature typically uses the Infectious Disease Equity Market Volatility Tracker (IDEMV) proposed by Baker et al. (2020) to measure infectious disease uncertainty (Zhang and Hamori, 2021). Most studies on infectious disease uncertainty focused on its linkage with international stock markets (Lan et al., 2023), interest rates (Gupta et al., 2021) and energy markets (Zhang and Hamori, 2021).

Based on the above analyses, new types of risks including economic policy uncertainty, geopolitical risks and uncertainty due to infectious diseases are becoming crucial drivers of energy price and volatility. Recent major events with a high degree of uncertainty, such as the US-China trade conflict, the COVID-19 crisis, and the Russian-Ukrainian war, have caused dramatic fluctuations in energy prices, and these emergencies generate interest in the study of connection between uncertainty and energy volatility. This also motivates us to study spillovers among volatilities of oil and gas, and uncertainties induced by economic policy, infectious disease as well as geopolitical risk. The importance of the research is that it provides governments and investors with appropriate risk management and investment strategies under different risk conditions.

Various models and approaches have been developed to measure volatility spillovers over the last decades. One of the most commonly used methods is the spillover index methodology of Diebold and Yilmaz (2012). A long list of studies on volatility spillover effect have applied Diebold and Yilmaz framework thus far (Kang, McIver and Yoon, 2017; Ji et al., 2019). However, this method has been criticized for the drawbacks such as arbitrary choice of rolling-window size and loss of observations. To overcome these shortcomings, Antonakakis, Chatziantoniou and Gabauer (2020) proposed a TVP-VAR framework. In addition, Baruník and Křehlík (2018) developed a frequency decomposition approach, which is able to decompose connectedness into the short- and long-term connectedness. The approaches of Antonakakis, Chatziantoniou and Gabauer (2020) and Baruník and Křehlík (2018) are widely utilized in the spillover literature (Naeem et al., 2023). This paper combines the two approaches to analyze the time and frequency domain spillover among crude oil, natural gas as well as three types of uncertainty.

This paper has the following contributions. First, unlike previous studies in the literature that focus on a single uncertainty, we attempt to incorporate three uncertainty indicators with potential impact on energy markets into the research framework to analyze volatility spillovers and risk contagion. Second, the paper decomposes the realized volatility of natural gas and crude oil into the corresponding positive and negative semi-variances and investigates the asymmetric spillovers among crude oil volatility, natural gas volatility as well as uncertainties. This analysis is able to shed light on whether volatility spillovers exhibit different characteristics under different market environments (upside and downside market), which extends previous studies in the literature. Third, the research methodology in this paper combines a time-varying parameter vector autoregressive (TVP-VAR) based spillover method and a frequency decomposition method, allowing for analysis in time-frequency domains. Specifically, the former method is able to overcome some drawbacks of the traditional rolling-window VAR approach and provides more accurate dynamic spillovers. The latter method is capable of identifying long- and short-term connectedness of variables within the network.

2. Methodology and data

2.1 Realized measures

We utilize the realized volatility developed by Andersen and Bollerslev (1998) to measure volatility of crude oil and natural gas. We construct the realized variance on month t as follows:

$$RV_t = \sum_{i=1}^{M} r_{t,i}^2, \tag{1}$$

where $r_{t,i}$ denotes the daily logarithmic return on day i in month t, and M is the total number of trading days in the given month t.

Barndorff-Nielsen, Kinnebrock and Shephard (2008) decomposed RV into positive and negative realized semi-variances to capture upside and downside risk, respectively. The definitions for positive and negative realized semi-variances in month t are given by

$$RS_t^+ = \sum_{i=1}^{M} r_{t,i}^2 \, I(r_{t,i} > 0), \tag{2}$$

$$RS_t^- = \sum_{i=1}^{M} r_{t,i}^2 \, I(r_{t,i} < 0), \tag{3}$$

where $I(*)$ is an indicator function. RS^+ and RS^- often represent good and bad volatility, respectively, and $RV_t = RS_t^+ + RS_t^-$ by definition.

2.2 Spillover method

To measure volatility spillovers, we employ the time and frequency domain spillover framework developed by Chatziantoniou, Gabauer and Gupta (2023) who combine the TVP-VAR-based spillover approach of Antonakakis, Chatziantoniou and Gabauer (2020) and the frequency domain connectedness approach of Baruník and Křehlík (2018). Specifically, we estimate the following TVP-VAR(1) model according to the Bayesian information criterion (BIC):

$$Y_t = A_t Y_{t-1} + \epsilon_t; \epsilon_t \sim N(0, \Sigma_t), \tag{4}$$

$$vec(A_t) = vec(A_{t-1}) + v_t; v_t \sim N(0, R_t), \tag{5}$$

where $N \times 1$ vector Y_t denotes all variables of interest including three uncertainty indices (EPU, GPR and IDEMV) and RVs for crude oil and natural gas. ϵ_t is an $N \times 1$ error vector with the time-varying $N \times N$ dimensional variance-covariance matrix Σ_t. A_t is $N \times N$ dimensional coefficient matrices, and $N^2 \times 1$ vector $vec(A_t)$ represents the vectorization of A_t. Moreover, v_t is an $N^2 \times 1$ error vector with $N^2 \times N^2$ dimensional variance-covariance matrix R_t.

