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Alarming contagion effects: The dangerous ripple effect of extreme price spillovers across crude oil, carbon emission allowance, and agriculture futures markets

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ABSTRACT

The inherent financial interconnections between crude oil prices, carbon emission allowances, and agriculture commodity futures warrant a thorough investigation as fossil energy consumption, carbon emissions, and agriculture plants are three critical components of global environmental protection. This paper aims to quantify not only the normal (mean quantile) static and dynamic spillover effects among them in both time and frequency domains but also the more critical extreme spillovers that occur across various time horizons. Additionally, we explore the vital role of carbon futures in hedging risk and enhancing the performance of oil and agricultural portfolios. Empirical results indicate that, under extreme market situations, the total spillovers among oil, carbon, and agriculture commodity futures are much larger than those under normal conditions. Furthermore, soybean and corn are generally the most potent information transmitters over other futures in the time domain, while carbon emission allowance futures act as an obvious spillover receiver at both normal and extreme market conditions across various time frequencies. Both the total spillover and the net spillover are centered at a short-term frequency (i.e., one to four weeks). Finally, we find that carbon futures can contribute to improving the hedge effectiveness and performance of oil and agricultural portfolios. These findings have valuable implications for policymakers, relevant producers/consumers, as well as futures investors.

1. Introduction

The increasing concern over the severe impacts of greenhouse gas emissions on the global natural environment and ecosystems has triggered significant research into the interdependence among fossil energy, carbon emission allowance, and agriculture commodity markets (Neagu and Teodoru, 2019). On the one hand, the extensive use of fossil fuels in industrial production and agriculture plants has unquestionably contributed to greenhouse gas emissions. On the other hand, there are still many controversies regarding whether the development of agricultural plants will increase or decrease greenhouse gas emissions. Specifically, the positive side argues that through photosynthesis in agricultural plants, carbon dioxide in the earth's air will be absorbed by plants and then broken down into carbon and oxygen. The carbon is then processed and transformed into plant bodies (roots, stems, leaves), bio-materials, and fuels for human needs. In addition, the accelerated use of biofuels, such as biomass alcohol and biomass fuels

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produced primarily from corn and soybeans, has significantly reduced dependence on fossil energy sources, thereby reducing carbon emissions (Mathews, 2008; Fargione et al., 2008; Kauppi and Saikku, 2009; Lippke et al., 2012; DeCicco, 2012; Kim et al., 2020; Zhang et al., 2023). However, the opposing view suggests that large-scale cultivation of agricultural products, such as oil palm, could lead to deforestation and loss of biodiversity in the primitive forests, as well as increased carbon emissions from fertilizer and pesticide production and agricultural machinery use (Persson et al., 2014; Burton et al., 2017; McCalmont et al., 2021; Taheripour et al., 2019). For example, the Kalimantan region of Indonesia has experienced massive deforestation, turning it into palm plantations with no biodiversity. To make matters worse, it is not just any forest that has been destroyed, but peatland forests. Peatlands are special bogs filled with large amounts of under-degraded, black carbon-rich humus that store vast amounts of carbon that are not released into the atmosphere. The peatlands' powerful carbon storage capacity makes peatland rainforests twelve times more effective at carbon storage than typical tropical rainforests. The destruction of the Kalimantan mudflats would release as much carbon as the entire state of California or 72 large coal power plants emit in an entire year (Carlson et al., 2013; Findlay, 2020). Regardless of which side one takes, crude oil, carbon emission allowance, and agriculture commodity markets are closely interconnected due to their fundamental relationships, particularly after the commodity financialization trend that started in the 21st century. However, most existing studies have only focused on the relationship between two of the three markets mentioned above and have not fully examined the complex interdependencies of all three markets, particularly the role of the carbon market.

Therefore, the major aim of this paper is to investigate the interdependence effects among crude oil, carbon emission allowance and agriculture commodity prices, especially the potentially important status of carbon emissions in the system, which may help us to understand better the different roles of crude oil, carbon emission allowance and agriculture commodity markets in this tightly connected system, and help policymakers, agriculture producers and relevant investors to make better emission and agriculture development decisions, develop appropriate green and low-carbon production plans, as well as better portfolio allocation and hedging strategies.

Moreover, relevant studies commonly adopt the Granger causality test, variance decomposition, multivariate GARCH model, or quantile-on-quantile regression to identify the interactions between crude oil, carbon and agriculture commodity markets (Cai et al., 2022; Pata, 2021; Reboredo, 2014; Ren et al., 2022; Yu et al., 2015; Zheng et al., 2021a; Zheng et al., 2021b). However, the drawbacks of these methods are also very clear. For example, the Granger causality test and its various extensions, as well as quantile-on-quantile regression can only examine the dependence between two variables, which are unable to quantify the complicated spillover effects among multiple factors. Moreover, results based on variance decomposition, such as the information share method of Hasbrouck (1995), are heavily dependent on variable ordering and are also typically applied in a bivariate environment. Finally, although the multivariate GARCH model (MVGARCH) is more suitable to describe volatility spillover effects among multiple variables, it is not easy to explain a large number of spillover coefficients when there are more than three variables considered in this model, and it also cannot depict the time-varying volatility spillover effects. Therefore, recent studies turned to adopt a flexible but more powerful spillover measurement framework developed by a series of novel researches, such as the spillover index of Diebold and Yilmaz (2012) in the time domain (labeled as DY method hereafter), the spillover method of Baruník and Křehlík (2018) in the frequency domain (labeled as BK method hereafter), the quantile spillover approach of Ando et al. (2022), and the TVP-VAR based extensions of DY and BK methods by Antonakakis et al. (2020) and Ellington and Baruník (2020). By using these spillover measurement methods, many studies explore the spillover/co-movement/interaction/interdependence effects among crude oil, renewable energy, carbon emission allowance, commodity and financial markets (Adekoya and Oliyide, 2021; Bai et al., 2021; Bouri et al., 2021; Hung and Vo, 2021; Li et al., 2021; Liu and Gong, 2020; Reboredo and Ugolini, 2020; Saeed et al., 2021; So et al., 2021; Tiwari et al., 2020; Wei et al., 2019; Wei et al., 2022b; Wei et al., 2022c; Zhang and Broadstock, 2020; Zhang and Hamori, 2021; Wei et al., 2022; Wei et al., 2023; Wang et al., 2023).

By now, we do not find that existing studies have examined the price/return interdependence among crude oil, carbon emission allowance and agriculture commodity markets by using neither the connectedness framework of Diebold and Yilmaz (2012) in the time domain nor the connectedness measurement of Baruník and Křehlík (2018) in the frequency domain. In addition, existing studies also ignore the possibility of significantly different performances in information connectedness among crude oil, carbon emission allowance and agriculture commodity markets at different market conditions (i.e., various quantiles in their returns), especially the distinct roles of these markets at extreme market conditions. Additionally, it is well demonstrated that financial and commodity markets respond heterogeneously at different time frequencies/horizons to exogenous shocks (Baruník and Křehlík, 2018; Bouri et al., 2021; Li et al., 2021; Umar et al., 2021; Wei et al., 2022b; Wei et al., 2022c). This means that, when facing different market conditions, e.g., extreme bullish or bearish markets, and at different time frequencies/horizons, policymakers, energy and agriculture producers, as well as investors should make customized regulatory, production and investment decisions accordingly.

More importantly, the interdependence relationships among crude oil, carbon emission allowance and agriculture commodity markets during extreme market conditions may be quite different from those under normal market environments, which may provide valuable decision-support information for policymakers, energy and agriculture producers, as well as relevant investors. Additionally, it is well known that crude oil, carbon emission allowance and agriculture commodity markets respond heterogeneously at different time frequencies/horizons to exogenous shocks, such as economic uncertainty, geopolitical conflict, regulatory policy change, and public health emergency (Baruník and Křehlík, 2018; Umar et al., 2021; Wei et al., 2022b). Therefore, we think that quantifying clearly the extreme interdependence among crude oil, carbon emission allowance and agriculture commodity markets at various time frequencies/horizons is more significant for regulatory policy making and risk management during turmoil market conditions, and can help to develop appropriate energy and low-carbon agriculture production plans, promote green and low-carbon agricultural technologies, and establish green and low-carbon agricultural production systems.

Our empirical results suggest that first, the static mean (average) spillover effects measured by traditional DY and BK methods show that crude oil, carbon and agriculture commodity futures markets are moderately connected, and the major parts of the total spillover are concentrated in short-term frequency. In addition, soybean and corn futures are two major return information contributors. Second, the dynamic mean spillover evidence based on TVP-VAR-DY and TVP-VAR-BK models indicate that the total spillover among crude oil, carbon and agriculture commodity futures fluctuates violently from about 20% to 70%, and this overall spillover increase significantly during three turmoil periods: 2008–2009 global subprime mortgage crisis and global food crisis, European debt crisis during 2011 to 2012, and the outbreak of COVID-19 pandemic at the beginning of 2020. The time-varying net spillover findings also suggest that in general soybean and corn dominate other futures, especially during the above three fluctuating time periods. Furthermore, the major parts of TSI are centered at short- and medium-term frequencies and the long-term total spillover only has a tiny share in the overall TSI. Then, the frequency net spillover results demonstrate that different futures play various roles in information transmission with time and across different time frequencies. Third, through the quantile spillover analysis, we reveal that the total spillover effects among these futures markets at extreme market situations, i.e., at return quantiles of 0.05 and 0.95, are much larger than the one at median quantile of 0.5, implying that interdependences among crude oil, carbon and agriculture futures markets will increase sharply during great turmoil environment. Then, the net spillover indices demonstrate again that soybean and corn futures are the two prime return information contributors to other markets across different return quantiles. However, in terms of major information receivers, we find quite different outcomes in these futures markets. Fourthly, we find that carbon futures can actually contribute to improving the hedge effectiveness and performance of oil and agricultural portfolios, in terms of hedge effectiveness, cumulative returns, and Sharpe ratio. Finally and most importantly, the quantile-frequency spillover results show that the major net spillover senders and receivers swing across different quantiles and various time frequencies, suggesting that policymakers, relevant producers/consumers, and investors should understand the unique role of each future in the information transmission mechanism among these markets.

In summary, this paper makes several contributions to relevant studies. First, it is the first to investigate the dynamic normal connectedness effects among crude oil, carbon emission allowance, and agriculture commodity markets by using TVP-VAR-based extensions of DY and BK connectedness methods, referred to as TVP-VAR-DY and TVP-VAR-BK hereafter. These methods offer a better understanding of the time-varying features of the interdependence relationship among these markets at both time and frequency domains. Second, this paper employs the quantile connectedness measurement approach of Ando et al. (2022) to capture extreme interactions among the markets, allowing for quantification of extreme downside and upside connectedness effects and enabling better risk management strategies under market turmoil conditions. Third, using a new quantile-frequency connectedness proposed by Wei et al. (2022b), this paper investigates extreme connectedness effects across various time frequencies, providing deeper interaction information among the markets in terms of different market conditions and various time frequencies. Finally, this paper investigates the role of carbon futures in hedging risk and enhancing the performance of oil and agricultural portfolios, expanding the boundaries of existing research on carbon futures and offering new scenarios for practical applications.

The rest of this paper is organized as: Section 2 briefly reviews the extant literature. Section 3 introduces the major methodologies adopted; Section 4 describes the data; Section 5 illustrates the empirical results; Section 6 makes some robustness checks and finally Section 7 concludes.

2. Literature review

2.1. Research gap identification

There is a vast body of academic literature on the interdependencies among crude oil, carbon emission allowance, and agriculture commodity markets. However, the overwhelming majority of studies have only examined the linkages between two of the three markets mentioned.

Most existing studies on the topic of crude oil, carbon emission allowance, and agriculture commodity markets focus solely on the relationship between crude oil and agricultural commodity markets. The primary debate in these studies is whether the spillover effect is more robust in the crude oil or agricultural markets. Recent studies, however, have produced mixed results. Some scholars argue that the oil market has a stronger spillover effect on the agricultural market because fossil energy is a crucial input in agricultural production. For instance, Hasanov et al. (2016) find compelling evidence of causality from crude oil price volatility to all edible oil prices by using an asymmetric and unrestricted VAR-GARCH-in-mean-BEKK model. Conversely, several studies suggest that agricultural commodity markets have clear spillover effects on crude oil markets. Kang et al. (2019), for example, examine time-frequency connectedness and network among crude oil and agricultural commodities and discover that vegetable oils are the most significant volatility spillover transmitter to other agricultural commodities, such as dairy products, grains, meat, and sugar, as well as crude oil. Additionally, they find bidirectional and asymmetric linkages between crude oil and agricultural commodity markets across all different frequency bands. Dahl et al. (2020) investigate the volatility spillover effects between crude oil and ten major agricultural commodities using the connectedness measurements of Diebold and Yilmaz (2012). Their findings reveal that information transmission between crude oil and agricultural products is minimal in the pre-2006 sub-sample; however, crude oil becomes a net recipient of the information in the post-2006 sub-sample. Moreover, information asymmetry and bidirectional flows between crude oil and agricultural commodities strengthen during periods of financial and economic turmoil.

For the sake of clarity, we summarize the relevant research in Table 1. The summary shows that the results are mixed as to whether the crude oil market or the agricultural commodity market has a larger spillover effect on the other. Moreover, these studies mainly focus on volatility or risk spillovers between crude oil and agricultural commodity markets. Little is known about the return

Table 1
Summary of literature review on the spillover effects between crude oil and agriculture markets.

Literature	Data and data sample	Data frequency	Method	Key findings	Spillover direction
Chen et al. (2010)	NYMEX WTI crude oil future, CBOT soybeans, corn and wheat futures (1983–2010)	Weekly	Autoregressive distributed lag (ARDL) model	The change in each grain price is significantly influenced by the changes in the crude oil price and other grain prices	Oil price → Agriculture price
Du et al. (2011)	NYMEX WTI crude oil future, CBOT corn and wheat futures (1998–2009)	Weekly	Bivariate stochastic volatility (SV) model	There is significant volatility spillover from corn and wheat markets to crude oil market after the fall of 2006.	Agriculture volatility → Oil volatility
Serra (2011)	WTI oil, Brazilian ethanol and sugar (2000–2009)	Weekly	Semi-parametric GARCH model	Crude oil and sugar prices lead ethanol prices. Crude oil and sugar market shocks lead to increased ethanol price volatility.	Oil and Agriculture volatility → Ethanol volatility
Nazlioglu and Soytas (2011)	Average oil price of Brent, Dubai, and WTI; Turkish wheat, maize, cotton, soybeans, and sunflower (1994–2010)	Monthly	Toda and Yamamoto causality tests; generalized impulse response analysis	Turkish agricultural prices do not significantly react to oil price; The changes in oil prices and appreciation/depreciation of the Turkish lira are not transmitted to agricultural commodity prices in Turkey.	Oil price ×→ Agriculture price
Gardebroek and Hernandez (2013)	WTI crude oil FOB spot prices, CBOT denatured fuel ethanol spot prices, and No. 2 yellow corn FOB Gulf prices (1997–2011)	Weekly	T-BEKK and DCC MVGARCH model.	There are significant volatility spillovers from corn to ethanol prices, but not the converse. There are no major cross-volatility effects from oil to corn markets.	Corn volatility → Ethanol volatility; Oil volatility ×→ Corn volatility
Nazlioglu et al. (2013)	Spot prices of world oil, corn, soybeans, wheat, and sugar (1986–2011)	Weekly	Causality in variance test	There is a volatility spillover from the wheat to the oil returns before 2006. There is also evidence of a bidirectional volatility spillover between oil-soybeans and oil-wheat markets after 2006.	Wheat volatility → Oil volatility before 2006; Wheat and Soybeans volatility ↔ Oil volatility after 2006
Hasanov et al. (2016)	Brent spot crude oil, rapeseed oil, soybean oil, and sunflower oil (2008–2015)	Daily	An asymmetric and unrestricted VAR-GARCH-in-mean-BEKK model	There is strong evidence of causality from crude oil price volatility to all edible oil prices.	Oil volatility → Agriculture volatility
Mensi et al. (2017)	The crude oil volatility index (OVX), the wheat volatility index (WIV), and the corn volatility index (CIV) (2012–2016)	Daily	Wavelet and copula approaches	The results support evidence of time-varying asymmetric tail dependence between the pair of cereals as well as between oil and the two cereals at different time horizons.	Oil-agriculture dependence is detected, but no spillover direction for the copula method adopted.
Ji et al. (2018)	NYMEX WTI crude oil, natural gas futures, IGC's grains and oilseeds index (IGCI) and four commodities: maize, rice, soybean and wheat (2000–2017)	Daily	Copula, VaRs and CoVaRs	The significant risk spillovers from energy to agricultural commodities are verified by measuring the conditional value-at-risk (CoVaR) and delta CoVaR.	Oil risk → Agriculture risk
Shahzad et al. (2018)	WTI crude oil, IGC Commodities: wheat, maize, soybeans, and rice (2000–2017)	Daily	Copula, VaRs and CoVaRs	Varying levels of bi-directional spillover effects are depicted, running from crude oil to commodity markets or vice versa.	Oil risk ↔ Agriculture risk
Dahl et al. (2020)	Crude oil, wheat, sugar, soybean, soybean oil, cotton, corn, coffee, cocoa, canola, and soybeans meal (1986–2016)	Daily	Spillover index method of DY	There is minuscule information transmission among crude oil and agricultural commodities over the pre-2006 subsample, however, crude oil becomes the net receiver of information over the post-2006 subsample.	Agriculture return and volatility → Oil return and volatility after 2006

(continued on next page)

Table 1 (*continued*).

Yip et al. (2020)	CBOE commodity implied volatility indices of crude oil (OVX), corn (CIV), soybean (SIV), and wheat (WIV) (2012–2017)	Daily	Granger causality test, and spillover index method of DY	OVX does not Granger cause with CIV, SIV, and WIV. CIV and WIV act as the net transmitters, whereas OVX and SIV are the net receivers most of the time during the sample period.	Agriculture volatility → Oil volatility
Kumar et al. (2021)	WTI crude oil, corn, soybean oil, oats, soybeans, and wheat futures (2002–2017)	Daily	Copula, CoVaR and ΔCoVaR	Results indicate important risk spillover from oil to agricultural markets, especially around the financial crisis.	Oil risk → Agriculture risk
Dai et al. (2022)	Chinese commodity futures indices: Nanhua industrial index, agricultural index, metal index, and energy and chemical index. Chinese stock market index, WTI spot price, Chinese economic policy uncertainty index (EPU) and the Chinese investor sentiment index. (2004–2021)	Monthly	Maximum overlapping discrete wave transform (MODWT), spillover index method of DY, and cross-quantilogram dependence.	Table 3 in this paper shows that agricultural index is net spillover transmitter, while crude oil is receptor at medium and long terms.	In short term: Oil return → Agriculture return In medium and long terms: Agriculture return → Oil return
Naeem et al. (2022)	Oil shocks, grains and oilseeds, livestock, and softs prices (2006–2020)	Daily	Spillover index methods of DY and BK	It finds time-varying bi-directional spillovers in the crude oil and agricultural markets in both the time and frequency domains. In addition, spillovers within agricultural commodities are significantly larger than spillovers across product categories.	Oil return ↔ Agriculture return
Tiwari et al. (2022a)	Wheat, corn, sugar, soyabean, coffee, cotton, gasoline, crude oil, natural gas, and ethanol futures (2012–2021)	Daily	Quantile connectedness framework developed by Ando et al. (2022).	There are significant volatility spillovers from agricultural markets to energy markets during extreme markets conditions and the dominance of agricultural markets over energy markets.	Agriculture volatility → Oil volatility

Notes: DY and BK indicates the spillover index methods proposed by Diebold and Yilmaz (2012), Baruník and Křehlík (2018), respectively. The symbol → denotes the spillover direction, ×→ indicates no such spillover direction, and ↔ means a bidirectional spillover effects.

linkages between these two markets, especially in extreme market conditions and across different time frequencies. Therefore, there is a strong need to fill this research gap by using updated data samples and more powerful econometric models.

