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**Connectedness mechanisms in the "Carbon-Commodity-Finance" system: Investment and management policy implications for emerging economies**

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**Abstract** Most studies investigating the interactions between the carbon market with other markets are confined to developed countries, largely overlooking emerging economies' contexts encountering environmental dilemmas caused by high carbon emission coupling with an economic boom. This study examines the connectedness mechanisms in the "Carbon-Commodity-Finance" system in emerging economies applying a spillover index approach with the estimated vector autoregression model. Given the recent green development of tackling climate change, this study also looks into the role of green bonds and new energy index stocks in the system. Our results suggest that: (i) the nature of system-wide spillovers changes over time and is notably driven by economic policy uncertainties; (ii) the stock market, on average, is the system's primary source of shock contagion, with green bonds being the largest shock receiver; (iii) the carbon market is heterogeneously connected with other markets, it mostly receives shocks from financial and metal markets, and transmits the shock to energy markets, particularly coal; and (iv) investment risk in most markets can be greatly reduced by creating portfolios with other markets in the system, except for green bonds, which are difficult to hedge and cannot help hedge others. These findings have significant implications for investors and policy makers in emerging economies in terms of asset allocation optimization and market risk management.

## Highlights

- The connectedness across Carbon-Commodity-Financial markets shows dynamics.
- Carbon market is a shock receiver of stocks and metals but a transmitter in energy.
- Stocks are the primary contagion source, while green bonds are the most vulnerable.
- System-wide spillovers are EPU-driven and all series are affected heterogeneously.
- The portfolio weights strategy outperforms hedge ratios in hedging effectiveness.

**Keywords** Dynamic spillovers, Carbon-Commodity-Financial markets, Connectedness network, Economic policy uncertainty, Investment portfolio management

## 1 Introduction

Price volatilities in different markets influence one another directly (Rigobon and Sack, 2003). During crises, such volatilities are likely to increase drastically, spilling over into other markets (Reinhart and Rogoff, 2008). Naturally, measuring and monitoring such spillovers can provide an "early alert" for impending crises and trace the progress of ongoing crises (Diebold and Yilmaz, 2012) help in establishing policy responses to preserve market stability and prevent shock contagion (Shen et al., 2018). More importantly, such spillovers among different markets offer investors and policy makers effective information on connectedness mechanisms in seeking investment opportunities and risk management (Antonakakis et al., 2020). With the rising financialization of carbon, carbon emission allowances, an emerging global asset class, attract increasing attention and adoption by investors to diversify portfolios in dealing with the uncertainty and risks posed by other markets (Vardar et al., 2018). As a result, the analysis of connectedness mechanisms of the complex systems involved in the carbon market is essential for both researchers and market participants.

A lively debate has been developing around this issue employing advanced econometric approaches, with themes mainly focusing on spillovers between the carbon market and other markets, including but are not limited to renewable energy markets, fossil energy markets, and financial markets. Despite the fact that results vary on the data, scope, and techniques used, one general conclusion is that the carbon market and other markets are linked. Moreover, as the carbon market is metamorphosing, growing evidence suggests that it is increasingly influenced by joint commodity and financial markets instead of the unidimensional markets considered in previous research (Adekoya, 2021). However, there is still no consensus on the correlations between markets in this complex “Carbon-Commodity-Finance” system (Gronwald et al., 2011). The erratic and heterogeneous results of this issue may lead to difficulties for investors in managing portfolios, such as the intangible loss of potential returns if only the shock transmission in the carbon and energy market is seen without considering the volatility of the stock market. Therefore, modeling a real situation in which to consider-within a single study-the connectedness mechanisms among carbon emission allowances, commodities, and financial assets is crucial to advance knowledge of potential systemic risks and thus make informed preventive interventions.

Research investigating connectedness mechanisms between the carbon market and other markets has been featured by various levels of carbon financialization. Most studies have focused on developed economies, particularly Europe, as the European Union Emissions Trading System (EU ETS) is to date the most efficient (Zeng et al., 2021). Meanwhile, studies on connectedness mechanisms in emerging economies’ contexts are seriously lacking. Emerging economies often target at boosting economic growth, which is deemed to be a more immediate priority than addressing climate change. These economies are the main damaging source for global warming because of their large emissions potential (Wara, 2007). However, their level of carbon financialization levels is still in its infancy. On the other hand, financial market conditions, types of carbon emissions, economic growth rates, institution structures, and technology availability in emerging economies are significantly different relative to developed economies (Mensah, 2014; Paramati et al., 2018). Evidence on the connectedness mechanisms of the “Carbon-Commodity-Finance” markets in emerging economies could provide economic and management implications for investors and policy makers, deserving more research attention (Gronwald et al., 2011).

In view of the research gaps, this study examines a comprehensive "Carbon-Commodity-Finance" system in emerging countries by including five detailed classes, that is, carbon market, energy commodities, metal commodities, traditional financial (stock and foreign exchange) markets, and green financial (new energy index stock and green bonds) markets. We not only combine the widely scrutinized carbon, energy, and traditional financial markets, but also link metal markets and green financial markets to them with the aim to provide multidimensional spillover information. Citing the financialization of common precious and industrial metals and the important role of green finance in successfully managing carbon market risks, it is also important to consider hedging asset classes that need to be examined for their exact roles in the system (Jin et al., 2020a; McInerney and Bunn, 2019). Meanwhile, emerging economies are more vulnerable to sudden changes in trade, stocks, and capital flows during economic upswings which may be attributable to the occurrence of economic shocks (Bloom, 2009). We further investigate the contribution of economic policy uncertainty (EPU), as an index closely related to economic growth and corporate investment, to the system-wide connectedness in order to provide important signals for systemic risk monitoring and intervention. Additionally, given the limited research available on the potential role of systematic risk hedging and portfolio management, this study conducts a holistic investigation into the portfolio weights, hedging strategies, and hedging effectiveness among several influential markets identified by spillover performance.

The novel theorization and findings of this study offer a wide range of implications to investment and management policy in emerging countries. First, this work provides supportive insights into shock transmissions over time, including magnitudes and directions, and identifies key risk triggers for each market in the system to supplement previous studies. As such, it contributes to risk management research on how to stabilize markets with a novel understanding that is important for both research and practice. Examining connectedness mechanisms of a system with a multidimensional perspective not only clarifies the interactions and dependencies among carbon, commodity, and financial markets, but also contributes to the enrichment of a risk management theory concerning the carbon market in emerging economies. Furthermore, this study offers investors empirically based explanations about effective strategies for creating portfolios. As investment efforts involve capital allocations and risk assessments (Mensi et al., 2020), it is important to inform investors precisely how shocks propagate across markets and which assets can be effectively hedged.

The arrangement of the rest of this study is organized in the following order: Section 2 conducts a literature review, while Section 3 provides the approaches adopted and describes the underlying data. Sections 4, 5, and 6 present the empirical results, investment and management implications, and conclusions, respectively.

## 2 Literature review

Since the start of the EU ETS - the earliest and relatively mature carbon market - the main concern of prior studies revolves around the issue of carbon trading thickness and market efficiency (Daskalakis, 2013; del Rio, 2017; Montagnoli and De Vries, 2010; Wu and Qin, 2021), whereas recent publications address issues associated with linkages between the carbon market with other important energy, non-energy, and financial markets aimed at investment diversification alongside carbon financialization (Bouri, 2015; Chang et al., 2018; Dai et al., 2021b; de Menezes et al., 2016; Hammoudeh et al., 2015; Keppler and Mansanet-Bataller, 2010; Reboredo, 2013; Sousa et al., 2014; Tan and Wang, 2017; Zhang and Sun, 2016). Among these studies, the debate focuses on correlations between different markets, relying on Granger-causality tests (Keppler and Mansanet-Bataller, 2010), nonlinear autoregressive distributed lag models (Hammoudeh et al., 2015), and quantile regression models (Tan and Wang, 2017), autocorrelation functions (de Menezes et al., 2016), and how price or return volatilities transmit across markets using copula models (Reboredo, 2013), wavelet approach (Sousa et al., 2014), or BEKK, DCC, and other GARCH models (Bouri, 2015; Chang et al., 2018; Zhang and Sun, 2016). These studies examined how one market index affects a particular market, especially energy sector, and how potential risks should be addressed by market participants, with an emphasis on the contribution of market trend forecasting to investment and management.