The TVP-VAR model can be written in the following corresponding moving average form:

$$Y_t = \sum_{i=0}^{p} A_{it}\, Y_{t-i} + \epsilon_t = \sum_{j=0}^{\infty} \Psi_{jt}\, \epsilon_{t-j} \tag{6}$$

Then the generalized forecast error variance decompositions (GFEVD) can be expressed as the following form:

$$\theta_{ijt}(H) = \frac{(\Sigma_t)_{jj}^{-1} \sum_{h=0}^{H} ((\Psi_h \Sigma_t)_{ijt})^2}{\sum_{h=0}^{H} (\Psi_h \Sigma_t \Psi_h')_{ii}} \tag{7}$$

We generally have that $\sum_{j=1}^{N} \theta_{ijt}\,(H) \neq 1$, so that we normalize as follows:

$$\tilde{\theta}_{ijt}(H) = \frac{\theta_{ijt}(H)}{\sum_{j=1}^{N} \theta_{ijt}(H)} \tag{8}$$

with $\sum_{j=1}^{N} \tilde{\theta}_{ijt}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ijt}(H) = N$ by construction. The element $\tilde{\theta}_{ijt}(H)$ of the $N \times N$ dimensional matrix denotes the contribution of variable j to the forecast error variance of variable i. In particular, the diagonal element represents the contribution of a variable to itself.

Based on the normalized GFEVD matrix $[\tilde{\theta}_{ijt}(H)]_{N\times N}$, all spillover measures can be obtained. Following Chatziantoniou and Gabauer (2021), we construct the following adjusted total spillover index (TSI):

$$TSI_t(H) = \frac{1}{N-1} \sum_{i,j=1, i\neq j}^{N} \tilde{\theta}_{ijt}(H). \tag{9}$$

TSI reflects the average spillovers of the variables in the network. A higher value of TSI indicates a higher level of risk contagion across markets and vice versa. In order to measure how many shocks the ith variable receives from all other variables, we define the following directional spillover index:

$$\mathcal{S}_{i\leftarrow *,t}(H) = \sum_{j=1, i\neq j}^{N} \tilde{\theta}_{ijt}(H). \tag{10}$$

Analogously, the directional spillover measure of the ith variable transmitted to all other variables can be defined as:

$$\mathcal{S}_{i\rightarrow *,t}(H) = \sum_{j=1, i\neq j}^{N} \tilde{\theta}_{jit}(H). \tag{11}$$

The difference between directional spillover of ith variable transmitted to and received from all other variables yields the following net directional spillover index:

$$NET_{it}(H) = \mathcal{S}_{i\rightarrow *,t}(H) - \mathcal{S}_{i\leftarrow *,t}(H), \tag{12}$$

where a positive (negative) value indicates that the ith variable is a net transmitter (receiver) of shocks. Finally, the net pairwise spillover index can be defined as follows,

$$\mathcal{S}_{i\to j,t}(H) = \tilde{\theta}_{jit}(H) - \tilde{\theta}_{ijt}(H), \tag{13}$$

where a positive (negative) value suggests that the ith variable is a net transmitter (receiver) of shocks with respect to jth variable.

So far we have introduced the time domain spillover framework based upon the TVP-VAR model, and calculated several spillover indices. We now move on to the connectedness measure in the frequency domain proposed by Baruník and Křehlík (2018). The frequency GFEVD can be expressed as follows:

$$\theta_{ijt}(\omega) = \frac{(\Sigma_t)_{jj}^{-1}(\sum_{h=0}^{\infty}(\Psi_t(e^{-i\omega h})\Sigma_t)_{ijt})^2}{\sum_{h=0}^{\infty}(\Psi_t(e^{-i\omega h})\Sigma_t\Psi_t(e^{i\omega h}))_{ii}} \tag{14}$$

We then perform normalization to achieve the following formula:

$$\tilde{\theta}_{ijt}(\omega) = \frac{\theta_{ijt}(\omega)}{\sum_{j=1}^{N}\theta_{ijt}(\omega)}. \tag{15}$$

To investigate spillover effect in different frequency domains, we aggregate frequencies within a specific frequency band, $d = (a, b)$: $a, b \in (-\pi, \pi), a < b$:

$$\tilde{\theta}_{ijt}(d) = \int_a^b \tilde{\theta}_{ijt}(\omega)d\omega, \tag{16}$$

which measures how many shocks the jth variable transmitted to ith variable over a particular frequency band d.

In analogy with the connectedness measures calculated in Equations (9)-(12), we can obtain the corresponding frequency spillover measures in frequency range d based on the normalized matrix $[\tilde{\theta}_{ijt}(d)]_{N\times N}$. The frequency spillover indices measure spillovers in frequency band d rather than the overall spillover effect.

2.3 Asymmetric spillover method

Baruník, Kočenda and Vácha (2016) proposed an asymmetric spillover approach by combining the spillover index framework and realized semi-variances. Following Baruník, Kočenda and Vácha (2016), we calculate spillover measures based on realized semi-variances RS^+ and RS^- to examine whether they exhibit different spillover effect, i.e. asymmetric volatility spillovers.

To be more specific, we first calculate RS^+ and RS^- of gas and oil according to Equations (2) and (3). Following the same procedure introduced in Section 2.2, we next calculate the following positive volatility spillover measures of variables including three uncertainty indices (EPU, GPR, IDEMV) and RS^+ of gas and oil: ($TSI_t^+(H)$, $\mathcal{S}_{i\leftarrow *,t}^+(H)$, $\mathcal{S}_{i\to *,t}^+(H)$, $NET_{it}^+(H)$, $\mathcal{S}_{i\to j,t}^+(H)$) and negative volatility spillover measures of variables including EPU, GPR, IDEMV and RS^- of gas and oil: ($TSI_t^-(H)$, $\mathcal{S}_{i\leftarrow *,t}^-(H)$, $\mathcal{S}_{i\to *,t}^-(H)$, $NET_{it}^-(H)$,$\mathcal{S}_{i\to j,t}^-(H)$).

The inequality of the corresponding positive and negative spillover measures leads to asymmetric spillovers. Specifically, we construct the following total spillover asymmetry index:

$$\mathcal{SAM}_t(H) = TSI_t^+(H) - TSI_t^-(H). \tag{17}$$

A non-zero $\mathcal{SAM}_t(H)$ means an asymmetric spillover effect, and specifically a positive (negative) value implies that volatility spillovers are stronger in an upward (downward) market environment. Likewise, to evaluate the degree of asymmetry in directional spillover of ith variable received from and transmitted to all other variables, we define the following directional spillover asymmetry indices:

$$\mathcal{SAM}_{i\leftarrow *,t}(H) = \mathcal{S}_{i\leftarrow *,t}^+(H) - \mathcal{S}_{i\leftarrow *,t}^-(H) \tag{18}$$

$$\mathcal{SAM}_{i\to *,t}(H) = \mathcal{S}_{i\to *,t}^+(H) - \mathcal{S}_{i\to *,t}^-(H), \tag{19}$$

where a positive (negative) value suggests that directional volatility spillovers are stronger under upward (downward) risk.

2.4 Data

This paper investigates connectedness among three uncertainties and volatilities of crude oil and natural gas. Considering the financial and geopolitical attributes of energy markets and unprecedented shocks of COVID-19 to energy markets, we focus on three uncertainty indices in this study: EPU, GPR and IDEMV. These three uncertainty indices capture uncertainty and risk associated with economic policy, geopolitics and infectious disease, respectively.

We use monthly data on the US EPU, GPR, IDEMV and realized volatilities of WTI oil futures as well as natural gas futures in US market, covering April 1990 to July 2023. The monthly RVs of oil and gas futures are constructed by their daily logarithmic returns which are collected from the website of Investing. The data on EPU, GPR and IDEMV is available at *http://policyuncertainty.com*. In order to examine asymmetric spillover effect, we also construct monthly RS^{+} and RS^{-} of WTI oil and natural gas futures, following Equations (2) and (3).

Table 1 gives descriptive statistics for the three uncertainty indices and monthly RV, RS^{+} and RS^{-} of oil and gas futures. The table shows that all the variables are distributed with positive skewness and high kurtosis suggesting that their distributions are leptokurtic. We observe from ADF tests that all the variables are stationary.

Table 1 Descriptive statistics

	RV_{WTI}	RS^{+}_{WTI}	RS^{-}_{WTI}	RV_{NG}	RS^{+}_{NG}	RS^{-}_{NG}	EPU	GPR	IDEMV
Mean	4.14	0.67	3.46	2.63	1.35	1.28	127.36	101.05	2.05
Median	0.81	0.38	0.37	1.85	0.84	0.83	110.29	90.09	0.43
Std. Dev.	56.88	1.64	55.44	2.61	1.53	1.50	60.34	50.88	5.30
Skew	19.88	13.48	19.90	3.03	3.47	4.03	2.08	4.19	4.50
Kurt	396.79	225.45	397.36	17.50	22.08	30.10	10.17	27.90	28.91
Jarque-Bera	2610877*	836823*	2618355*	4118*	6868*	13319*	1145*	11504*	12539*
ADF	-19.41*	-13.16*	-19.61*	-11.56*	-14.21*	-12.50*	-4.24*	-6.70*	-4.72*

*Notes: ADF reports the Augmented Dickey-Fuller test, where * refers to significance at the 1% level. The subscripts WTI and NG denote WTI crude oil and natural gas, respectively.*

3. Empirical results

3.1. Static spillover

3.1.1. Spillover analysis

Table 2 reports the results of static spillover between natural gas volatility, crude oil volatility, and the three uncertainty indices. The results show that TSI averages 42.28% over the entire sample period, which indicates that on average 42.28% of the forecast error variance can be explained by our variables, with the remaining 57.72% due to the idiosyncratic components of each variable. Furthermore, the spillovers are mainly driven by long-run factors (29.36%). We note that IDEMV is the main transmitter of risks within the network (67.79%), with EPU (35.36%) and GPR (29.26%) following, so that the three uncertainty indices are the major shock exporters. These findings are in line with those of Gu, Zhu and Yu (2021), and Zhang and Hamori (2021), whose results demonstrate the significant effects of the three uncertainties on energy prices and volatility. In terms of frequency bands, IDEMV and EPU are mainly driven by long-run components with values of 59.83% and 24.25%, respectively, whereas the opposite holds true for GPR with shocks being transmitted mainly in the short-run (16.61%). This suggests that IDEMV and EPU have a more profound impact on the expectations of energy market participants. EPU (e.g., the US-China trade conflict) and IDEMV (e.g., the COVID-19 crisis) may lead to disruptions in supply chains and changes in consumption patterns, all of which can affect energy price volatility over longer periods of time. However, the impact of geopolitical events tends to be short-term and sudden, with investor panic behavior causing energy prices to move dramatically, but once the event subsides, markets typically return to normal quickly. Furthermore, GPR and WTI are the main recipients of shocks with values of 52.09% and 51.66%, respectively. The spillover effect of these two variables dominates in the long term, particularly for WTI, with a value of 36.47%. With regard to net spillovers, IDEMV acts as the leading net transmitter of risks (51.26%), followed by EPU (7.19%), while the net receivers are WTI (-24.10%), GPR (-22.83%), and natural gas (-11.51%).

Table 2 Static spillovers among three uncertainty indices and realized volatilities of gas and oil

	NG	WTI	EPU	GPR	IDEMV	***From***
NG	79.32[16.81]	3.74[1.72]	4.79[2.75]	4.28[1.64]	7.87[6.85]	20.68[12.96]
WTI	3.33[0.88]	48.34[13.34]	8.24[5.96]	12.74[4.24]	27.35[25.39]	51.66[36.47]
EPU	1.63[0.91]	5.83[3.48]	71.83[38.61]	10.43[5.13]	10.29[9.28]	28.17[18.8]
GPR	3.32[1.87]	10.77[3.96]	15.71[9.08]	47.91[22.29]	22.28[18.31]	52.09[33.22]
IDEMV	0.89[0.84]	7.22[7.02]	6.62[6.47]	1.80[1.64]	83.47[81.1]	16.53[15.97]
To	9.17[4.51]	27.56[16.19]	35.36[24.25]	29.26[12.65]	67.79[59.83]	***TSI***
Net	-11.51[-8.45]	-24.10[-20.28]	7.19[5.46]	-22.83[-20.58]	51.26[43.85]	42.28[29.36]

Notes: The table presents spillover measures, where the values in [ ] represent long-term (>5 months) frequency spillover measures and the short-term (1-5 months) measures are the difference between the two. Results are based upon a TVP-VAR(1) model according to BIC and a 10-step-ahead variance decomposition for the forecast error. From and To refer to the directional spillovers of a particular variable received from and transmitted to all other variables. NG and WTI denote natural gas and WTI crude oil, respectively.

Looking at pairwise connectedness, we observe a weak link between volatility of oil and gas, with contributing only 3.74% and 3.33% to each other. This is consistent with the findings of Lovcha and Perez-Laborda (2020). It is worth noting that all three types of uncertainty contribute very little to natural gas volatility. However, the contribution of IDEMV and GPR to WTI volatility is substantial with values of 27.35% and 12.74%, respectively. The implication from these findings is that uncertainty has a high risk contagion effect on WTI, but seems to have little impact on natural gas. This result is in line with the findings of Qin et al. (2020), which confirmed a significant shock of GPR to crude oil volatility, but only a small impact on natural gas. With regard to frequency domain analysis, the GPR mainly delivers short-run risk to WTI oil, while IDEMV affects WTI in the long-term. Interestingly, WTI volatility seems in turn to have some extent of short-term impact on geopolitics, considering that the spillover index of WTI volatility on GPR is 10.77% which is mostly in the short-run (6.81%). Additionally, there is a high degree of connectedness between various uncertainties. For example, IDEMV has a substantial spillover effect on GPR, with a value of 22.28%, dominated by long-run components (18.31%).

3.1.2 Asymmetric spillover analysis

So far, we have studied the static spillover effect, but have not taken into account the asymmetric spillover from good and bad volatility. Table 3 provides the static spillover between three uncertainties and realized semi-variances of WTI and natural gas.

It can be found that, firstly, the total spillover index for RS^{+} reaches 34.35%, which is lower than that of RS^{-} (45.27%), yielding $\mathcal{SAM} = -10.92\%$. This suggests that the volatility connectedness under downward risk tends to be stronger than that in an upward risk environment, supporting asymmetry in volatility spillover. This requires investors and policymakers to be more aware of risk contagion during market declines. Second, the positive and negative pairwise spillover indices of oil and gas range from 2.05% to 3.92%, suggesting a weak static volatility connectedness between them in both upside and downside market environments. Third, IDEMV remains the most significant transmitter of shocks (76.16%) under negative spillovers, but the influence of IDEMV is considerably weakened with a value of 44.85% for its positive spillovers. We expect the IDEMV index to primarily cause negative shocks to energy markets, which is consistent with observations during epidemic. Moreover, WTI proves to be the main receiver of "bad" shocks, with a value of 57.28%, which is much higher than the case of "good" volatility (25.65%). This finding demonstrates a high extent of asymmetry in volatility spillovers.

Table 3 Static spillovers among three uncertainty indices and realized semi-variances of gas and oil

Panel A: positive spillovers among uncertainties and RS^{+} of gas and oil						
	NG	WTI	EPU	GPR	IDEMV	***From***
NG	75.87	2.73	8.58	9.06	3.75	24.13
WTI	2.86	74.35	5.53	10.05	7.21	25.65
EPU	1.59	2.76	74.03	10.19	11.42	25.97
GPR	4.36	5.55	17.47	50.15	22.47	49.85
IDEMV	0.91	1.38	7.90	1.60	88.22	11.78
To	9.72	12.43	39.48	30.90	44.85	***TSI***
Net	-14.41	-13.23	13.52	-18.95	33.07	34.35
Panel B: negative spillovers among uncertainties and RS^{-} of gas and oil						
	NG	WTI	EPU	GPR	IDEMV	***From***
NG	76.51	3.92	4.42	5.36	9.79	23.49
WTI	2.05	42.72	10.92	9.82	34.50	57.28
EPU	1.37	6.82	71.19	9.90	10.72	28.81
GPR	3.19	10.03	17.39	48.23	21.16	51.77
IDEMV	0.85	11.03	6.27	1.57	80.28	19.72
To	7.46	31.80	38.99	26.65	76.16	***TSI***
Net	-16.03	-25.48	10.18	-25.12	56.45	45.27
Panel C: asymmetric spillover measures						
To	2.26	-19.37	0.49	4.25	-31.31	$\boldsymbol{\mathcal{SAM}(H)}$
From	0.64	-31.63	-2.84	-1.92	-7.94	-10.92

Notes: Results are based upon a TVP-VAR(1) model according to BIC and a 10-step-ahead variance decomposition for the forecast error.

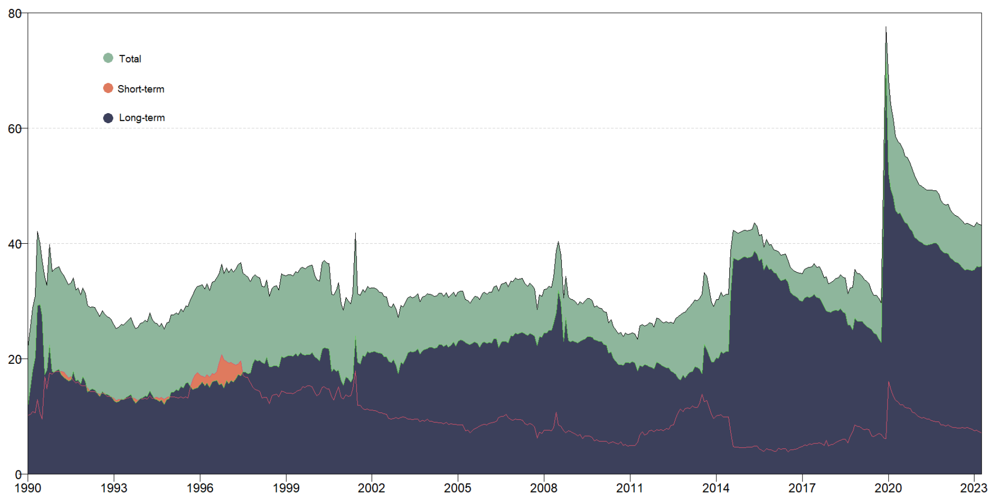
3.2 Dynamic total spillover

3.2.1 Spillover analysis

Figure 1 depicts the dynamics of TSI and its frequency decomposition. TSI is relatively flat over most periods, fluctuating between approximately 20% and 40%. However, peaks can be observed when some economic and political events occur, which has also been confirmed by existing literature such as Nusair and Olson (2019) and Ferrer et al. (2018). These major events often involve high levels of uncertainties and risks of economic policy, geopolitics and infectious disease. For example, the TSI reaches 42.11% in August 1990 during the Gulf War, a period overshadowed by an extremely high degree of geopolitical risk. The disruption of Iraq's crude oil supply caused a dramatic increase in crude oil prices, which rose from $17 per barrel to a peak of $41 per barrel in three months, before falling quickly to around $20. A few years later, the TSI experienced a second peak as geopolitical risk contagion increased as a result of the 9/11 terrorist attacks in 2001. The GFC of 2007-08 forced oil and gas prices into a downward trend, intensifying risk contagion between energy markets and EPU, when TSI hits its third peak. At the end of 2014, the economic slowdown in developing countries such as China and Brazil resulted in weak oil demand growth, while the supply of oil has gradually increased following the US shale oil revolution, which ultimately led to a sharp fall of oil prices and a high level of spillover effect. The highest peak value of the TSI appears during the COVID-19 epidemic in 2020, with a value of 77.61%, which is consistent with Zhang and Hamori (2021) as their study claims that the influence of COVID-19 on energy volatility is even stronger than that of the 2007-08 GFC. Energy prices suffered from considerable declines and fluctuations and were negatively affected by infectious diseases uncertainty in the period of COVID-19 (Zhang and Hamori, 2021).

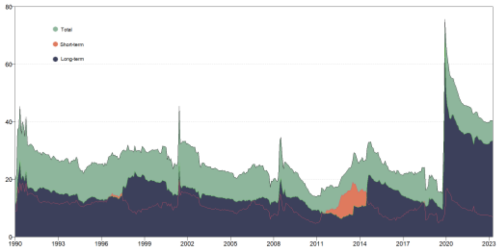
Figure 1 also reveals whether the time-varying connectedness is short-run or long-run. Overall, spillovers are dominated by long-term components most of the time. During the 1990s, the long- and short-run TSIs were roughly equal, with the short-run connectedness prevailing for a while during the Asian Financial Crisis (AFC) in 1997. Since then, however, the dominance of the long-run connectedness became more prominent and never again fell below the short-run TSI. The long-run TSI reaches an unprecedented peak of 71.51% in March 2020 during the COVID-19 crisis. All of these findings imply that major events have lasting and far-reaching impacts on variables in the network that become apparent over time.

Figure 1: Plot of dynamic TSI

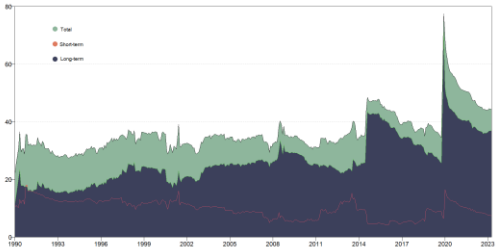


Notes: The figure plots the dynamic TSI in green, and the frequency decomposition of short- and long-term TSIs in orange and dark blue, respectively.

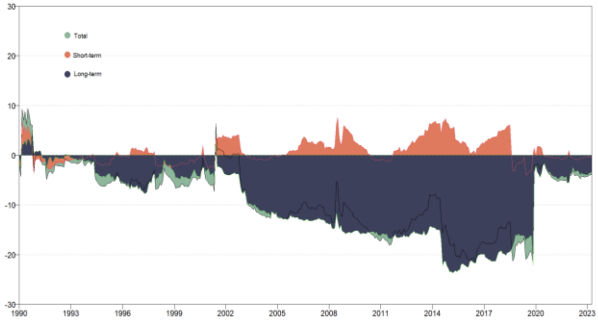
Figure 2: Dynamics of positive and negative TSIs, and the corresponding total spillover asymmetry index



(a) Dynamics of positive TSI



(b) Dynamics of negative TSI

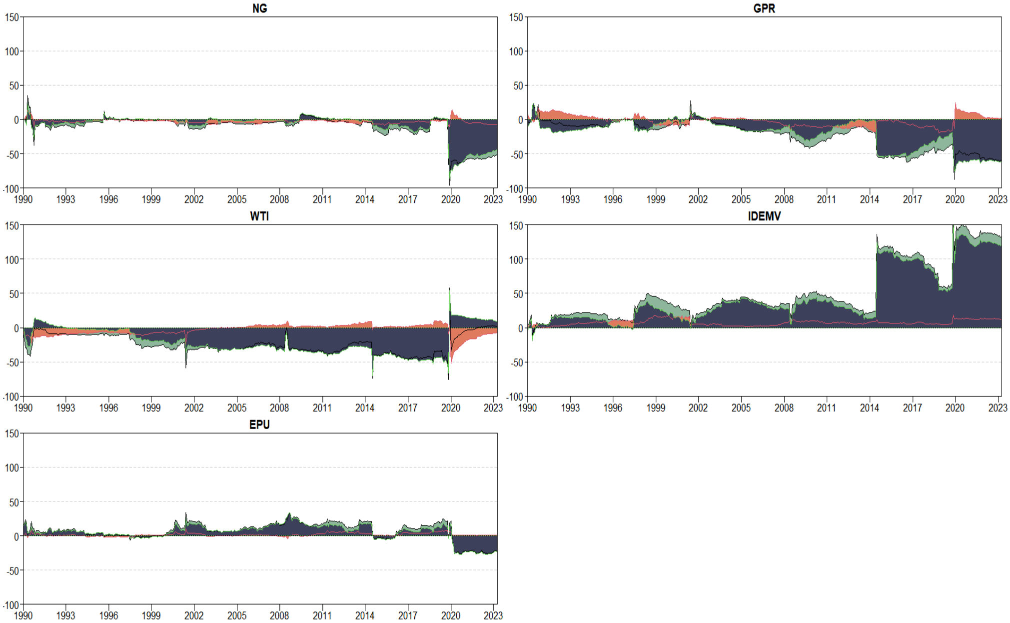


(c) Dynamics of total spillover asymmetry index

3.2.2 Asymmetric spillover analysis

To further investigate the asymmetric spillover dynamics, we construct the positive and negative dynamic TSIs in Panel (a) and (b) of Figure 2. To compare the positive and negative TSIs more straightforwardly, Panel (c) plots the corresponding total spillover asymmetry index of Equation (17).

Figure 3: Plot of dynamic net directional spillover index for each variable



Notes: The figure plots the dynamic net directional spillover index in green, and the corresponding frequency decomposition of the short- and long-term indices in orange and dark blue, respectively.

We find that the time-varying positive and negative TSIs move in a similar pattern as the overall TSI, with both peaking at some specific major events. However, it is clear from Panel (c) that the positive and negative TSIs were roughly equal in the 1990s, but in the last two decades the negative TSI have been significantly higher than the positive, providing convincing evidence of asymmetry in volatility spillovers. This finding suggests that "bad" volatility in oil and gas is more closely linked to uncertainties. Therefore more attention needs to be paid to cross market risk contagion in a downward risk environment.

Turning to the frequency decomposition, the positive volatility spillovers mainly stem from the short-run during 2012-2014, while they are mainly driven by long-run components in the other periods. We note from Panel (b) of the figure that long-run components are absolutely dominant in the negative volatility spillovers. This suggests that in the downside risk environment, the impact of bad news on the market is more persistent, leading to risk contagion within the network more profound.

3.3 Net directional spillover

3.3.1 Spillover analysis

In order to examine whether a variable within the system is net spillover contributor or receiver over time, we provide the time-varying net directional spillover index in Figure 3. We can observe that net directional spillover indices of all five variables in the network are characterized by bidirectionality.

Starting with natural gas, we note that natural gas remains a net recipient of shocks for most of the time. Notably, the level of net receipts of natural gas increases considerably and reaches a peak after the COVID-19. It is highly likely that infectious diseases and economic policy related uncertainties caused by COVID-19 have severely hit the natural gas market. With respect to frequency decomposition, clearly the shocks of COVID-19 to natural gas markets are long-run and persistent.

Similar to natural gas, but to a far greater extent, WTI oil acts as a net receiver for most of the period. Many of the local peaks and dramatic changes in WTI's net directional spillover index were associated with specific emergencies such as the Gulf War and COVID-19 crisis. This finding implies that unexpected events tend to induce risk contagion to crude oil markets. In terms of frequency bands, during the COVID-19 period, WTI remains a net transmitter of risk in the long term while it acts as a net recipient in the short term. Therefore COVID-19 outbreak exposes the WTI market to substantial risk in the short term, meanwhile WTI also affects global economic and production activities over the long run.

EPU remains a net transmitter of shocks for most of time, but converts to a net receiver after 2020. We attribute this to the high level of EPU affected by COVID-19 (Zhou, Liu and Wu, 2022). In terms of frequency bands, EPU is almost dominated by the low frequency bands, implying that shocks and impacts induced by EPU tend to be more persistent.

The GPR has been a net recipient of risks in the system after 2002, and the degree of receipt has strengthened significantly in 2015 and 2020. This could be related to the fact that GPR received shocks as a result of economic slowdown in developing countries in 2015 and the COVID-19 risk in 2020. It is important to note that, similar to WTI, GPR shows inconsistencies in long- and short-run connectedness. For example, during the Iraq War, the GPR transmitted short-run risks, while simultaneously received long-term shocks. Similar phenomena can also be observed during period of the COVID-19.

We finally consider IDEMV, which is the leading net contributor of shocks. The connectedness index reached the highest value during the COVID-19 epidemic, demonstrating the enormous shocks of infectious disease uncertainty to economics, geopolitics and energy prices. Furthermore, the shocks are long-term and persistent from the result of the frequency decomposition.

Overall, the variables within the network show local peaks or switch between net contributor and receiver states when some specific major events occur. IDEMV and EPU remain the main net transmitters, while GPR, WTI and natural gas are net recipients of risks most of the time.

3.3.2 Asymmetric spillover analysis

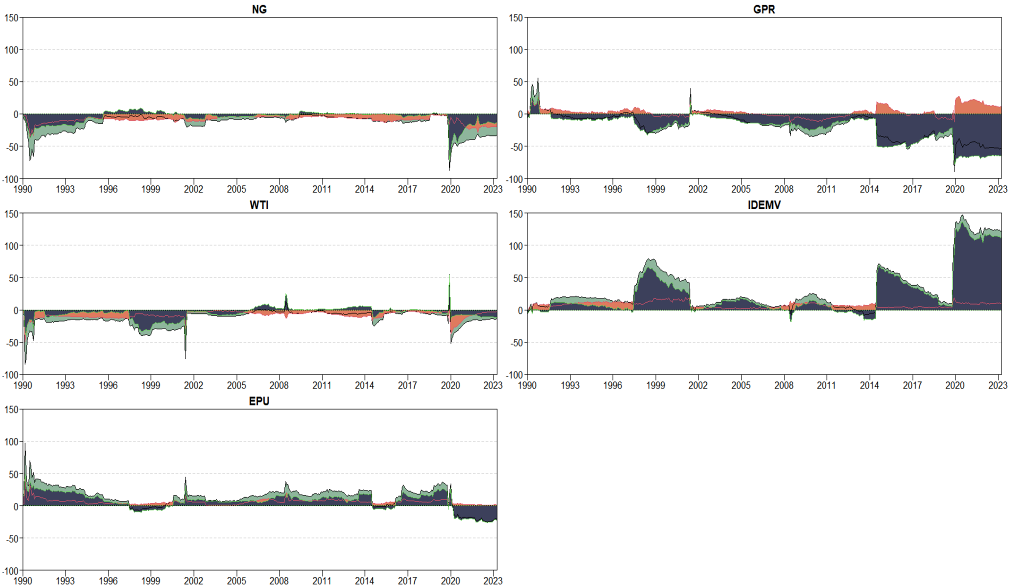
Figure 4 depicts the positive and negative net directional spillover indices and we can find that both indices evolve in a different pattern for each variable in the network. Specifically, WTI is more sensitive to "bad" news shocks, considering that crude oil receives significantly stronger negative shocks than positive shocks. Furthermore, the IDEMV index exhibits a different evolution after realized volatility decomposition. It is apparent that the extent of the negative net directional spillovers for IDEMV is larger than the positive one. In fact, the uncertainty associated with infectious diseases is bound to be transmitted as "bad" news to the other variables in the system, leading to an increase in "bad" volatility spillovers. Overall, the net directional spillovers for each variable exhibit some extent of asymmetry.

3.4 Net pairwise spillover

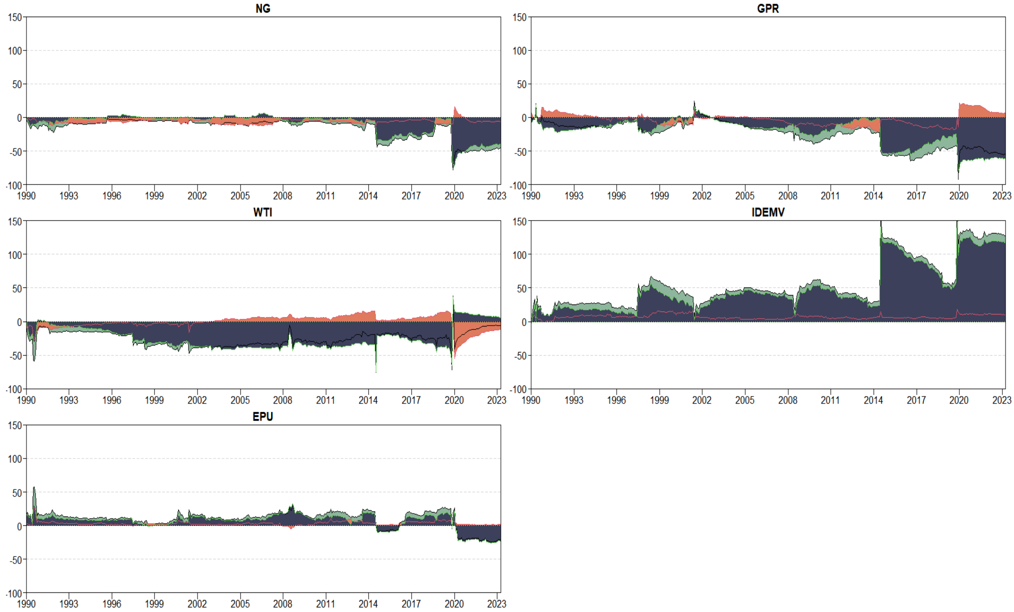
Finally, we analyze the spillovers of different variable pairs in the network. Figure 5 illustrates the net pairwise spillover index over time. It is necessary to notice the order of the paired variables in the headings for each panel of Figure 5. For ease of explanation, we take the first panel "NG-WTI" as an example, where a positive value suggests a net output shock from natural gas to WTI oil, while a negative value means a net shock from oil to gas.

We start our analysis with panels related to natural gas. Natural gas transmits net risk to WTI primarily over the long term, during the Gulf War. However, during the COVID-19 pandemic, natural gas transmits net volatility to WTI in the short run while receives long-run net shocks from WTI. For most periods beyond that, the net pairwise volatility spillovers of gas and oil seem not significant. Similarly, the NG-EPU and NG-GPR indices do not reflect strong net pairwise spillovers in most periods, except for short peaks during some specific events. Interestingly, the results show a close connectedness between gas and IDEMV. In particular, ever since the COVID-19 outbreak, IDEMV has transmitted a substantial amount of long-run net risk to natural gas.

Figure 4: Dynamics of positive and negative net spillover indices for each variable

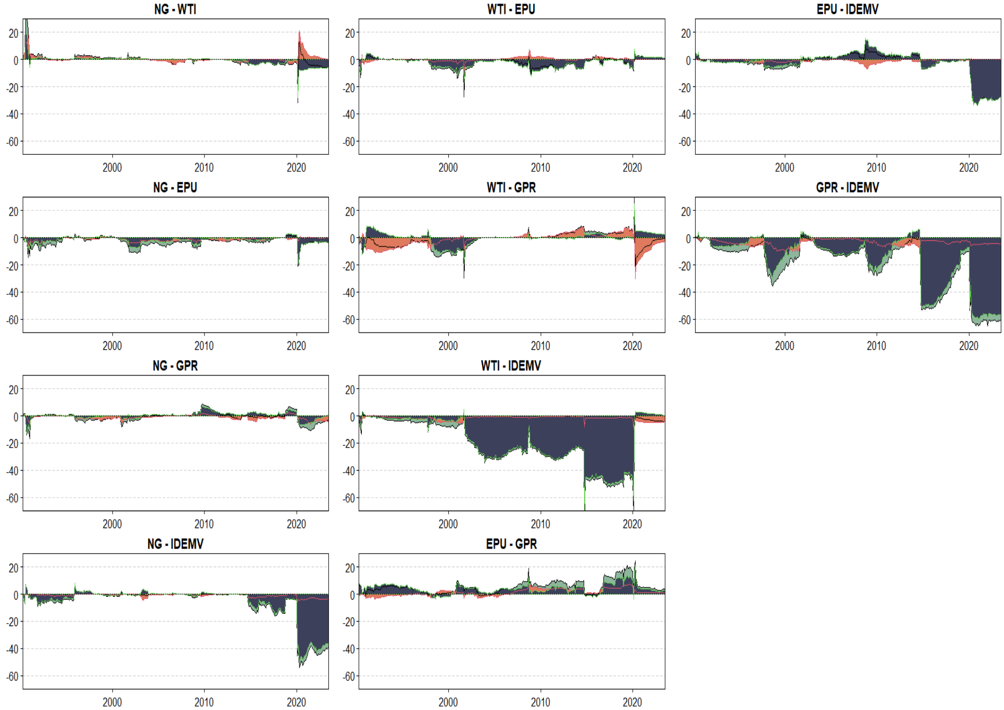


(a) Dynamics of positive net spillover index



(b) Dynamics of negative net spillover index

Figure 5: Plot of dynamic net pairwise directional spillover index



Notes: The figure plots the dynamic net pairwise directional spillover index in green, and the corresponding frequency decomposition of the short- and long-run indices in orange and dark blue, respectively.

Compared to natural gas, WTI is more sensitive to shocks from EPU, GPR and IDEMV. WTI receives moderate net shocks from EPU during the AFC of 1997-98, the internet bubble of 2000 and GFC of 2007-08. The net pairwise connectedness between WTI and GPR is even more noteworthy. During the 1990s and after the outbreak of COVID-19, WTI not only receives short-run net risks from GPR, but also transmits long-run shocks to GPR, implying that WTI and GPR affect each other.

Finally, a notable finding can be made from the results of the net pairwise connectedness among the three uncertainty indices. IDEMV is the most prominent net transmitter among the three uncertainty indices. During the COVID-19 crisis, IDEMV transmits high level of net shocks to EPU and GPR. Throughout the sample period, EPU transmits moderate net shocks to the GPR index, mostly in the long term, while the net transmission of spillovers from GPR to EPU is mostly short-run.

Therefore crude oil receives more net risks from the three types of uncertainty than natural gas. Of the three uncertainty indices, the one with the greatest risk spillover effect on energy markets is the IDEMV.

4. Conclusion and policy implications

We investigate the asymmetric volatility spillovers and risk contagion of crude oil, natural gas and uncertainties due to economic policy, geopolitics, and infectious disease. We utilize a time-frequency domain spillover framework and an asymmetric spillover method. We obtain the following main findings.

Firstly, static connectedness results indicate that TSI averages 42.28% over the entire sample period, which is mainly attributed to long-term components. IDEMV and WTI are major net shock transmitter and receiver, respectively. Regarding pairwise connectedness, unlike the close link between oil and gas prices, they are found to be less connected in terms of volatility on average over the sample period. Uncertainties have a high risk contagion effect on WTI, but seem to have little impact on natural gas.

Secondly, the dynamic TSI exhibits a time-varying fluctuation between approximately 20% and 40% and reaches its peaks at major events including the Gulf War, 2007-08 GFC and COVID-19 crisis, which often involve high levels of GPR, EPU and IDEMV. The dynamic TSI proves to be strongly responsive to external shock from emergencies, which may amplify risk contagion between variables in the system. The level of risk transmission is even higher during the COVID-19 than during the 2007-08 GFC. The asymmetric analysis demonstrates that the level of volatility connectedness under downward markets tends to be greater than in upside markets.

Thirdly, the variables experience local peaks in the directional spillover index or switch between net contributor and receiver states when some specific major events take place. Of the three uncertainty indices, the one with the greatest long-run risk spillover effect on energy markets is the IDEMV. The asymmetric spillover analysis indicates that IDEMV is mainly transmitted as "bad" news to other variables in the system, leading to an increase in negative volatility spillovers, and meanwhile WTI is more sensitive to "bad" news shocks.

This research will be valuable to investors, risk managers and policymakers. Our findings emphasize that the risk spillovers of various uncertainties on energy markets are time-varying and significant. Thus when investing in the energy markets, investors are advised to remain attentive of the impact of uncertainty. Additionally, the risk transmission between uncertainties and energy markets is found to be highly event-dependent and sensitive to market conditions, so that in case of extreme shocks, investors need to establish a cross-market risk warning system and construct dynamic portfolios to hedge against risks. To minimize the adverse consequences of uncertainty and effectively prevent cross-market risks, policymakers should incorporate uncertainty indicators into the scope of regulation, and improve the dynamic monitoring of the level of uncertainty related to economic policy, geopolitics, and infectious disease. It is necessary for policymakers to accurately capture spillovers of uncertainty and energy markets, with a particular focus on the risk resonance caused by major crises and extreme emergencies. Finally, given the dominant long-run spillovers within the network, policymakers should quickly stabilize market expectations and adjust the strength of policies so as to avoid risk contagion in the long term.

The limitation of this paper is that we only study the risk contagion between energy markets and uncertainties, without identifying the mechanisms of risk spillovers. In addition, we ignore asset classes such as the stock market, the bond market, and the cryptocurrency market. It is also of high research interest to study the risk contagion between these markets and various types of uncertainty. These will be left for future research.

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