Regarding the interdependence between carbon emission allowances and agricultural commodity markets, research to date has mainly focused on demonstrating that the agricultural industry can reduce carbon emissions and that there is a long-term relationship between these two factors. For instance, González-Ramírez et al. (2012) describes the basic characteristics of carbon offset markets, as well as the potential supply of offsets from agricultural sources and associated cost considerations. Cai et al. (2022) examine the impact of renewable energy consumption, non-renewable energy consumption, agriculture, urbanization, and economic growth on carbon emissions in selected South Asian economies from 1990 to 2018, using a fully modified ordinary least square method and variance decomposition analysis. Their empirical results show that renewable energy consumption and the agriculture industry reduce carbon emissions, while non-renewable energy consumption and urbanization increase environmental degradation. Burton et al. (2017) prove that the growing demand for palm oil is driving its expansion into tropical Africa, which could lead to significant carbon emissions if tropical forests are converted to monoculture palm trees. They find that using an agricultural suitability model, prudent national land use planning can go a long way toward avoiding high carbon emissions while meeting palm oil production targets. Taheripour et al. (2019) also show that global demand for palm oil has grown rapidly over the past decades. Most of the production growth has occurred in the carbon and biodiversity-rich forest lands of Malaysia and Indonesia, resulting in record terrestrial carbon emissions and biodiversity loss. Pata (2021) adopt Fourier cointegration and causality tests to analyze the impact of renewable energy generation, globalization, and agricultural activities on the ecological footprint and carbon emissions in BRICS countries during the period 1971–2016. They find the existence of a long-run relationship between the variables considered for Brazil and China. Long-run elasticities show that globalization increases pollution indicators, while renewable energy generation significantly reduces environmental pressure in China. The causality results show a bidirectional causality between agriculture and environmental degradation; and a unidirectional relationship between globalization and the ecological footprint and CO_2 emissions.

Many recent studies also concentrate on the nexus between crude oil and carbon markets by employing various statistical and econometric methods (Reboredo, 2014; Yu et al., 2015; Zheng et al., 2021a; Zheng et al., 2021b; Anh Tu and Rasoulinezhad, 2022; Ren et al., 2022; Tran, 2022). Almost all of these researches have demonstrated a strong linkage between these two markets. For instance, Ren et al. (2022) utilize the quantile Granger causality test and the quantile-on-quantile regression methods to prove the asymmetric interdependence of carbon futures and crude oil futures prices at different time scales. Reboredo (2014) propose a multivariate conditional autoregressive range model to examine volatility dynamics and volatility spillovers between crude oil and

EUA carbon markets. However, they find no significant spillover effects between these two markets. Yu et al. (2015) analyze the causal relationship between carbon and crude oil markets using bivariate empirical model decomposition (BEMD) and combined linear and nonlinear Granger tests using data samples from EUA carbon futures and Brent futures prices. Their study finds that at the raw data level (without multi-scale decomposition), there is no Granger causality between the carbon and crude oil markets. At short time scales, the two markets may be uncorrelated; while for medium time scales (more than one week and less than one year), there are strong bidirectional linear and nonlinear spillover effects between them due to certain additional factors with medium-term effects, such as major policy changes. For long time scales, a clear linear relationship emerges between the long-term trends of the two markets. Zheng et al. (2021a) examines the effect of oil shocks on the returns of EUA carbon emission allowances (EUAs) under different market conditions by using quantile regressions. Its empirical results show that oil supply and demand shocks have a positive impact on the return of EUAs, but oil risk shocks have a negative impact. Meanwhile, oil shocks tend to be stronger in bear and normal market conditions. Moreover, the asymmetry of oil demand and risk shocks is more pronounced in bearish market conditions.

Finally, only a few papers investigate the linkages between the three markets: crude oil, carbon emission allowance, and agriculture commodity markets. The main conclusion of these studies is that the expansion of the biofuels market in recent years has greatly increased the interdependence between crude oil, carbon emission allowance, and agricultural commodity markets. However, no quantitative measures of such interdependencies are provided, nor are the possible financial implications of these interdependencies discussed. By way of example, Dodder et al. (2015) argue that the rapid growth of the biofuels market has both created and strengthened the link between agriculture and energy markets. The evolution of the biofuels market over the next 10–20 years and the impact on energy, agriculture, and the environment is uncertain. The biofuels market is more influenced by crude oil prices than natural gas prices. In addition, scenarios without cellulosic feedstocks reduce total ethanol production and raise ethanol and corn prices. In terms of environmental impact, higher ethanol consumption due to higher crude oil prices will reduce CO_2 emissions. Cheng et al. (2018) investigates some determinants of carbon intensity, including non-fossil energy sources, economic growth, energy consumption, and oil prices, for 28 countries in the European Union (EU) using a panel quantile regression approach. The empirical results show that the effects of these determinants on carbon intensity are heterogeneous and asymmetric at different orders of magnitude. Specifically, non-fossil energy sources can significantly reduce carbon intensity but show a U-shaped relationship. In addition, they find an inverse U-shaped relationship between crude oil prices and carbon intensity.

To date, the existing literature has not investigated the price/return interdependence among crude oil, carbon emission allowance, and agriculture commodity markets using either the connectedness measurements in the time domain or in the frequency domain. Given the multifaceted and complex interlinkages between these markets, as identified in our literature review, it is vital to explore these relationships more fully. Therefore, in our research, we delve into the spillover effects among crude oil, carbon emission allowance, and agriculture commodity markets in both time and frequency domains.

Furthermore, while previous research has indicated that purchasing carbon futures contracts may mitigate the impacts of price fluctuations in the carbon markets for companies or portfolios exposed to carbon emissions or carbon pricing risk, there is a noticeable gap in the literature demonstrating the potential crucial role of the carbon market in hedging risk and improving the performance of oil-agriculture portfolios using real-world data. Accordingly, our research explores how carbon futures may serve as a mechanism to hedge risk and enhance the performance of oil and agricultural portfolios.

3. Methodology

3.1. The new quantile-frequency connectedness method

A recent research of Wei et al. (2022a) proposes a new quantile-frequency spillover measurement, combining the quantile spillover method of Ando et al. (2022) and the frequency spillover by Baruník and Křehlík (2018). This new approach can calculate the spillover effects among assets across various quantiles (i.e., market conditions) and time frequencies (i.e., time horizons), which provides researchers a more powerful tool to investigate the normal and extreme spillover among assets in frequency domain. This method is firstly extended from the quantile spillover rising from a quantile VAR (QVAR) approach at τ quantile. A QVAR model is presented as Eq. (1):

$$Y_t = \beta_{(\tau)} + \sum_{lag=1}^{p} B_{lag(\tau)} Y_{t-lag} + \epsilon_{t(\tau)}, \epsilon_{t(\tau)} \sim N(0, \Sigma_{(\tau)}), \tag{1}$$

where Y_t is a n dimension interested variable, e.g., the returns of n assets. τ is the set conditional quantile that are examined in this QVAR model with value from 0 to 1, and p is the lags of this QVAR determined by some information criteria. $\beta_{(\tau)}$ is the intercept item, $B_{lag(\tau)}$ is the autoregressive coefficient matrix, and $\epsilon_{t(\tau)}$ is the residual item with the variance–covariance matrix $\Sigma_{(\tau)}$. Following the approach of standard spillover measurement process, the forecast error variance decomposition (FEVD) at quantile τ is presented by a moving average construction of QVAR model as Eq. (2):

$$Q_\tau(Y_t|\Psi_{t-1}) = \sum_{i=0}^{\infty} C_{i(\tau)} \epsilon_{t-i(\tau)}, \epsilon_{t(\tau)} \sim N(0, \Sigma_{(\tau)}), \tag{2}$$

where Ψ_{t-1} denotes information set known by the time of t-1. $C_{i(\tau)} = \sum_{lag=1}^{p} B_{lag(\tau)} C_{i-lag(\tau)}$ and $C_{i(\tau)} = 0$ when $i < 0$. Next, through the generalized forecast error variance decomposition (GFEVD), we can identify the contribution of each variable to the other ones. Then the H-step-ahead GFEVD is measured as Eq. (3):

$$GFEVD(y_j, \epsilon_{k(\tau)}, H) = \frac{\Sigma_{kk}^{-1} \sum_{h=0}^{H-1} ((C_{h(\tau)} \Sigma)_{jk})^2}{\sum_{h=0}^{H-1} (C_{h(\tau)} \Sigma C'_{h(\tau)})_{jj}}, \tag{3}$$

where $GFEVD(y_j, \epsilon_{k(\tau)}, H)$ measures the contribution of the kth innovation $\epsilon_{k(\alpha)}$ at quantile τ, to the H-step-ahead GFEVD of the jth variable. Moreover, we label Eq. (3) as $\Theta_{jk,(\tau)}(H)$, and standardize it as follows Eq. (4):

$$\tilde{\Theta}_{jk,(\tau)}(H) = \frac{\Theta_{jk,(\tau)}(H)}{\sum_{j,k=1}^{n} \Theta_{jk,(\tau)}(H)}. \tag{4}$$

In Eq. (4), we define $\sum_{k=-1}^{n} \tilde{\Theta}_{jk,(\tau)}(H) = 1$ and $\sum_{j=1,k=1}^{n} \tilde{\Theta}_{jk,(\tau)}(H) = n$. After the calculation of Eq. (4), five categories of spillover indices are defined as Eqs. (5)–(9):

$$TSI_{(\tau)}(H) = \frac{\sum_{j=1,k=1,j\neq k}^{n} \tilde{\Theta}_{jk,(\tau)}(H)}{\sum_{j=1,k=1}^{n} \tilde{\Theta}_{jk,(\tau)}(H)} \times 100, \tag{5}$$

$$TO_{j\to *,(\tau)}(H) = \frac{\sum_{k=1,k\neq j}^{n} \tilde{\Theta}_{kj,(\tau)}(H)}{\sum_{j=1,k=1}^{n} \tilde{\Theta}_{jk,(\tau)}(H)} \times 100, \tag{6}$$

$$FROM_{j\leftarrow *,(\tau)}(H) = \frac{\sum_{k=1,j\neq k}^{n} \tilde{\Theta}_{jk,(\tau)}(H)}{\sum_{j=1,k=1}^{n} \tilde{\Theta}_{jk,(\tau)}(H)} \times 100, \tag{7}$$

$$NET_{j,(\tau)}(H) = TO_{j\to *,(\tau)}(H) - FROM_{j\leftarrow *,(\tau)}(H) \tag{8}$$

$$NPDS_{jk,(\tau)}(H) = \left(\frac{\tilde{\Theta}_{kj,(\tau)}(H)}{\sum_{j=1,k=1}^{n} \tilde{\Theta}_{jk,(\tau)}(H)} - \frac{\tilde{\Theta}_{jk,(\tau)}(H)}{\sum_{j=1,k=1}^{n} \tilde{\Theta}_{jk,(\tau)}(H)}\right) \times 100. \tag{9}$$

The Eq. (5) $TSI_{(\tau)}(H)$ depicts the total spillover index at quantile τ, indicating the overall spillover effects among all the variables. Then Eqs. (6) and (7), i.e., $TO_{j\to *,(\tau)}(H)$ and $FROM_{j\leftarrow *,(\alpha)}(H)$, denote the spillover effects sent and received by variable j to (from) all the others at quantile τ. In addition, Eq. (8) $NET_{j,(\tau)}(H)$ measures the difference of TO and FROM effects in variable j. Lastly, $NPDS_{jk,(\alpha)}(H)$ defined in Eq. (9) calculate the net pairwise directional spillover between variables j and k.

These spillover indices introduced in Ando et al. (2022) can be labeled as quantile spillover measures, which enable us to investigate both the normal and extreme spillover effects, i.e., interactions at median and extreme tails, among a variety of assets. However, this quantile spillover approach of Ando et al. (2022) can only tell us what happens in the dependences among variables spanning various quantiles in time domain, which means that it cannot identify these quantile spillover effects across different time frequencies. However, the benchmark research of Baruník and Křehlík (2018) and many other relative papers have demonstrated that the interdependence effects among assets response idiosyncratically to shocks at different time frequencies/horizons. Thus, we employ a new quantile-frequency spillover measurement recently proposed by Wei et al. (2022a) to further inspect the spillover among crude oil, carbon and agriculture commodity futures at both normal and extreme market conditions across different time horizons. This new quantile-frequency spillover measurement is built as follows:

First, at a specific quantile of τ, the frequency spillover response at frequency ω is defined as Eq. (10):

$$C_{(\tau)}(e^{-i\omega}) = \sum_{h=0}^{H-1} e^{-i\omega h} C_{h(\tau)}, i = \sqrt{-1} \tag{10}$$

Then, the generalized causality spectrum across frequency band $\omega \in (-\pi, \pi)$ is defined as Eq. (11):

$$(f_{(\tau)}(\omega))_{jk} = \frac{\sum_{kk}^{-1} |(C_{(\tau)}(e^{-i\omega}) \sum)_{jk}|^2}{(C_{(\tau)}(e^{-i\omega}) \sum C'_{(\tau)}(e^{+i\omega}))_{jj}}. \tag{11}$$

where $(f_{(\tau)}(\omega))_{jk}$ is the part of the response in variable j at the frequency ω due to the shock of variable k at both the τ quantiles of j and k. Therefore, the new definition of GFEVD can be calculated through a weighted averaging process as Eq. (12):

$$\Theta_{jk,(\tau)}(d) = \frac{1}{2\pi} \int_{d} W_{j,(\tau)}(\omega) (f_{(\tau)}(\omega))_{jk} d\omega, \tag{12}$$

where d is a predetermined frequency band between s and l and $s, l \in (-\pi, \pi)$. Moreover, the weighting function is calculated as Eq. (13):

$$W_{j,(\tau)}(\omega) = \frac{C_{\tau}(e^{-i\omega}) \sum C'_{\tau}(e^{+i\omega})_{jj}}{\frac{1}{2\pi} \int_{-\pi}^{\pi} (C_{(\tau)}(e^{-ir}) \sum C'_{t}(e^{+ir}))_{jj} dr} \tag{13}$$

Then the contribution of kth innovation at quantile τ, i.e., $\epsilon_{k(\tau)}$, to the H-step-ahead FEVD of variable j is measured as Eq. (14):

$$\tilde{\Theta}_{jk,(\tau)}(d) = \frac{\Theta_{jk,(\tau)}(d)}{\sum_{j,k=1}^{n} \Theta_{jk,(\tau)}(\infty)}, \tag{14}$$

where,

$$\Theta_{jk,(\tau)}(\infty) = \frac{1}{2\pi}\int_{-\pi}^{\pi} W_{j,(\tau)}(\omega)(f_{(\tau)}(\omega))_{jk} d\omega. \tag{15}$$

Finally, we can define five quantile-frequency spillover indices (at quantile τ, and through a specific frequency band *d)* analogous to the quantile spillover ones calculated in Eq. (5) to Eq. (9) as follows Eqs. (16)–(20):

$$TSI_{(\tau)}(d) = (\frac{\sum_{j=1,k=1}^{n}\tilde{\Theta}_{jk,(\tau)}(d)}{\sum_{j=1,k=1}^{n}\tilde{\Theta}_{jk,(\tau)}(\infty)} - \frac{Tr\{\tilde{\Theta}_{jk,(\tau)}(d)\}}{\sum_{j=1,k=1}^{n}\tilde{\Theta}_{jk,(\tau)}(\infty)}) \times 100, \tag{16}$$

$$To_{j\to *,(\tau)}(d) = ((\sum_{k=1,j\neq k}^{n}\tilde{\Theta}_{kj,(\tau)}(d))\frac{\sum_{j=1,k=1}^{n}\tilde{\Theta}_{jk,(\tau)}(d)}{\sum_{j=1,k=1}^{n}\tilde{\Theta}_{jk,(\tau)}(\infty)}) \times 100, \tag{17}$$

$$FROM_{j\leftarrow *,(\tau)}(d) = ((\sum_{k=1,j\neq k}^{n}\tilde{\Theta}_{jk,(\tau)}(d))\frac{\sum_{j=1,k=1}^{n}\tilde{\Theta}_{jk,(\tau)}(d)}{\sum_{j=1,k=1}^{n}\tilde{\Theta}_{jk,(\tau)}(\infty)}) \times 100, \tag{18}$$

$$NET_{(\tau)}(d) = TO_{j\to *,(\tau)}(d) - FROM_{j\leftarrow *,(\tau)}(d), \tag{19}$$

$$NPDS_{jk,(\tau)} = ((\tilde{\Theta}_{jk,(\tau)}(d) - \tilde{\Theta}_{kj,(\tau)}(d))\frac{\sum_{j=1,k=1}^{n}\tilde{\Theta}_{jk,(\tau)}(d)}{\sum_{j=1,k=1}^{n}\tilde{\Theta}_{jk,(\tau)}(\infty)}) \times 100. \tag{20}$$

where $Tr(\cdot)$ in Eq. (16) is the trace operator, calculating the sum of the elements on the main diagonal of an $n \times n$ matrix.

3.2. Portfolio allocation and evaluation methods

In this paper, we adopt two traditional portfolio allocation methods, namely the minimum variance portfolio (MVP) of Miller (1960) and the minimum correlation portfolio (MCP) of Christoffersen et al. (2014) to construct the crude oil and agriculture commodity portfolios. Furthermore, as noted in Broadstock et al. (2022), connectedness information among assets are valuable for portfolio optimization, and those portfolios based on minimum connectedness (MCoP) are observed to be superior to some traditional ones, such as MVP and MCP portfolios. Following the method of Broadstock et al. (2022), a minimum connectedness portfolio with n assets, labeled as MCoP1, is designed as Eq. (21):

$$MCoP1 : W_{PCI_t} = \frac{PCI_t^{-1}I}{IPCI_t^{-1}I} \tag{21}$$

where w_{PCI_t} is the $n \times 1$ weights vector, I represents a $n \times 1$ vector of ones. PCI_t denotes the PCI matrix at time *t*, and PCI is the pairwise connectedness index between two assets defined in Broadstock et al. (2022). Furthermore, a recent work of Chen et al. (2010) further suggest that the net pairwise directional connectedness (NPDC) is another effective measures of interdependences between two assets in a multi-asset system, and then offer another minimum connectedness portfolio, labeled as MCoP2, as Eq. (22):

$$MCoP2 : W_{NPDC_t} = \frac{NPDC_t^{-1}I}{INPDC_t^{-1}I} \tag{22}$$

where $NPDC_t$ is the matrix of the net pairwise directional connectedness at time *t*. Moreover, we choose three commonly used measurements to evaluate the performances of various portfolio allocations. The first one is cumulative return, which is calculated by summing a portfolio's returns over a holding period. The other two is the hedge effectiveness (HE) of the Ederington (1979) and the Sharpe ratio proposed by Sharpe (1966), which are defined as Eqs. (23) and (24):

$$HE = 1 - \frac{var(R_{portfolio})}{var(R_i)}, \tag{23}$$

and

$$SR = \frac{\bar{R}_{portfolio}}{\sqrt{var(R_{portfolio})}}, \tag{24}$$

where $var(R_{portfolio})$ is the variance of different portfolio returns, and $var(R_i)$ denotes the return variance of a specific un-hedged asset. $\bar{R}_{portfolio}$ is the mean return of a portfolio. A higher HE indicates a better hedging effect on a portfolio and vice versa. Similar to HE, a higher Sharpe ratio indicates better portfolio performance.

4. Data

4.1. Futures markets variables' selection

This paper aims to quantify the connectedness effects among crude oil, carbon emission allowance and agriculture commodity futures. Thus, we select weekly prices of nine leading futures worldwide traded at different futures exchanges as: (1). Brent oil

Table 2
Descriptive statistic of weekly returns for crude oil, carbon and agriculture futures.

	Brent oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	Palm oil
Obs.	746	746	746	746	746	746	746	746	746
Mean	2.21E−05	9.40E−03	6.09E−04	7.40E−04	3.71E−05	7.68E−04	8.48E−04	9.73E−04	2.67E−04
Std. dev.	0.049	0.283	0.034	0.042	0.043	0.044	0.039	0.041	0.035
Skewness	−0.677	20.274	−0.901	−0.461	0.024	0.049	−0.166	0.178	−0.462
Kurtosis	7.342	521.767	6.269	6.272	4.403	4.03	5.738	3.982	6.357
Jarque–Bera	643.007***	8416228.603***	432.988***	359.175***	61.227***	33.288***	236.510***	33.891***	376.834***
Q (4)	3.008	2.144	3.744	11.046**	6.343	7.718	3.184	5.704	10.401**
Q (26)	49.131***	60.010***	39.927**	34.519	27.785	23.832	40.875**	29.814	28.335
Q (52)	66.512*	62.352	83.095***	76.391**	80.655***	51.194	92.608***	60.982	61.829
ADF	−26.520***	−25.974***	−26.706***	−28.976***	−27.720***	−27.026***	−27.225***	−26.001***	−28.183***
P-P	−26.502***	−25.982***	−26.695***	−28.966***	−27.702***	−27.016***	−27.217***	−25.995***	−28.165***

Notes: The Jarque–Bera statistic tests for the null hypothesis of normality in the distribution. $Q(n)$ is the Ljung–Box Q statistics with lag length of n. ADF and P-P are statistics of Augmented Dickey–Fuller and Phillips–Perron unit root test.

*Indicate rejection at the 10% significant level.

**Indicate rejection at the 5% significant level.

***Indicate rejection at the 1% significant level.

futures traded in ICE (labeled as Brent oil hereafter). For the crude oil aspect, brent crude oil is commonly used as a benchmark for the crude oil market due to its easy transportability, wide trading, and reliable price movements that are viewed as a good indicator of global oil market conditions. Many previous studies used Brent crude oil prices as a measure of oil prices in their analysis (Abbas et al., 2018, Zhang and Liu, 2019, Halkos and Tzeremes, 2020, Adeniran et al., 2020); (2). Carbon futures of the European Union Allowances (EUA) in the European Climate Exchange (EUA carbon); (3). Soybean futures in Chicago Board of Trade (Soybean); (4). Corn futures in Chicago Board of Trade (Corn); (5). Chicago soft red winter wheat futures in Chicago Board of Trade (Wheat); (6). Sugar #11 futures in ICE (Sugar); (7). Cotton #2 futures in ICE (Cotton); (8). Coffee C futures in ICE (Coffee) and (9). RBD palm olein futures in Dalian Commodity Exchange (DCE Palm oil).

This study applies the weekly frequency data. Weekly data is more suitable for capturing the time-varying interdependences among asset prices than daily and monthly data (Kang et al., 2017; Wei et al., 2022a; Gharbi et al., 2023; Focacci, 2023). According to Kang et al. (2017), on the one hand, daily prices often face bias in bid–ask spreads and the problem of asynchronous trading. On the other hand, monthly data has defects of time summation and compensation effects that will obscure the true interaction relationships among assets. The data sample in this paper spans from October 29, 2007 to February 18, 2022 with 747 weekly price observations. The reason for choosing October 29, 2007 as the starting date of the sample is that Dalian Commodity Exchange launched its RBD palm olein futures on October 29, 2007 and this contract is listed as the second largest agriculture commodity futures.[1] All the weekly futures prices are turned into logarithm returns for further analysis.

Table 2 reports the descriptive statistics of these return series and it shows several commonly recognized stylized facts for speculative asset returns. For example, the unconditional means of these futures returns are very small compared with their standard deviations. Except for the return of EUA carbon, most returns have small skewness, and all the returns show quite a high degree of kurtosis. The Jarque–Bera tests indicate that all the return series are not normally distributed, but the Ljung–Box Q statistics demonstrate no united evidence of autocorrelations in these returns. Finally and most importantly, the Augmented Dickey–Fuller and Phillips–Perron unit root tests prove that all the return series are stationary, and can be modeled directly without further transmission.

5. Empirical results

5.1. Static mean spillover evidence by simple DY and BK models

In this subsection, we first use the simple spillover methods of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) to depict the static mean (average) interactions among crude oil, carbon and agriculture commodity futures in time and frequency domain, respectively. Table 3 shows the results of DY method, and Tables 4 to 6 present the results of BK approach.

Firstly, Table 3 indicates that the total spillover (TSI) among crude oil, carbon and agriculture commodity futures is measured as 36.53%, indicating a moderate connection among them in the time domain. Moreover, the pairwise directional spillover effects among them are generally low with measurements generally smaller than 10%. Within them, we find that the pairwise directional spillover indices between EUA carbon and other futures are all very tiny with values no more than 1%, indicating its loose dependence with other futures markets. However, we also see some relatively large pairwise directional spillover indices between soybean, corn and wheat futures. For instance, the pairwise spillover between corn and wheat are as high as 20.69% and 18.13%, respectively, which may be determined by the inherent substitution effects among them. Finally, the net spillover indices shown at the bottom row of Table 3 imply that soybean and corn futures are the two major return spillover information senders, and coffee and palm oil seem to be the two main spillover information receivers.

[1] According to the 'Global futures and options trading reaches record level in 2020' released by Futures Industry Association https://www.fia.org/resources/fia-releases-data-futures-and-options-volume-trends-first-half-2021.

Table 3
Static mean spillover measurements among crude oil, carbon and agriculture futures markets by DY method in the time domain.

	Brent oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	Palm oil	FROM
Brent oil	68.28	0.3	6.25	4.75	1.36	5.04	4.78	2.4	6.84	3.52
EUA carbon	0.39	96.22	0.13	1.15	0.18	0.13	1.42	0.06	0.32	0.42
Soybean	4.04	0.13	46.28	18.48	10.31	3.93	3.97	3.44	9.43	5.97
Corn	2.9	0.37	18.15	46.23	18.13	3.54	4.54	2.91	3.21	5.97
Wheat	1.1	0.22	11.65	20.69	52.56	2.67	4.02	3.09	4.01	5.27
Sugar	4.94	0.73	5.6	5.05	3.39	65.58	5.04	5.43	4.26	3.82
Cotton	4.67	0.95	6.17	6.72	4.9	4.81	64.36	3.05	4.38	3.96
Coffee	2.5	0.08	5.36	4.7	4.24	5.86	3.39	71.41	2.44	3.18
Palm oil	6.78	0.25	12.96	4.6	4.61	3.85	4.11	2.53	60.31	4.41
TO	3.04	0.34	7.36	7.35	5.24	3.31	3.48	2.55	3.88	**TSI**
NET	−0.49	−0.08	1.39	1.37	−0.03	−0.51	−0.49	−0.63	−0.53	**36.53**

Notes: This table reports the directional spillover among crude oil, carbon and agriculture futures markets by the method of Baruník and Křehlík (2018) in time domain. The rightmost column (FROM) of this table indicates the directional spillover from all others to a specific futures market. The penultimate row (TO) of this table indicates the directional spillover to all others from a specific futures market. The bottom row (NET) shows the net spillover, i.e., the difference between TO and FROM spillover of a specific futures market. The number in the bottom right corner of this table (indicated in bold face) is the TOTAL spillover index (TSI) of all the futures markets.

Table 4
Static mean spillover measurements among crude oil, carbon and agriculture futures markets by BK method at short-term frequency (1 to 4 weeks).

	Brent oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	Palm oil	FROM
Brent oil	50.66	0.17	4.16	2.99	1	3.56	3.51	1.88	5.21	2.5
EUA carbon	0.25	69.93	0.07	0.66	0.17	0.07	1.18	0.06	0.3	0.31
Soybean	2.93	0.08	34.43	12.96	7.4	3.01	2.99	2.37	7.27	4.33
Corn	2.28	0.28	14.04	35.95	13.54	2.67	3.62	2.14	2.54	4.57
Wheat	0.76	0.18	8.74	15.49	39.89	1.8	3.17	2.16	3.26	3.95
Sugar	4.14	0.55	4.44	3.87	2.89	49.32	4.2	4.32	3.49	3.1
Cotton	3.14	0.79	3.82	4.32	3.67	3.71	48.25	2.28	3.13	2.76
Coffee	1.85	0.05	3.59	3.09	2.85	4.32	2.46	52.12	1.73	2.21
Palm oil	4.23	0.23	8.45	2.79	3.17	2.72	2.92	1.49	46.19	2.89
TO	2.18	0.26	5.26	5.13	3.85	2.43	2.67	1.86	2.99	**TSI**
NET	−0.32	−0.05	0.92	0.56	−0.1	−0.67	−0.09	−0.36	0.1	**26.62**

Notes: This table reports the directional spillover among crude oil, carbon and agriculture futures markets by the method of Baruník and Křehlík (2018) in frequency domain. The rightmost column (FROM) of this table indicates the directional spillover from all others to a specific futures market. The penultimate row (TO) of this table indicates the directional spillover to all others from a specific futures market. The bottom row (NET) shows the net spillover, i.e., the difference between TO and FROM spillover of a specific futures market. The number in the bottom right corner of this table (indicated in bold face) is the TOTAL spillover index (TSI) of all the futures markets.

Then Tables 4 to 6 show the frequency spillover among crude oil, carbon and agriculture commodity futures across three different time horizons, i.e., roughly 1 to 4 weeks (one week to one month), 4 to 26 weeks (one month to half a year), and longer than 26 weeks. Firstly, the total spillover indices at three time frequencies are 26.62%, 8.71% and 1.20%, respectively. This means that the major part of TSI is centered at short time frequency (roughly 1 to 4 weeks), and only very tiny part of it is observed at long time frequency (longer than 26 weeks). Secondly, regarding to the pairwise directional spillover indices, in Tables 4 to 6 we also find that the relatively large ones are estimated between soybean, corn and wheat futures, confirming again the findings in Table 3. Finally, net spillover evidence shows that, soybean and corn futures are always the dominant information contributors to other futures, and other agriculture futures, such as sugar, cotton, coffee and palm oil, are major information receivers at different time frequencies.

All in all, the static mean (average) spillover effects shown in Tables 3 to 6 indicate that in general, crude oil, carbon and agriculture commodity futures markets are moderately connected, and the major part of the total spillover are concentrated at short-term frequency. In addition, soybean and corn futures seem to be the two major return information contributors. However, no time-varying spillover results are revealed in section, which are more significant for timely regulatory decisions and flexible investment strategies.

5.2. Dynamic mean spillover evidence by TVP-VAR-DY and TVP-VAR-BK models

In this sub-section, we employ two TVP-VAR based extensions of DY and BK models proposed by Antonakakis et al. (2020) and Ellington and Baruník (2020), which we call as TVP-VAR-DY and TVP-VAR-BK, respectively. Although many recent researches using rolling-window method to get the time-varying spillover proof among assets, Antonakakis et al. (2020) show that TVP-VAR based spillover method have three clear advantages over DY and BK methods based on traditional constant coefficient VAR (CC-VAR): (1) TVP-VAR based spillover measures are not sensitive to outliers in data sample; (2) it does not loose initial data observations as CC-VAR when estimating the first rolling-window results; and (3) TVP-VAR based spillover approach does not need choose the

Table 5
Static mean spillover measurements among crude oil, carbon and agriculture futures markets by BK method at medium-term frequency (4 to 26 weeks).

	Brent oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	Palm oil	FROM
Brent oil	15.5	0.11	1.83	1.55	0.31	1.3	1.12	0.46	1.44	0.9
EUA carbon	0.12	23.09	0.05	0.43	0.02	0.05	0.21	0	0.02	0.1
Soybean	0.97	0.05	10.43	4.85	2.56	0.81	0.86	0.94	1.9	1.44
Corn	0.54	0.08	3.62	9.06	4.04	0.76	0.82	0.68	0.6	1.24
Wheat	0.3	0.03	2.57	4.58	11.15	0.76	0.75	0.82	0.67	1.16
Sugar	0.7	0.16	1.02	1.04	0.44	14.32	0.75	0.98	0.67	0.64
Cotton	1.35	0.15	2.05	2.1	1.08	0.97	14.17	0.67	1.1	1.05
Coffee	0.57	0.03	1.55	1.42	1.22	1.36	0.82	16.95	0.63	0.84
Palm oil	2.24	0.02	3.96	1.58	1.26	0.99	1.04	0.91	12.43	1.33
TO	0.76	0.07	1.85	1.95	1.22	0.78	0.71	0.61	0.78	**TSI**
NET	−0.15	−0.03	0.41	0.71	0.05	0.14	−0.34	−0.24	−0.55	**8.71**

Notes: This table reports the directional spillover among crude oil, carbon and agriculture futures markets by the method of Baruník and Křehlík (2018) in frequency domain. The rightmost column (FROM) of this table indicates the directional spillover from all others to a specific futures market. The penultimate row (TO) of this table indicates the directional spillover to all others from a specific futures market. The bottom row (NET) shows the net spillover, i.e., the difference between TO and FROM spillover of a specific futures market. The number in the bottom right corner of this table (indicated in bold face) is the TOTAL spillover index (TSI) of all the futures markets.

Table 6
Static mean spillover measurements among crude oil, carbon and agriculture futures markets by BK method at long-term frequency (longer than 26 weeks).

	Brent oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	Palm oil	FROM
Brent oil	2.11	0.02	0.25	0.22	0.04	0.18	0.15	0.06	0.2	0.12
EUA carbon	0.02	3.2	0.01	0.06	0	0.01	0.03	0	0	0.01
Soybean	0.13	0.01	1.42	0.67	0.35	0.11	0.12	0.13	0.26	0.2
Corn	0.07	0.01	0.49	1.22	0.55	0.1	0.11	0.09	0.08	0.17
Wheat	0.04	0	0.35	0.62	1.51	0.11	0.1	0.11	0.09	0.16
Sugar	0.09	0.02	0.13	0.14	0.05	1.94	0.09	0.13	0.09	0.08
Cotton	0.19	0.02	0.29	0.3	0.15	0.13	1.94	0.09	0.15	0.15
Coffee	0.08	0	0.22	0.2	0.17	0.19	0.11	2.34	0.09	0.12
Palm oil	0.31	0	0.56	0.23	0.18	0.14	0.14	0.13	1.69	0.19
TO	0.1	0.01	0.26	0.27	0.17	0.11	0.1	0.08	0.11	**TSI**
NET	−0.02	0	0.06	0.1	0.01	0.02	−0.05	−0.03	−0.08	**1.20**

Notes: This table reports the directional spillover among crude oil, carbon and agriculture futures markets by the method of Baruník and Křehlík (2018) in frequency domain. The rightmost column (FROM) of this table indicates the directional spillover from all others to a specific futures market. The penultimate row (TO) of this table indicates the directional spillover to all others from a specific futures market. The bottom row (NET) shows the net spillover, i.e., the difference between TO and FROM spillover of a specific futures market. The number in the bottom right corner of this table (indicated in bold face) is the TOTAL spillover index (TSI) of all the futures markets.

rolling-window size as CC-VAR method does, which may be very subjective and lead to estimation bias. Therefore, in this sub-section we present the TVP-VAR based mean spillover measurements in Figs. 1 to 3.

The upper panel of Fig. 1 shows the dynamic mean TSI throughout the whole data sample, i.e., October 29, 2007 to February 18, 2022. First of all, we find that the total spillover among crude oil, carbon and agriculture commodity futures fluctuate violently from about 20% to 70%. Across the whole data sample, three special time periods should be mentioned. The first one is the turmoil period of 2008–2009 global subprime mortgage crisis and global food crisis. During that time, the Brent oil price rises to about 140 USD per barrel in July 2008 and drops sharply to about 39 USD per barrel in December 2008, and the global price of food index released by IMF also swings dramatically between about 124 points on June 2008 and 85 points on February 2009. In the period of 2008–2009, we also find high degree of TSI among crude oil, carbon and agriculture commodity futures over 40%, implying that large oil and food price volatility may drive stronger connections among these futures markets. The second one is the period of European debt crisis during 2011 to 2012. At that time, Brent oil price keeps very high levels ranging from about 100 to 125 USD per barrel, and the global price of food index are also running at high levels between about 110 to 130 points. The third time period is after the outbreak of COVID-19 pandemic at the beginning of 2020. During that time, Brent oil price crashes from approximate 67 USD per barrel on December 2019 to about 18 USD per barrel on April 2020, and since then, crude oil prices have soared all the way to over $100 a barrel. Similarly, the global price of food index drops from about 104 points on January 2020 to 92 points on April 2020, and then have soared to over 139 points at the end of January 2022, reaching a new all-time peak. Clearly, the TSI in Fig. 1 also experiences a sudden and extremely rapid rise and keeps a relatively high level of about 30% to 50%.

Then the lower panel of Fig. 1 demonstrates the dynamic mean net spillover at time domain. It shows that for most of the time, the net spillover indices of soybean (light gray area) and corn (yellow area) dominate other futures with positive measurements, especially during the turmoil periods of 2008–2009 global financial crisis, the European debt crisis of 2011–2012, and 2020 COVID-19 pandemic, implying their leading role of information transmission among these futures markets. However, sugar (green area),

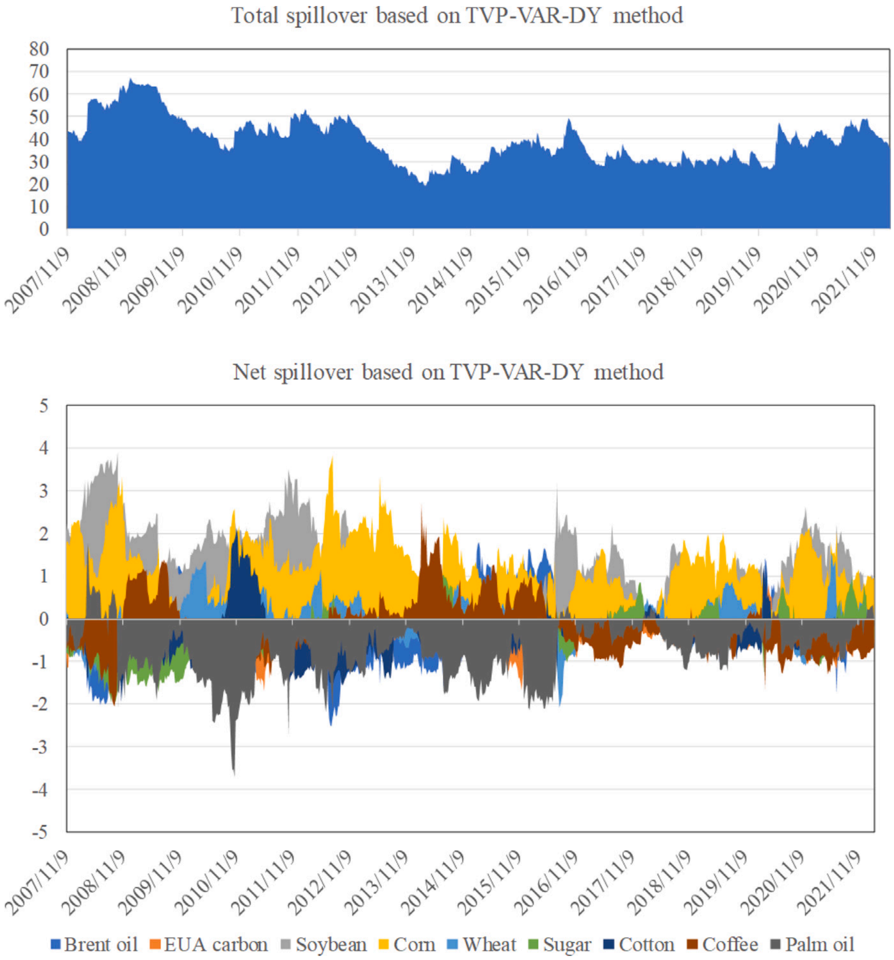

Fig. 1. Total and net spillover measurements of crude oil, carbon and agriculture commodity futures markets based on TVP-VAR-DY method.

coffee (brown area) and palm oil (dark gray area) futures seems to keep negative net spillover indices, indicating that they are net information receivers at most of the time.

Figs. 2 and 3 further present the dynamic total and net spillover effects at three different time frequencies. Fig. 2 shows that the major parts of TSI are centered at short- and medium-term frequencies, i.e., the blue and orange area, while the long-term total spillover only has very small share in the overall TSI. This means that most investors have more consistent investment behavior in short term; while in the medium and long term, investors' behavior shows greater heterogeneity (Kang et al., 2019). Moreover, we also find that the short- and medium-term TSIs swing more violently with time than the one at long-term frequency, especially during the three turmoil time periods of 2008–2009 global financial crisis, 2011–2012 European debt crisis, and 2020 COVID-19 pandemic. Fig. 3 further illustrates the net spillover effects of these nine futures at three time frequencies. From the three panels of Fig. 3, we can see the roles of these futures in net spillover change a lot with time from short-term frequency to medium- and long-term ones. On the one hand, in the first half of the data sample, roughly from December 2007 to December 2014, soybean, palm oil and cotton look more impressive to other futures, and sugar is clearly the major information receiver at short-term frequency. Nevertheless, at medium- and long-term frequencies, corn and sugar become the main information senders, and palm oil futures turns to be the primary information recipient. On the other hand, in the second half of the data sample, roughly from December 2014 to February 2022, corn and soybean are the major information transmitters, while palm oil is the principle receiver at short-term frequency. However, no distinct futures are observed to the stable information senders of recipients at medium- and long-term frequencies.

These outcomes reveal consistent but more fruitful conclusions in Fig. 1 and Tables 3 to 6. For one thing, Figs. 2 and 3 demonstrate that both the total and net spillover effects among crude oil, carbon and agriculture commodity futures are centered at short-term frequency, and both of them increase significantly during turmoil market conditions. For another, it shows that different futures play various roles in information transmission with time and across different time frequencies, suggesting that policy makers and investors should be very cautious when making regulatory policy or investment strategy in turmoil market environment with different decision rounds.

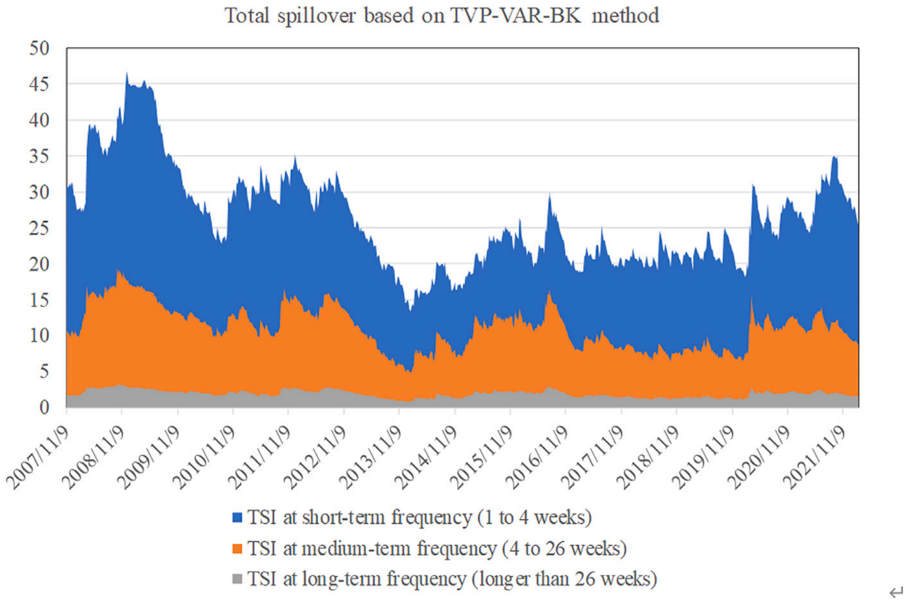

Fig. 2. Total spillover measurements of crude oil, carbon and agriculture commodity futures markets at various frequencies based on TVP-VAR-BK method. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5.3. Extreme spillover evidence by a new quantile-frequency spillover method

The empirical analysis in Section 5.1 and Section 5.2 can only reveal the mean (normal) spillover effects among crude oil, carbon and agriculture commodity futures. As noted above, these spillover effects increase significantly during turmoil market conditions and switch remarkably across different time frequencies. We therefore want to know not only the mean (normal) spillover effects but these interactions at extreme market conditions across various time frequencies. To achieve this purpose, we utilize the new quantile-frequency spillover approach introduced in Section 3. The empirical results are shown in Tables 7 to 10, and Figs. 4 to 7.

Firstly, Table 7 indicates the median (quantile = 0.5) spillover, including total, pairwise directional, to and from spillover, in time domain among crude oil, carbon and agriculture futures markets, which is comparable to the findings in Table 3 measured at mean quantile. It is no surprise that the results in Tables 7 and 3 show a high degree of agreement. For example, the TSI in Table 6 is estimated as 36.27%, and the one in Table 3 is 36.53%. Furthermore, the TO and FROM spillover effects in Tables 7 and 3 are also very close to each other. Finally, the bottom row (NPDC) in Table 7 shows the counts of positive net pairwise directional spillover of one specific futures market, i.e., the larger the number is, the more powerful information spillover of this market than the others. It indicates that corn soybean and wheat have 8, 6 and 5 counts of positive net pairwise directional spillover, indicating their dominant role in information transmission among these futures markets. This result is also in line with the one revealed in Table 3.

Then, Tables 8 and 9 demonstrate the extreme downside (left-tail, quantile = 0.05), and extreme upside (right-tail, quantile = 0.95) spillover, respectively, in time domain among crude oil, carbon and agriculture futures markets. We can find that, firstly, the total spillover at extreme downside and upside tails are 78.42% and 77.23%, which are much larger than the one at normal condition. This means that the interactions among crude oil, carbon and agriculture futures markets goes up dramatically at extreme market conditions. Next, we find that the there is no clear difference between the extreme downside and upside TSI among these futures markets, implying that crude oil, carbon and agriculture commodity futures similarly connected with each other tightly no matter in bearish or bullish market environment. Then, in terms of TO and FROM spillover measurements, we can see that these two indices for EUA carbon futures are all the smallest ones in Tables 7 to 9, e.g., 0.36% and 0.31% in Table 7, indicating that the carbon futures market seems to be a very week player in the information transmission mechanism at either normal or extreme market conditions. Finally, according to the counts of NPDC in Tables 8 and 9, soybean, corn and wheat futures obtain 7, 8 and 6 times of positive net pairwise directional spillover, further confirming their leading roles in information transmission among crude oil, carbon and agriculture commodity futures markets. Nevertheless, Brent crude oil and EUA carbon futures get relatively small numbers of NPDC counts in Tables 8 and 9, revealing their vulnerable roles in extreme market environment.

In order to gain a better understanding of the pairwise directional connectedness effects among crude oil, carbon, and agriculture commodity futures markets, we present in Fig. 4 a network diagram depicting the net pairwise directional connectedness at normal (quantile = 0.5), extreme downside (left-tail, quantile = 0.05), and extreme upside (right-tail, quantile = 0.95) conditions. The two red/green circles in each panel of Fig. 4 represent the two primary NPDC senders/receptors based on the total NPDC they transmitted or received, while the bold straight line with arrow in each panel depicts the largest NPDC between two futures markets, with the pink numbers beside the straight lines indicating the corresponding NPDC measures. Our results reveal that the connectedness

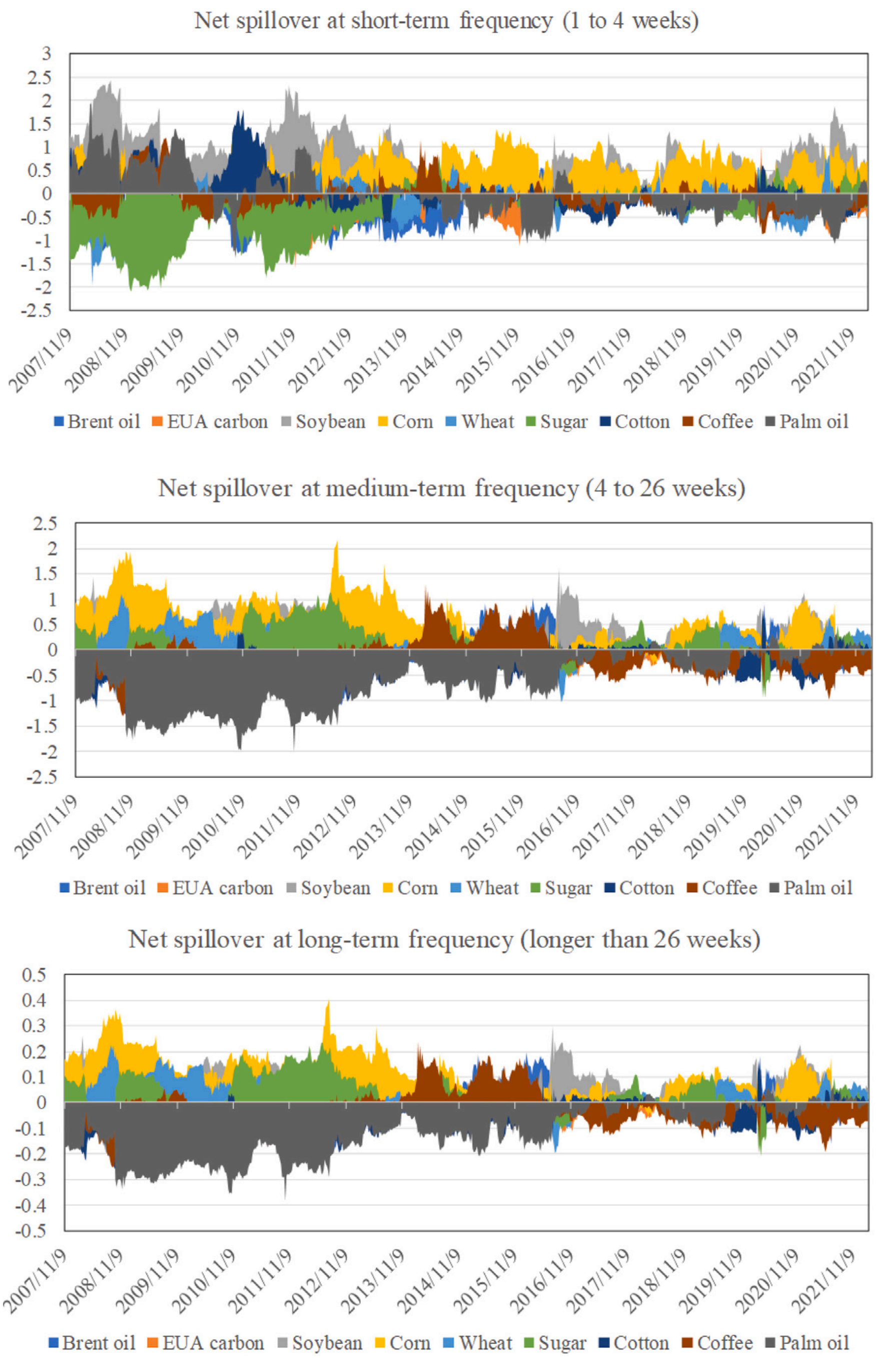

Fig. 3. Total spillover measurements of crude oil, carbon and agriculture commodity futures markets at various frequencies based on TVP-VAR-BK method. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

structure of each panel in Fig. 4 varies depending on the NPDC measured at different return quantiles, i.e., 0.5, 0.05, and 0.95, which correspond to normal, extreme left-tail, and extreme right-tail conditions, respectively. This indicates that the pairwise return connectedness patterns among crude oil, carbon, and agriculture commodity futures markets are quantile-dependent, and that the roles of each futures market evolve in different market environments. Specifically, under normal market conditions (quantile = 0.5), corn and soybean futures are the two primary information senders, with soybean futures having the largest NPDC effect on the palm oil market. However, Brent oil and coffee futures markets are the two primary information receivers. Under extreme bearish market conditions (quantile = 0.05), while corn and soybean futures remain the two major information transmitters, EUA carbon and coffee

Table 7
Normal (quantile = 0.50) spillover in time domain among crude oil, carbon and agriculture futures markets.

	Brent oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	Palm oil	FROM
Brent oil	68.56	0.32	6.09	4.68	1.31	4.97	4.8	2.66	6.61	3.49
EUA carbon	0.39	97.23	0.07	0.69	0.03	0.01	1.44	0.04	0.1	0.31
Soybean	4.13	0.16	46.38	18.29	10.3	3.92	3.92	3.46	9.43	5.96
Corn	2.91	0.35	18.13	46.49	17.91	3.53	4.53	2.93	3.22	5.95
Wheat	1.19	0.33	11.65	20.39	52.76	2.77	3.93	3.06	3.93	5.25
Sugar	4.85	0.71	5.56	4.99	3.4	66.08	4.95	5.34	4.13	3.77
Cotton	4.54	1.06	6.57	6.97	4.86	4.74	63.97	3.08	4.22	4
Coffee	2.52	0.04	5.57	4.82	4.52	5.78	3.46	70.97	2.33	3.23
Palm oil	6.5	0.27	12.77	4.5	4.55	4.09	3.99	2.17	61.17	4.31
TO	3	0.36	7.38	7.26	5.21	3.31	3.45	2.53	3.77	**TSI**
NPDC	1	4	6	8	5	2	4	2	4	**36.27**

Notes: This table reports the directional spillover among crude oil, carbon and agriculture futures markets at quantile of 0.5 (median) in time domain. The rightmost column (FROM) of this table indicates the directional spillover from all others to a specific futures market. The penultimate row (TO) of this table indicates the directional spillover to all others from a specific futures market. The bottom row (NPDC) shows the counts of positive net pairwise directional spillover of one specific futures market, i.e., the larger the number is, the more powerful information spillover of this market than the others. The number in the bottom right corner of this table (indicated in bold face) is the TOTAL spillover index (TSI) of all the futures markets.

Table 8
Extreme downside (left-tail, quantile = 0.05) spillover in time domain among crude oil, carbon and agriculture futures markets.

	Brent oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	Palm oil	FROM
Brent oil	18.49	2.71	11.49	11.41	10.53	11.71	11.44	10.64	11.57	9.06
EUA carbon	6.72	49.91	5.87	6.99	5.9	5.87	7.87	5.72	5.17	5.57
Soybean	10.79	2.07	17.21	13.82	12.39	10.54	10.77	10.53	11.88	9.2
Corn	10.4	2.33	13.64	17.08	13.64	10.69	11.2	10.37	10.66	9.21
Wheat	9.94	1.95	12.7	14.2	17.87	10.66	11.22	10.67	10.79	9.13
Sugar	11.45	2.14	11.34	11.57	11.04	18.4	11.79	11.32	10.94	9.07
Cotton	10.91	2.72	11.48	11.91	11.41	11.72	18.22	10.87	10.76	9.09
Coffee	10.88	2.13	11.61	11.44	11.37	11.63	11.28	18.99	10.67	9
Palm oil	12.18	1.8	12.82	11.65	11.29	10.77	10.76	10.67	18.07	9.1
TO	9.25	1.98	10.11	10.33	9.73	9.29	9.59	8.98	9.16	**TSI**
NPDC	3	0	7	8	6	3	5	2	2	**78.42**

Notes: This table reports the directional spillover among crude oil, carbon and agriculture futures markets at quantile of 0.05 (left tail) in time domain. The rightmost column (FROM) of this table indicates the directional spillover from all others to a specific futures market. The penultimate row (TO) of this table indicates the directional spillover to all others from a specific futures market. The bottom row (NPDC) shows the counts of positive net pairwise directional spillover of one specific futures market, i.e., the larger the number is, the more powerful information spillover of this market than the others. The number in the bottom right corner of this table (indicated in bold face) is the TOTAL spillover index (TSI) of all the futures markets.

Table 9
Extreme upside (right-tail, quantile = 0.95) spillover in time domain among crude oil, carbon and agriculture futures markets.

	Brent oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	Palm oil	FROM
Brent oil	19.26	1.84	11.4	11.21	10.16	11.86	11.14	11.32	11.82	8.97
EUA carbon	5.61	56.34	5.14	6.23	5.21	5.03	6.53	5.39	4.51	4.85
Soybean	10.75	1.51	17.98	13.42	11.95	10.89	10.45	10.79	12.25	9.11
Corn	10.4	1.75	13.22	17.53	13.53	10.92	11.12	10.7	10.83	9.16
Wheat	9.54	1.54	12.1	14.19	18.31	11.11	11.12	11.49	10.6	9.08
Sugar	11.41	1.4	11.19	11.61	11.31	18.58	11.72	11.8	10.98	9.05
Cotton	10.94	1.96	11.01	11.74	11.56	11.98	18.9	11.03	10.88	9.01
Coffee	10.78	1.63	11.35	11.46	11.86	12.03	11.01	19.08	10.81	8.99
Palm oil	11.57	1.55	12.67	11.55	10.93	11.25	10.86	10.68	18.94	9.01
TO	9	1.46	9.79	10.16	9.61	9.45	9.33	9.25	9.19	**TSI**
NPDC	1	0	7	8	6	5	2	3	4	**77.23**

Notes: This table reports the directional spillover among crude oil, carbon and agriculture futures markets at a quantile of 0.95 (right tail) in the time domain. The rightmost column (FROM) of this table indicates the directional spillover from all others to a specific futures market. The penultimate row (TO) of this table indicates the directional spillover to all others from a specific futures market. The bottom row (NPDC) shows the counts of positive net pairwise directional spillover of one specific futures market, i.e., the larger the number is, the more powerful information spillover of this market than the others. The number in the bottom right corner of this table (indicated in boldface) is the TOTAL spillover index (TSI) of all the futures markets.

futures become the primary information receivers. Furthermore, in extreme bullish market environments (quantile = 0.95), corn and soybean continue to be the two primary information deliverers, but EUA carbon and Brent oil futures markets switch to being the two primary information recipients. These findings highlight the complexity of the return information linkages among crude oil, carbon, and agriculture commodity futures markets, with the major NPDC information receivers changing significantly under different market conditions, despite corn and soybean futures appearing to be the major information senders.

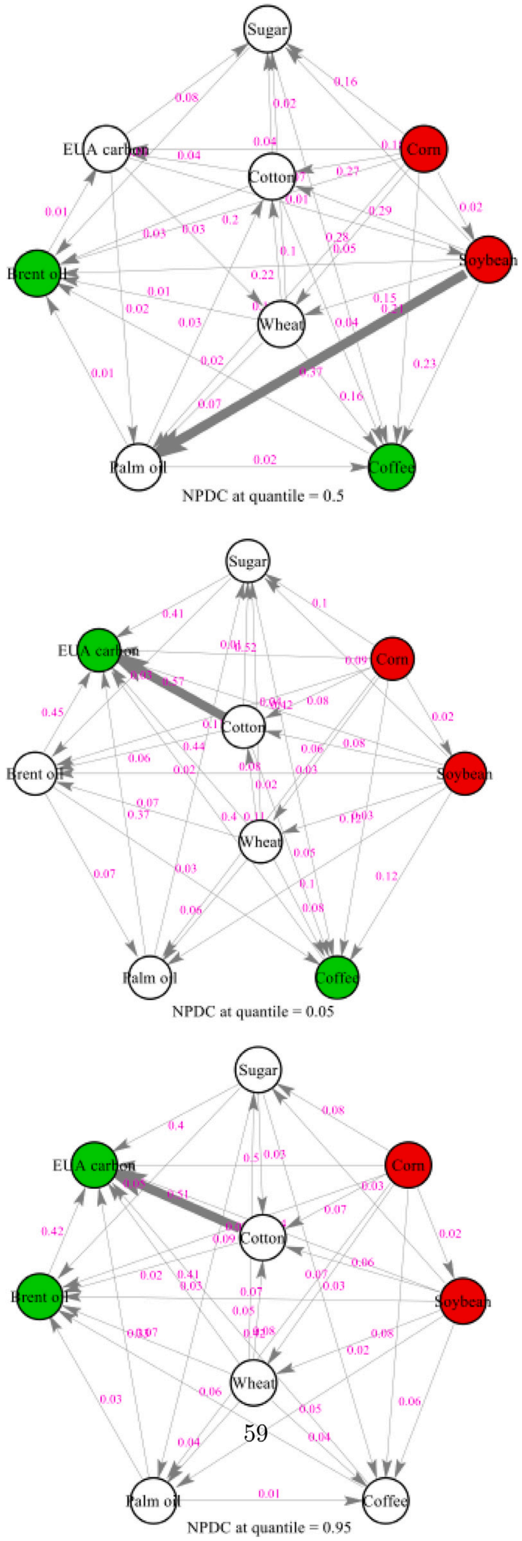

Fig. 4. Normal and extreme net pairwise directional connectedness (NPDC) in time domain (quantile = 0.5, 0.05 and 0.95 respectively).
Notes: The two red/green circles in each panel of this figure indicate the two major NPDC senders/receptors counted by the total NPDC they transmitted or received. The bold straight line with arrow in each panel presents the largest NPDC between two futures markets, and the pink numbers beside straight lines with arrows are the NPDC measures. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Additionally, Figs. 5 to 7 provide further insight into the NPDC effects among crude oil, carbon, and agriculture commodity futures markets at different return quantiles and various time frequencies. These figures help to understand the return connectedness structures not only at normal and extreme market situations but also their differences across different time horizons. In Fig. 5, the three panels depict the NPDC effects at normal market conditions (quantile = 0.5) across short to long terms, respectively. Comparing Fig. 5 with the left panel of Fig. 4, it can be observed that at normal situations, corn and soybean futures are consistently the two major information transmitters to other markets across different time frequencies. However, at short time frequency (1 to 4 weeks), sugar and coffee futures become the two primary information recipients, while cotton and palm oil futures are the chief information receivers at medium- and long-term frequencies. Moreover, comparing Fig. 6 with the middle panel of Fig. 4 reveals that the NPDC structures at extreme bearish market (quantile = 0.05) differ significantly from those in the time domain. For instance, corn and soybean futures are no longer the two major information senders. Instead, Brent crude oil and palm oil futures dominate message sending at short-term frequency, Fig. 7 and sugar and wheat futures become prime information transmitters at medium- and long-term frequencies. Finally, illustrates the NPDC network at extreme bullish market (quantile = 0.95). Similarly, at short-term frequency, corn and wheat are the two key information deliverers, while EUA carbon and Brent oil markets are major receivers at short-term frequency. At medium- and long-term frequencies, corn and Brent oil become the two significant information senders, and wheat and coffee futures are the two major acceptors.

To sum up, Table 10 reports the quantile net and total spillover in both time and frequency domain among crude oil, carbon and agriculture futures markets. Panel A of Table 10 mainly summarizes the net and total spillover of these futures markets in time domain. These results suggest that, first of all, the total spillover effects at extreme quantiles, i.e., 78.42% at quantile of 0.05 and 77.23% at quantile of 0.95, are much larger than the one at median quantile, i.e., 36.27% at quantile 0.5, implying that interdependences among crude oil, carbon and agriculture futures markets will increase sharply during great turmoil situations. Then, the net spillover indices demonstrate again that soybean and corn futures are the two prime return information contributors to other markets across different return quantiles, suggesting their dominant roles in information exchanges among these futures in no matter normal or extreme market conditions. However, in terms of major information receivers, we find quite different outcomes. At normal market conditions, coffee, cotton and Brent oil futures seem to be the main receivers, while at both extreme bearish and bullish markets, EUA carbon futures accepts most of the net spillover from other markets, indicating its clear passive position in the information exchange mechanism.

On the other hand, the frequency spillover evidence shown in Panel B of Table 10 offers us deeper view into the information interdependences among crude oil, carbon and agriculture commodity futures markets. On the one side, the total spillover effects are found to centered at short-term frequency, implying that the primary information exchanges among these futures markets happen within 1 to 4 weeks. On the other side, we also find that the major net spillover senders and receivers swing across different quantiles and various time frequencies, suggesting that policy makers, relevant producers/consumers, and investors should understand the unique role of each futures in the information transmission mechanism among these markets. To be specific, at normal market conditions (quantile = 0.5), soybean and corn futures remain the two primary net spillover transmitters to others spanning from short- to long-term frequencies. Regarding to net spillover receptors, sugar, coffee and Brent oil futures are the three major receptors at short-term frequency, while cotton and palm oil turn to the prime receivers at medium- and long-term frequencies. When referring to the situations of extreme bearish market (quantile = 0.05), the major net spillover senders and receptors are very different from those at normal market conditions (quantile = 0.5). For instance, at short-term frequency, Brent crude oil and palm oil futures become the two dominant information senders, and EUA carbon and sugar futures are the two major information receivers. Nevertheless, at medium- and long-term frequencies, we can see that wheat and sugar futures turn to be the key information transmitters, while Brent oil and palm oil futures switch to be obvious net spillover recipients. This means that Brent crude oil and palm oil futures can lead other futures markets in short term, but lag others in medium and long terms when facing extreme downside market environment. In addition, we observe that the EUA carbon market obtains three negative net spillover indices across all time frequencies in extreme bearish market situations, indicating its passive role in the information exchanges among these futures markets. Finally, in terms of extreme bullish market situations (quantile = 0.95), we find that the performances of these futures are more complicated than what they do in normal and extreme bearish market conditions. At short term frequency, corn and wheat futures dominate others by their large positive net spillover indices. Moreover, all the other agriculture commodity futures, including soybean, sugar, cotton, coffee and palm oil, get positive net spillover measures, while the net spillover for EUA carbon and Brent oil are −0.36 and −3.20, respectively, indicating the leading characters of agriculture commodity futures in information transmission over crude oil and carbon futures markets. At medium- and long-term frequencies, corn futures is still the powerful information sender, but Brent oil switches from net spillover receiver at short term to information contributor in these cases. In addition, wheat, coffee and palm oil futures also turn to be net spillover receivers at medium- and long-term frequencies. Moreover, in line with the findings at extreme downside market situations, EUA carbon market gets three negative net spillover indices spanning all time frequencies here, further confirming its reactive character in the information exchanges among these futures markets.

To summarize, the overall evidence in Table 10 demonstrates that, firstly, the total spillover among crude oil, carbon and agriculture commodity futures in extreme market conditions (quantiles = 0.05 and 0.95) are much larger than the one at normal market situations (quantile = 0.5), and these total spillover effects are centered at short-term frequency (1 to 4 weeks). Secondly, soybean and corn futures are two major net spillover senders to other futures across all quantiles in time domain, and at normal market cases spanning from short-term to long-term frequencies. Thirdly, the findings revealed at extreme market situations offer us quite different and more complicated net spillover evidence from those at normal environments. Brent oil and palm oil can lead information transmission to other futures during extreme bearish market at short-term frequency, while they reverse to be net spillover receptors at medium- and long-term frequencies (4 to 26 weeks and longer). These reversion roles in net spillover effects are

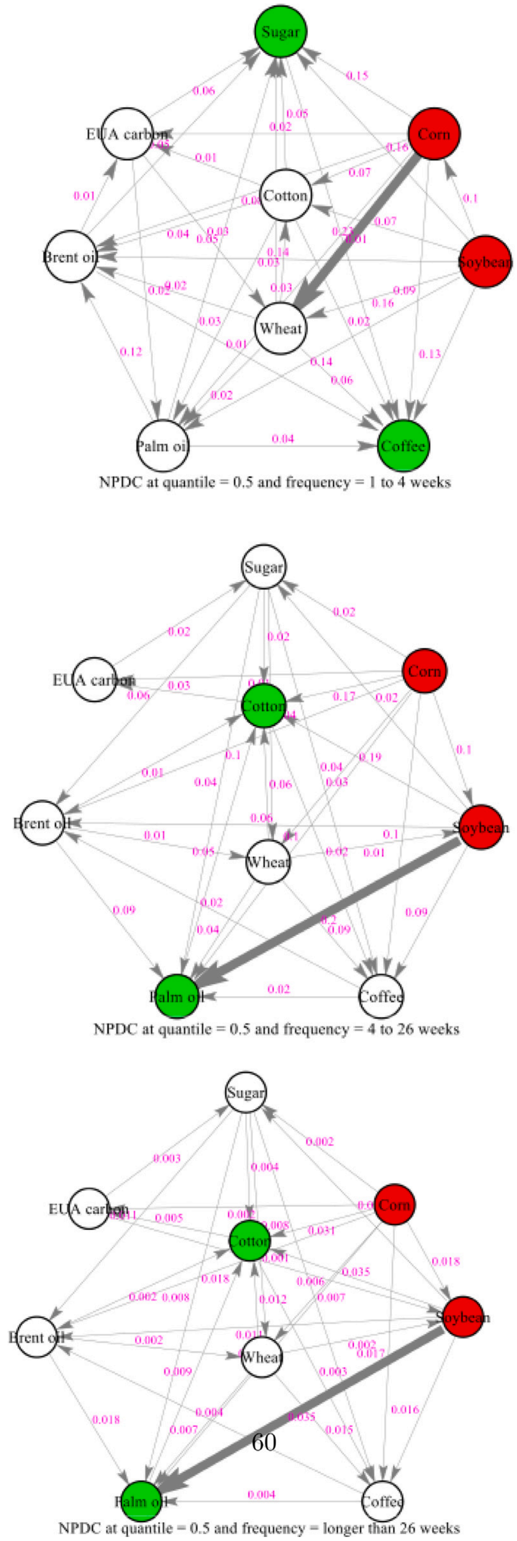

Fig. 5. Normal (quantile = 0.5) net pairwise directional connectedness (NPDC) in frequency domain.
Notes: The two red/green circles in each panel of this figure indicate the two major NPDC senders/receptors counted by the total NPDC they transmitted or received. The bold straight line with arrow in each panel presents the largest NPDC between two futures markets, and the pink numbers beside straight lines with arrows are the NPDC measures. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

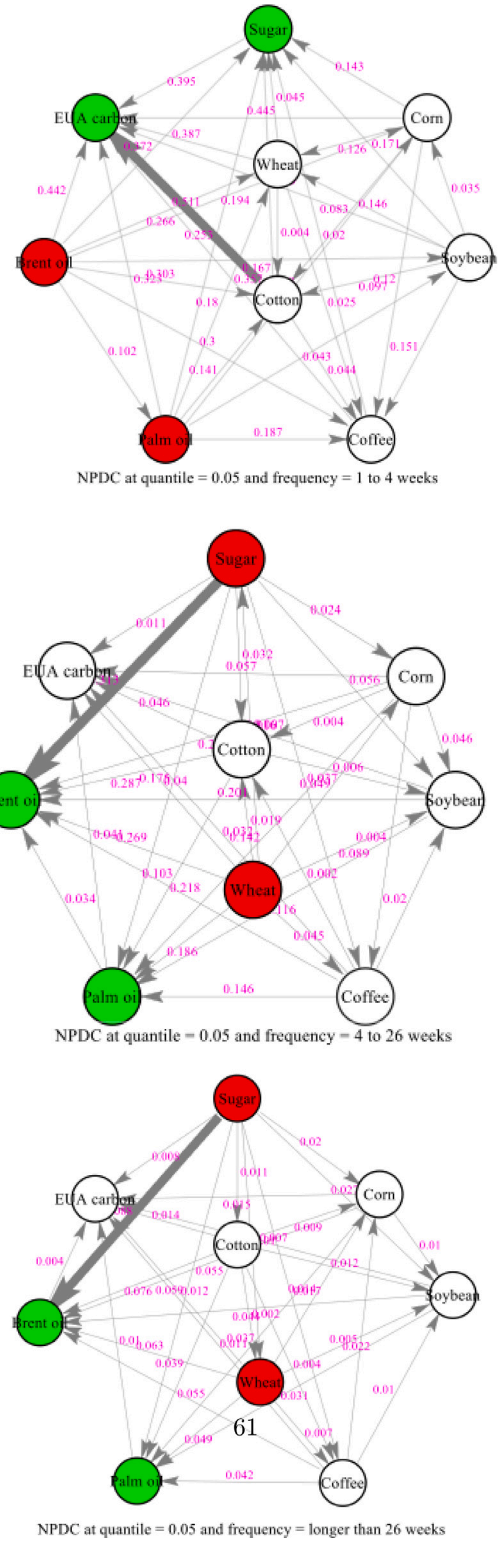

Fig. 6. Extreme left-tail (quantile = 0.05) net pairwise directional connectedness (NPDC) in frequency domain.
Notes: The two red/green circles in each panel of this figure indicate the two major NPDC senders/receptors counted by the total NPDC they transmitted or received. The bold straight line with arrow in each panel presents the largest NPDC between two futures markets, and the pink numbers beside straight lines with arrows are the NPDC measures. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

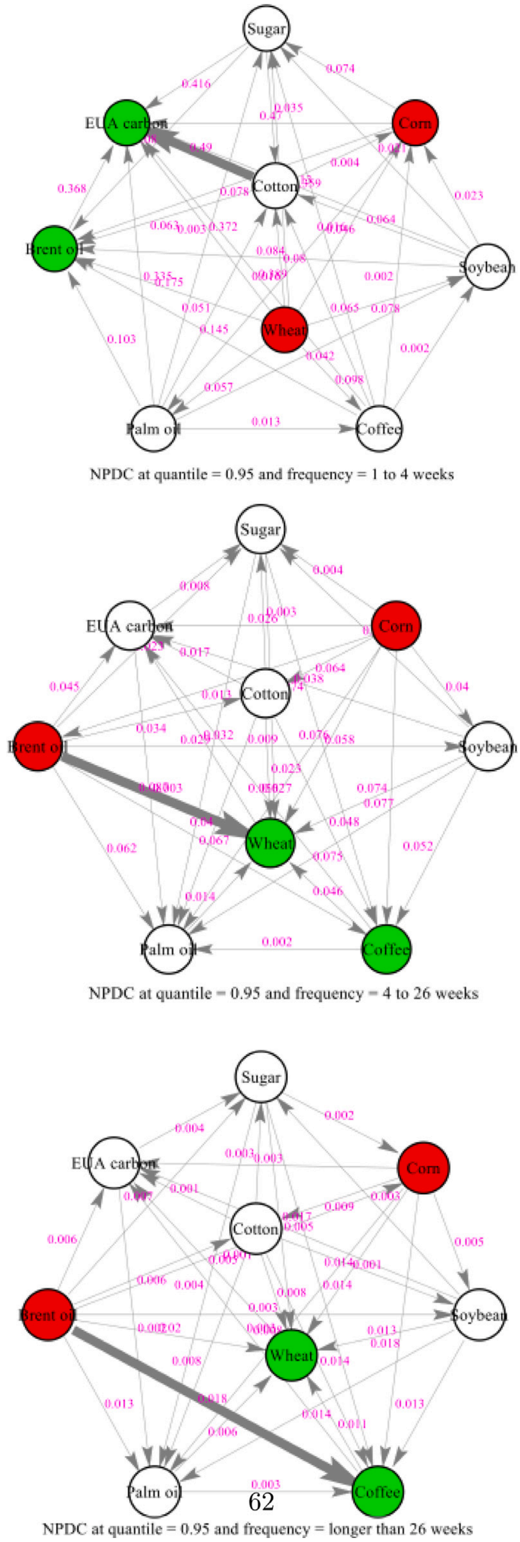

Fig. 7. Extreme right-tail (quantile = 0.95) net pairwise directional connectedness (NPDC) in frequency domain.
Notes: The two red/green circles in each panel of this figure indicate the two major NPDC senders/receptors counted by the total NPDC they transmitted or received. The bold straight line with arrow in each panel presents the largest NPDC between two futures markets, and the pink numbers beside straight lines with arrows are the NPDC measures. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 10
Quantile net and total spillover in time and frequency domain among crude oil, carbon and agriculture futures markets.

	Net									Total
	Brent oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	Palm oil	
Panel A: Spillover in time domain										
Quantile 1: 0.50	−0.49	0.05	**1.42**	**1.31**	−0.04	−0.46	−0.56	−0.70	−0.54	36.27
Quantile 2: 0.05	0.20	−3.58	**0.91**	**1.12**	0.60	0.22	0.50	−0.02	0.05	78.42
Quantile 3: 0.95	0.03	−3.39	**0.67**	**0.99**	0.54	0.40	0.31	0.25	0.18	77.23
Panel B: Spillover in frequency domain										
Quantile 1: 0.50										
Frequency 1: 1 to 4 weeks	−0.34	0.06	**0.90**	**0.58**	−0.16	−0.63	−0.02	−0.36	−0.02	25.71
Frequency 2: 4 to 26 weeks	−0.13	−0.01	**0.45**	**0.62**	0.10	0.14	−0.45	−0.28	−0.44	9.03
Frequency 3: longer than 26 weeks	−0.02	0.00	**0.08**	**0.11**	0.02	0.03	−0.08	−0.05	−0.08	1.52
Quantile 2: 0.05										
Frequency 1: 1 to 4 weeks	**2.15**	−3.26	0.79	0.62	−0.26	−0.66	−0.02	−0.45	**1.09**	52.69
Frequency 2: 4 to 26 weeks	−1.57	−0.24	0.11	0.43	**0.71**	**0.64**	0.38	0.33	−0.79	21.80
Frequency 3: longer than 26 weeks	−0.38	−0.08	0.00	0.07	**0.16**	**0.24**	0.14	0.09	−0.25	3.92
Quantile 3: 0.95										
Frequency 1: 1 to 4 weeks	−0.36	−3.20	0.43	**0.59**	**0.99**	0.27	0.26	0.54	0.47	60.42
Frequency 2: 4 to 26 weeks	**0.31**	−0.17	0.20	**0.35**	−0.36	0.11	0.03	−0.22	−0.25	14.44
Frequency 3: longer than 26 weeks	**0.07**	−0.02	0.04	**0.05**	−0.09	0.02	0.02	−0.06	−0.04	2.36

Notes: This table reports the static net and total quantile spillover indices among crude oil, carbon and agriculture futures markets in time and frequency domains across different time frequencies. The bold numbers indicate the two largest net spillover indices at a specific quantile. The underlined numbers indicate the two smallest net spillover indices at a specific quantile. Frequency 1 to 3 are set be 1 to 4 weeks (one month), 4 to 26 weeks (about half a year), and longer than 26 weeks, respectively.

also found in sugar, wheat and coffee futures at extreme market conditions, suggesting the fickle states of crude oil and agriculture futures in information exchanges at different time frequencies during turmoil market environments. Finally, no matter in normal or extreme market situations, EUA carbon futures are proved to be passive information receiver across various time frequencies, implying that it is very susceptible by information from crude oil and agriculture futures markets.

5.4. Economics and financial mechanisms behind spillover analysis

The first research gap, which states that spillover effects exist among crude oil, carbon emission allowance, and agriculture commodity markets in both time and frequency domains, is supported by the statistical results mentioned above. The economics and financial mechanisms behind the spillover analysis can be concluded as follows.

The spillover connectedness between crude oil, carbon, and agriculture commodity futures markets is primarily driven by the economic principles of supply and demand, as well as speculation and hedging. In the case of crude oil, the futures market allows producers to hedge against price fluctuations and ensure a stable income stream, while buyers can secure future supplies at a known price. The market also allows for speculation, as investors can bet on future price movements based on various economic and geopolitical factors. The same principles apply to carbon and agriculture commodities, where the futures market provides a mechanism for hedging against price risk and speculating on future price movements.

Short-term spillovers between these markets are primarily driven by changes in supply and demand, as well as economic and geopolitical events that affect one or more of these markets. For example, a severe drought could impact agriculture prices, which may in turn affect the prices of carbon credits and crude oil if they are used in agricultural production. Similarly, changes in oil prices could impact the cost of production for agriculture commodities, which could lead to short-term spillover effects. Since soybean and corn futures have been evidenced as the primary sources of return spillover (especially in the short term), they could be perceived as leading indicators for short-term price variations in the crude oil and carbon markets. Therefore, they might serve as effective predictors of price shifts in these markets. However, this potential predictive power is time-varying and may not remain consistent across different market conditions (e.g., stable versus extreme markets) and temporal horizons.

The findings in this section may seem counterintuitive at first glance, as soybean and corn serve as the information transmitter while crude oil acts as the recipient in some cases. However, there are several possible explanations for this result. First, there is a substitutive relationship between fossil fuels and biofuels. Biodiesel and bioethanol, which are mainly extracted from soybean and corn, respectively, are regarded as substitutes for fossil fuels such as crude oil (Naeem et al., 2022). Changes in the relative prices of biofuels and fossil fuels motivate users to switch their energy consumption mix (Chang and Su, 2010), affecting the demand for fossil fuels. Therefore, any shocks to soybean and corn prices can lead to changes in the price of crude oil. Similarly, Sun et al. (2021) found significant causality running from agricultural commodity prices to crude oil prices. Second, producing agricultural products entails large expenditures on fossil energy sources and electricity (Kirikkaleli and Güngör, 2021), due to oil-dependent inputs such as fertilizers, transportation, and machinery (Rafiq et al., 2009; Sun et al., 2021). Accordingly, price fluctuations in agricultural futures can channel agricultural production activities to fossil energy markets. Third, the much greater global emphasis and reliance on biofuels, particularly ethanol and soy-diesel, as energy sources during the last 10–15 years may have contributed to the facilitation of information transfer from agricultural markets to energy markets (Miljkovic et al., 2016). The mandates that have

Table 11
Simple statistics for portfolio weights and hedge effectiveness for crude oil and agriculture commodity portfolios with/without EUA carbon futures. (Weekly returns, full sample from October 2007 to February 2022).

	Mean	Std. Dev.	HE
Brent oil	0.06/0.07	0.05/0.05	0.79/0.79
Soybean	0.12/0.12	0.05/0.05	0.57/0.56
Corn	0.03/0.03	0.04/0.04	0.72/0.72
Wheat	0.09/0.08	0.03/0.03	0.72/0.72
Sugar	0.09/0.08	0.04/0.04	0.74/0.73
Cotton	0.16/0.17	0.08/0.08	0.66/0.66
Coffee	0.17/0.18	0.11/0.11	0.70/0.69
DCE Palm oil	0.26/0.27	0.09/0.08	0.58/0.57

Notes: The numbers in the columns of Mean and Std. Dev. are the means and standard deviations of asset weights for each asset in the crude oil and agriculture commodity portfolios with/without EUA carbon futures. HE column reports the hedge effectiveness for each asset in the crude oil and agriculture commodity portfolios with/without EUA carbon futures. Numbers before and after "/" are those measurements for portfolios with and without carbon futures.

led to an increased amount of ethanol being blended into gasoline in the United States and Brazil, two of the leading agricultural exporters worldwide, may have transformed the pricing mechanism of agricultural commodities related to biofuels, such as soybeans and corn, enhancing their influence on energy prices (Vatsa and Miljkovic, 2022). In addition, due to portfolio diversification and risk management, the financialization of commodities may also be responsible for information transmission from agriculture markets to energy markets (Nguyen et al., 2020). It is well established that agricultural yield anomalies are highly vulnerable to climate oscillations (Anderson et al., 2017; Li et al., 2020), and there is a great deal of volatility in agricultural commodity markets due to climate deterioration and the increased frequency of climate risk events (Bonato et al., 2022). Consequently, there is a considerable amount of information transmission from the agricultural market to the energy market. Equally, Tiwari et al. (2022a) discovered the dominance of agricultural commodities over energy markets during extreme market states. Fasanya and Akinbowale (2019) show that the returns on crude oil are a net receiver of returns spillover, while the returns on soybeans are a net transmitter of returns spillover. Borgards et al. (2021) also demonstrate that compared to energy commodities, agricultural commodities seem to undergo greater price overreactions regarding magnitude and frequency during financial turmoil. Finally, geopolitical factors that affect agricultural producing regions can also have an impact on crude oil prices. If there is unrest in a major agricultural producing country, it could disrupt the supply of these commodities and lead to higher prices, which could also impact the price of crude oil (Campbell, 2016; Leibfritz et al., 2016).

5.5. The roles of carbon futures in crude oil and agriculture portfolios

The connectedness evidence shown in Sections 5.1 to 5.3 indicates that EUA carbon futures is a major net connectedness receiver in this system, especially during extreme market conditions (i.e., quantile = 0.05 and 0.95). As pointed out by the several recent researches (Borgards et al., 2021; Chen et al., 2010; Tiwari et al., 2022a; Tiwari et al., 2022b), the major net connectedness receiver in a multi-asset system is usually weakly correlated with other assets. Therefore, it can be used as a hedge instrument for others for the reason that the price movement of this asset usually lags behind other assets. In this sub-section we further test whether carbon futures can provide hedging effects on the crude oil and agriculture commodity portfolios.

Firstly, we report the asset weights and hedge effectiveness for crude oil and agriculture commodity portfolios with or without EUA carbon futures to demonstrate the hedging effects of carbon futures. We can find in Table 11 that, the crude oil and agriculture commodity portfolios with or without EUA carbon futures have no significant differences in the asset weights for Brent oil and various agriculture commodity futures, indicating the incorporation of carbon futures does not change much the asset allocations in crude oil and agriculture commodity portfolios. However, the HE column in Table 11 shows that the hedge effectiveness for all the crude oil and agriculture commodity futures with carbon futures are not less than those without carbon futures. In particular, soybean, sugar, coffee and palm oil futures get higher HE in the portfolio with carbon futures than those in the portfolio without it. This finding suggests oil-agriculture portfolios may get hedging benefits by incorporating carbon futures in these portfolios, even without much adjustment to the existing asset weights in the portfolio.

Secondly, in addition to HE, cumulative return, which are calculated by summing a portfolio's returns over a holding period, is another important criterion for evaluating the performance of different portfolios. Therefore, we report the cumulative returns of crude oil and agriculture commodity portfolios with or without carbon futures by different portfolio allocation methods in Fig. 8. It indicates clearly that in all four allocation methods, i.e., minimum variance portfolio (MVP), minimum correlation portfolio (MCP), minimum connectedness portfolio by PCI (MCoP1), and minimum connectedness portfolio by NPDC (MCoP2), the portfolios with carbon futures have significantly larger cumulative returns than the ones without carbon futures. This evidence further confirms that carbon futures can enhance the profits of crude oil and agriculture commodity portfolios by providing additional hedging effects on them.

Thirdly, the cumulative return criterion only takes into account the profitability of the portfolios, but ignores the volatility of the portfolio's returns (market risk). Therefore, we further indicate the Sharpe ratio (SR), which can be considered as a risk-adjusted return, of various crude oil and agriculture commodity portfolios with or without carbon futures in Table 12. For more robust conclusions, we consider not only the "crude oil + agriculture commodity" portfolios, but also the portfolios with various

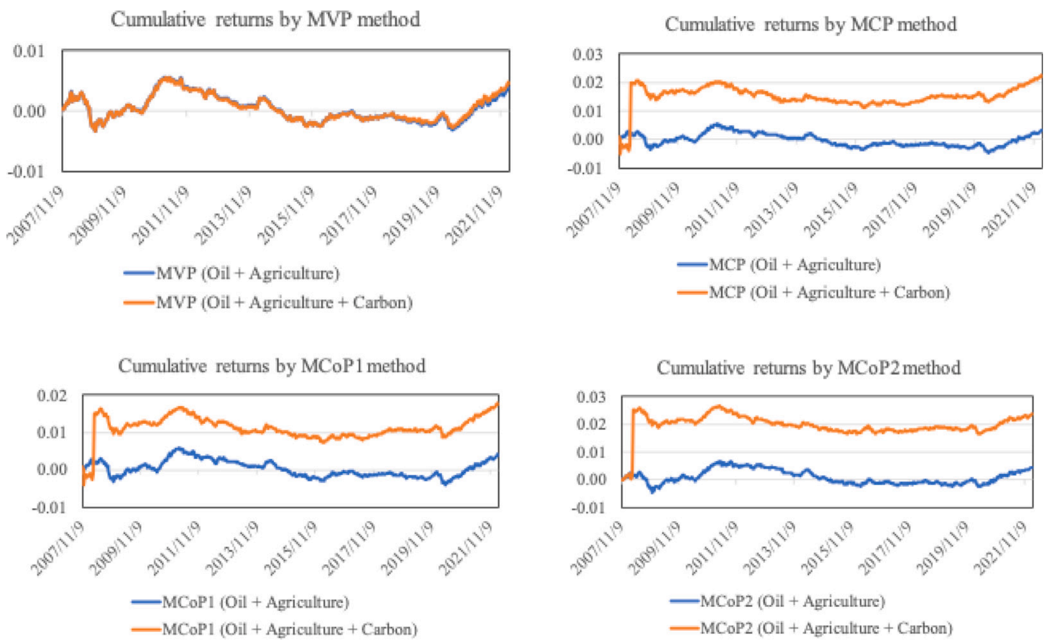

Fig. 8. Cumulative returns of crude oil and agriculture portfolios with or without carbon futures by different portfolio allocation methods.

Table 12
Sharpe ratio (SR) for MVP, MCP, and MCoP portfolios of crude oil and agriculture futures portfolios with/without carbon futures in full sample and different crisis periods.

Portfolios	Sharpe ratio							
	MVP	Δ SR	MCP	Δ SR	MCoP1	Δ SR	MCoP2	Δ SR
Panel A: Full sample								
Oil + Agriculture	0.0229		0.0171		0.0216		0.0265	
Oil + Agriculture + Carbon	0.0276	**0.0047**	0.0343	**0.0172**	0.0357	**0.0141**	0.0343	**0.0078**
Agriculture	0.0294		0.022		0.0229		0.0406	
Agriculture + Carbon	0.0344	**0.0050**	0.0356	**0.0136**	0.0361	**0.0132**	−0.0099	−0.0505
Panel B: Global financial crisis								
Oil + Agriculture	0.0023		0.0136		0.0169		−0.0023	
Oil + Agriculture + Carbon	−0.0257	−0.028	0.0892	**0.0756**	−0.0313	−0.0482	0.009	**0.0113**
Agriculture	0.0094		0.025		0.0182		−0.0098	
Agriculture + Carbon	−0.0182	−0.0276	0.0917	**0.0667**	0.0701	**0.0519**	0.0919	**0.1017**
Panel C: European debt crisis								
Oil + Agriculture	0.0202		0.0272		0.0267		0.062	
Oil + Agriculture + Carbon	−0.0027	−0.0229	−0.0205	−0.0477	−0.014	−0.0407	−0.0089	−0.0709
Agriculture	0.0073		0.0029		0.0201		−0.02	
Agriculture + Carbon	−0.0122	−0.0195	−0.0391	−0.042	−0.019	−0.0391	0.0214	**0.0414**
Panel D: COVID-19 pandemic								
Oil + Agriculture	0.1791		0.1182		0.0977		0.0938	
Oil + Agriculture + Carbon	0.1923	**0.0132**	0.1936	**0.0754**	0.1636	**0.0659**	0.1377	**0.0439**
Agriculture	0.1764		0.1392		0.1223		0.1238	
Agriculture + Carbon	0.1886	**0.0122**	0.1949	**0.0557**	0.2067	**0.0867**	0.2068	**0.083**

Notes: This table reports the Sharpe ratios for MVP, MCP, and MCoP portfolios of crude oil and agriculture futures portfolios with/without carbon futures. MVP and MCP are minimum variance and minimum correlation portfolios. MCoP1 and MCoP2 indicate the minimum connectedness portfolios based on PCI and NPDC criteria, respectively. Full sample indicates data sample used is from Oct., 2007 to Feb., 2022. Global financial crisis, European debt crisis, and COVID-19 pandemic denote data samples are from Jan., 2008 to Dec. 2009, Jan., 2009 to Dec., 2012, and Jan., 2020 to Dec., 2021, respectively. The bold numbers indicate the positive ΔSRs, which mean that the portfolios with carbon futures have larger SR than those without carbon futures.

agriculture commodity futures in Table 12. Similarly, MVP, MCP, MCoP1 and MCoP2 are four allocation methods adopted in this paper. Table 12 reports not only the Sharpe ratio, but also the difference in SR (ΔSR) between portfolio with carbon futures and the one without carbon futures. On the one hand, the SR results based on full sample in Panel A of Table 12 show that there are 7 out of 8 (ΔSRs) are positive, suggesting clearly that portfolios with carbon futures generally perform better than those without it. This finding furthers prove the hedging effects of carbon futures on both crude oil and agriculture commodity markets. On the other hand, Panels B to D reveal the Sharpe ratio results during three major crisis periods, i.e., global financial crisis, European debt crisis, and COVID-19 pandemic. Panels B to D show that portfolios with carbon futures have different Sharpe ratios during different crisis periods. For example, portfolios with carbon futures have higher SRs during recent COVID-19 pandemic than those in global financial crisis and European debt crisis. To be more specific, the SRs of portfolios with carbon futures are all larger than those without it during COVID-19 pandemic, while almost all of the portfolios with carbon futures perform worse than those without it during European debt crisis. These findings may suggest that the carbon futures plays different roles during various crisis periods that are caused by different shocks. In summary, we find in Table 12 that 21 out of 32 (ΔSRs) are observed to be positive, further confirming the benefits of adding carbon futures into crude oil and agriculture commodity portfolios.

To sum up, the statistical analysis of the roles played by carbon futures in crude oil and agriculture portfolios suggests that carbon futures can effectively hedge risk and improve the performance of these portfolios. These findings not only can fill our second research gap but also have important financial implications that highlight the potential benefits of using carbon futures in managing investment risk. Carbon futures can be used to hedge risk and enhance the performance of oil and agricultural portfolios because of the relationship (in other words, connectedness, which we have proven above) between carbon prices and the prices of these commodities. Carbon prices are affected by government policies and regulations aimed at reducing carbon emissions, while the prices of oil and agricultural commodities are affected by a wide range of factors such as weather conditions, supply and demand, and geopolitical events. Carbon futures can be used as a hedge against regulatory risk, as they allow investors to lock in a price for carbon emissions in the future. This can be particularly useful for oil and agricultural companies, as they may face increasing regulatory pressure to reduce their carbon emissions in the coming years. By using carbon futures to hedge against this risk, these companies can protect themselves against the potential negative impact of future carbon regulations on their profitability. In addition to hedging risk, carbon futures can also enhance the performance of oil and agricultural portfolios by providing diversification benefits. Carbon futures have low correlation with traditional asset classes, such as stocks and bonds, and can therefore provide a source of diversification for a portfolio. This can help to reduce overall portfolio risk and increase returns. Furthermore, as the world transitions to a low-carbon economy, demand for carbon credits is likely to increase, which could result in higher carbon prices. This could benefit companies that have invested in carbon futures as a way to hedge against regulatory risk, as well as those that have invested in renewable energy and other low-carbon technologies.

6. Robustness checks

The objective of this study is to not only measure the usual (mean quantile) static and dynamic spillover effects among them in both time and frequency domains but also to quantify the significant extreme spillovers a cross different time horizons using a recently proposed quantile-frequency spillover approach. However, there are some potential issues in our main empirical analysis, so several robustness tests should be processed.

6.1. Results of return connectedness based on daily returns

First, in this study, we try to explore the extreme price volatility among crude oil, carbon emission allowance and agriculture futures market, the reasons why we only Brent crude oil futures for the study are based on the following reasons. Firstly, Brent crude oil futures are among the most liquid and actively traded futures contracts in the world, which can provide better statistical power and reliability to the results. Secondly, Brent crude oil futures are considered as the international benchmark for crude oil pricing, and many other crude oil futures, including West Texas Intermediate (WTI), are priced relative to Brent. Hence, it may be easier to compare the spillover effects with other markets using a common benchmark. In the end, the research period we selected is 2007 to 2022. It may be easier to obtain reliable and consistent data for Brent crude oil futures compared to other crude oil futures. This could be because Brent crude oil futures have been traded for a longer time and are more established in the global market. However, to strengthen the robustness of our conclusions, we have chosen to re-examine the main analysis using the NYMEX WTI crude oil futures price.

Secondly, the reason for using RBD palm olein futures in the Dalian Commodity Exchange (DCE) is that it is currently the most heavily traded palm oil futures contract globally, as reported by the Futures Industry Association (FIA).[2] The Crude Palm Oil (FCPO) Futures traded on the Malaysia Derivatives Exchange (MDE) is now the second largest palm oil futures contract. Therefore, for this robustness check, we have opted to use the palm oil futures traded on the Malaysia Derivatives Exchange (MDE) to repeat the empirical analysis.

Thirdly, data at higher frequencies offer more advantages as they can capture additional information related to trading activities inherent in daily returns. Therefore, we have chosen to use daily returns of crude oil, carbon, and agriculture commodity futures as another robustness check to re-conduct the empirical analysis.

Table 13 presents a summary of all the new results. The table shows that even when using daily returns of WTI oil, carbon, and agricultural commodity futures, the empirical results are highly consistent with those reported in Table 10 based on weekly returns. Firstly, the time-frequency evidence in Panel A of Table 13 indicates that the total connectedness effect among WTI crude oil, carbon, and agriculture futures markets during extreme turmoil environments (i.e., 76.95% at 0.05 quantile and 76.26% at 0.95 quantile) is much larger than that observed during normal market conditions (i.e., 26.39% at 0.50 quantile). Furthermore, the net connectedness measures in Panel A of Table 13 reveal that soybean, corn, and wheat futures are the three primary contributors to return information for other markets across different return quantiles, consistent with the findings in Table 10. However, there

[2] https://www.fia.org/resources/fia-releases-data-futures-and-options-volume-trends-first-half-2021

Table 13
Quantile net and total connectedness among daily crude oil, carbon and agriculture futures returns (Full sample).

	Net									Total
	WTI oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	MDE Palm oil	
Panel A: Connectedness in time domain										
Quantile 1: 0.50	−0.24	0.04	**1.03**	**0.78**	0.26	−0.21	−0.30	−0.27	−1.09	26.39
Quantile 2: 0.05	−0.14	−3.26	**0.92**	0.56	**0.74**	0.35	**0.74**	0.43	−0.34	76.95
Quantile 3: 0.95	−0.41	−3.03	**0.91**	0.61	**0.88**	0.54	0.39	0.25	−0.14	76.26
Panel B: Connectedness in frequency domain										
Quantile 1: 0.50										
Frequency 1: 1 to 5 days	−0.21	0.05	**0.73**	**0.65**	0.17	−0.23	−0.26	−0.28	−0.62	21.16
Frequency 2: 5 to 22 days	−0.02	−0.01	**0.22**	**0.10**	0.07	0.01	−0.03	0.01	−0.35	3.85
Frequency 3: longer than 22 days	−0.01	0.00	**0.08**	**0.03**	**0.03**	0.01	−0.01	0.00	−0.13	1.38
Quantile 2: 0.05										
Frequency 1: 1 to 5 days	0.14	−2.66	**0.91**	0.75	−0.23	0.09	0.51	−0.38	**0.89**	57.37
Frequency 2: 5 to 22 days	−0.20	−0.44	0.02	−0.13	**0.70**	0.19	0.16	**0.58**	−0.88	14.32
Frequency 3: longer than 22 days	−0.08	−0.16	−0.01	−0.06	**0.28**	0.07	0.07	**0.23**	−0.35	5.25
Quantile 3: 0.95										
Frequency 1: 1 to 5 days	−0.63	−2.68	**0.69**	0.43	**0.71**	0.00	0.55	0.57	0.36	61.41
Frequency 2: 5 to 22 days	**0.16**	−0.27	**0.16**	0.14	0.13	**0.40**	−0.11	−0.23	−0.37	10.92
Frequency 3: longer than 22 days	**0.06**	−0.09	**0.06**	0.05	0.04	**0.15**	−0.05	−0.09	−0.14	3.92

Notes: This table reports the static net and total quantile connectedness indices among crude oil, carbon and agriculture futures markets in time and frequency domains across different time frequencies. The bold numbers indicate the two largest net connectedness indices at a specific quantile. The underlined numbers indicate the two smallest net connectedness indices at a specific quantile. Frequency 1 to 3 are set be 1 to 5 days (one week), 5 to 22 days (about one month), and longer than 22 days, respectively.

are some slightly different findings with regards to connectedness receivers. For example, with daily returns, MDE palm oil futures become a major net connectedness receptor at 0.05 and 0.50 quantiles, whereas in Panel A of Table 10, coffee futures are a primary receiver. Nevertheless, both Tables 10 and 13 demonstrate that EUA carbon futures are the primary net connectedness receptors in both weekly and daily return conditions at 0.05 and 0.95 quantiles. Moreover, Panel A of Table 13 indicates that in the daily return case, WTI crude oil futures are weak information receivers across different market conditions. This finding is consistent with the conclusions of several previous studies (Dahl et al., 2020, Du et al., 2011, Nazlioglu et al., 2013, Tiwari et al., 2020, Yip et al., 2020).

Secondly, the connectedness measurements in the frequency domain across different return quantiles shown in Panel B of Table 13 generally confirm the findings in Table 10. Firstly, all the total connectedness effects across different market conditions are centered at the short-term frequency, indicating that information transfer in this system primarily focuses on the short-term frequency. Secondly, the main net connectedness senders and receivers oscillate at different market conditions and across various frequencies. Similar to the results in Table 10, in a normal market environment (quantile = 0.50), soybean and corn futures remain the two main transmitters of net connectedness to others from short to long frequencies. Regarding net connectedness receivers, sugar, cotton, coffee, and palm oil futures are the major receptors at the short-term frequency, and cotton and palm oil are the prime receivers at medium- and long-term frequencies. It is worth noting that, even using daily returns, although not very significantly, WTI oil futures are always a net connectedness recipient at normal market conditions across different time frequencies, further confirming the results shown in Table 10. Regarding extreme bearish market conditions (quantile = 0.05), the daily return connectedness effects are also roughly in line with those findings based on weekly returns in Table 10. For instance, at the short-term frequency (1–5 days), soybean, palm oil, and corn futures are the three major information senders, and EUA carbon is still the largest connectedness receptor. A slight difference is that crude oil is no longer the largest daily return information transmitter, but it still maintains a positive net connectedness. Similar to Table 10, at medium- and long-term frequencies, wheat remains the main information sender, while coffee instead of sugar becomes the second-largest information receiver. Moreover, we see that palm oil is still the major net connectedness receptor, and EUA carbon instead of crude oil turns out to be another main information recipient. It is also worth mentioning that, consistent with the results in Table 10, crude oil is still a net connectedness receiver at medium- and long-term frequencies during an extreme bearish situation. Finally, in terms of extreme bullish market conditions (quantile = 0.95), the outcomes in Table 13 are essentially consistent with those revealed in Table 10. For example, at the short-term frequency (1–5 days), soybean, corn, and wheat are the three primary information senders, while carbon and crude oil futures are the two major recipients. These findings are highly consistent with those in Table 10. Furthermore, at medium- and long-term frequencies, although soybean instead of corn becomes the largest information transmitter, sugar, corn, and wheat still have positive net connectedness, indicating their leading role in daily return information exchange in this system. Moreover, also consistent with those in Table 10, crude oil keeps its role as an information sender at medium- and long-term frequencies during an extreme bullish market.

Finally, in summary, we find that even when using daily returns, which contain more market information than those in weekly returns, the connectedness measures are highly consistent with the findings revealed in Table 10 based on weekly returns. Specifically, each table in Tables 10 and 13 contains 108 net connectedness measurements. If we disregard the absolute numerical magnitude and only examine the positive and negative signs of these net connectedness indices, we find that among the 108 numbers in each table, 90 numbers have the same positive and negative signs, resulting in an 83.33% agreement rate for their sign agreement.

Table 14
Quantile net and total connectedness among weekly crude oil, carbon and agriculture futures returns (Global financial crisis, 2008–2009).

	Net									Total
	WTI oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	MDE Palm oil	
Panel A: Connectedness in time domain										
Quantile 1: 0.50	−0.13	0.02	**1.70**	**1.00**	−0.32	−1.49	−0.49	0.01	−0.31	55.62
Quantile 2: 0.05	1.62	−10.45	−3.89	−4.39	**14.24**	−3.03	4.06	**8.71**	−6.87	88.89
Quantile 3: 0.95	−5.64	−9.61	−2.58	3.44	**17.12**	**14.76**	−9.96	0.51	−8.04	88.88
Panel B: Connectedness in frequency domain										
Quantile 1: 0.50										
Frequency 1: 1 to 4 weeks	−0.23	0.12	**1.33**	−0.60	−0.19	−0.69	**0.50**	−0.58	0.33	41.79
Frequency 2: 4 to 26 weeks	0.09	−0.08	0.32	**1.36**	−0.12	−0.68	−0.83	**0.49**	−0.55	11.94
Frequency 3: longer than 26 weeks	0.01	−0.02	0.05	**0.24**	−0.01	−0.12	−0.16	**0.10**	−0.09	1.88
Quantile 2: 0.05										
Frequency 1: 1 to 4 weeks	1.59	−10.20	−3.80	−4.28	**13.90**	−2.96	3.97	**8.50**	−6.71	86.79
Frequency 2: 4 to 26 weeks	0.03	−0.22	−0.08	−0.09	**0.30**	−0.06	0.08	**0.18**	−0.14	1.86
Frequency 3: longer than 26 weeks	0.00	−0.03	−0.01	−0.01	**0.04**	−0.01	0.01	**0.02**	−0.02	0.24
Quantile 3: 0.95										
Frequency 1: 1 to 4 weeks	−0.38	−0.63	−0.16	0.23	**1.12**	**0.96**	−0.65	0.04	−0.53	47.88
Frequency 2: 4 to 26 weeks	−2.23	−3.80	−1.03	1.36	**6.78**	**5.85**	−3.95	0.20	−3.18	35.20
Frequency 3: longer than 26 weeks	−3.03	−5.17	−1.40	1.85	**9.22**	**7.95**	−5.37	0.27	−4.33	5.80

Notes: This table reports the static net and total quantile connectedness indices among crude oil, carbon and agriculture futures markets in time and frequency domains across different time frequencies. The bold numbers indicate the two largest net connectedness indices at a specific quantile. The underlined numbers indicate the two smallest net connectedness indices at a specific quantile. Frequency 1 to 3 are set be 1 to 4 weeks (one month), 4 to 26 weeks (about half a year), and longer than 26 weeks, respectively.

Table 15
Quantile net and total connectedness among weekly crude oil, carbon and agriculture futures returns (European debt crisis, 2010–2012).

	Net									
	WTI oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	MDE Palm oil	
Panel A: Connectedness in time domain										
Quantile 1: 0.50	−0.29	−0.51	**1.80**	**1.43**	0.25	−1.01	−0.53	−0.61	−0.54	41.92
Quantile 2: 0.05	0.49	−0.59	0.20	**1.33**	**0.59**	−0.41	0.12	−1.84	0.11	84.08
Quantile 3: 0.95	0.33	−1.81	0.15	**0.35**	**0.97**	0.15	−0.24	0.25	−0.15	82.92
Panel B: Connectedness in frequency domain										
Quantile 1: 0.50										
Frequency 1: 1 to 4 weeks	0.15	−0.65	**1.18**	**0.67**	0.56	−1.91	−0.01	−0.13	0.15	29.38
Frequency 2: 4 to 26 weeks	−0.37	0.13	0.53	**0.67**	−0.26	**0.77**	−0.45	−0.41	−0.60	11.03
Frequency 3: longer than 26 weeks	−0.06	0.02	**0.10**	0.09	0.05	**0.14**	−0.07	−0.07	−0.09	1.50
Quantile 2: 0.05										
Frequency 1: 1 to 4 weeks	**1.21**	−0.33	−0.05	−1.07	0.97	−2.08	**2.30**	−0.07	−0.88	58.56
Frequency 2: 4 to 26 weeks	−0.69	−0.28	0.06	**2.13**	−0.28	**1.60**	−1.76	−1.46	0.69	22.81
Frequency 3: longer than 26 weeks	−0.03	0.03	0.19	**0.27**	−0.11	0.06	−0.41	−0.30	**0.30**	2.71
Quantile 3: 0.95										
Frequency 1: 1 to 4 weeks	−0.44	−4.49	−0.30	**1.49**	1.21	0.71	−0.05	**2.43**	−0.57	49.33
Frequency 2: 4 to 26 weeks	**0.61**	**2.20**	0.38	−0.92	−0.14	−0.50	−0.20	−1.74	0.31	28.64
Frequency 3: longer than 26 weeks	**0.15**	**0.48**	0.06	−0.22	−0.10	−0.06	0.01	−0.44	0.10	4.95

Notes: This table reports the static net and total quantile connectedness indices among crude oil, carbon and agriculture futures markets in time and frequency domains across different time frequencies. The bold numbers indicate the two largest net connectedness indices at a specific quantile. The underlined numbers indicate the two smallest net connectedness indices at a specific quantile. Frequency 1 to 3 are set be 1 to 4 weeks (one month), 4 to 26 weeks (about half a year), and longer than 26 weeks, respectively.

More importantly, if we compare only the signs of net connectedness for crude oil and carbon futures in Tables 10 and 13, we can find that 21 out of 24 numbers have the same signs, indicating an 87.5% agreement rate for the roles of crude oil and carbon futures in this system. Therefore, the results in Table 13 confirm that our major findings in our main empirical analysis are quite robust.

6.2. Results of return connectedness during different crisis periods

In this subsection, we aim to test the robustness of our findings by evaluating the connectedness effects among crude oil, carbon, and agricultural commodity futures during three major crisis periods: the global financial crisis (GFC) from 2008 to 2009, the European debt crisis from 2010 to 2012, and the COVID-19 pandemic from 2020 to 2021. The empirical results are summarized in Tables 14 to 16, respectively.

Firstly, Tables 14–16 show that the total connectedness effects among the three markets during the three turmoil periods are all larger than those in the full sample shown in Table 10. For instance, the TCI during the three crises at quantiles of 0.50, 0.05, and

Table 16
Quantile net and total connectedness among weekly crude oil, carbon and agriculture futures returns (COVID-19 pandemic, 2020–2021).

	Net									Total
	WTI oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	DCE Palm oil	
Panel A: Connectedness in time domain										
Quantile 1: 0.50	0.58	−1.13	**1.10**	**1.48**	−0.74	−0.18	−0.59	−0.21	−0.31	42.84
Quantile 2: 0.05	−10.47	−6.99	**10.52**	−10.79	**9.83**	3.65	9.51	−9.25	3.98	89.05
Quantile 3: 0.95	0.52	**1.03**	−0.95	−0.74	−0.56	**1.79**	−0.39	−1.00	0.31	81.12
Panel B: Connectedness in frequency domain										
Quantile 1: 0.50										
Frequency 1: 1 to 4 weeks	−0.03	−0.05	**1.00**	**1.45**	−1.02	−0.61	−0.67	−0.05	−0.03	32.98
Frequency 2: 4 to 26 weeks	**0.52**	−0.94	0.10	0.03	0.25	**0.36**	0.06	−0.14	−0.23	8.68
Frequency 3: longer than 26 weeks	**0.08**	−0.14	0.01	0.00	0.04	**0.06**	0.01	−0.03	−0.04	1.18
Quantile 2: 0.05										
Frequency 1: 1 to 4 weeks	−10.34	−6.89	**10.30**	−10.70	**9.77**	3.66	9.48	−9.16	3.88	86.67
Frequency 2: 4 to 26 weeks	−0.34	−0.23	**0.34**	−0.36	**0.33**	0.12	0.32	−0.31	0.13	2.85
Frequency 3: longer than 26 weeks	−0.04	−0.03	**0.04**	−0.05	**0.04**	0.02	**0.04**	−0.04	0.02	0.37
Quantile 3: 0.95										
Frequency 1: 1 to 4 weeks	0.19	**0.64**	0.03	−0.19	−1.70	**2.46**	−0.49	−1.54	0.60	68.64
Frequency 2: 4 to 26 weeks	0.31	0.35	−0.87	−0.48	**1.01**	−0.60	0.08	**0.46**	−0.27	11.08
Frequency 3: longer than 26 weeks	0.01	0.05	−0.12	−0.07	**0.13**	−0.07	0.02	**0.08**	−0.02	1.39

Notes: This table reports the static net and total quantile connectedness indices among crude oil, carbon and agriculture futures markets in time and frequency domains across different time frequencies. The bold numbers indicate the two largest net connectedness indices at a specific quantile. The underlined numbers indicate the two smallest net connectedness indices at a specific quantile. Frequency 1 to 3 are set be 1 to 4 weeks (one month), 4 to 26 weeks (about half a year), and longer than 26 weeks, respectively.

0.95 are over 41%, 84%, and 81%, respectively, while in the full sample, these figures are estimated to be about 36%, 78%, and 77%, respectively. This evidence is consistent with the stylized fact that dependence among markets increases during turmoil periods, particularly during market crashing time. The total spillover connectedness of crude oil, carbon emission allowance, and agriculture futures markets during the GFC, European Debt Crisis, and the COVID-19 pandemic periods are all larger than the non-turmoil periods because during crisis periods, financial markets experience increased uncertainty and volatility. As a result, shocks in one market can spill over and affect other markets, leading to a higher level of connectedness among markets. Additionally, during crisis periods, investors tend to shift their portfolio allocations, which can also increase the degree of interdependence among markets. Therefore, the total volatility spillover connectedness among these markets tends to be higher during crisis periods than during non-turmoil periods. Secondly, we find that even during different crisis environments, agriculture commodity futures, such as soybean, corn, and wheat, generally maintain their roles as net connectedness senders. Additionally, EUA carbon futures are generally major net connectedness receptors across different crisis periods, especially at extreme bearish market conditions (quantile = 0.05). Finally, the role of the crude oil market appears to have varied during different crises. For example, during the global financial crisis, it is a weak net connectedness transmitter at quantiles of 0.50 and 0.05, while it becomes a clear receiver at the quantile of 0.95. In the European debt crisis, crude oil futures played more of a role as a net connectedness sender, especially at extreme market conditions. However, during the recent COVID-19 pandemic, crude oil futures were obviously a net connectedness receptor at extreme bearish environments and a moderate transmitter at normal and extreme bullish conditions. The reasons of these statistical results can be linked to the demand for agricultural commodities tends to be more stable and less sensitive to economic fluctuations, as people still need to eat even during a recession. On the other hand, crude oil and carbon emission allowance markets are more volatile during financial crises because they are more sensitive to changes in economic activity and investor sentiment. As a result, agricultural commodity futures tend to maintain their roles as net connectedness senders, as they are less affected by financial crises and can still provide stability to the other markets.

In conclusion, the connectedness effects of EUA carbon and agriculture commodity futures in Tables 14 to 16 during crisis periods are generally consistent with those in Table 10 based on the full data sample. However, crude oil futures show different roles in information transmission during these crises. These differences may be attributed to the fact that the performance of crude oil markets is highly dependent on the shocks from economic fundamentals, which are affected differently by different crises. For example, the 2008 global financial crisis was mainly caused by excessive innovation and speculation in the derivatives of the U.S. real estate market. The European debt crisis was mainly triggered by the serious government deficits and sovereign debt defaults of some countries, such as Greece. These two crises may not have had direct impacts on the crude oil markets, but the COVID-19 pandemic, on the other hand, had a huge direct impact on the supply and demand side of all real economies, and thus on the supply and demand behavior of the crude oil market. The above findings suggest that the connectedness effects among crude oil, carbon, and agriculture commodity futures will vary in different crisis periods. As a result, we need to be very careful when allocating portfolios of crude oil, carbon, and agriculture assets, especially during turmoil market conditions.

6.3. Results of volatility connectedness

The previous analyses have yielded a relatively clear understanding of the return connectedness among crude oil, carbon, and agriculture commodity markets. However, this approach alone cannot provide information about the risk (volatility) connectedness

Table 17
Quantile net and total connectedness among weekly crude oil, carbon and agriculture futures volatility (Full sample).

	Net									Total
	WTI oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	DCE Palm oil	
Panel A: Connectedness in time domain										
Quantile 1: 0.50	−0.42	**0.76**	0.01	**1.39**	−1.12	−0.91	0.07	−0.13	0.35	30.55
Quantile 2: 0.05	−0.12	−0.02	0.04	**0.40**	**0.29**	0.05	0.03	−0.55	−0.12	40.47
Quantile 3: 0.95	**38.28**	−9.81	−5.10	−5.26	−4.75	−3.75	−5.71	−3.93	**0.01**	94.15
Panel B: Connectedness in frequency domain										
Quantile 1: 0.50										
Frequency 1: 1 to 4 weeks	0.03	−0.04	−0.24	−0.14	**0.26**	**0.16**	−0.02	−0.13	0.12	1.96
Frequency 2: 4 to 26 weeks	−0.10	0.07	−0.53	−0.32	**0.75**	0.33	−0.18	−0.39	**0.37**	7.84
Frequency 3: longer than 26 weeks	−0.35	0.73	**0.78**	**1.86**	−2.14	−1.40	0.26	0.38	−0.13	20.79
Quantile 2: 0.05										
Frequency 1: 1 to 4 weeks	−0.10	−0.06	−0.38	−0.36	**0.53**	**0.37**	−0.02	−0.29	0.30	4.87
Frequency 2: 4 to 26 weeks	−0.42	−0.04	−0.69	−0.61	**1.37**	**0.83**	−0.33	−0.76	0.66	16.49
Frequency 3: longer than 26 weeks	0.40	0.08	**1.11**	**1.37**	−1.60	−1.15	0.38	0.50	−1.08	19.10
Quantile 3: 0.95										
Frequency 1: 1 to 4 weeks	**10.85**	−2.55	−1.67	−1.55	−2.07	−0.81	−1.74	−1.30	**0.83**	23.14
Frequency 2: 4 to 26 weeks	**21.92**	−5.57	−2.92	−2.94	−2.93	−2.27	−3.29	−2.32	**0.31**	52.68
Frequency 3: longer than 26 weeks	**5.51**	−1.69	−0.51	−0.77	**0.25**	−0.67	−0.68	−0.31	−1.13	18.33

Notes: This table reports the static net and total quantile connectedness indices among crude oil, carbon and agriculture futures markets in time and frequency domains across different time frequencies. The bold numbers indicate the two largest net connectedness indices at a specific quantile. The underlined numbers indicate the two smallest net connectedness indices at a specific quantile. Frequencies 1 to 3 are set to be 1 to 4 weeks (one month), 4 to 26 weeks (about half a year), and longer than 26 weeks, respectively.

Table 18
Quantile net and total connectedness among daily crude oil, carbon and agriculture futures volatility (Full sample).

	Net									Total
	WTI oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	MDE Palm oil	
Panel A: Connectedness in time domain										
Quantile 1: 0.50	**0.07**	**2.53**	−0.41	−0.10	−0.23	−0.31	−1.10	−0.01	−0.45	12.30
Quantile 2: 0.05	−0.13	−0.04	−0.09	−0.14	**0.28**	0.02	−0.05	−0.02	**0.17**	16.96
Quantile 3: 0.95	**40.58**	−11.08	−7.27	−7.90	−5.20	−4.96	−3.12	−4.28	**3.23**	88.89
Panel B: Connectedness in frequency domain										
Quantile 1: 0.50										
Frequency 1: 1 to 5 days	−0.05	−0.03	−0.01	0.01	−0.02	**0.04**	0.01	−0.02	**0.07**	0.43
Frequency 2: 5 to 22 days	−0.10	0.02	−0.04	0.02	−0.07	**0.10**	−0.01	−0.05	**0.12**	1.24
Frequency 3: longer than 22 days	**0.22**	**2.54**	−0.36	−0.13	−0.13	−0.45	−1.10	0.05	−0.64	10.62
Quantile 2: 0.05										
Frequency 1: 1 to 5 days	−0.11	−0.02	−0.02	0.02	−0.05	**0.12**	0.01	−0.02	**0.07**	1.18
Frequency 2: 5 to 22 days	−0.18	−0.04	−0.06	0.05	−0.11	**0.29**	0.02	−0.06	**0.10**	3.04
Frequency 3: longer than 22 days	**0.17**	0.01	0.00	−0.21	**0.44**	−0.39	−0.08	0.06	0.00	12.74
Quantile 3: 0.95										
Frequency 1: 1 to 5 days	**9.69**	−2.65	−1.74	−1.87	−1.25	−1.19	−0.75	−1.02	**0.77**	21.22
Frequency 2: 5 to 22 days	**15.96**	−4.36	−2.86	−3.10	−2.05	−1.95	−1.23	−1.68	**1.27**	34.96
Frequency 3: longer than 22 days	**14.93**	−4.08	−2.67	−2.93	−1.90	−1.82	−1.15	−1.57	**1.19**	32.71

Notes: This table reports the static net and total quantile connectedness indices among crude oil, carbon and agriculture futures markets in time and frequency domains across different time frequencies. The bold numbers indicate the two largest net connectedness indices at a specific quantile. The underlined numbers indicate the two smallest net connectedness indices at a specific quantile. Frequency 1 to 3 are set be 1 to 5 days (one week), 5 to 22 days (about one month), and longer than 22 days, respectively.

among these markets. Understanding volatility connectedness is equally important for policy makers and investors to better comprehend the interdependencies among these markets. Therefore, this sub-section aims to address this gap by presenting more evidence on volatility connectedness under different time frequencies and market conditions. Firstly, we use the commonly employed GARCH model to estimate the weekly and daily volatility of crude oil, carbon, and agriculture commodity futures. Next, we adopt the quantile-frequency connectedness method to estimate the results for weekly and daily volatility, as shown in Tables 17 and 18, respectively.

We employ the simple and powerful GARCH(1,1) model to gauge the conditional volatilities of the crude oil, carbon, and agriculture commodity markets. The reason for choosing the GARCH(1,1) model in this paper is twofold: on the one hand, Hansen and Lunde (2005) compare 330 ARCH-type models in terms of their ability to describe and forecast the conditional variance, and find no evidence that a GARCH(1,1) is outperformed by more sophisticated GARCH-type models. On the other hand, although some relevant studies continue to use the EGARCH or GJR-GARCH model to incorporate the volatility leverage effect in their volatility spillover analyses, the seminal work of Merton (1974) points out that the volatility leverage effect arises from the fact that a drop

Table 19
Quantile net and total connectedness among weekly crude oil, carbon and agriculture futures volatility (Full sample, based on GJR-GARCH model).

	Net									Total
	Brent oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	DCE Palm oil	
Panel A: Connectedness in time domain										
Quantile 1: 0.50	0.46	**0.51**	−0.72	**1.91**	−1.00	−0.96	−0.57	−0.09	0.45	27.45
Quantile 2: 0.05	−0.46	−0.05	**0.42**	**0.44**	0.19	0.22	−0.10	−0.65	−0.02	35.35
Quantile 3: 0.95	**12.49**	−10.97	0.48	0.76	−2.54	0.38	−0.38	−3.84	**3.63**	88.89
Panel B: Connectedness in frequency domain										
Quantile 1: 0.50										
Frequency 1: 1 to 4 weeks	−0.29	−0.11	−0.03	−0.17	**0.18**	**0.18**	**0.18**	−0.08	**0.14**	2.09
Frequency 2: 4 to 26 weeks	−0.46	0.06	−0.34	0.23	0.05	−0.05	**0.32**	−0.20	**0.39**	10.38
Frequency 3: longer than 26 weeks	**1.21**	0.56	−0.35	**1.85**	−1.23	−1.08	−1.07	0.19	−0.08	14.97
Quantile 2: 0.05										
Frequency 1: 1 to 4 weeks	−0.35	−0.12	−0.04	−0.41	**0.34**	**0.32**	0.28	−0.24	0.22	4.31
Frequency 2: 4 to 26 weeks	−0.64	−0.09	−0.16	−0.32	**0.58**	**0.54**	0.41	−0.57	0.26	17.32
Frequency 3: longer than 26 weeks	0.54	0.16	**0.63**	**1.16**	−0.72	−0.64	−0.78	0.16	−0.50	13.73
Quantile 3: 0.95										
Frequency 1: 1 to 4 weeks	**3.60**	−3.16	0.14	0.22	−0.73	0.11	−0.11	−1.11	**1.05**	25.62
Frequency 2: 4 to 26 weeks	**7.06**	−6.20	0.27	0.43	−1.43	0.21	−0.22	−2.17	2.05	50.23
Frequency 3: longer than 26 weeks	**1.83**	−1.61	0.07	0.11	−0.37	0.06	−0.06	−0.56	0.53	13.04

Notes: This table reports the static net and total quantile connectedness indices among crude oil, carbon and agriculture futures markets in time and frequency domains across different time frequencies. The bold numbers indicate the two largest net connectedness indices at a specific quantile. The underlined numbers indicate the two smallest net connectedness indices at a specific quantile. Frequency 1 to 3 are set be 1 to 4 weeks (one month), 4 to 26 weeks (about half a year), and longer than 26 weeks, respectively.

in a stock price will increase the leverage of the firm as long as debt stays constant. This increase in leverage might explain the increase variance associated with the price drop. However, there are no such economic fundamentals in futures markets as there are in stock markets. Therefore, we argue that this leverage effect is not present in the futures markets for crude oil, carbon and agricultural commodities, and we do not use these volatility models that incorporate the leverage effect. In addition, many related researches focusing on the risk/volatility spillover effects on crude oil, carbon, and agriculture commodity markets also adopt this simple GARCH(1,1) model to measure the conditional volatilities (Nazlioglu et al., 2013; Al-Maadid et al., 2017; Boubaker and Raza, 2017; Hamadi et al., 2017; Shahzad et al., 2018).

Tables 17 and 18 present novel and more comprehensive evidence on the time and frequency volatility connectedness among crude oil, carbon, and agriculture commodity futures under different market conditions, extending the research of Tiwari et al. (2020). Tiwari et al. (2020) demonstrate significant volatility spillovers from agricultural markets to energy markets during extreme market conditions, and report the dominance of agricultural markets over energy markets, using the QVAR-based connectedness method of Ando et al. (2022). However, their research has some limitations in distinguishing different volatility statuses. Specifically, they treat a quantile of 0.05 (0.95) as an extreme negative (positive) market condition. As volatility estimations are always positive, a lower quantile (e.g., 0.05) indicates a very low volatile market environment, rather than an extreme negative (bearish) market condition. Similarly, a higher quantile (e.g., 0.95) reflects a highly turbulent market condition, instead of an extreme positive (bullish) market condition. Moreover, their research lacks evidence on extreme connectedness at different time frequencies. Therefore, we re-examine the quantile volatility connectedness among crude oil, carbon, and agriculture commodity futures by redefining volatility statuses at various quantiles, and further explore these connectedness effects across different time frequencies.

Tables 17 and 18 provide highly consistent evidence on the time and frequency volatility connectedness among crude oil, carbon, and agriculture commodity futures across different volatility statuses (quantiles). At very low (quantile = 0.05) and moderate (quantile = 0.50) volatile market conditions, measured by daily or weekly data, agriculture commodities, such as soybean, corn, wheat, sugar, and palm oil, are the dominant net connectedness senders. However, at very high volatile market environments (quantile = 0.95), crude oil is the dominant net connectedness sender to other futures across short to long terms. These findings suggest that agriculture futures, while not very strong, act as information senders of volatility connectedness effects at low and moderate turmoil market conditions, whereas crude oil is an absolute leading volatility connectedness transmitter to other futures under very high volatile market environments. Moreover, EUA carbon futures are generally a net connectedness receptor at different market conditions and frequencies, particularly during very high turmoil circumstances.

In summary, the results of volatility connectedness presented in Tables 17 and 18 differ from those of return connectedness, further highlighting the fact that return and volatility are distinct measures of asset performance. While return evaluates profits, volatility assesses risk, indicating that return and volatility connectedness effects among different assets need not be perfectly aligned. The information on connectedness in returns can be useful for better portfolio allocation, whereas that in volatilities may aid in superior risk management strategies.

To prove our arguments above, we further use the GJR-GARCH(1,1) model to re-estimate the weekly and daily volatilities of the crude oil, carbon, and agriculture commodity markets, and then calculate the quantile-frequency connectedness results in Tables 19 and 20, respectively. Comparing the results of Tables 19 and 20 with those of Tables 17 and 18, we find very consistent findings between them. To be simple, in very low (quantile = 0.05) and moderate (quantile = 0.50) volatile market environments, whether

Table 20
Quantile net and total connectedness among daily crude oil, carbon and agriculture futures volatility (Full sample, based on GJR-GARCH model).

	Net									Total
	WTI oil	EUA carbon	Soybean	Corn	Wheat	Sugar	Cotton	Coffee	DCE Palm oil	
Panel A: Connectedness in time domain										
Quantile 1: 0.50	**0.10**	**1.85**	−0.19	−0.14	−0.03	−0.07	<u>−0.87</u>	0.01	<u>−0.66</u>	10.33
Quantile 2: 0.05	<u>−0.09</u>	0.00	0.02	<u>−0.10</u>	**0.28**	**0.04**	−0.01	<u>−0.10</u>	−0.05	14.40
Quantile 3: 0.95	**23.31**	<u>−10.80</u>	−2.43	<u>−7.05</u>	−2.69	−2.45	−3.61	**8.04**	−2.31	89.13
Panel B: Connectedness in frequency domain										
Quantile 1: 0.50										
Frequency 1: 1 to 5 days	<u>−0.02</u>	0.00	0.00	0.00	<u>−0.02</u>	**0.03**	0.00	<u>−0.01</u>	**0.02**	0.24
Frequency 2: 5 to 22 days	<u>−0.12</u>	**0.14**	−0.03	0.02	<u>−0.13</u>	**0.18**	−0.05	−0.09	0.08	1.80
Frequency 3: longer than 22 days	**0.24**	**1.71**	−0.16	−0.17	0.12	−0.28	<u>−0.82</u>	0.11	<u>−0.76</u>	8.29
Quantile 2: 0.05										
Frequency 1: 1 to 5 days	<u>−0.04</u>	0.00	−0.01	0.01	<u>−0.04</u>	**0.08**	0.00	<u>−0.03</u>	**0.05**	0.66
Frequency 2: 5 to 22 days	<u>−0.21</u>	0.00	−0.07	0.04	<u>−0.22</u>	**0.45**	−0.06	−0.19	**0.24**	4.21
Frequency 3: longer than 22 days	**0.16**	0.01	0.10	−0.16	**0.54**	<u>−0.49</u>	0.06	0.12	<u>−0.34</u>	9.54
Quantile 3: 0.95										
Frequency 1: 1 to 5 days	**2.64**	<u>−1.02</u>	−0.46	<u>−0.75</u>	−0.34	−0.27	−0.67	**1.12**	−0.25	10.66
Frequency 2: 5 to 22 days	**12.18**	<u>−5.29</u>	−1.59	<u>−3.64</u>	−1.45	−1.30	−2.28	**4.56**	−1.19	47.55
Frequency 3: longer than 22 days	**8.32**	<u>−4.49</u>	−0.41	<u>−2.66</u>	−0.86	−0.89	−0.62	**2.45**	−0.85	30.95

This table reports the static net and total quantile connectedness indices among crude oil, carbon and agriculture futures markets in time and frequency domains across different time frequencies. The bold numbers indicate the two largest net connectedness indices at a specific quantile. The underlined numbers indicate the two smallest net connectedness indices at a specific quantile. Frequency 1 to 3 are set be 1 to 5 days (one week), 5 to 22 days (about one month), and longer than 22 days, respectively.

measured by daily or weekly data, most net connectedness senders are agricultural commodities such as soybeans, corn, wheat, sugar and palm oil. However, when the market environment is very volatile (quantile = 0.95), we find that crude oil is a dominant net connectedness sender to other futures over the short to long term. These results suggest that agricultural futures, although not very strong, act as information senders of volatility connectedness effects in low and moderately turbulent market conditions. Crude oil, on the other hand, is an absolute leading transmitter of volatility connectedness effects to other futures in very highly volatile market environments. Moreover, we find that EUA carbon futures is roughly a net connectedness receptor under different market conditions and different time frequencies, especially under very high turbulence conditions.

7. Conclusions

The key roles of crude oil price, carbon emission allowance, and agriculture plantations in global environmental protection and sustainable development have garnered a great deal of academic attentions. Therefore, quantifying the interactions among the prices of crude oil, carbon emission allowance and agriculture commodity futures can help us to make better regulatory policy and investment decisions in this field. However, there is no literature focusing on the spillover, especially the spillover at extreme market conditions, among crude oil, carbon emission allowance and agriculture commodity futures, which is the gap that this paper seeks to fill. More importantly, there is no literature concentrating on the potential roles of the carbon market in hedging risk and improving the performance of oil-agriculture portfolios, which could provide policymakers and investors with a new angle on their regulatory and investment strategies. Besides adopting a series of mean (normal market) spillover measures, such as those commonly used static DY and BK, TVP-VAR-DY, and TVP-VAR-BK methods (Antonakakis et al., 2020; Ellington and Baruník, 2020; Baruník and Křehlík, 2018;Diebold and Yilmaz, 2012), this paper also utilizes a new quantile-frequency spillover approach of Wei et al. (2022a) and Bai et al. (2023) to identify these spillover effects at extreme market environments spanning various time frequencies, which may contributes more valuable information for market risk management during turmoil market periods.

The major empirical findings of our study have significant policy and economic implications. Firstly, we observe that the spillover effects among crude oil, carbon emission allowance, and agricultural commodity futures markets are considerably higher during extreme market conditions compared to normal situations. This implies a faster contagion of market risks among these futures markets and a decrease in diversification effects during extremely volatile market environments. In such scenarios, policy makers, particularly financial market supervisors, should develop timely firewall policies and implement risk assessment tools such as stress testing and value-at-risk estimation and backtesting models. These measures can monitor market risks and prevent the rapid spread of severe failures among different futures markets. Futures portfolio managers should hedge market risks by using other types of instruments to offset the damping diversification effects.

Secondly, we find that soybean and corn futures play a crucial role in information transmissions across different market situations at time domain. This indicates the significant influence of soybean and corn futures on both fossil energy and carbon emission allowance prices. As they are essential agriculture plants and the main source of biofuel production, policy makers and portfolio managers should closely monitor their price movements. Price regulation, planting and reclamation policy, as well as asset allocation decisions concerning soybean and corn commodities can be more conducive to the efficient promotion of global environmental protection and sustainable development.

Thirdly, we observe a passive position of carbon futures in the information spillover under almost all situations. This suggests that the price of carbon emission allowance is more likely to be influenced by the prices of other futures, particularly the strong ones such as soybean and corn futures. Thus, proactive policy makers and portfolio managers should focus more on the price fluctuations in oil and agriculture commodities instead of carbon products.

Fourthly, our new quantile-frequency spillover results show that during extreme bearish market environments in short-term frequency and extreme bullish market conditions in medium- and long-term frequencies, crude oil futures become the powerful information contributor over others. This implies that policy makers and fund managers should watch for the leadership effect of crude oil markets in extreme situations at specific time horizons. For example, when facing a market crash, futures trading managers must promptly adjust their crude oil position in their portfolio in the short term to avoid the risk contagion effects due to crude oil price volatility in the face of extreme market collapse scenarios.

Furthermore, we show that carbon futures contribute significantly to improving hedging effects and performance (e.g., cumulative returns and Sharpe ratios) of various oil/agricultural portfolios. This encourages not only policy makers to further support the development of carbon markets, but also portfolio managers, oil/agriculture producers and consumers to actively adopt carbon futures in their risk management and production applications. Fourth, the new quantile-frequency connectedness results show that crude oil futures turn out to be the strongest volatility information sender in extreme bullish market conditions (quantile = 0.95) across different time frequencies, suggesting that policy makers and portfolio managers should pay close attention to the leading effect of the crude oil market in extreme bullish markets and adjust the crude oil position in their portfolio promptly for fear of risk contagion effects from crude oil price volatility.

Finally, we observe that the major parts of both total and net spillover effects are concentrated at short-term frequency (1 to 4 weeks), implying that, on the one hand, policy makers should focus on developing short-term policy combinations to achieve more effective regulation outcomes rather than long-term regulatory policies. On the other hand, futures traders should pay more attention to the short-term risks and spillovers of their positions and strive to strike a balance between investment returns and risks through more short-term investments.

CRediT authorship contribution statement

Yu Wei: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Yizhi Wang:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Samuel A. Vigne:** Resources, Writing – review & editing, Supervision, Project administration. **Zhenyu Ma:** Conceptualization, Data curation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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