Of particular importance in understanding the connectedness mechanisms across markets is to understand the directional interactions, a powerlessness of the above techniques, which is further explored by Diebold and Yılmaz (Diebold and Yilmaz, 2012). This approach is particularly well suited to developing a system thinking for a complex economic system with interactive markets, and so was quickly being applied to investigate the various dynamic spillovers related to carbon and energy markets as well as financial markets (Dai et al., 2021b; Ji et al., 2019; Ji et al., 2018; Wang and Guo, 2018). However, few studies have looked into the role of each possible market index in the "Carbon-Commodity-Finance" system's overall connectedness, resulting in decisions that are often fragmented and piecemeal, to the detriment of fundamental environmental and economic objectives. In a study by Tan et al. (Tan et al., 2020), where the European carbon market was investigated in connection with energy and financial markets, the authors stressed the closeness of oil and EU carbon markets to financial markets and the need to set macroeconomic determinants as important factors in system-wide spillovers. Similarly, Adekoya et al. (Adekoya et al., 2021) divided this time-domain spillover into different frequencies to provide intelligence for both short- and long-term investors, and argued for much more systematic thinking was needed to make better investment choices. These studies are mostly confined to the EU. The analysis of emerging economies is necessary and meaningful in that the connectedness mechanisms among carbon, commodity, and financial markets are considered inconsistent in emerging and developed economies, yet the former is rarely investigated in the existing literature.

In addition, a recurring topic in some studies expresses a viewpoint that economic or financial events-along with control and support policies- have often brought shocks into the interactions between different markets. As a result, investors are compelled to seek an alternative investment strategy to hedge downside and upside risks with related assets. In this context, the diversified role of commodity and carbon markets has attracted particular interest and attention, leading to a closer integration between commodity and carbon as well as financial assets such as stocks (Antonakakis et al., 2018b, 2020; Jin et al., 2020a, b; Lahiani et al., 2021; Mensi et al., 2020). However, the hedging results are mixed or even contradictory. For example, some studies find commodities, particularly oil, have strong potential to hedge stocks (Mensi et al., 2016), while others demonstrate that commodities are ineffective in hedging stock market risks (Olson et al., 2017). These studies' potential utility in advising portfolio hedging and risk management remains limited. We undertake a rigorous examination of the hedging effectiveness of four main market indices in a "Carbon-Commodity-Finance" system to provide a comprehensive empirical investigation of this research question. This will provide investors with flexibility when it comes to devising effective hedging strategies (Jin et al., 2020a).

## 3 Methodology and data

### 3.1 Methodology

3.1.1 Dynamic spillover approach of Diebold and Yilmaz [DY] (2012)

Diebold and Yilmaz [DY] (2012), based on the generalized forecast error variance decomposition (GFEVD) of the estimated vector autoregression (VAR) model, is the cornerstone approach used to assess the connectedness mechanisms in this study. Compared with other methods, such as the Granger-causality test (Keppler and Mansanet-Bataller, 2010), the wavelet approach (Sousa et al., 2014), quantile autoregressive distributed lag model (Lahiani et al., 2017), and MGARCH techniques (Zhang and Sun, 2016), this spillover approach is able to evaluate the unidirectional and bidirectional spillovers (transmission and reception). It provides a more comprehensive interpretation of the strength and the source of contagion of each market into the whole system (Mensi et al., 2020). Following the DY (2012) spillover approach, the GFEVD is defined as follows:

$$\theta_{ij}^{H} = \frac{\sum_{h=0}^{H-1}\left(e_i'\Psi_h\Sigma e_j\right)^2}{e_j'\Sigma e_j \times \sum_{h=0}^{H-1} e_i'(\Psi_h\Sigma\Psi_h')e_i} = \frac{1}{\sigma_{jj}} \times \frac{\sum_{h=0}^{H-1}\left((\Psi_h\Sigma)_{ij}\right)^2}{\sum_{h=0}^{H-1}(\Psi_h\Sigma\Psi_h')_{ii}} \tag{1}$$

Where $\sigma_{jj}$ represents the standard deviation, $e_j$ is a selection vector with the $j_{th}$ element being 1 and the rest being 0. The $j_{th}$ series' contribution to the forecast error variance of the variable $i$ at the horizontal $h$ is defined by $\theta_{ij}^{H}$. Then, we standardize it by rows to obtain the following result:

$$\bar{\theta}_{ij}^{H} = \frac{\theta_{ij}^{H}}{\sum_{j=1}^{H}\theta_{ij}^{H}} \tag{2}$$

Where $\sum_{j=1}^{H}\bar{\theta}_{ij}^{H} = 1$ and $\sum_{i,j=1}^{n}\bar{\theta}_{ij}^{H} = n$. Consequently, DY (2012) prove that the total spillover is the relative contribution of other system variables to the prediction variance, as computed thus:

$$C^H = \frac{\sum_{i\neq j}^{n} \sum_{j=1}^{n} \bar{\theta}_{ij}^H}{\sum_{i,j=1}^{n} \bar{\theta}_{ij}^H} = \frac{1}{n} \sum_{i\neq j}^{n} \sum_{j=1}^{n} \bar{\theta}_{ij}^H \tag{3}$$

Furthermore, the directional spillovers (to) and vice versa (from) of a given variable $i$ to other system variables $j$, as well as the net spillovers of variable $i$, i.e., the difference between the directional spillovers of "to" and "from", are computed respectively in eq. (4):

$$C_{i\rightarrow\cdot}^H = \sum_{i\neq j}^{n} \bar{\theta}_{ij}^H, C_{i\leftarrow\cdot}^H = \sum_{j\neq i}^{n} \bar{\theta}_{ji}^H, C_{i,net}^H = C_{i\rightarrow\cdot}^H - C_{i\leftarrow\cdot}^H \tag{4}$$

3.1.2 Bilateral hedge ratios and portfolio weights

Hedge ratios and optimal portfolio weights can be estimated using a conditional variance. According to Kroner and Sultan (Kroner and Sultan, 1993), an investor should long/short $\$\beta$ position in asset $j$ to reduce the shock of a portfolio with \$1 long position in asset $i$. Then, the hedge ratio between two assets is defined as:

$$\beta_{ij,t} = \frac{h_{ij,t}}{h_{ij,t}} \tag{5}$$

Then, as described by Kroner and Ng (Kroner and Ng, 1998), we calculate the optimal portfolio weights of asset $i$ as below:

$$w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{jj,t} - 2h_{ij,t} + h_{ii,t}} \tag{6}$$

With

$$w_{ij,t} = \begin{cases} 0, & \text{if } w_{ij,t} < 0 \\ w_{ij,t}, & \text{if } 0 \leq w_{ij,t} \leq 1 \\ 1, & \text{if } w_{ij,t} > 1 \end{cases}$$

Where $h_{ij,t}, h_{ii,t}, h_{jj,t}$ represent the conditional variance of asset $i$ , conditional variance of asset $j$, and the conditional covariance between two assets volatility at time $t$, respectively. Thus, $1 - w_{ij,t}$ is the optimal weight of asset $j$. The estimation of $w_{ij,t}$ for each pair of two assets in this study is derived by referring the dynamic conditional correlations (DCC) GARCH framework used in the literature of Antonakakis et al. (Antonakakis et al., 2018b, 2020).

Finally, it is important to make a comparison between these two hedging methods, which is conducted by hedging effectiveness (HE), as follows:

$$HE = 1 - \frac{h_{\beta,w}}{h_{ii,jj}} \tag{7}$$

Where $h_{\beta,w}$ and $h_{ii,jj}$ denote the variance of the hedge and unhedged portfolio, respectively. Higher hedging ratio values indicate stronger hedging effectiveness, thus implying that the underlying investment policy is a superior hedging strategy (Mensi et al., 2020).

### 3.2 Data description

We employ daily closing price series covering various assets from three main markets, including carbon, commodity, and financial markets, which are listed in Table 1 along with the data sources. Our dataset is mainly from China, as it is a mega-economy and the world's largest carbon emitter, having established a national carbon trading market (Van der Hoeven, 2014). The sample period is January 7, 2015-December 31, 2021, yielding 1524 daily observations as dictated by data availability. Guangdong, as the earliest carbon trading pilot in China, has its carbon emission used as the carbon market variable. In terms of the commodity market, we adopt three energy variables, coal, oil, and gas, to represent different energy markets, while gold, silver, and copper are used to represent metal markets. In addition, we choose four different financial market indices to illuminate the price information in the financial market. Specifically, the CSI 300 Index, a capitalization-weighted stock market index, is considered as the behaviour of the stock market, while the RMB exchange rate is used to capture the foreign exchange market's dynamics. In order to ensure that some assets (oil and gas) are traded in the same currency, we convert foreign currencies to RMB based on the currency exchange rates using the US dollar as the base currency. Further, two points on financing green projects to help the transition to a green economy are considered, namely, new energy index stocks and green bonds.

Table 1 Description of the variables of the "Carbon-Commodity-Finance" system

| Primary Market | | Abbreviations | Index Name | Data Sources |
|---|---|---|---|---|
| Carbon Market | Guangdong Carbon Market | GDEA | Guangdong Carbon Allowance Prices | CSMAR [a] |
| Commodity Market | Energy Markets | COAL | Power Coal Futures | CSMAR |
| | | OIL | Brent Oil Futures | Investing.com [b] |
| | | GAS | Natural Gas Futures | Investing.com |
| | Metal Markets | GOLD | Gold Futures | CSMAR |
| | | SILVER | Silver Futures | CSMAR |
| | | COPPER | Copper Futures | CSMAR |
| Financial Market | Stock Market | CSIR | CSI 300 Index | Investing.com |
| | Foreign Exchange Market | CNY | RMB Exchange Rate | Investing.com |
| | Green Financial Markets | CGBI | China Bond Green Bonds (Full Price Index) | WIND [c] |
| | | CNI | CNI New Energy Index | WIND |

Notes: ([a]), ([b]), ([c]) denote the dataset website of http://www.csmar.com/, https://www.investing.com/, and http://www.wind.com.cn/.

The daily returns of the "Carbon-Commodity-Finance" system are determined by subtracting the logarithms of two consecutive prices, that is, $R_t = \ln{(P_t/P_{t-1})} \times 100$, where $P_t$ is the price at time $t$. Descriptive statistics are provided in Table 2. On average, the indices except for COPPER, CSIR, and CGBI have positive returns. As for the daily variance, GDEA has the highest variance compared to others, indicating the high volatility of the carbon market, followed by energy markets, while CGBI has the lowest variance. Furthermore, we find that the distributions of all return series are skewed and leptokurtic because the nonzero skewness statistics and all kurtosis statistics are greater than three. The augmented Dickey-Fuller (ADF) test confirms that all return series are stationary.

Table 2 Descriptive statistics of variables of the “Carbon-Commodity-Finance” system

| | Mean | Variance | Skewness | Kurtosis | JB | Q (20) | ADF |
|---|---|---|---|---|---|---|---|
| GDEA | 0.033 | 21.4 | -0.611 | 10.971 | 7737.218*** | 27.429*** | -14.226*** |
| COAL | 0.059 | 5.608 | -2.464 | 28.745 | 54010.235*** | 22.008*** | -9.679*** |
| OIL | 0.001 | 13.649 | 0.943 | 14.747 | 14036.098*** | 406.042*** | -18.345*** |
| GAS | 0.027 | 9.957 | 0.215 | 4.386 | 1233.429*** | 20.581** | -11.46*** |
| GOLD | 0.00005 | 1.539 | 0.128 | 3.027 | 586.126*** | 392.218*** | -19.649*** |
| SILVER | 0.001 | 2.719 | -0.041 | 5.938 | 2239.195*** | 473.379*** | -18.351*** |
| COPPER | -0.003 | 2.485 | -0.335 | 6.168 | 2444.337*** | 35.896*** | -11.163*** |
| CSIR | -0.019 | 2.167 | -1.025 | 6.521 | 2967.163*** | 27.338*** | -9.921*** |
| CNY | 0.002 | 0.075 | -0.180 | 3.787 | 918.738*** | 18.124** | -10.324*** |
| CGBI | -0.00017 | 0.008 | -0.495 | 13.350 | 11380.112*** | 498.332*** | -8.912*** |
| CNI | 0.002 | 4.159 | -0.765 | 3.094 | 756.725*** | 27.080*** | -9.704*** |

Notes: (***), (**), (*) denote significance level at 1%, 5% and 10%; Skewness: D'Agostino test(D'Agostino, 1970); Kurtosis: Anscombe and Glynn test(Anscombe and Glynn, 1983); JB: Jarque and Bera normality test(Jarque and Bera, 1980); Q (20): Fisher and Gallagher weighted portmanteau test(Fisher and Gallagher, 2012); ADF: Cheung and Lai augmented Dickey-Fuller test(Cheung and Lai, 1995).

## 4 Empirical results

This section presents connectedness mechanisms, the role of economic policy uncertainty on the spillover index, and the corresponding portfolio diversification of the “Carbon-Commodity-Finance” system. We first report the estimation findings for the total spillovers adopting the approach of DY (2012), followed by the analysis of directional spillovers, including the average “from”, “to”, and “net” spillovers, as well as the dynamic net directional results over time. Next, the cross-market connectedness frameworks are discussed to reveal the spillover linkages during the whole period. We then derive the role of economic policy uncertainty on the system-wide spillover index using a quantile-regression method. Furthermore, simplified bivariate portfolios are used to explore potential hedging opportunities.

### 4.1 Total spillovers

It is widely assumed that spillovers vary over time and that intermarket correlations may strengthen or diminish under uncertainty and unexpected shocks such as economic recessions, financial crises, political events, and disasters (Antonakakis et al., 2018a; Diebold and Yilmaz, 2012; Lahiani et al., 2021). Fig.1 shows the total spillovers for the full sample period, with a rolling window of 200 days and an ahead forecast horizon of 100 days, which following Baruník and Křehlík (Baruník and Křehlík, 2018). Judging from the given total average time-domain spillover index of 36.35%, market interdependence is not insignificant, but strong. In terms of overall trends, this total spillover index fluctuates from about 35% to almost 45% over time, providing market participants with significant information about the influence of various events in the political and financial spheres (Antonakakis et al., 2018b). It starts to show an increasing pattern due to China’s financial crisis and reaches its first peak in 2016 before the implementation of China's strict financial "deleveraging" regulation. It then falls to below 35% at the end of 2016, followed by two small swings in 2017, likely caused by the spike in oil prices and interest rate hikes of the US Federal Reserve System (Fed). Furthermore, the second phase of high spillovers is observed during the period between 2018 and 2020. A possible explanation for this continuity can be found in the events of Sino-US trade frictions and oil price crashes, which create uncertainty in the “Carbon-Commodity-Finance” system. Importantly, it also shows that the spillovers do not diminish immediately when the trade tension ends, but peak and persist until the end of 2021. Obviously, this increased spillovers because of the outbreak of the COVID-19 pandemic. The shocks caused by the rapid spread of the pandemic have brought dramatic impacts on global markets, but then decreases rapidly as China’s segregation and blocking policies significantly alter market demand and operating patterns. With the overall economic expectations moving toward a relative recovery, China proposed a carbon capping and carbon neutrality (dual carbon) strategy and established a national carbon emission trading market in March and July 2021, respectively. Thereafter, the spillover fluctuates smoothly at 30%-35%.

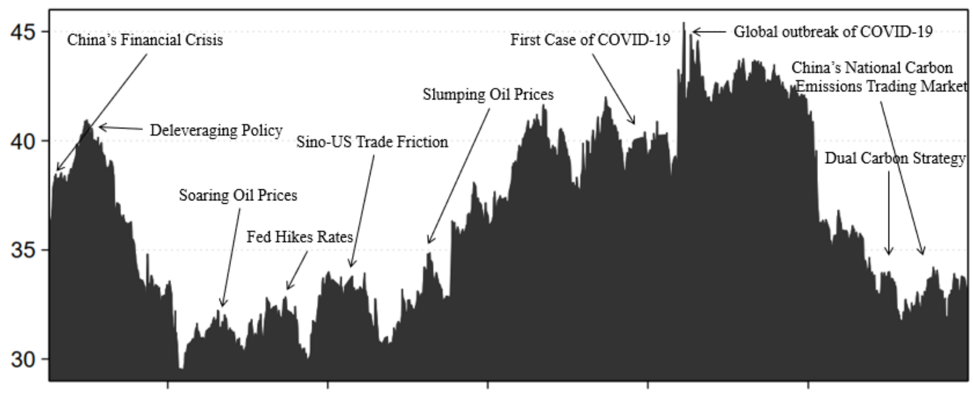



Fig. 1 Total dynamic spillovers

**4.2 Directional spillovers**

Fig. 2 provides a clearer description of directional spillover levels between carbon, commodity, and financial markets. Overall, the spillovers “to” (spillovers from one particular market to other markets) and “from” (spillovers from all other markets to one particular market) are positively correlated, which means that markets with high levels of outputs are also higher in inputs. Also, it reveals that carbon, financial, and commodity markets have stable dual-directional spillovers. Specifically, CSIR, CNI, and SILVER have relatively high spillovers in both from and to directions, implying that they have strong market influence in the system. COPPER and GOLD, although contributing less than SILVER, play non-negligible roles in the systemic spillovers. That is a key reason for the phenomenon that metal markets are now increasingly viewed as important components of investment portfolios (Mensi et al., 2020). However, CNY, CGBI, energy markets, and GDEA, have relatively low dual-directional spillovers with other markets, indicating the relatively weak linkages between them and other markets. In terms of GDEA, the low carbon market activity caused by loose allowances and wait-and-see sentiment of emission control firms may be one reason.

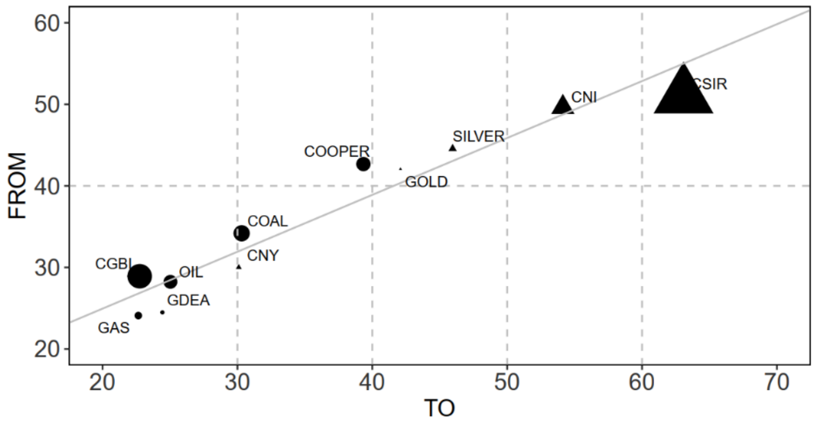



Fig.2 To, from and net directional spillovers

A positive (negative) net directional spillover indicates that the variable is a net transmitter (receiver) of spillovers, and it transmits gross volatility shocks to all other markets more than receives from them (Diebold and Yilmaz, 2012). Fig. 2 also shows the characteristics of the net directional spillovers in the "Carbon-Commodity-Finance" system, where positive and negative values are presented as triangles and circles, respectively. GDEA and all energy markets are net spillover receivers, as well as COPPER. While other metals of SILVER and GOLD are positive, which indicates that they are net transmitters. In terms of the financial market, CGBI is vulnerable to spillovers from other markets, and in contrast, CSIR, CNI, and CNY are net spillover transmitters. It is noted that the larger size of the triangles and circles, the bigger the absolute value of the directional spillovers indicated. Thus, the combinations (CSIR, CGBI) and (SILVER, COAL) are the largest net transmitters and net receivers of the financial market and commodity market, respectively, while GDEA exists only as a net receiver. The directional spillovers depicted above provide a useful description of average net directional spillover behaviour, but may overlook potentially important dynamic spillover movements. Therefore, it is necessary to further examine the changes in the net directional spillovers of the markets over time.

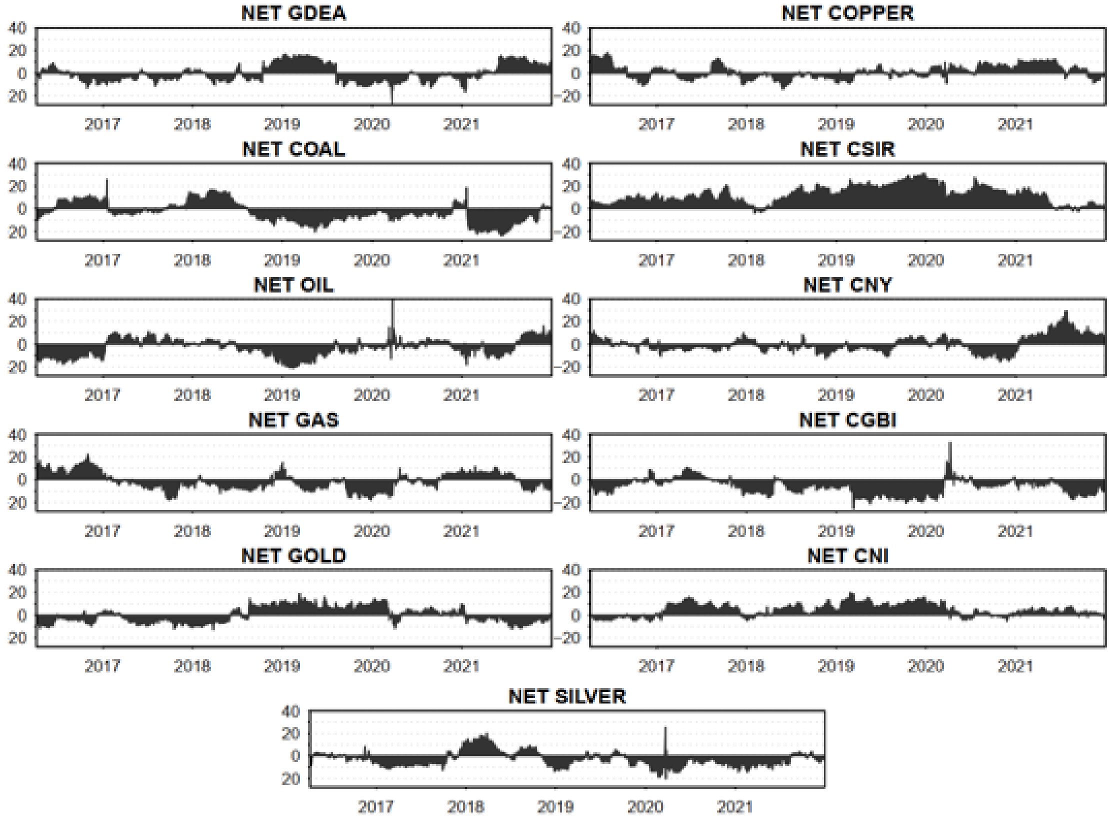



Fig.3 Net dynamic directional spillovers

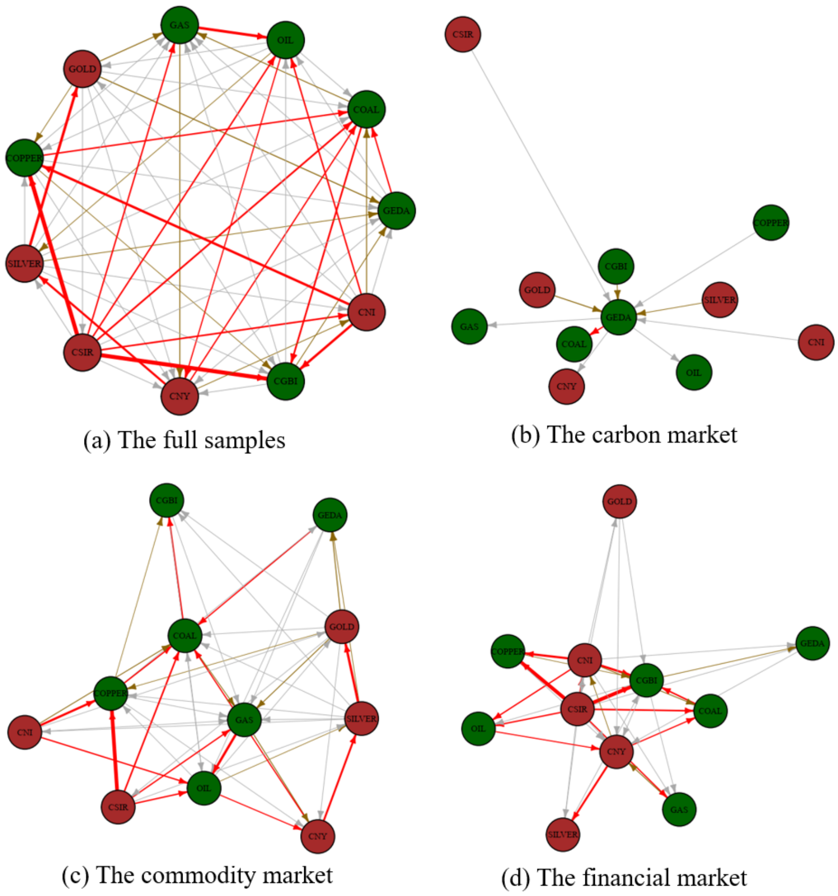
Clearly, many changes take place throughout time, some of which are well-described in Fig.3 as a more-or-less continuous evolution. The first observation is that the carbon market acts mainly as a net spillover receiver. Large fluctuations happen probably due to major uncertainties or crisis events. For example, China's dual carbon strategy proposed in early 2021 and the establishment of the national carbon emission trading market, not only change GDEA from a net receiver to a net transmitter, but also cause significant volatility in other markets such as COAL, OIL, and GAS. Regarding energy markets, before 2017, OIL is a net receiver while COAL and GAS are net transmitters, but then things change. GAS and COAL stay negative values for most periods except for the stages such as the Fed rates hike and the dual carbon strategy. OIL mainly acts as a transmitter during 2017-2018, with spillovers turning negative as oil prices decline and trade tension intensify after 2018, and positive in 2020 when the COVID-19 pandemic breaks out and in 2021 after the carbon market is established, respectively.

Metal markets undergo significant volatility. Prior to 2018, SILVER primarily acts as a net receiver. This happens probably because of the sensitive nature of SILVER relative to other markets. In 2018, SILVER switched from a net receiver to a net transmitter as demand declined due to the Fed rates hike and the U.S.-China trade war. With the implementation of a series of measures to stimulate economic growth, including tax cuts and accommodative monetary policy, negative market sentiment eased and volatilities tapered off. SILVER has a big swing in 2019 due to investment sentiments surge in the economic markets with successive Fed interest rate cuts, becoming a receiver again. Later, it faces another big volatility in 2020 due to the pandemic. Although GOLD also experiences several volatilities during the whole period, it acts as a net receiver except for the period during the second half of 2018 to 2021, which is related to the fact that it has both commodity and financial attributes and is used as a safe-haven and investment tool. Copper is an important basic raw material and is considered as a macroeconomic “barometer”. Thus, COPPER is more volatile, switching back and forth between acting as a net receiver and transmitter until 2020, while it acted mainly as a net transmitter during the COVID-19 pandemic.

In terms of the financial market, CSIR and CNI exhibit similar volatility trends as net spillover transmitters, mainly because CSIR reflects the overall trend of the A-share market, including the new energy sector. CNY reflects supply and demand in the foreign exchange market and is subject to market liquidity, thus acting as a net spillover receiver for most periods. But it changes to a large transmitter when the market experiences extreme pessimism, especially after the pandemic outbreak in 2020, it transmits much more shocks to other markets than receives from them. CGBI is a net transmitter in early 2017 and then becomes a receiver as it is subject to shocks from other markets during the trade tension and the pandemic. In summary, we can argue that although all these markets are at both the transmitting and receiving ends of the net directional spillovers, shocks are mainly transmitted into the “Carbon-Commodity-Finance” system through CSIR, CNI, and SILVER. This performance is more pronounced after the COVID-19 pandemic outbreak. However, it is still unclear about the aggregate information on how much each market contributes to the volatility of the pairwise markets. Thus, we further analyze their pairwise directional connections by using a network diagram, in net terms.

### 4.3 Connectedness network

Complex network theory describes the linkages of a system as a network composed of nodes and inter-nodes relationships to effectively characterize the structural connection in cross-market spillovers (Wang et al., 2020). Thus, a network diagram is used to identify the specific sources, directions, and magnitudes of spillover shocks transmitted (received) by each market in the system in this section (Geng et al., 2021), as shown in Fig. 5. The nodes are the 11 variables from the carbon, commodity, and finance markets. The arrows denote the directions of spillovers. The edges’ sizes show the magnitude of the pairwise connectedness, which is also reflected through the colors of the edges (red [strong], dark golden [medium], grey [weak]). The top figures depict the connectedness network for the full samples and the carbon market, while the bottom ones depict the network for the commodity and financial markets. The net spillover transmitters are represented by brown nodes, while the net spillover receivers are represented by dark green nodes.



(a) The full samples (b) The carbon market

(c) The commodity market (d) The financial market

Fig.4 Connectedness network framework

The net connectedness for all samples is presented in Fig.4 (a). Overall, financial markets (except CGBI) and metal markets (except COPPER) are the main transmitters, while energy markets and the carbon market, as well as CGBI and COPPER, are the main receivers. There are some extents of connectedness between different markets but the intensity manifests itself in different ways. Specifically, discuss the carbon market first. Markets except for energy markets and CNY are net contributors to the carbon market. Of these, CGBI is somewhat more impacts on GEDA. This illustrates the considerable role of green bonds play in the carbon market by financing environmentally friendly projects (Hammoudeh et al., 2020).

Meanwhile, the connection between energy markets of OIL, GAS, and COAL exists, but it is not as strong as expected. GAS receives net shocks from COAL, which are transmitted by OIL and then transmitted to OIL again, forming a small closed-loop transmission. In practice, OIL and GAS are very close fuel substitutes in terms of industrial production, which is one of the main reasons for the strong connectedness. It is noted that OIL is indirectly connected to SILVER via CNY. One explanation for this relationship is that higher oil prices spur inflation, bringing about great turmoil in the silver market. In terms of the intermetallic market, SILVER has a stronger connection with GOLD than COPPER because of their shared financial attributes. This finding is in line with previous evidence obtained in the preliminary analysis that suggests a strong volatility dependence between gold and silver (Dutta, 2018; Mensi et al., 2019).

Moreover, our study further argues that GOLD receives more shocks volatility from SILVER than it transmits, as the net pairwise value from SILVER to GOLD is positive.

The impact of the commodity market on the financial market is mainly through commodity price fluctuations and high leverage amplification effects. Nevertheless, CSIR and CNI have a much greater impact on the commodity and carbon markets than they receive. Especially for COPPER, as a major industrial feedstock, it is extremely vulnerable to stock market shocks. Moreover, the financial market has internal spillovers, with CSIR being the main transmitter. Therefore, we can assume that the contagion of shocks within the "Carbon-Commodity-Finance" system is mainly caused by the stock market. Furthermore, CSIR is a net shock transmitter to CNI and CGBI, implying the overall impact of the traditional stock market tends to spread to the green market, which is in line with Pham's findings(Pham, 2016). Due to the long-term property of green bonds, it does not exhibit sufficient stability in the short term, so CGBI is more vulnerable to contagion from other markets.

### 4.4 The role of economic policy uncertainty on system-wide connectedness

This section is to advance the empirical analysis by examining how spillovers in the "Carbon- Commodity- Finance" system is affected by economic policy uncertainty (EPU). The analysis of EPU is inspired by the increasing uncertainty generated by economic policies that are found to influence investment and management decisions(Reboredo and Uddin, 2016). To provide a more elaborated and holistic picture, we source for China's EPU index, obtained from the website http://www.policyuncertainty.com, to investigate how it drives the interconnectedness in the "Carbon-Commodity-Finance" system. Furthermore, we run a quantile regression model as Eq. (8) to analyze the role of EPU on the dynamic spillover indexes, as it enables for the examination of co-movement in different market conditions, including bearish (lower quantile), bullish (upper quantile), and normal (intermediate quantile) markets, which cannot be captured by other techniques (Koenker and Bassett Jr, 1978).

$$CI_t^{\tau} = \alpha_0^{\tau} + \alpha_1^{\tau} EPU_t + e_t^{\tau} \tag{8}$$

Where $CI_t^{\tau}$ represents the spillover index at $\tau^{th}$ quantile. $\alpha_1^{\tau}$ denotes the EPU impact coefficient of the connectedness at the $\tau^{th}$ quantile.

The estimated parameters of the total and net directional spillovers at varying quantiles are documented in Table 5 and vividly presented in Fig.6. We observe that most parameters are statistically significant for different quantile orders, indicating that EPU has a strong influence on the connectedness in the "Carbon-Commodity-Finance" system. The positive coefficients in the table imply that a rise in EPU increases the spillover index, while negative coefficients lead to a fall. Moreover, the null hypothesis of insignificance coefficients is firmly rejected in most cases (Adekoya, 2021). Take CNI as an example. The results show the irrelevance of EPU in shaping the new energy stock market at upper quantiles, which is possibly explained by the fact that EPU is not crucial in determining its returns in an economic upswing and therefore investors and policy makers have no need to protect markets from its risk.

Table 3 The role of EPU on the system-wide connectedness at different quantiles

| | $\tau = 0.1$ | $\tau = 0.3$ | $\tau = 0.5$ | $\tau = 0.7$ | $\tau = 0.9$ |
|---|---|---|---|---|---|
| Total spillovers | | | | | |
| TOTAL | 0.0167*** | 0.0183*** | 0.0213*** | 0.0170*** | 0.0104*** |
| | (0.0021) | (0.0010) | (0.0021) | (0.0021) | (0.0007) |
| Net spillovers of the carbon market | | | | | |
| NET GDEA | -0.0037* | 0.0019 | 0.0042*** | 0.0130*** | 0.0181*** |
| | (0.0019) | (0.0021) | (0.0013) | (0.0021) | (0.0034) |
| Net spillovers of the commodity market | | | | | |
| NET COAL | 0.0047 | -0.0207*** | -0.0193*** | -0.0250*** | -0.0227*** |
| | (0.0038) | (0.0019) | (0.0025) | (0.0027) | (0.0025) |
| NET OIL | 0.0078*** | 0.0166*** | 0.0052** | -0.0018 | -0.0123*** |
| | (0.0023) | (0.0015) | (0.0025) | (0.0018) | (0.0018) |
| NET GAS | 0.0077*** | -0.0014 | -0.0084*** | -0.0232*** | -0.0142*** |
| | (0.0018) | (0.0016) | (0.0022) | (0.0022) | (0.0028) |
| NET GOLD | 0.0220*** | 0.0274*** | 0.0297*** | 0.0323*** | 0.0195*** |
| | (0.0011) | (0.0014) | (0.0015) | (0.0021) | (0.0062) |
| NET COPPER | -0.0037 | -0.0003 | -0.0075*** | -0.0100*** | -0.0118*** |
| | (0.0034) | (0.0009) | (0.0012) | (0.0014) | (0.0021) |
| NET SILVER | 0.0216*** | 0.0183*** | 0.0111*** | 0.0039*** | -0.0110*** |
| | (0.0011) | (0.0018) | (0.0017) | (0.0009) | (0.0008) |
| Net spillovers of the financial market | | | | | |
| NET CSIR | 0.0248*** | 0.0213*** | 0.0286*** | 0.0315*** | 0.0205*** |
| | (0.0028) | (0.0012) | (0.0021) | (0.0021) | (0.0069) |
| NET CNY | -0.0214*** | -0.0193*** | -0.0161*** | -0.0158*** | -0.0346*** |
| | (0.0013) | (0.0011) | (0.0023) | (0.0021) | (0.0029) |
| NET CGBI | -0.0224*** | -0.0116*** | -0.0086*** | -0.0101*** | -0.0131*** |
| | (0.0028) | (0.0025) | (0.0029) | (0.0019) | (0.0021) |
| NET CNI | 0.0031*** | 0.0055*** | 0.0067 | 0.0010 | 0.0015 |
| | (0.0011) | (0.0015) | (0.0052) | (0.0016) | (0.0023) |

Notes: This table provides the parameter $\alpha_1^\tau$ and related estimated standard errors, i.e., the numbers in parentheses. (***), (**), (*) respectively indicate significance at the 1%, 5%, and 10% levels.

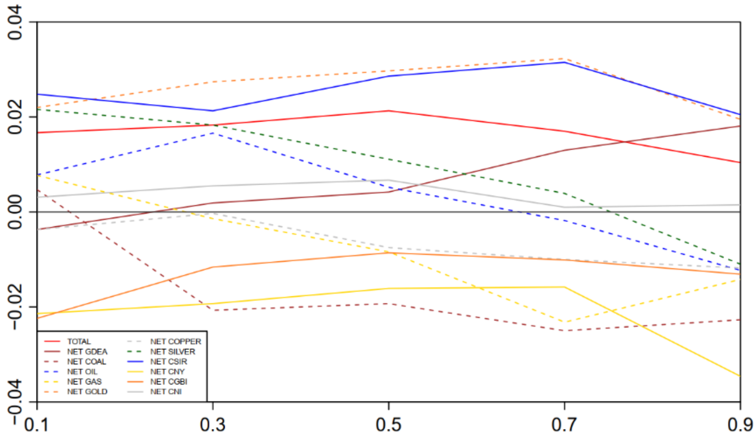



Fig. 5 Coefficients of EPU on the system-wide connectedness

Overall, the estimation results highlight a clear positive impact of EPU on the system-wide total spillovers at all quantiles, indicating that EPU is the notable driver of inter-system connectedness. Moreover, EPU positively affects GDEA, GOLD, and CSIR at all quantiles. As EPU increases, these three markets have greater influence in the system due to the rise of their net spillovers, providing investors and policy makers with investment and risk warnings information. In fact, EPU guides the stock market and gold market more strongly, which may be explained by the fact that CSIR and GOLD could be one cause of economic uncertainty. Moreover, EPU has a negative impact on COAL, GAS, COPPER, CNY, and CGBI, with COAL and CNY being the most negatively impacted. Thus, the increase in EPU makes them more sensitive to other markets. This means that they are likely to receive more shocks across the markets than they transmit, with COAL and CNY bearing the brunt. This finding is informative for these markets participants in that the changeable economic policy uncertainty should be taken into full account when they make investment and management decisions (Dai et al., 2021a). Interestingly, from the lower to the higher quantiles, the coefficients of EPU on COAL, GAS, and SILVER range from positive to negative. Similarly for OIL, and indeed, the role of EPU on oil prices is still under debate, with existing literature concluding both positive (Joëts et al., 2017) and negative effects (Mo et al., 2018), as well as insignificant effects (Reboredo and Uddin, 2016). Our results provide evidence that EPU has a positive impact on the oil market at lower quantiles, but a weakly negative impact on the oil market in the case of better economic conditions. Also, it should be noted that at lower quantiles, the impact of EPU on GDEA, COPPER, and CNI is negligible. A possible explanation is that when the market has a symmetric effect in the system, i.e., when the transmitter and received are offset, or when the market has a lower influence in the system, that markets are virtually immune to external economic and financial influences. They offer potential pathways for risk management, so investors could consider resorting to these assets to hedge their portfolios in times of financial, economic, or pandemic crises (Huynh et al., 2020).

### 4.5 Further analysis on the investment strategies

To the extent that we may further bolster our findings based on the connectedness mechanism and the role of EPU on it, we conducted a portfolio and hedging exercise. In particular, we create bivariate investment portfolios necessary to include CSIR (i.e., the largest transmitter of the financial market), SILVER (i.e., the largest transmitter of the commodity market), CGBI (i.e., the largest receiver of the system), and GDEA (i.e., the carbon market).

Table 4 summarizes the statistics of optimal portfolio weights and hedge ratios for the aforementioned four markets. Meanwhile, hedging effectiveness refers to the risk reduction that investors can achieve using portfolio weight or hedge ratio strategies (Antonakakis et al., 2020). The portfolio weights reflect the portions that needed to be invested in GDEA, SILVER, CSIR, and CGBI in any ￥1 portfolio. We note that portfolio investments in all assets, except for the portfolio weights between CGBI/other assets and CSIR/CNI, reduce the volatility of each paired asset due to the positive HE values. For all optimal portfolios, GDEA assumes less than 50% weight, indicating that investors should hold more other assets than the carbon market. For instance, in the GDEA/COAL portfolio, ￥0.38 should be invested in GDEA and ￥0.62 in COAL, which would reduce the volatility of GDEA and COAL by 84.37% and 40.36%, respectively. Generally, the weights of SILVER in the portfolios with other assets range from about 6% to 80% (except CGBI). CNY is a better portfolio choice when investors own less than 10% of SILVER, and GOLD, COAL, COPPER, CSIR as well as CNI are more effective in hedging risk when owning more SILVER. In terms of CSIR, when investors hold less than 50%, it is more beneficial to invest in metal markets, especially GOLD, otherwise, they should choose energy markets, where COAL outperforms OIL and GAS. One interesting point is that while CSIR transmits a lot of shocks to CNI, the latter is not effective in reducing the volatility of CSIR in a portfolio, but in turn, the former effectively hedges risks of CNI. Furthermore, CGBI is a notable finding that, when combined with other assets, significantly reduces their investment risk; however, few portfolios have been found to significantly reduce the investment risk of green bonds (Tiwari et al., 2022).

Table 4 Average portfolio weights $W_{ij}$, hedge ratios $\beta_{ij}$, and hedging effectiveness $HE$

| | $W_{ij}$ | $HE$ (%) | $\beta_{ij}, \beta_{ji}$ | $HE$ (%) |
|---|---|---|---|---|
| Panel A: GDEA | | | | |
| GDEA, COAL | 0.38 | 84.37, 40.36 | 0.01, 0.01 | -0.17, 0.06 |
| GDEA, OIL | 0.49 | 74.79, 60.48 | 0.05, 0.04 | 0.05, 0.38 |
| GDEA, GAS | 0.49 | 80.51, 58.11 | -0.04, -0.04 | 0.07, -0.10 |
| GDEA, GOLD | 0.21 | 94.83, 28.16 | -0.03, 0.00 | 0.32, 0.20 |
| GDEA, SILVER | 0.26 | 91.48, 32.94 | 0.09, 0.02 | -0.15, -0.14 |
| GDEA, COPPER | 0.27 | 93.97, 48.06 | 0.05, 0.01 | 0.00, 0.04 |
| GDEA, CSIR | 0.23 | 91.72, 18.26 | 0.04, 0.01 | -0.32, -0.50 |
| GDEA, CNY | 0.02 | 99.66, 2.72 | -0.50, 0.00 | 0.22, 0.08 |
| GDEA, CGBI | 0.00 | 99.96, -0.18 | 1.66, 0.00 | -0.09, 0.30 |
| GDEA, CNI | 0.35 | 87.33, 34.82 | -0.01, 0.00 | -0.22, -0.27 |
| Panel B: SILVER | | | | |

| | | | | |
|---|---|---|---|---|
| SILVER, COAL | 0.70 | 34.69, 68.34 | 0.18, 0.37 | 4.12, 7.63 |
| SILVER, OIL | 0.78 | 22.63, 84.59 | 0.03, 0.15 | 0.69, 0.80 |
| SILVER, GAS | 0.77 | 32.89, 81.68 | 0.00, 0.00 | -0.12, -0.01 |
| SILVER, GOLD | 0.38 | 65.29, 38.69 | 0.08, 0.04 | 0.79, 1.17 |
| SILVER, COPPER | 0.46 | 52.23, 47.74 | 0.27, 0.23 | 5.95, 6.82 |
| SILVER, CSIR | 0.42 | 59.35, 49.00 | 0.26, 0.19 | 3.29, 4.33 |
| SILVER, CNY | 0.06 | 97.49, 8.74 | -0.44, -0.01 | 0.59, 0.44 |
| SILVER, CGBI | 0.01 | 99.70, -0.17 | -0.45, 0.00 | -0.03, -0.45 |
| SILVER, CNI | 0.62 | 42.78, 62.6 | 0.14, 0.22 | 2.89, 4.17 |
| Panel C: CSIR | | | | |
| CSIR, COAL | 0.72 | 49.1, 80.33 | 0.13, 0.35 | 1.64, 3.46 |
| CSIR, OIL | 0.83 | 21.05, 87.47 | 0.04, 0.21 | 1.01, 0.34 |
| CSIR, GAS | 0.81 | 33.29, 85.48 | 0.01, 0.05 | 0.08, 0.21 |
| CSIR, GOLD | 0.45 | 67.1, 53.68 | -0.03, -0.02 | 0.30, -0.20 |
| CSIR, COPPER | 0.55 | 57.68, 63.10 | 0.12, 0.15 | 3.74, 2.22 |
| CSIR, CNY | 0.09 | 96.99, 12.74 | -0.8, -0.04 | 1.33, 2.14 |
| CSIR, CGBI | 0.01 | 99.62, -2.33 | -1.26, 0.00 | -0.61, 0.20 |
| CSIR, CNI | 0.92 | -2.86, 46.41 | 0.50, 1.09 | 56.23, 62.82 |
| Panel D: CGBI | | | | |
| CGBI, COAL | 1.00 | 2.53, 99.86 | 0.00, -1.14 | 0.00, 0.01 |
| CGBI, OIL | 1.00 | 0.06, 99.94 | 0.00, 0.88 | 0.00, 0.00 |
| CGBI, GAS | 1.00 | -1.45, 99.92 | 0.00, 0.27 | 0.00, 0.00 |
| CGBI, GOLD | 0.99 | 0.08, 99.47 | 0.00, 0.83 | 0.00, 0.00 |
| CGBI, COPPER | 1.00 | -7.17, 99.65 | 0.00, 0.98 | 0.00, 0.00 |
| CGBI, CNY | 0.89 | 23.14, 91.62 | 0.01, 0.10 | 0.00, 0.00 |
| CGBI, CNI | 0.99 | -0.19, 99.80 | 0.00, -1.03 | 0.00, 0.00 |

The bilateral hedges ratios and hedging effectiveness between each pairwise asset are also shown to help us better comprehend the investment implications of our study. The hedge is formed by either being long or short on both assets (Basher and Sadorsky, 2016). Table 4 reports that the average hedge ratios, indicating a ￥1 long position in one asset are protected by the average value of a long/short position in another asset (Tiwari et al., 2022). When the hedge ratio is positive, a short position in the asset should be added to the portfolio (Jin et al., 2020a). For example, hedge ratio estimates for GDEA/OIL of 0.05 show that a ￥1 long position in GDEA can be hedged by ￥0.05 investment in OIL, while 0.04 means taking a short position of about ￥0.04 in GDEA to hedge ￥1 investment in OIL, yielding HE values of about 0.05 and 0.38, respectively. It is noteworthy to mention the negative hedge ratios of GDEA/GAS, GDEA/GOLD, and GDEA/CNY. This arises when the asset pairs are negatively corrected (Tiwari et al., 2022). Thus, long positions in GAS, GOLD, CNY can also be an ideal hedge in the simplistic design of GDEA's hedging strategies. Our bilateral results also suggest that GDEA can act as a hedge against COAL, OIL, and COPPER. However, in general, the hedge ratios of GDEA are weak and sensitive to the instabilities in commodity and financial markets.

Arguably, the average ratio in the hedging instrument can be considered as a proxy for the transaction cost (Chen and Sutcliffe, 2012). Comparing the transaction costs and the hedging effectiveness of paired assets, in Table 4, the cheapest hedge for a ￥1 long position in SILVER is obtained with a short position in OIL (￥0.03), while the most expensive and effective is COPPER (￥0.27). Turning to CSIR, the transaction costs of hedging a ￥1 long position in CSIR suing a short position in other assets are quite varied. For instance, ￥0.01 in GAS and ￥0.50 in CNI are needed to hedge CSIR. Also, it can be found that CNI is the most expensive hedge against CSIR, but with the highest hedging effectiveness. Moreover, we observe that both CNY and GOLD can be regarded as good hedges for SILVER and CSIR. In terms of CGBI, although the portfolio created with it have been shown to help lower investment risk of other assets significantly, it is not an ideal hedge instrument when it comes to hedge rations, as it is difficult to hedge and ineffective for hedging other assets, in line with the findings of Tiwari et al. (Tiwari et al., 2022).

As a new era of carbon market participation dawns, the ensuing dynamics across markets become more complex, and it is particularly important for investors and policy makers to diversify their portfolios and manage market risks. Our empirical evidence provides new insights, which are detailed in the next section. Overall, the portfolio management analysis reveals that most mixed portfolios offer better hedging than individuals. Although the optimal hedge ratio strategy also reduces risk levels for some specific markets, the optimal portfolio weight strategy reduces risk more effectively by comparison, suggesting that the optimal weight strategy is the more preferred hedging strategy during our sample period.

## 5 Discussion on investment and management policy implications

It is desirable for governments in emerging economies to introduce a financial framework that allows carbon emissions to be valued and traded like other financial and commodity assets (Adekoya et al., 2021). However, the examination of the carbon market shows that it is a net receiver of shocks and that such shocks increase with economic uncertainty as to the positive impact of EPU on it, so it is economically indicative of its vulnerability to external market risks. Our findings could help policy makers to avoid risk contagion and maintain the stability of the carbon market. Green bonds and metal markets have the strongest linkages to the carbon market and are thus considered as the primary cause of the carbon market shocks, which should be carefully monitored. Also, it is important to note that the carbon market can transmit such shocks to energy markets, especially the coal market. Precautionary measures for energy market crises should be taken in a timely manner if the carbon market is turbulent. We also provide significant results with potential interest to investors, particularly risk-averse investors who are seeking risk reduction, that an investment portfolio including carbon assets could help reduce the volatility of one asset (Tan et al., 2020).

Given the environmental and economic implications of holding various commodities, it is imperative to examine the exact sources of contagion (Batten et al., 2015). Our results show that gold and silver markets are net transmitters to shocks in the system, while other commodities are net receivers. Although the dependence between metals and energy markets is not tight, other commodities will receive more shocks as contagion increases in the gold and silver markets during economic uncertainty events. Policy makers should adopt targeted measures to strengthen their prevention capabilities. In some circumstances, emerging economy investors may benefit from the ideal hedge in gold and silver because of their safe-haven role but not in every commodity market; silver, for example, is not an ideal hedge for natural gas. In our analysis, while energy markets have potential as a mechanism to diversify system shocks, it is advised that energy investors to hold more gold and silver assets than energy assets to reduce the instability and the uncertainty of energy markets. In addition, despite the tighter connectedness between silver and gold compared to copper, a mixed portfolio with copper offers a better hedge than gold. In short, investors in emerging economies can allocate and balance their portfolios appropriately by taking into the role of commodities to diversify investment risk.

Studying financial market spillovers is critical in an emerging economy, as the degree of its volatility has consequences for the stability of the whole system (Yavas and Dedi, 2016). Our results provide significant evidence that the stock market is the primary source of intra-system contagion, and that an unexpected occurrence in it may affect not only its volatility and returns, but also triggers liquidity crises exacerbating volatility in other markets. Policy makers need to be aware of extreme economic or unexpected events, such as stock market crashes, housing crises, and financial scandals, to prevent panic and contagion of risk. In order to reduce the overall risk without lowering the expected return, commodities should be an integral part of a diversified portfolio of stocks but in relatively small amounts. In addition to the stock market, green financial markets are becoming well-established investment instruments that have been gaining popularity, considered in our study as the new energy index stock and green bonds. They appear to offer another possible pathway for investors and policy makers in markets related to environmental protection to seek risk diversification and management. However, our results highlight that new energy index stock receives large shocks from the stock market and can be a good hedge for the stock market, but adding it into a portfolio cannot reduce stock market volatility. Moreover, green bonds are the most vulnerable assets to uncertain events. We corroborate green bonds have implications for investors in boosting environmentally friendly portfolios, as they can reduce the volatilities of other assets, but has negligible benefits in terms of hedging. Furthermore, our study also identifies a potential market shocks transmitter, i.e., the foreign exchange rate, which may offer information value for commodity investors. The foreign exchange rate of a commodity-exporting country may have an impact on the commodity prices of coal and silver. However, there is more evidence that the foreign exchange rate is influenced by commodities than the other way around (Clements and Fry, 2008). Therefore, emerging economies should emphasize exchange rate risk management and implement strict and orderly controls, as well as reasonably adopt financial instruments for effective hedging to gradually enhance the resistance of the foreign exchange market in extreme economic environments (Ding et al., 2021).

## 6 Conclusion

This study examines the pattern of shock transmission among commodity and financial markets as well as the carbon market in emerging economies. To achieve this, we apply a dynamic connectedness approach derived from VARs to model the interconnectedness of our prespecified network. It reveals the spillover hierarchy, magnitude, directions, and patterns in the "Carbon-Commodity-Finance" system. Furthermore, connectedness patterns of all series are examined in conjunction with the network diagrams. Then, whether and how economic policy uncertainty drives the system-wide spillover indices is investigated via a quantile regression approach. With more attention being paid to the interdependencies across these markets, how investors might benefit from portfolio diversification is becoming a topic issue. This makes it essential, last but not the least of this study, to construct bivariate portfolios that allow us better understand the hedging effectiveness of selected series that have a greater influence on the system.

Our findings provide the economic and management policy implications for investors and policy makers, however, there are still some limits. For instance, the "Carbon-Commodity-Finance" system has been divided into 11 markets due to data availability. A more detailed classification should improve the estimation of the connectedness of various markets and thus provide a better judgment of the investment strategies. Nevertheless, the description of such a system could be a great challenge. Another concern is the investment portfolios, a dynamic portfolio weights and hedge ratios could better reflect the volatilities at all periods as the average values, although important, do not provide the full picture (Antonakakis et al., 2018b). Future studies could scope out to the Asia-Pacific markets; alternatively, a joint investigation of developed and emerging economies is a promising direction.

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**References**

Adekoya, O.B., 2021. Predicting carbon allowance prices with energy prices: A new approach. Journal of Cleaner Production 282, 124519.

Adekoya, O.B., Oliyide, J.A., Noman, A., 2021. The volatility connectedness of the EU carbon market with commodity and financial markets in time-and frequency-domain: The role of the US economic policy uncertainty. Resources Policy 74, 102252.

Anscombe, F.J., Glynn, W.J., 1983. Distribution of the kurtosis statistic b 2 for normal samples. Biometrika 70, 227-234.

Antonakakis, N., Chatziantoniou, I., Floros, C., Gabauer, D., 2018a. The dynamic connectedness of UK regional property returns. Urban Studies 55, 3110-3134.

Antonakakis, N., Cunado, J., Filis, G., Gabauer, D., De Gracia, F.P., 2018b. Oil volatility, oil and gas firms and portfolio diversification. Energy Economics 70, 499-515.

Antonakakis, N., Cunado, J., Filis, G., Gabauer, D., de Gracia, F.P., 2020. Oil and asset classes implied volatilities: Investment strategies and hedging effectiveness. Energy Economics 91, 104762.

Baruník, J., Křehlík, T., 2018. Measuring the frequency dynamics of financial connectedness and systemic risk. Journal of Financial Econometrics 16, 271-296.
Basher, S.A., Sadorsky, P., 2016. Hedging emerging market stock prices with oil, gold, VIX, and bonds: A comparison between DCC, ADCC and GO-GARCH. Energy Economics 54, 235-247.
Batten, J.A., Szilagyi, P.G., Wagner, N.F., 2015. Should emerging market investors buy commodities? Applied Economics 47, 4228-4246.
Bloom, N., 2009. The impact of uncertainty shocks. econometrica 77, 623-685.
Bouri, E., 2015. A broadened causality in variance approach to assess the risk dynamics between crude oil prices and the Jordanian stock market. Energy Policy 85, 271-279.
Chang, C.L., McAleer, M., Wang, Y.A., 2018. Modelling volatility spillovers for bio-ethanol, sugarcane and corn spot and futures prices. Renew Sust Energ Rev 81, 1002-1018.
Chen, F., Sutcliffe, C., 2012. Better cross hedges with composite hedging? Hedging equity portfolios using financial and commodity futures. The European Journal of Finance 18, 575-595.
Cheung, Y.-W., Lai, K.S., 1995. Lag order and critical values of the augmented Dickey–Fuller test. Journal of Business & Economic Statistics 13, 277-280.
Clements, K.W., Fry, R., 2008. Commodity currencies and currency commodities. Resources Policy 33, 55-73.
D'Agostino, R.B., 1970. Transformation to normality of the null distribution of g1. Biometrika, 679-681.
Dai, P.-F., Xiong, X., Huynh, T.L.D., Wang, J., 2021a. The impact of economic policy uncertainties on the volatility of European carbon market. Journal of Commodity Markets, 100208.
Dai, X.Y., Xiao, L., Wang, Q.W., Dhesi, G., 2021b. Multiscale interplay of higher-order moments between the carbon and energy markets during Phase III of the EU ETS. Energy Policy 156.
Daskalakis, G., 2013. On the efficiency of the European carbon market: New evidence from Phase II. Energy Policy 54, 369-375.
de Menezes, L.M., Houllier, M.A., Tamvakis, M., 2016. Time-varying convergence in European electricity spot markets and their association with carbon and fuel prices. Energy Policy 88, 613-627.
del Rio, P., 2017. Why does the combination of the European Union Emissions Trading Scheme and a renewable energy target makes economic sense? Renew Sust Energ Rev 74, 824-834.
Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of forecasting 28, 57-66.
Ding, Q., Huang, J., Chen, J., 2021. Dynamic and frequency-domain risk spillovers among oil, gold, and foreign exchange markets: Evidence from implied volatility. Energy Economics 102, 105514.
Dutta, A., 2018. Impacts of oil volatility shocks on metal markets: a research note. Resources Policy 55, 9-19.
Fisher, T.J., Gallagher, C.M., 2012. New weighted portmanteau statistics for time series goodness of fit testing. Journal of the American Statistical Association 107, 777-787.
Geng, J.-B., Chen, F.-R., Ji, Q., Liu, B.-Y., 2021. