

The impact of external uncertainties on the extreme return connectedness between food, fossil energy, and clean energy markets

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Abstract

We investigate the extreme return connectedness between the food, fossil energy, and clean energy markets using the quantile connectedness approach, which combines the traditional spillover index with quantile regression. Our results show that return connectedness at the tails (57.91% for the right tail and 61.47% for the left tail) is significantly higher than at the median (23.02%). Furthermore, dynamic analysis reveals that connectedness fluctuates over time, with notable increases during extreme events. Among these markets, fossil energy market consistently acts as the net receiver, while clean energy market primarily serves as the net transmitter. Additionally, we use linear and nonlinear ARDL models to examine the role of external uncertainties on return connectedness. We find that climate policy uncertainty (CPU), geopolitical risk (GPR), and the COVID-19 pandemic significantly impact median connectedness, while economic policy uncertainty (EPU), GPR, and trade policy uncertainty (TPU) are crucial drivers of extreme connectedness. Our findings provide valuable insights for investors and policymakers on risk spillover effects between food and energy markets under both normal and extreme market conditions.

Keywords: Extreme spillover, Energy market, Food market, External uncertainty

JEL: G28, C1, Q4, Q1

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1. Introduction

Energy and food security are essential for sustainable development and human well-being (Taghizadeh-Hesary et al., 2019; Guo and Tanaka, 2022). With increasing mechanization in agriculture, energy (particularly fossil fuels, like crude oil, coal, and their derivatives) has become a key input in agricultural production, affecting irrigation, transportation, and the production of chemicals and fertilizers (Zimmer and Marques, 2021). Given that energy costs represents a large proportion of production expenses, food prices experienced sharp increases during the periods of energy crisis (Youssef and Mokni, 2021). The connection between energy and food prices is commonly mediated through production costs, a relationship demonstrated by numerous studies (Ericsson et al., 2009; Georgiou et al., 2018). The explosion of global biofuel industry in the second half of 2000s provides a new dimension to this connection, with rising energy prices triggering demand for biofuels made from crops like corn and soybeans (Myers et al., 2014; Yoon, 2022; Tanaka et al., 2023). This, in turn, leads to higher food prices as corn and soybeans compete with other crops for land, water, and profits, and then raise the production costs of other food, like oil, meat and dairy (Atems and Mette, 2024). In addition, broader macroeconomic factors, including inflation and economic policy, contribute to the co-movement of food and energy prices (Adil et al., 2022).

In recent years, climate change has emerged as a global challenge faced by human-beings. Scholars believe that climate change is mainly caused by human activities, among which agricultural production is a typical sector with high energy consumption and high pollution (Hartter et al., 2018). In this context, many governments are embarking on a green transformation of agricultural production. For example, Indian central government has pledged to provide solar power to farms as part of efforts to reduce reliance of agriculture on conventional energy sources (Chatterjee, 2024). The availability and cost of clean energy are increasingly recognized as critical for ensuring food security, with studies highlighting both positive and negative influences of clean energy on agricultural outcomes (Haque and Khan, 2022; Li et al., 2024). Furthermore, Han et al. (2022) take the case of China to study the rural energy transition in developing countries. Their results reveal that urbanization has a positive effect on the usage of clean energy in agriculture. With the

energy transformation of the whole society and the development of green agriculture, prices of clean energy and food are increasingly linked.

Research on food-energy nexus is growing ([Abdelradi and Serra, 2015](#); [Lucotte, 2016](#); [Diab and Karaki, 2023](#)). On the one hand, since food and energy are essential substances for the development of human society, the interaction between food and energy prices has a noteworthy effect on economic stability ([Lucotte, 2016](#)). On the other hand, the financialization of commodities has made food and energy commodities important asset classes for global investors, increasing the vulnerability of commodity prices to financial market factors, such as exchange rate ([Adil et al., 2022](#)). Indeed, researchers find that food and energy commodity markets have negative relations with equity markets, and they have positive relations themselves ([Han et al., 2015](#)). Therefore, the dependencies of food and energy prices provide important references for investors in portfolio hedging and risk management.

Existing works mainly focus on food-oil nexus and have come to mixed results. Most of these research find a significantly positive relationship between food and oil prices ([Mohammed, 2022](#); [Yu et al., 2023](#)), while others find weak linkages ([Zmami and Ben-Salha, 2019](#)) or heterogeneous and asymmetric impacts across different food categories ([Chen et al., 2022](#)). In addition, there are also studies that examine the relationship between food and other fossil energy, such as coal, natural gas, and gasoline ([Diab and Karaki, 2023](#); [Vatsa et al., 2023](#); [Miljkovic and Vatsa, 2023](#)). However, although the energy applied in the agricultural sector is transmitting from fossil energy to clean energy gradually and this process will continue to move forward, there remains a lack of studies that incorporate clean energy into the research framework ([Chatterjee, 2024](#); [Haque and Khan, 2022](#)).

In this work, we focus on the interactions between food, fossil energy, and clean energy markets. To begin with, we analysis their return connectedness at normal and extreme market conditions by using a quantile-based spillover approach which combines the [Diebold and Yilmaz \(2012\)](#) spillover index with a quantile regression approach. Our results show that the connectedness between food, fossil energy, and clean energy markets are much stronger at both the extreme upper and lower quantiles than at the conditional median. Moreover, the return connectedness is asymmetric, specifically, it is higher at the left tail than at the right tail. We next conduct the dynamic

analysis using the rolling window method to capture the time-varying characteristics of connectedness. The results reveal that the total spillover fluctuates significantly during the sample periods, and it increases notably when extreme events occur, such as the signing and implementation of the Paris Agreement in 2015 and 2016, the withdrawal of the US from the Paris Agreement in 2017 and its return in early 2021, the COVID-19 pandemic in 2020, and the Russia-Ukraine conflict in 2022. The index at tails is less volatile than at the median. In addition, the net spillover analysis indicates that fossil energy market always act as the net receiver, while clean energy market plays more role of a net transmitter. This is consistent with the results of previous research that clean energy has a significant spillover effect to fossil energy as energy consumption transmitting from fossil fuels to clean energy (Raza et al., 2024).

Motivated by the aforementioned results of the fluctuations of connectedness, we consider the effects of external uncertainties, including economic policy uncertainty (Baker et al., 2016), climate policy uncertainty (Gavriilidis, 2021), trade policy uncertainty (Baker et al., 2016), and geopolitical risk index (Caldara and Iacoviello, 2022). Besides, we take COVID-19 as a dummy variable, which takes the value of 1 during the pandemic between January 2020 and December 2020, and 0 otherwise. We apply the linear and nonlinear autoregressive distributed lags (ARDL) models, incorporating the logarithm of these uncertainty indexes as the predictor variables and the total return connectedness index as the dependent variable. We run the regression for the connectedness at the conditional median and the extreme quantiles. For the median connectedness, CPU, GPR, and COVID-19 pandemic has significant impact. For extreme connectedness, EPU, GPR, and TPU are key drivers. Additionally, the results of NARDL models reveal the asymmetric effects of external uncertainties, specifically, CPU has a short-term asymmetric effect on connectedness at the extreme upper quantile ($\tau = 0.95$), while for the long-term asymmetry, EPU is significant on the conditional median, and CPU, TPU, and GPR are significant on the extreme lower quantile ($\tau = 0.05$).

The remainder of the paper is organized as follows. Section 2 reviews the related studies. Section 3 introduces the quantile connectedness methods and describes the data we use. Section 4 provides the empirical results regarding the spillovers between food, fossil energy, and clean energy markets under normal and extreme conditions. Section 5 explores the impacts of external

uncertainties on the connectedness between these markets, and Section 6 concludes the work and presents policy implications.

2. Literature Review

The relationship between food and energy markets has been the focus of growing literature. From the spillover effects point of view, existing studies consider the price level (Youssef and Mokni, 2021) and volatility level transmissions (Chatziantoniou et al., 2021). From the perspective of methodologies, the literature includes linear (Roman et al., 2020) and nonlinear methods (Yu et al., 2023).

Early literature is more undertaken the linear framework to study the relationship between food and energy markets (Hassouneh et al., 2012; Roman et al., 2020). Hassouneh et al. (2012) find a long-run equilibrium relationship between agriculture and crude oil prices by using multivariate linear regression method, and they confirm the biofuel channel as the effect mechanism. Roman et al. (2020) employ the cointegration test and Granger causality test to examine the linkage between crude oil and the price indexes of five categories of food. Their findings reveal a long-term relationship between crude oil and meat prices, while shorter-term linkages are observed between crude oil and cereal or oil prices. Additionally, Fasanya and Akinbowale (2019) provide the evidence of the interdependence between crude oil and food prices from the perspective of spillovers by using the Diebold and Yilmaz (2012) method.

In more recent studies, researchers explore the non-linear characteristics of this relationship. They find that the interaction between food and energy prices exhibits diverse features at different market conditions (Youssef and Mokni, 2021). Youssef and Mokni (2021) apply the MRS-QR model to examine how food prices respond to different oil price shocks. Their results confirm that the contagion effect between the two markets during the periods of crisis, but the reaction of food price to oil price shocks changes with the structure of the shocks. Yu et al. (2023) use the quantile-on-quantile estimation method and find that oil and food prices present nonlinear dependences, specifically, the correlation is negative for lower and medium quantiles and positive for higher quantile. Along with Yu et al. (2023), Sun et al. (2023) also employ the quantile-on-quantile method and categorize oil prices into demand and supply shocks. According to their results, food

price subindices are correlated with oil price shocks in varying degrees, depending on the quantile and the type of shock. Similarly, [Wang et al. \(2024\)](#) adopt the quantile impulse response approach and find that the speed of food prices adjust to oil price shocks differs across quantiles. [Hanif et al. \(2021\)](#) focus on tail dependence and reveal that oil and food prices are independent at both the left and right tails. Nonlinear autoregressive distributed lags (NARDL) models are also widely used in examining their nonlinear relationship. [Almalki et al. \(2022\)](#) and [Chowdhury et al. \(2021\)](#) adopt this method and confirm the asymmetric effects of energy prices on food prices.

Although most existing studies focus on the relationships on price level, several works have also explored the volatility spillover effect between food and energy markets ([Chatziantoniou et al., 2021](#)). [Chatziantoniou et al. \(2021\)](#) employ the HAR and MIDAS-HAR approach to examine the out-of-sample predictability of oil price volatility on food price volatility. Their findings indicate that oil price volatility has weak effect in the out-of-sample prediction of food price volatility, which contrasts with the in-sample results from previous studies ([Algieri and Leccadito, 2017](#); [Zhang and Broadstock, 2020](#)). [Ucak et al. \(2022\)](#) use the [Diebold and Yilmaz \(2012\)](#) approach to examine the volatility spillover between energy and foods markets, revealing that the volatility spillover is significant from energy prices to vegetable prices but not to fruit prices. [Liu and Serletis \(2024\)](#) adopt the GARCH-in-Mean copula models to study the volatility dynamics and dependence of crude oil and major agricultural commodity prices.

Besides crude oil, the most extensively studied energy category, researchers have also explored the relationship between food and other types of energy. For example, [Miljkovic and Vatsa \(2023\)](#) adopt the dynamic time warping method and find the lead-lag relationship between coal, natural gas prices and six major agricultural commodities. [Vatsa et al. \(2023\)](#) explore the linkages between natural gas and cereals. The authors find that cereal prices respond to natural gas price shocks with slight and transitory characteristics. Moreover, gasoline, as one of the most important derivatives of crude oil, its price shocks also have a significantly positive effect on food prices ([Diab and Karaki, 2023](#)).

Our work contributes to the literature on the return connectedness between food, fossil energy, and clean energy markets, and the impacts of external uncertainties. In a similar study, [Yousfi and Bouzgarrou \(2024\)](#) examine the volatility connectedness between these markets by employing the

DCC-GARCH approach, and further analysis the effect of EPU and GPR on the connectedness using the quantile-on-quantile model. Their findings reveal that the dynamic volatility spillovers between these markets are sensitive to EPU and GPR. There are three key differences that distinguish our work from theirs. First, while [Yousfi and Bouzgarrou \(2024\)](#) focus on volatility connectedness, we center our analysis on the price level. Second, their study uses sub-indices of fossil and clean energy, while we opt for a more comprehensive index as the representative measure for both fossil and clean energy. Lastly, [Yousfi and Bouzgarrou \(2024\)](#) use the quantile-on-quantile model to analysis the effects of individual uncertainty separately. This method focuses on the impact of single factor and is not suitable for the multivariate case. In contrast, we adopt the linear and non-linear ARDL model to capture the effects of multiple uncertainties, thus offering a more holistic understanding of the role of external uncertainties.

3. Methodology and Data

3.1. Quantile TVP-VAR-DY approach

Following [Koenker and Bassett \(1978\)](#), for different quantiles $\tau \in (0, 1)$, the dependence of y_t on x_t can be estimated using the following equation:

$$y_t = c(\tau) + \sum_{i=1}^p B_i(\tau)y_{t-i} + e_t(\tau), t = 1, \dots, T \quad (1)$$

According to [Koop et al. \(1996\)](#) and [Pesaran and Shin \(1998\)](#), the generalized forecast error variance decomposition (GFEVD) with forecast horizon H is calculated as follows:

$$Q_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' h_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' h_h \sum e_j)}, \quad (2)$$

The normalization of each vector in the decomposition matrix is:

$$\tilde{Q}_{ij}^g(H) = \frac{Q_{ij}^g(H)}{\sum_{j=1}^N Q_{ij}^g(H)}. \quad (3)$$

Various quantile spillover measures can be defined using the GFEVD method based on the

approach of [Diebold and Yilmaz \(2012\)](#):

$$TSI(\tau) = \frac{\sum_{i=1}^N \sum_{j=1, i \neq j}^N \omega_{ij}^h(\tau)}{\sum_{i=1}^N \sum_{j=1}^N \omega_{ij}^h(\tau)} \times 100. \quad (4)$$

$$S_{\text{all} \rightarrow i}(\tau) = \frac{\sum_{j=1, i \neq j}^N \omega_{ij}^h(\tau)}{\sum_{j=1}^N \omega_{ij}^h(\tau)} \times 100 \quad (5)$$

$$S_{i \rightarrow \text{all}}(\tau) = \frac{\sum_{j=1, i \neq j}^N \omega_{ji}^h(\tau)}{\sum_{j=1}^N \omega_{ji}^h(\tau)} \times 100 \quad (6)$$

$$NS_i(\tau) = S_{i \rightarrow \text{all}}(\tau) - S_{\text{all} \rightarrow i}(\tau) \quad (7)$$

TSI indicates the total spillover index. $S_{\text{all} \rightarrow i}$ and $S_{i \rightarrow \text{all}}$ represent the directional spillover index of index i received from all indices and transfer to all indices, respectively. NS_i is the net spillover index that can be calculated by the disparity between $S_{\text{all} \rightarrow i}(\tau)$ and $S_{i \rightarrow \text{all}}(\tau)$, wherein a positive (negative) value indicates the net spillover transmitter (recipient).

3.2. Autoregressive Distributed Lag (ARDL) model

In order to test the long-run and short-run effects of uncertainties on the spillovers, we consider the Autoregressive Distributed Lag (ARDL) model proposed by [Pesaran et al., 2001](#) as follows:

$$\begin{aligned} \Delta \ln TSI_t = & \alpha_0 + \alpha_1 \ln TSI_{t-1} + \alpha_2 \ln EPU_{t-1} + \alpha_3 \ln CPU_{t-1} + \alpha_4 \ln TPU_{t-1} + \alpha_5 \ln GPR_{t-1} + \alpha_6 \text{COVID-19} \\ & + \sum_{i=1}^{n_1} \beta_i \Delta \ln TSI_{t-i} + \sum_{i=0}^{n_2} \gamma_i \Delta \ln EPU_{t-i} + \sum_{i=0}^{n_3} \lambda_i \Delta \ln CPU_{t-i} + \sum_{i=0}^{n_4} \delta_i \Delta \ln TPU_{t-i} + \sum_{i=0}^{n_5} \omega_i \Delta \ln GPR_{t-i} + \epsilon_t \end{aligned} \quad (8)$$

where Δ is the first different operator, n_i ($i = 1, 2, \dots, 5$) is the optimal lag order determined by the Akaike information criterion (AIC), and ϵ_t refers to the error term.

The existence of long-run cointegration can be examined by using the bound test ([Pesaran et al., 2001](#)). The null hypothesis of no cointegration among underlying variables is $H_0 : \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = 0$ against the alternative hypothesis $H_1 : \alpha_1 \neq \alpha_2 \neq \alpha_3 \neq \alpha_4 \neq \alpha_5 \neq \alpha_6 \neq 0$. If the long-run cointegration exists, then we can construct an error correction term (ECT) and model (8)

can be converted to:

$$\begin{aligned} \Delta \ln TSI_t = & \alpha_0 + \sum_{i=1}^{n_1} \beta_i \Delta \ln TSI_{t-i} + \sum_{i=0}^{n_2} \gamma_i \Delta \ln EPU_{t-i} + \sum_{i=0}^{n_3} \lambda_i \Delta \ln CPU_{t-i} \\ & + \sum_{i=0}^{n_4} \delta_i \Delta \ln TPU_{t-i} + \sum_{i=0}^{n_5} \omega_i \Delta \ln GPR_{t-i} + \phi ECT_{t-1} + \epsilon_t \end{aligned} \quad (9)$$

Furthermore, we construct nonlinear autoregressive distributed lag (NARDL) model of [Shin et al. \(2014\)](#). In NARDL model, the exogenous variables are decomposed into positive and negative partial sum series to capture the asymmetric relationships between total spillovers and the external uncertainties:

$$X_t^+ = \sum_{j=1}^t \Delta X_j^+ = \sum_{j=1}^t \max(\Delta X_j, 0) \quad (10)$$

$$X_t^- = \sum_{j=1}^t \Delta X_j^- = \sum_{j=1}^t \min(\Delta X_j, 0) \quad (11)$$

where X refer to the external uncertainty index. Then, we compute the decomposition of $\ln EPU$, $\ln CPU$, $\ln TPU$, and $\ln GPR$ and represent them into the NARDL model as follows:

$$\begin{aligned} \Delta \ln TSI_t = & \alpha_0 + \alpha_1 \ln TSI_{t-1} + \sum_{i=1}^{n_1} \beta_i \Delta \ln TSI_{t-i} \\ & + \alpha_2^+ \ln EPU_{t-1}^+ + \alpha_2^- \ln EPU_{t-1}^- + \sum_{i=0}^{n_2} (\gamma_i^+ \Delta \ln EPU_{t-i}^+ + \gamma_i^- \Delta \ln EPU_{t-i}^-) \\ & + \alpha_3^+ \ln CPU_{t-1}^+ + \alpha_3^- \ln CPU_{t-1}^- + \sum_{i=0}^{n_3} (\lambda_i^+ \Delta \ln CPU_{t-i}^+ + \lambda_i^- \Delta \ln CPU_{t-i}^-) \\ & + \alpha_4^+ \ln TPU_{t-1}^+ + \alpha_4^- \ln TPU_{t-1}^- + \sum_{i=0}^{n_4} (\delta_i^+ \Delta \ln TPU_{t-i}^+ + \delta_i^- \Delta \ln TPU_{t-i}^-) \\ & + \alpha_5^+ \ln GPR_{t-1}^+ + \alpha_5^- \ln GPR_{t-1}^- + \sum_{i=0}^{n_5} (\omega_i^+ \Delta \ln GPR_{t-i}^+ + \omega_i^- \Delta \ln GPR_{t-i}^-) \\ & + \alpha_6 \text{COVID} - 19 + \epsilon_t \end{aligned} \quad (12)$$

Accordingly, the ECT form NARDL model can be written as:

$$\begin{aligned}
\Delta \ln TSI_t = & \alpha_0 + \sum_{i=1}^{n_1} \beta_i \Delta \ln TSI_{t-i} + \sum_{i=0}^{n_2} (\gamma_i^+ \Delta \ln EPU_{t-i}^+ + \gamma_i^- \Delta \ln EPU_{t-i}^-) \\
& + \sum_{i=0}^{n_3} (\lambda_i^+ \Delta \ln CPU_{t-i}^+ + \lambda_i^- \Delta \ln CPU_{t-i}^-) + \sum_{i=0}^{n_4} (\delta_i^+ \Delta \ln TPU_{t-i}^+ + \delta_i^- \Delta \ln TPU_{t-i}^-) \\
& + \sum_{i=0}^{n_5} (\omega_i^+ \Delta \ln GPR_{t-i}^+ + \omega_i^- \Delta \ln GPR_{t-i}^-) + \phi ECT_{t-1} + \epsilon_t
\end{aligned} \tag{13}$$

If $\alpha_i^+ \neq \alpha_i^-$ ($i = 2, 3, \dots, 5$), we would conclude that the effect is asymmetric in the long-run. Similarly, if $\gamma_i^+ \neq \gamma_i^-$, $\lambda_i^+ \neq \lambda_i^-$, $\delta_i^+ \neq \delta_i^-$, or $\omega_i^+ \neq \omega_i^-$, then the asymmetric effect exists for the corresponding variable in the short-run. We also examine the long-run cointegration by using the bound test (Pesaran et al., 2001).

3.3. Data description

To track the price changes in the food market, we adopt the Food Price Index (FPI) released by the Food and Agricultural Organization (FAO).¹ For the fossil energy market, we use the iShares US Oil & Gas Exploration & Production ETF (IEO), which tracks US-based companies involved in the exploration and production of oil and gas. For the clean energy market, we use the iShares Global Clean Energy ETF (ICLN), which tracks companies involved in the production of renewable energy sources like solar and wind.² The sample period spans from January 2012 to December 2023, and all data are at a monthly frequency. Fig. 1 depicts the evolution of the monthly log returns of the FPI, IEO, and ICLN ETFs. Notably, the food price index peaked in early 2022 due to the Russia-Ukraine conflict, followed by a sharp decline. Both fossil energy and clean energy ETFs experienced a rapid drop in early 2020 due to the COVID-19 pandemic, followed by a subsequent rebound.

Panel A of Table 1 reports the descriptive statistics and results of the unit root test for the log returns of the variables. The mean returns are negative for food price and clean energy, and positive for fossil energy. The fossil energy market exhibits the highest volatility, with a standard

¹We obtain FPI from <https://www.fao.org/>.

²Data on these ETFs is extracted from the Wind Database (<https://www.wind.com.cn/>).

deviation of 0.1020, followed by clean energy at 0.0898, both exceeding the food market's standard deviation of 0.0238. The food price index is positively skewed, while both fossil energy and clean energy are negatively skewed. The kurtosis of all variables are larger than three, indicating the thick tails of the distributions. Moreover, Jarque-Bera's statistics show that the variables are not normally distributed. The ADF test results indicate that all variables are stationary. Panel B of Table 1 presents the Pearson correlation coefficients, highlighting a significantly positive correlation between the food and fossil energy market. However, the correlation is not significant between food and clean energy markets. Fossil energy and clean energy markets also exhibit positive correlation at 0.231.

Table 1
Descriptive statistics.

Variable	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF
<i>Panel A: Descriptive statistics</i>						
Food Price	-0.0002	0.0238	0.6564	8.2797	176.3627***	-3.6251**
Fossil Energy	0.0037	0.1020	-0.7542	10.1492	318.0887***	-4.7320***
Clean Energy	-0.0005	0.0898	-1.7873	12.9431	665.1999***	-4.9140***
	Food Price	Fossil Energy	Clean Energy			
<i>Panel B: Correlations</i>						
Food Price	1.000					
Fossil Energy	0.263***	1.000				
Clean Energy	0.107	0.231***	1.000			

Note: The superscripts ***, **, and * denote the statistical significance at the levels of 1%, 5%, and 10%, respectively.

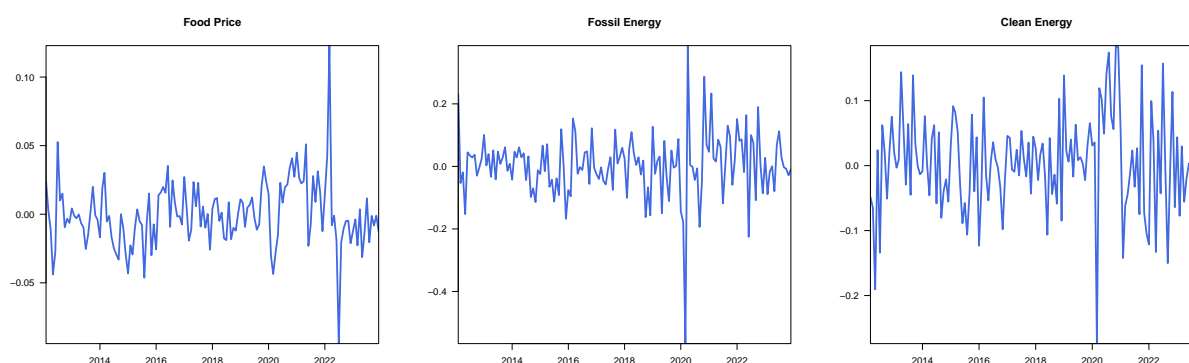


Fig. 1. Retruns of food price index, fossil energy, and clean energy ETFs.

4. Results and discussion

4.1. Static quantile spillovers

Table 2 reports the static spillover index between food, fossil energy, and clean energy markets. Panel A shows the results estimated at the conditional median ($\tau = 0.5$). Food market is the least affected by other markets, as it predominantly comprises its own spillover effects, accounting for 81.33% of the total. In addition, food market also makes the least contributions to the other markets, with a proportion of 16.90%. In contrast, fossil energy market receives the largest impact from the other markets (26.99%), while the clean energy market is the largest contributor to others (29.43%). As for the net spillovers, clean energy market stands out as the primary transmitter of spillover effects, which is consistent with the results of [Ahmad \(2017\)](#) and [Saeed et al. \(2021\)](#) who reported that return shocks always transmit from clean energy market to fossil energy market. The larger spillover contributions of the clean energy market may reflect its role in the energy transition, which, in turn, influences both fossil energy and food prices. The total return connectedness between these markets is 23.02%, indicating a moderate level of spillovers between food and energy markets.

To explore the spillover effects associate with positive and negative return shocks, we assess the connectedness between these markets at the extreme quantiles ($\tau = 0.05$ and $\tau = 0.95$). The results are presented in Panel B and Panel C of Table 2. Notably, return spillovers at the tails are significantly higher than that at the median. Specifically, the total spillover index is 61.4% at the extreme lower quantile and 57.91% at the extreme upper quantile, both of which are considerably higher than the 23.02% spillover observed at the median. The ‘To’ and ‘From’ indexes at the extreme quantiles are also stronger than those at the median. Moreover, clean energy market remains the net transmitter across all market conditions. Compared to the results at the median, fossil energy market shifts from being a net receiver to a net transmitter at the extremely negative market conditions, while food market changes from a net receiver to a net transmitter under extremely positive shocks.

Moreover, Fig. 2 illustrates that the total spillover index at various quantiles follows a U-shape, presenting clear evidence that the total spillover index varies across quantiles and is stronger at the

Table 2

Static return spillovers at different quantiles.

	Food Price	Clean Energy	Fossil Energy	From
<i>Panel A: Median quantile $\tau = 0.5$</i>				
Food Price	81.33	10.76	7.91	18.67
Clean Energy	8.58	76.59	14.83	23.41
Fossil Energy	8.32	18.67	73.01	26.99
To	16.90	29.43	22.73	69.07
Inc. Own	98.24	106.02	95.74	<i>TSI =</i>
Net	-1.76	6.02	-4.26	23.02
<i>Panel B: Extreme lower quantile $\tau = 0.05$</i>				
Food Price	37.26	31.68	31.06	62.74
Clean Energy	28.39	40.00	31.61	60.00
Fossil Energy	28.62	33.07	38.31	61.69
To	57.01	64.75	62.66	184.42
Inc. Own	94.28	104.75	100.98	<i>TSI =</i>
Net	-5.72	4.75	0.98	61.47
<i>Panel C: Extreme upper quantile $\tau = 0.95$</i>				
Food Price	45.57	28.30	26.13	54.43
Clean Energy	28.61	41.61	29.78	58.39
Fossil Energy	29.27	31.64	39.09	60.91
To	57.88	59.94	55.91	173.72
Inc. Own	103.45	101.55	95.00	<i>TSI =</i>
Net	3.45	1.55	-5.00	57.91

Note: 'To' indicates the spillover effects that the market transmits to other markets except itself. 'Inc. Own' indicates the spillover effects that the market transmits to other markets including itself. 'From' indicates the spillover effects of the market received from other markets. 'Net' is the disparity between 'To' and 'From'. 'TSI' indicates the total spillover index between food, clean energy, and fossil energy markets.

tails. The figure also reveals an asymmetrical pattern, with the index at the left tail being higher than that at the right tail.

4.2. Dynamic quantile spillovers

To further capture the time-varying characteristics of the connectedness between food and energy markets, we estimate the dynamic spillover effects using the rolling window method, with window size of 36 and forecast horizon of 12.

The left panel of Fig. 3 shows that the total spillovers estimated at the median quantile, which

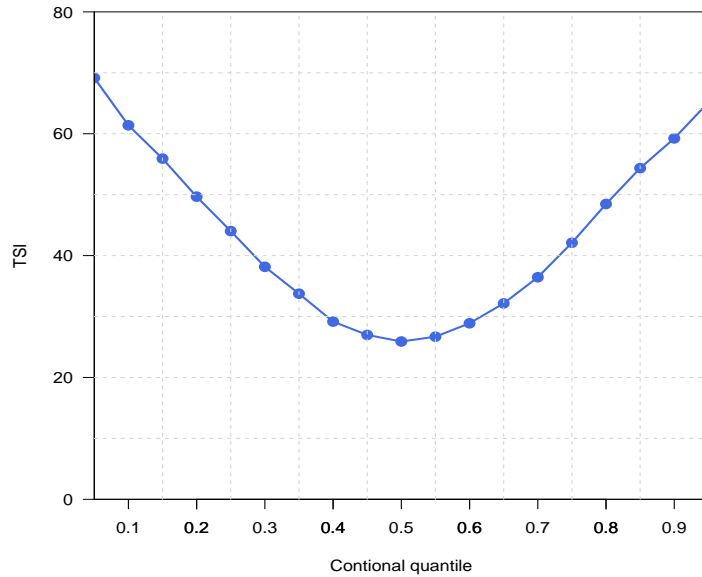


Fig. 2. Variation in the *TSI* across various quantiles.

fluctuate between 7.87% and 42.79%, with a standard deviation of 8.95. Moreover, the variation trend of the spillover index indicates that the connectedness between food and energy markets increases significantly during extreme events, such as the signing and implementation of the Paris Agreement in 2015 and 2016, the withdrawal of the US from the Paris Agreement in 2017 and its return in early 2021, the COVID-19 pandemic in 2020, and the Russia-Ukraine conflict in 2022. This result is consistent with the finding of [Cao and Xie \(2024\)](#) that extreme events strengthen the connectedness between markets. Furthermore, we analyze the dynamic spillovers between these markets at the extreme quantiles, and the results are presented in the right panel of Fig. 3. The total spillovers at the tails are substantially higher compared to the median. The total spillover index fluctuates less at the tails, varying between 56.18% and 75.00% with standard deviation of 5.15 at the right tail and between 56.05% and 75.78% with standard deviation of 5.39 at the left tail. These findings highlight that spillovers are not only stronger at the extremes but also more stable in comparison to the median, underscoring the heightened market interdependence during periods of significant positive or negative shocks.

To assess the potential presence of asymmetry as shown in Fig. 2, we calculate the relative tail dependence (*RTD*, $TSI_{\tau=0.95} - TSI_{\tau=0.05}$) ([Saeed et al., 2021](#)). Fig. 4 shows that 5% *RTD* varies

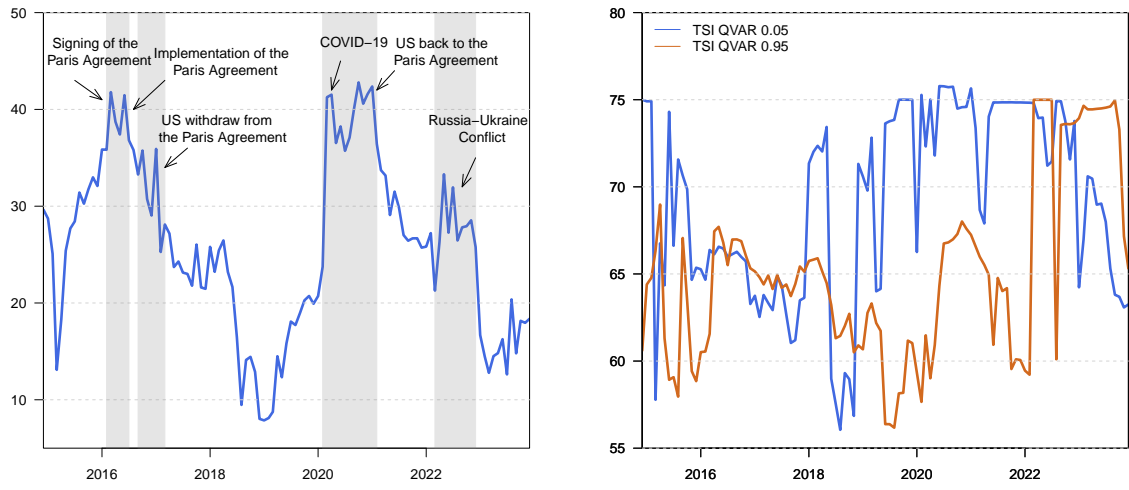


Fig. 3. Total return spillovers for median quantile $\tau = 0.5$ (left panel) and extreme lower and upper quantiles $\tau = 0.05$ and $\tau = 0.95$ (right panel).

between positive and negative values. A greater proportion of the values are negative, indicating that the spillovers are stronger at the left tail than at the right tail.



Fig. 4. Relative tail dependence ($TSI_{\tau=0.95} - TSI_{\tau=0.05}$).

The net spillover effects estimated at the median, extreme upper, and extreme lower quantiles are shown in the left, middle, and right panels of Fig. 5, respectively. The left panel shows that food market alternates between serving as a net transmitter and a net receiver. Clean energy market

acts as a net transmitter, as its net spillover index is positive throughout most of the sample period. Conversely, the net return spillover index for fossil energy market are predominantly negative, indicating they are net recipients. This aligns with the view that the spillover effects from the clean energy market to the other markets increase as energy consumption shifting from fossil fuels to clean energy (Raza et al., 2024). The median and right panels of Fig. 5 show that the patterns of net spillovers are not identical for the left and right tails. The estimates fluctuate significantly at tails, indicating that fossil energy, clean energy, and food markets are changing between net transmitters and net recipients under extreme market conditions.

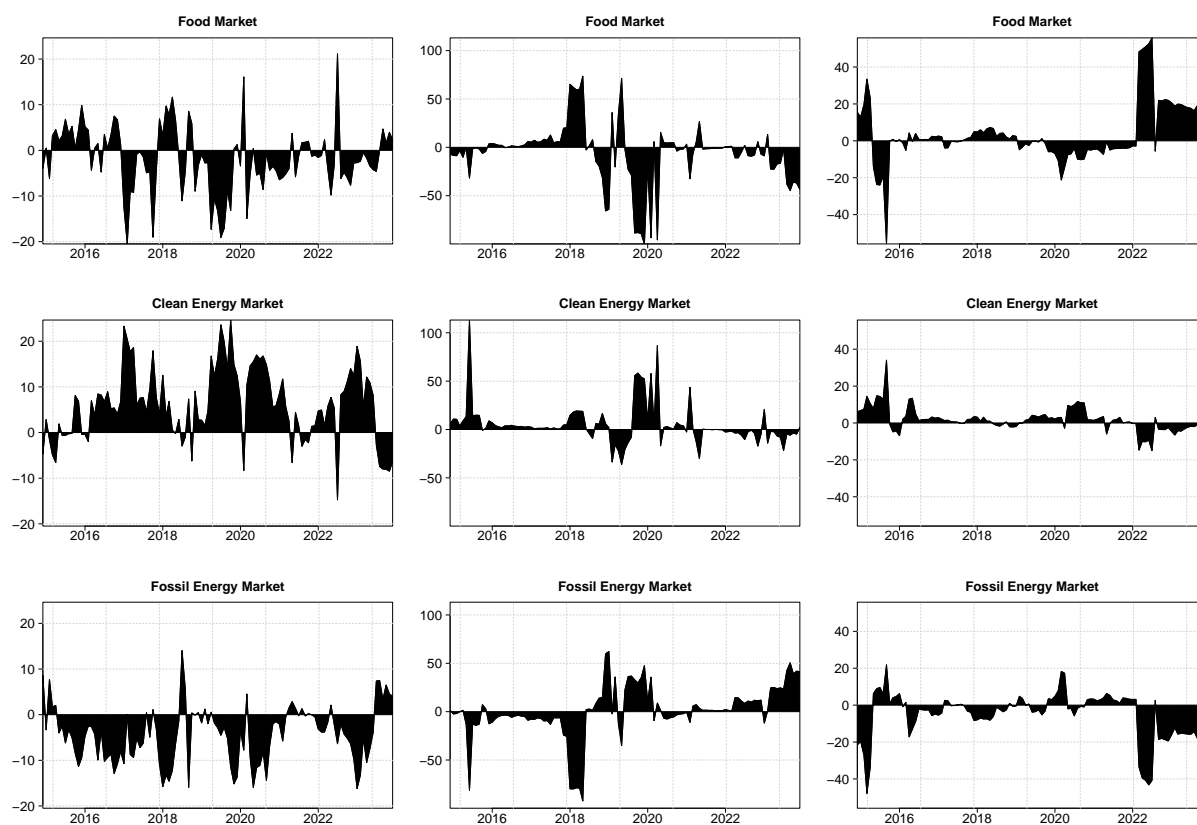


Fig. 5. Net return spillovers. The left, middle, and right panels correspond to $\tau = 0.5$, $\tau = 0.05$, and $\tau = 0.95$, respectively.

4.3. Robustness tests

On the one hand, we assess the robustness of the aforementioned results by varying the rolling-window size and the forecast horizon. First, we consider window sizes of 48 months or 60 months

while keeping the forecast horizon fixed at 12. The results, as reported in left panel of Fig. 6, show that the pattern of the spillover is not shaped by the window size. Second, we adjust the forecast horizon to 8 or 14. The results presented in the right panel of Fig. 6 show that the spillovers are still robust when the forecast horizon is changed.

On the other hand, we examine the 0.01 and 0.99 quantiles for extreme positive and negative conditions, respectively. When compared with the right panel of Fig. 3, the results in Fig. 7 for the 1% extreme quantiles are similar to the previous trends.

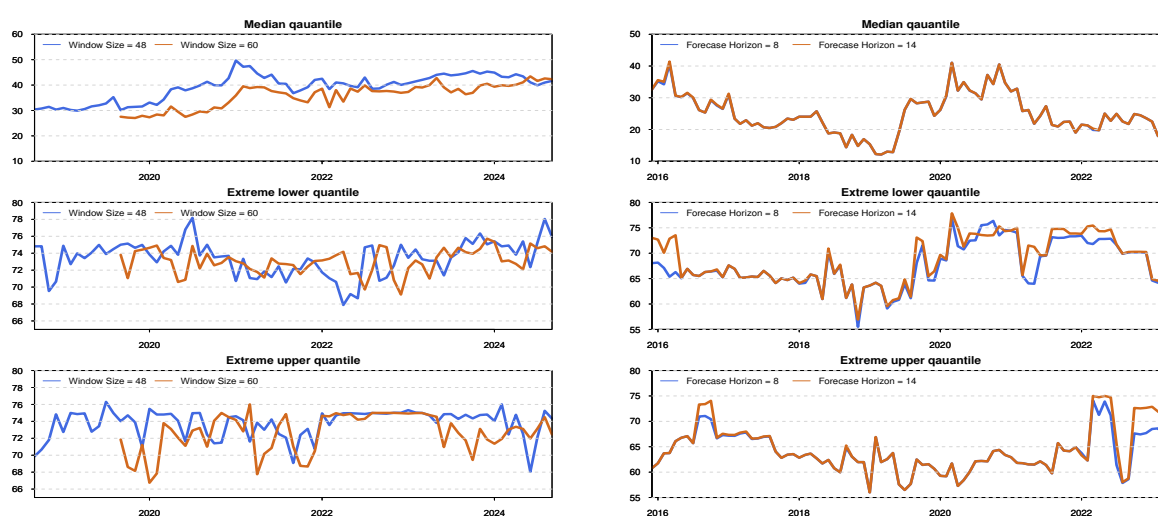


Fig. 6. Total return spillovers in quantile VAR. Left: Window size = 48 or 60, forecast horizon = 12; Right: Window size = 36, forecast horizon = 8 or 14.

5. The role of external uncertainties

According to Fig. 3, the total spillover indexes are prominently affected by the external uncertainties, such as climate policy uncertainty (e.g., the signing and implementation of the Paris Agreement) and geopolitical risks (e.g., the Russia-Ukraine Conflict). In this section, we examine the impact of external uncertainties on the spillover effects between food and energy markets.

We examine five key types of external uncertainties in this study³. The first is economic policy uncertainty (EPU), which is computed from the GDP-weighted average of 21 nations' economic

³We obtain the data from <https://www.policyuncertainty.com>.

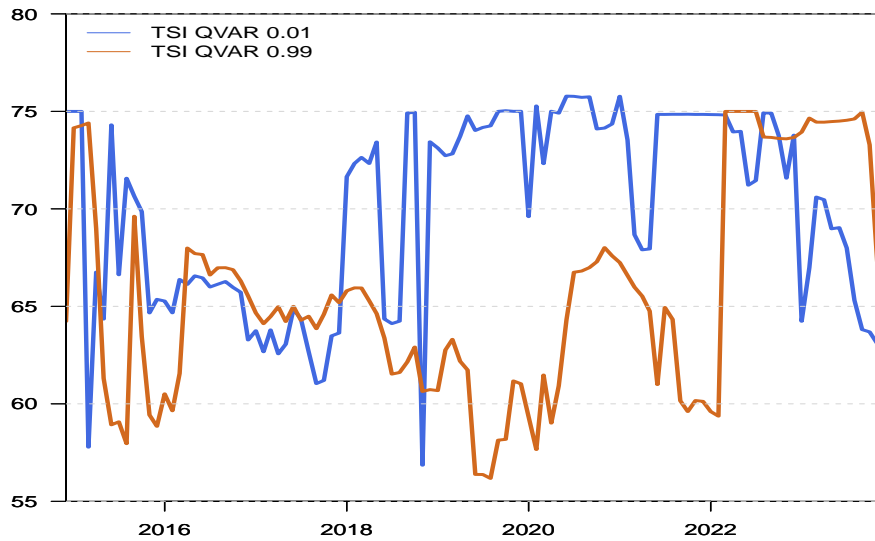


Fig. 7. Total return spillovers in quantile VAR (Extreme lower quantile $\tau = 0.01$ and extreme upper quantile $\tau = 0.99$.)

policy uncertainty indices (Baker et al., 2016). Researchers conclude that EPU complicates the food-energy cross-market return spillovers through direct and indirect channels (Cao et al., 2023). On the one hand, from the commodity attributes of food and energy, high EPU leads producers to lower investments and also reduces demands for commodities as raw materials. On the other hand, from the financial properties, high EPU prompts investors to hedge risks by investing financialized commodity markets. The second type is climate policy uncertainty (CPU), which is developed by analyzing newspaper articles on climate (Engle et al., 2020). The nexus between CPU and energy markets stems from the fact that climate policies have boosted the clean energy industry since the government introduced development goals and policies aimed at reducing greenhouse gas emissions, stimulating investors to switch the investment from traditional fossil energy to clean energy market (Uddin et al., 2023; Syed et al., 2023). For the CPU-food market nexus, climate policy works on the global climate environment and then affects food production (Liu et al., 2023; Chandio et al., 2023). The third one is trade policy uncertainty, which is constructed by integrating information related to trade policy on US newspaper articles (Baker et al., 2016). In the context

of global trade war, the connectedness between food and energy market are affected by channels of commodity trading and risk hedging (Mei and Xie, 2022; Yang et al., 2024). Geopolitical risk (GPR) is the forth uncertainty since food, fossil energy, and clean energy markets are sensitive to both geopolitical threats and acts (Yousfi and Bouzgarrou, 2024). Lastly, we introduce COVID-19 as a dummy variable, where it takes a value of 1 between January 2020 and December 2020 and 0 otherwise.

We reveal the effect of these external uncertainties on the total spillovers at the conditional median ($TSI_{\tau=0.5}$), extreme lower quantile ($TSI_{\tau=0.05}$), and extreme upper quantile ($TSI_{\tau=0.95}$). First of all, we examine the existence of unit roots for each variable by using ADF test (Dickey and Fuller, 1979), PP test (Phillips and Perron, 1988), and KPSS test (Kwiatkowski et al., 1992). As the results presented in Table 3, all variables are either $I(0)$ or $I(1)$ processes. It is find that the application of ARDL and NARDL models is valid.

5.1. Results of ARDL models

According to the Akaike information criterion, we obtain $(n_1, n_2, n_3, n_4, n_5)$ as $(1, 1, 4, 1, 2, 0)$, $(1, 1, 1, 3, 3, 0)$, and $(1, 3, 3, 1, 2, 0)$ in ARDL models when the dependent variable is $TSI_{\tau=0.5}$, $TSI_{\tau=0.05}$, and $TSI_{\tau=0.95}$, respectively. Results of ARDL models are presented in Table 4. The statistics of bound F test shown as F_{PSS} are 3.382, 4.265, and 4.252 for $TSI_{\tau=0.5}$, $TSI_{\tau=0.05}$, and $TSI_{\tau=0.95}$, respectively. They are all significant at either 10% or 5% levels, indicating the existence of long-run cointegration between the spillovers and external uncertainties under both normal and extreme market conditions.

For $TSI_{\tau=0.5}$, the short-run results show that contemporaneous $\Delta \ln EPU$ has a positive effect on $\Delta \ln TSI_{\tau=0.5}$, while $\Delta \ln CUP$, $\Delta \ln TUP$, and $\Delta \ln GPR$ each has a negative effect. However, the contemporaneous effects are not statistically significant, as indicated by the corresponding P -values. The coefficients for the first and third lags of $\Delta \ln CUP$ are significantly positive. The magnitude of coefficients indicate that a 1% increase in the first and third lags of $\ln CPU$, leads to a 0.096% and 0.112% increase in $\ln TSI_{\tau=0.5}$, respectively. The coefficient of first lag of $\ln GPR$ is significantly negative, with a magnitude of 0.176%. The long-run results are reported in Panel B of Table 4. $\ln CPU$ has a significantly negative long-run impact on $\ln TSI_{\tau=0.5}$, with a magnitude

of 0.548%, while $\ln GPR$ and $COVID - 19$ have significantly positive long-run impacts, with magnitudes of 0.712% and 0.969%, respectively.

We also examine the relationships between spillovers and external uncertainties at the extreme quantiles. For $TSI_{\tau=0.05}$, the coefficients for $\Delta \ln EPU$, $\Delta \ln CPU$, $\Delta \ln TPU$, and $\Delta \ln GPR$ are all positive, but only significant for $\Delta \ln EPU$ and $\Delta \ln GPR$. Specifically, a 1% increase in $\ln EPU$ and $\ln GPR$ contributes to the change of $\ln TSI_{\tau=0.05}$ in 0.048% and -0.051%, respectively. The coefficients of first and second lags of $\Delta \ln TPU$ and $\Delta \ln GPR$ are significantly positive. A 1% increase in the first and second lags of $\ln TPU$ results in change of 0.017% and 0.015% in $\ln TSI_{\tau=0.05}$, while the percentages for the first and second lags of $\ln GPR$ are 0.046% and 0.051%. The long-run results reveal that $\ln EPU$ has a significantly positive impacts to the total spillover at the lower quantile with a magnitude of 0.137, while $\ln GPR$ has a significantly negative impact with a magnitude of 0.205. For the spillover at the upper quantile, contemporaneous $\Delta \ln EPU$ and $\Delta \ln TPU$ have coefficients of 0.074 and -0.02 respectively, with statistical significance at 1% level. Moreover, the first and second lagged $\Delta \ln EPU$ and the first lagged $\Delta \ln GPR$ have significantly negative impacts on $\ln TSI_{\tau=0.95}$, while second lagged $\Delta \ln CPU$ has a significant positive impact. It is noted that all of the coefficients of ECT are significantly negative. The magnitudes of the coefficients of ECT imply the speed of adjustment toward long-run equilibrium from the short-run uncertainty shocks.

Additionally, We take residual diagnostics tests to approve the adequacy of the selected ARDL models, including the Breusch-Godfrey LM test (Breusch, 1978; Godfrey, 1978) for the autocorrelation, the Breusch-Pagan test (Breusch and Pagan, 1979) for the heteroskedasticity, the Ramsey RESET statistics test regress specification error (Ramsey, 1969) for the normality, and CUSUM test (Brown et al., 1975) for the model stability. The results outlined in Panel C of Table 4 provide the evidence that models pass these diagnostics except for the heteroskedasticity and normality of models for $TSI_{\tau=0.5}$.

5.2. Results of NARDL models

Following Shin et al. (2014), we use the Wald test to capture the long- and short-run asymmetric effects of the uncertainties on the total spillovers. The results shown in Table 5 reveal significant

Table 3

Results of conventional unit root tests

Variable	ADF		PP		KPSS	
	Intercept	Trend & intercept	Intercept	Trend & intercept	Intercept	Trend & intercept
<i>Panel A: Level</i>						
$\ln TSI_{\tau=0.5}$	-1.1794	-3.4292*	-1.1794	-3.5138**	1.1230***	0.1801**
$\ln TSI_{\tau=0.05}$	-4.1716***	-4.5447***	-4.2001***	-4.6347***	0.4845**	0.1599**
$\ln TSI_{\tau=0.95}$	-3.3966**	-3.8563**	-3.2652**	-3.7664**	0.4882**	0.1942**
$\ln EPU$	-2.2226	-4.7694***	-2.5217	-4.6378***	1.1591***	0.1172
$\ln CPU$	-10.0305***	-10.2271***	-10.0952***	-10.2163***	0.3140	0.0595
$\ln TPU$	-2.5755	-2.4557	-3.9257***	-3.9042**	0.3782*	0.2721***
$\ln GPR$	-5.1127***	-5.4250***	-5.0112***	-5.3600***	0.3014	0.1211*
<i>Panel B: First difference</i>						
$\Delta \ln TSI_{\tau=0.5}$	-11.6171***	-11.6192***	-11.6145***	-11.6167***	0.1028	0.0794
$\Delta \ln TSI_{\tau=0.05}$	-14.0546***	-13.9868***	-17.6571***	-17.5518***	0.1188	0.1187
$\Delta \ln TSI_{\tau=0.95}$	-7.2782***	-7.1848***	-14.1296***	-14.0499***	0.0576	0.0581
$\Delta \ln EPU$	-15.8287***	-15.7716***	-20.8516***	-20.7548***	0.0724	0.0721
$\Delta \ln CPU$	-9.0234***	-8.9968***	-51.9466***	-51.6527***	0.1100	0.0928
$\Delta \ln TPU$	-18.0481***	-18.0336***	-23.5253***	-27.5122***	0.4475*	0.3034***
$\Delta \ln GPR$	-15.3510***	-15.3029***	-23.5435***	-23.5737***	0.1065	0.0833

Note: The unit root tests are performed on the log levels of the series. For ADF test (Dickey and Fuller, 1979, 1981), the optimal lag length is chosen according to the smallest Schwarz information criterion (SIC). For both PP (Phillips and Perron, 1988) and KPSS (Kwiatkowski et al., 1992) tests, the bandwidth is selected using the Newey-West Bartlett kernel. Δ refers to the first difference. The superscripts ***, **, and * denote the statistical significance at the levels of 1%, 5%, and 10%, respectively.

short-run asymmetric effects of $\ln CPU$ on $\ln TSI_{\tau=0.95}$. For long-run asymmetric effects, $\ln EPU$ is significant to $TSI_{\tau=0.5}$, and $\ln CPU$, $\ln TPU$, and $\ln GPR$ are significant to $TSI_{\tau=0.05}$.

We select lag orders of NARDL models as (1, 1, 1, 1, 1, 0), (3, 1, 1, 1, 3, 0), and (1, 3, 3, 1, 1, 0) for $TSI_{\tau=0.5}$, $TSI_{\tau=0.05}$, and $TSI_{\tau=0.95}$, respectively. The F_{PSS} statistics indicate significant long-run cointegration. Results are shown in Table 6. For $TSI_{\tau=0.5}$, contemporaneous $\Delta \ln EPU^+$, $\Delta \ln CPU^+$, and $\Delta \ln TPU^-$ have significant impacts on $\Delta \ln TSI_{\tau=0.5}$, with the coefficients are 0.17, -0.113, and -0.051, respectively. The long-run results demonstrate that $\ln EPU^-$ and $COVID - 19$ are positively related to $\ln TSI_{\tau=0.5}$, while $\ln TPU^+$ and $\ln TPU^-$ are negatively related to $\ln TSI_{\tau=0.5}$. When move to the results of $TSI_{\tau=0.05}$, we find that the coefficients of contemporaneous variables are not statistically significant. The first lag of $\Delta \ln GPR^+$ and the second

lag of $\Delta \ln GPR^-$ have significant impact on $\Delta \ln TSI_{\tau=0.05}$. Meanwhile, the long-run results show that the coefficient is significantly positive for $\ln TPU^-$ and significantly negative for $\ln GPR^+$ and $\ln GPR^-$. For $TSI_{\tau=0.95}$, coefficients of contemporaneous and first lag $\Delta \ln EPU^+$ are significant. As with $\Delta \ln CPU$, the coefficients of the contemporaneous and all the lags of $\Delta \ln CPU^+$ are negative, while they are all positive for the contemporaneous and all the lags of $\Delta \ln CPU^-$. This is consistent with the asymmetric test in Table 5. Both $\Delta \ln TPU^+$ and $\Delta \ln TPU^-$ have significant negative coefficients, with similar magnitudes of 0.020 and 0.021. Additionally, panel C of Table 6 reports the results of residual diagnostics tests, which approve the adequacy of the selected NARDL models.

6. Conclusion and policy implications

This paper use a quantile regression-based [Diebold and Yilmaz \(2012, 2014\)](#) spillover measure to explore the return connectedness between food, fossil energy, and clean energy markets at the median and extreme quantiles. Additionally, we examine the role of external uncertainties on the spillover effects under different market conditions.

Our empirical results show that the return connectedness between these markets is much stronger at the tails (61.47% for left tail and 57.91% for right tail) than at the median (23.02%). The total spillover index presents a U-shaped curve across quantiles, indicating that returns between these markets are more tightly connected during the extreme market conditions. The net spillover analysis reveals that fossil energy market always act as the net receiver, while clean energy market primarily serves as the net transmitter. The dynamic analysis shows that spillover effects vary over time and intensify during period of extreme events, such as the signing and implementation of the Paris Agreement, and the COVID-19 pandemic. Furthermore, results from the ARDL and NARDL models show that external uncertainties have statistically significant impacts on total spillovers. At the median quantile, CPU, GPR, and the COVID-19 pandemic are the important drivers of spillovers. At the extreme quantiles, EPU, TPU, and GPR act as main drivers. In addition, the results of NARDL models reveal the asymmetric effects of external uncertainties.

Our findings have several practical implications for cross-market investments in food and energy markets. First, the significant return spillovers, particularly under extreme market conditions, highlight the risk contagions between these markets. Investors should carefully monitor these risks

Table 4

Results of ARDL models.

Variables	$TSI_{\tau=0.5}$		$TSI_{\tau=0.05}$		$TSI_{\tau=0.95}$	
	Coeff.	<i>p</i> -val.	Coeff.	<i>p</i> -val.	Coeff.	<i>p</i> -val.
<i>Panel A: Short-run results</i>						
<i>Intercept</i>	0.705	0.000***	1.699	0.000***	0.871	0.000***
$\Delta \ln EPU_t$	0.051	0.410	0.048	0.092*	0.074	0.003***
$\Delta \ln EPU_{t-1}$					-0.070	0.009***
$\Delta \ln EPU_{t-2}$					-0.047	0.063*
$\Delta \ln CPU_t$	-0.036	0.312	-0.001	0.926	-0.014	0.290
$\Delta \ln CPU_{t-1}$	0.096	0.010**			0.007	0.649
$\Delta \ln CPU_{t-2}$	0.056	0.135			0.026	0.058*
$\Delta \ln CPU_{t-3}$	0.112	0.002***				
$\Delta \ln TPU_t$	-0.015	0.302	0.001	0.950	-0.020	0.000***
$\Delta \ln TPU_{t-1}$			0.017	0.043**		
$\Delta \ln TPU_{t-2}$			0.015	0.037**		
$\Delta \ln GPR_t$	-0.041	0.432	-0.051	0.040**	0.028	0.158
$\Delta \ln GPR_{t-1}$	-0.176	0.001***	0.046	0.087*	-0.039	0.060*
$\Delta \ln GPR_{t-2}$			0.051	0.041**		
<i>ECT</i>	-0.173	0.000**	-0.348	0.000***	-0.293	0.000***
<i>Panel B: Long-run results</i>						
<i>Intercept</i>	4.075	0.031**	4.873	0.000***	2.973	0.000***
<i>lnEPU</i>	-0.257	0.485	0.137	0.083*	0.267	0.009***
<i>lnCPU</i>	-0.548	0.059*	-0.005	0.928	-0.122	0.121
<i>lnTPU</i>	-0.042	0.486	-0.024	0.100	-0.037	0.009***
<i>lnGPR</i>	0.712	0.051*	-0.205	0.015**	0.185	0.019**
<i>COVID – 19</i>	0.969	0.001***	-0.015	0.796	-0.007	0.902
<i>Panel C: Diagnostics tests</i>						
<i>F_{PSS}</i>	3.382	0.096*	4.265	0.023**	4.252	0.024**
<i>BG</i>	0.007	0.933	1.037	0.308	0.088	0.767
<i>BP</i>	28.893	0.011**	15.562	0.341	20.828	0.142
<i>Ramsey RESET</i>	2.335	0.009***	1.037	0.427	0.998	0.467
<i>CUSUM</i>	0.486	0.659	0.619	0.377	0.643	0.335

The superscripts ***, **, and * denote the statistical significance at the levels of 1%, 5%, and 10%, respectively.

and implement strategies to manage cross-market exposures. Second, as fossil energy primarily acts as a net receiver of shocks, investors in fossil energy markets need to track developments in food and clean energy markets and diversify their portfolios by incorporating food and clean energy assets. Third, given the significant influence of external uncertainties, investors should adjust

Table 5

Results of the Wald test for asymmetric effects.

Variables	$TSI_{\tau=0.5}$		$TSI_{\tau=0.05}$		$TSI_{\tau=0.95}$	
	Coeff.	<i>p</i> -val.	Coeff.	<i>p</i> -val.	Coeff.	<i>p</i> -val.
<i>Panel A: Short-run results</i>						
W_{EPU}	0.010	0.922	0.855	0.358	0.508	0.478
W_{CPU}	1.219	0.273	0.172	0.679	4.384	0.040**
W_{TPU}	0.438	0.510	0.201	0.655	0.005	0.942
W_{GPR}	1.507	0.223	0.047	0.830	0.455	0.502
<i>Panel B: Long-run results</i>						
W_{EPU}	4.360	0.016**	1.638	0.201	2.954	0.058*
W_{CPU}	0.920	0.402	2.937	0.059*	1.728	0.184
W_{TPU}	2.209	0.116	5.291	0.007***	1.798	0.172
W_{GPR}	0.131	0.877	4.795	0.011**	0.656	0.522

The superscripts ***, **, and * denote the statistical significance at the levels of 1%, 5%, and 10%, respectively.

their strategies during periods of heightened uncertainty related to EPU, CPU, TPU, or GPR to mitigate potential risks.

The results also carry critical implications for policymakers. First, the transition from fossil energy to clean energy is an important issue, which requires well-designed policies that account for the interconnectedness between these markets under varying conditions. Second, our research reveals the significant impact of external uncertainties on the connectedness between food and energy markets. Therefore, policymakers should closely monitor the changes in external uncertainties and employ useful policy tools to achieve policy coordination when uncertainty shocks occur, which is of great importance to ensuring the stability of food and energy markets.

Acknowledgment

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Table 6

Results of NARDL models.

Variables	$TSI_{\tau=0.5}$		$TSI_{\tau=0.05}$		$TSI_{\tau=0.95}$	
	Coeff.	<i>p</i> -val.	Coeff.	<i>p</i> -val.	Coeff.	<i>p</i> -val.
<i>Panel A: Short-run results</i>						
<i>Inetrcept</i>	1.507	0.000***	2.354	0.000***	1.700	0.000***
$\Delta \ln TSI_{t-1}$			0.036	0.700		
$\Delta \ln TSI_{t-2}$			0.170	0.036**		
$\Delta \ln EPU_t^+$	0.170	0.080*	-0.002	0.958	0.132	0.001***
$\Delta \ln EPU_{t-1}^+$					-0.088	0.027**
$\Delta \ln EPU_{t-2}^+$					-0.049	0.211
$\Delta \ln EPU_t^-$	0.149	0.205	0.081	0.110	0.047	0.340
$\Delta \ln EPU_{t-1}^-$					-0.034	0.470
$\Delta \ln EPU_{t-2}^-$					-0.010	0.836
$\Delta \ln CPU_t^+$	-0.113	0.049**	0.006	0.831	-0.059	0.019**
$\Delta \ln CPU_{t-1}^+$					-0.029	0.237
$\Delta \ln CPU_{t-2}^+$					-0.011	0.633
$\Delta \ln CPU_t^-$	0.010	0.865	-0.015	0.556	0.017	0.477
$\Delta \ln CPU_{t-1}^-$					0.054	0.049**
$\Delta \ln CPU_{t-2}^-$					0.064	0.028**
$\Delta \ln TPU_t^+$	-0.017	0.499	-0.007	0.546	-0.021	0.034**
$\Delta \ln TPU_t^-$	-0.051	0.074*	0.003	0.779	-0.020	0.091*
$\Delta \ln GPR_t^+$	-0.126	0.118	-0.029	0.395	-0.001	0.989
$\Delta \ln GPR_{t-1}^+$			0.128	0.002***		
$\Delta \ln GPR_{t-2}^+$			0.031	0.416		
$\Delta \ln GPR_t^-$	0.102	0.311	-0.038	0.395	0.050	0.194
$\Delta \ln GPR_{t-1}^-$			0.019	0.688		
$\Delta \ln GPR_{t-2}^-$			0.117	0.005***		
<i>ECT</i>	-0.392	0.000***	-0.527	0.000***	-0.375	0.000***
<i>Panel B: Long-run results</i>						
<i>Intercept</i>	3.839	0.000***	4.466	0.000***	4.537	0.000***
$\ln EPU^+$	0.186	0.441	0.001	0.997	0.293	0.042**
$\ln EPU^-$	0.634	0.007***	0.096	0.220	0.265	0.048**
$\ln CPU^+$	0.094	0.447	0.057	0.141	-0.124	0.109
$\ln CPU^-$	-0.025	0.872	-0.016	0.743	-0.151	0.102
$\ln TPU^+$	-0.122	0.017**	-0.012	0.451	-0.038	0.095*
$\ln TPU^-$	-0.120	0.014**	0.027	0.080*	-0.039	0.068*
$\ln GPR^+$	0.082	0.621	-0.124	0.078*	0.031	0.704
$\ln GPR^-$	0.027	0.890	-0.232	0.005***	0.102	0.293
<i>COVID – 19</i>	0.402	0.003***	-0.018	0.703	-0.063	0.256
<i>Panel C: Diagnostics tests</i>						
F_{PSS}	3.218	0.062*	3.569	0.027**	3.044	0.091*
BG	0.841	0.359	0.798	0.372	0.123	0.726
BP	31.849	0.023**	28.498	0.240	30.123	0.263
Ramsey RESET	0.718	0.781	0.827	0.688	0.885	0.624
CUSUM	0.373	0.891	0.680	0.278	1.011	0.031**

The superscripts ***, **, and * denote the statistical significance at the levels of 1%, 5%, and 10%, respectively.

References

- Abdelradi, F., Serra, T., 2015. Food-energy nexus in Europe: Price volatility approach. *Energy Econ.* 48, 157–167. doi:[10.1016/j.eneco.2014.11.022](https://doi.org/10.1016/j.eneco.2014.11.022).
- Adil, S., Bhatti, A.A., Waqar, S., Amin, S., 2022. Unleashing the indirect influence of oil prices on food prices via exchange rate: New evidence from Pakistan. *J. Public Aff.* 22, e2615. doi:[10.1002/pa.2615](https://doi.org/10.1002/pa.2615).
- Ahmad, W., 2017. On the dynamic dependence and investment performance of crude oil and clean energy stocks. *Res. Int. Bus. Financ.* 42, 376–389. doi:[10.1016/j.ribaf.2017.07.140](https://doi.org/10.1016/j.ribaf.2017.07.140).
- Algieri, B., Leccadito, A., 2017. Assessing contagion risk from energy and non-energy commodity markets. *Energy Econ.* 62, 312–322. doi:[10.1016/j.eneco.2017.01.006](https://doi.org/10.1016/j.eneco.2017.01.006).
- Almalki, A.M., Hassan, M.u., Bin Amin, M.F., 2022. The asymmetric relationship between structural oil shocks and food prices: Evidence from Saudi Arabia. *Appl. Econ.* 54, 6216–6233. doi:[10.1080/00036846.2022.2083065](https://doi.org/10.1080/00036846.2022.2083065).
- Atems, B., Mette, J., 2024. The impact of biomass consumption on US food prices. *J. Environ. Plan. Manag.* 67, 2459–2476. doi:[10.1080/09640568.2023.2192383](https://doi.org/10.1080/09640568.2023.2192383).
- Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty. *Quart. J. Econ.* 131, 1593–1636. doi:[10.1093/qje/qjw024](https://doi.org/10.1093/qje/qjw024).
- Breusch, T.S., 1978. Testing for autocorrelation in dynamic linear models. *Aust. Econ. Pap.* 17, 334–355. doi:[10.1111/j.1467-8454.1978.tb00635.x](https://doi.org/10.1111/j.1467-8454.1978.tb00635.x).
- Breusch, T.S., Pagan, A.R., 1979. A simple test for heteroscedasticity and random coefficient variation. *Econometrica* 47, 1287–1294. doi:[10.2307/1911963](https://doi.org/10.2307/1911963).
- Brown, R.L., Durbin, J., Evans, J.M., 1975. Techniques for testing the constancy of regression relationships over time. *J. R. Stat. Soc. B* 37, 149–163. doi:[10.1111/j.2517-6161.1975.tb01532.x](https://doi.org/10.1111/j.2517-6161.1975.tb01532.x).
- Caldara, D., Iacoviello, M., 2022. Measuring Geopolitical Risk. *Am. Econ. Rev.* 112, 1194–1225. doi:[10.1257/aer.20191823](https://doi.org/10.1257/aer.20191823).
- Cao, G., Xie, F., 2024. Extreme risk spillovers across energy and carbon markets: Evidence from the quantile extended joint connectedness approach. *Int. J. Financ. Econ.* 29, 2155–2175. doi:[10.1002/ijfe.2781](https://doi.org/10.1002/ijfe.2781).
- Cao, Y., Cheng, S., Li, X., 2023. How economic policy uncertainty affects asymmetric spillovers in food and oil prices: Evidence from wavelet analysis. *Resour. Policy* 86, 104086. doi:[10.1016/j.resourpol.2023.104086](https://doi.org/10.1016/j.resourpol.2023.104086).
- Chandio, A.A., Jiang, Y., Akram, W., Ozturk, I., Rauf, A., Mirani, A.A., Zhang, H., 2023. The impact of R&D investment on grain crops production in China: Analysing the role of agricultural credit and CO₂ emissions. *Int. J. Financ. Econ.* 28, 4120–4138. doi:[10.1002/ijfe.2638](https://doi.org/10.1002/ijfe.2638).
- Chatterjee, R., 2024. How state governance can offer a new paradigm to energy transition in Indian agriculture? *Energy Policy* 185, 113965. doi:[10.1016/j.enpol.2023.113965](https://doi.org/10.1016/j.enpol.2023.113965).
- Chatziantoniou, I., Degiannakis, S., Filis, G., Lloyd, T., 2021. Oil price volatility is effective in predicting food price

- volatility. Or is it? *Energy J.* 42, 25–48. doi:[10.5547/01956574.42.6.icha](https://doi.org/10.5547/01956574.42.6.icha).
- Chen, Z., Yan, B., Kang, H., 2022. Dynamic correlation between crude oil and agricultural futures markets. *Rev. Dev. Econ.* 26, 1798–1849. doi:[10.1111/rode.12885](https://doi.org/10.1111/rode.12885).
- Chowdhury, M.A.F., Meo, M.S., Uddin, A., Haque, M.M., 2021. Asymmetric effect of energy price on commodity price: New evidence from NARDL and time frequency wavelet approaches. *Energy* 231, 120934. doi:[10.1016/j.energy.2021.120934](https://doi.org/10.1016/j.energy.2021.120934).
- Diab, S., Karaki, M.B., 2023. Do increases in gasoline prices cause higher food prices? *Energy Econ.* 127, 107066. doi:[10.1016/j.eneco.2023.107066](https://doi.org/10.1016/j.eneco.2023.107066).
- Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. *J. Am. Stat. Assoc.* 74, 427–431.
- Dickey, D.A., Fuller, W.A., 1981. Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica* 49, 1057–1072.
- Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *Int. J. Forecast.* 28, 57–66. doi:[10.1016/j.ijforecast.2011.02.006](https://doi.org/10.1016/j.ijforecast.2011.02.006).
- Diebold, F.X., Yilmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *J. Econom.* 182, 119–134. doi:[10.1016/j.jeconom.2014.04.012](https://doi.org/10.1016/j.jeconom.2014.04.012).
- Engle, R.F., Giglio, S., Kelly, B., Lee, H., Stroebel, J., 2020. Hedging climate change news. *Rev. Financ. Stud.* 33, 1184–1216. doi:[10.1093/rfs/hhz072](https://doi.org/10.1093/rfs/hhz072).
- Ericsson, K., Rosenqvist, H., Nilsson, L.J., 2009. Energy crop production costs in the EU. *Biomass Bioenerg.* 33, 1577–1586. doi:[10.1016/j.biombioe.2009.08.002](https://doi.org/10.1016/j.biombioe.2009.08.002).
- Fasanya, I., Akinbowale, S., 2019. Modelling the return and volatility spillovers of crude oil and food prices in Nigeria. *Energy* 169, 186–205. doi:[10.1016/j.energy.2018.12.011](https://doi.org/10.1016/j.energy.2018.12.011).
- Gavriilidis, K., 2021. Measuring climate policy uncertainty. doi:[10.2139/ssrn.3847388](https://doi.org/10.2139/ssrn.3847388). <https://ssrn.com/abstract=3847388>.
- Georgiou, S., Acha, S., Shah, N., Markides, C.N., 2018. A generic tool for quantifying the energy requirements of glasshouse food production. *J. Clean Prod.* 191, 384–399. doi:[10.1016/j.jclepro.2018.03.278](https://doi.org/10.1016/j.jclepro.2018.03.278).
- Godfrey, L.G., 1978. Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables. *Econometrica* 46, 1293–1301. doi:[10.2307/1913829](https://doi.org/10.2307/1913829).
- Guo, J., Tanaka, T., 2022. Energy security versus food security: An analysis of fuel ethanol- related markets using the spillover index and partial wavelet coherence approaches. *Energy Econ.* 112, 106142. doi:[10.1016/j.eneco.2022.106142](https://doi.org/10.1016/j.eneco.2022.106142).
- Han, J., Zhang, L., Li, Y., 2022. Spatiotemporal analysis of rural energy transition and upgrading in developing countries: The case of China. *Appl. Energy* 307, 118225. doi:[10.1016/j.apenergy.2021.118225](https://doi.org/10.1016/j.apenergy.2021.118225).
- Han, L., Zhou, Y., Yin, L., 2015. Exogenous impacts on the links between energy and agricultural commodity markets.

- Energy Econ. 49, 350–358. doi:[10.1016/j.eneco.2015.02.021](https://doi.org/10.1016/j.eneco.2015.02.021).
- Hanif, W., Hernandez, J.A., Shahzad, S.J.H., Yoon, S.M., 2021. Tail dependence risk and spillovers between oil and food prices*. Q. Rev. Econ. Financ. 80, 195–209. doi:[10.1016/j.qref.2021.01.019](https://doi.org/10.1016/j.qref.2021.01.019).
- Haque, M.I., Khan, M.R., 2022. Impact of climate change on food security in Saudi Arabia: A roadmap to agriculture-water sustainability. J. Agribus. Dev. Emerg. Econ. 12, 1–18. doi:[10.1108/JADEE-06-2020-0127](https://doi.org/10.1108/JADEE-06-2020-0127).
- Hartter, J., Hamilton, L.C., Boag, A.E., Stevens, F.R., Ducey, M.J., Christoffersen, N.D., Oester, P.T., Palace, M.W., 2018. Does it matter if people think climate change is human caused? Clim. Serv. 10, 53–62. doi:[10.1016/j.cliser.2017.06.014](https://doi.org/10.1016/j.cliser.2017.06.014).
- Hassouneh, I., Serra, T., Goodwin, B.K., Gil, J.M., 2012. Non-parametric and parametric modeling of biodiesel, sunflower oil, and crude oil price relationships. Energy Econ. 34, 1507–1513. doi:[10.1016/j.eneco.2012.06.027](https://doi.org/10.1016/j.eneco.2012.06.027).
- Koenker, R., Bassett, G., 1978. Regression quantiles. Econometrica 46, 33–50.
- Koop, G.M., Pesaran, H., Potter, S.M., 1996. Impulse response analysis in nonlinear multivariate models. J. Econom. 74, 119–147. doi:[10.1016/0304-4076\(95\)01753-4](https://doi.org/10.1016/0304-4076(95)01753-4).
- Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., Shin, Y.C., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? J. Econometr. 54, 159–178.
- Li, N., Agene, D., Gu, L., Osabohien, R., Jaaffar, A.H., 2024. Promoting clean energy adoption for enhanced food security in Africa. Front. Sustain. Food Syst. 8, 1269160. doi:[10.3389/fsuifs.2024.1269160](https://doi.org/10.3389/fsuifs.2024.1269160).
- Liu, G., Luo, K., Xu, P., Zhang, S., 2023. Climate policy uncertainty and its impact on major grain futures. Financ. Res. Lett. 58, 104412. doi:[10.1016/j.fr1.2023.104412](https://doi.org/10.1016/j.fr1.2023.104412).
- Liu, J., Serletis, A., 2024. Volatility and dependence in crude oil and agricultural commodity markets. Appl. Econ. doi:[10.1080/00036846.2024.2312260](https://doi.org/10.1080/00036846.2024.2312260).
- Lucotte, Y., 2016. Co-movements between crude oil and food prices: A post-commodity boom perspective. Econ. Lett. 147, 142–147. doi:[10.1016/j.econlet.2016.08.032](https://doi.org/10.1016/j.econlet.2016.08.032).
- Mei, D., Xie, Y., 2022. US grain commodity futures price volatility: Does trade policy uncertainty matter? Financ. Res. Lett. 48, 103028. doi:[10.1016/j.fr1.2022.103028](https://doi.org/10.1016/j.fr1.2022.103028).
- Miljkovic, D., Vatsa, P., 2023. On the linkages between energy and agricultural commodity prices: A dynamic time warping analysis. Int. Rev. Financ. Anal. 90, 102834. doi:[10.1016/j.irfa.2023.102834](https://doi.org/10.1016/j.irfa.2023.102834).
- Mohammed, R., 2022. The impact of crude oil price on food prices in Iraq. OPEC Energy Rev. 46, 106–122. doi:[10.1111/opec.12225](https://doi.org/10.1111/opec.12225).
- Myers, R.J., Johnson, S.R., Helmar, M., Baumes, H., 2014. Long-run and short-run co-movements in energy prices and the prices of agricultural feedstocks for biofuel. Am. J. Agr. Econ. 96, 991–1008. doi:[10.1093/ajae/aau003](https://doi.org/10.1093/ajae/aau003).
- Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Econ. Lett. 58,

- 17–29. doi:[10.1016/S0165-1765\(97\)00214-0](https://doi.org/10.1016/S0165-1765(97)00214-0).
- Pesaran, M.H., Shin, Y., Smith, R.J., 2001. Bounds testing approaches to the analysis of level relationships. *J. Appl. Economet.* 16, 289–326. doi:[10.1002/jae.616](https://doi.org/10.1002/jae.616).
- Phillips, P.C.B., Perron, P., 1988. Testing for a unit root in time series regression. *Biometrika* 75, 335–346.
- Ramsey, J.B., 1969. Tests for specification errors in classical linear least-squares regression analysis. *J. R. Stat. Soc. B* 31, 350–371. doi:[10.1111/j.2517-6161.1969.tb00796.x](https://doi.org/10.1111/j.2517-6161.1969.tb00796.x).
- Raza, S.A., Khan, K.A., Benkraiem, R., Guesmi, K., 2024. The importance of climate policy uncertainty in forecasting the green, clean and sustainable financial markets volatility. *Int. Rev. Financ. Anal.* 91, 102984. doi:[10.1016/j.irfa.2023.102984](https://doi.org/10.1016/j.irfa.2023.102984).
- Roman, M., Gorecka, A., Domagala, J., 2020. The linkages between crude oil and food prices. *Energies* 13, 6545. doi:[10.3390/en13246545](https://doi.org/10.3390/en13246545).
- Saeed, T., Bouri, E., Alsulami, H., 2021. Extreme return connectedness and its determinants between clean/green and dirty energy investments. *Energy Econ.* 96, 105017. doi:[10.1016/j.eneco.2020.105017](https://doi.org/10.1016/j.eneco.2020.105017).
- Shin, Y., Yu, B., Greenwood-Nimmo, M., 2014. Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. *Festschrift in honor of Peter Schmidt*. Springer, New York.
- Sun, Y., Gao, P., Raza, S.A., Shah, N., Sharif, A., 2023. The asymmetric effects of oil price shocks on the world food prices: Fresh evidence from quantile-on-quantile regression approach. *Energy* 270, 126812. doi:[10.1016/j.energy.2023.126812](https://doi.org/10.1016/j.energy.2023.126812).
- Syed, Q.R., Apergis, N., Goh, S.K., 2023. The dynamic relationship between climate policy uncertainty and renewable energy in the US: Applying the novel fourier augmented autoregressive distributed lags approach. *Energy* 275, 127383. doi:[10.1016/j.energy.2023.127383](https://doi.org/10.1016/j.energy.2023.127383).
- Taghizadeh-Hesary, F., Rasoulinezhad, E., Yoshino, N., 2019. Energy and food security: Linkages through price volatility. *Energy Policy* 128, 796–806. doi:[10.1016/j.enpol.2018.12.043](https://doi.org/10.1016/j.enpol.2018.12.043).
- Tanaka, T., Guo, J., Wang, X., 2023. Price interconnection of fuel and food markets: Evidence from biodiesel in the United States. *GCB Bioenergy* 15, 886–899. doi:[10.1111/gcbb.13055](https://doi.org/10.1111/gcbb.13055).
- Ucak, H., Yelgen, E., Ari, Y., 2022. The role of energy on the price volatility of fruits and vegetables: Evidence from Turkey. *Bio-based Appl. Econ.* 11, 37–54. doi:[10.36253/bae-10896](https://doi.org/10.36253/bae-10896).
- Uddin, G.S., Sahamkhadam, M., Yahya, M., Tang, O., 2023. Investment opportunities in the energy market: What can be learnt from different energy sectors. *Int. J. Financ. Econ.* 28, 3611–3636. doi:[10.1002/ijfe.2610](https://doi.org/10.1002/ijfe.2610).
- Vatsa, P., Miljkovic, D., Baek, J., 2023. Linkages between natural gas, fertiliser and cereal prices: A note. *J. Agric. Econ.* 74, 935–940. doi:[10.1111/1477-9552.12532](https://doi.org/10.1111/1477-9552.12532).
- Wang, L., Chavas, J.P., Li, J., 2024. Dynamic linkages in agricultural and energy markets: A quantile impulse response approach. *Agric. Econ.* 55, 639–676. doi:[10.1111/agec.12837](https://doi.org/10.1111/agec.12837).
- Yang, C., Zhang, H., Qin, Y., Niu, Z., 2024. Partisan conflict, trade policy uncertainty, and the energy market. *Res.*

- Int. Bus. Financ. 71, 102450. doi:[10.1016/j.ribaf.2024.102450](https://doi.org/10.1016/j.ribaf.2024.102450).
- Yoon, S.M., 2022. On the interdependence between biofuel, fossil fuel and agricultural food prices: Evidence from quantile tests. *Renew. Energy* 199, 536–545. doi:[10.1016/j.renene.2022.08.136](https://doi.org/10.1016/j.renene.2022.08.136).
- Yousfi, M., Bouzgarrou, H., 2024. Geopolitical risk, economic policy uncertainty, and dynamic connectedness between clean energy, conventional energy, and food markets. *Environ. Sci. Pollut. Res.* 31, 4925–4945. doi:[10.1007/s11356-023-31379-7](https://doi.org/10.1007/s11356-023-31379-7).
- Youssef, M., Mokni, K., 2021. On the nonlinear impact of oil price shocks on the world food prices under different markets conditions. *Int. Econ. J.* 35, 73–95. doi:[10.1080/10168737.2020.1870524](https://doi.org/10.1080/10168737.2020.1870524).
- Yu, Y., Peng, C., Zakaria, M., Mahmood, H., Khalid, S., 2023. Nonlinear effects of crude oil dependency on food prices in China: Evidence from quantile-on-quantile approach. *J. Bus. Econ. Manag.* 24, 696–711. doi:[10.3846/jbem.2023.20192](https://doi.org/10.3846/jbem.2023.20192).
- Zhang, D., Broadstock, D.C., 2020. Global financial crisis and rising connectedness in the international commodity markets. *Int. Rev. Financ. Anal.* 68, 101239. doi:[10.1016/j.irfa.2018.08.003](https://doi.org/10.1016/j.irfa.2018.08.003).
- Zimmer, Y., Marques, Giulio, V., 2021. Energy cost to produce and transport crops-The driver for crop prices? Case study for Mato Grosso, Brazil. *Energy* 225, 120260. doi:[10.1016/j.energy.2021.120260](https://doi.org/10.1016/j.energy.2021.120260).
- Zmami, M., Ben-Salha, O., 2019. Does oil price drive world food prices? Evidence from linear and nonlinear ARDL modeling. *Economies* 7, 12. doi:[10.3390/economies7010012](https://doi.org/10.3390/economies7010012).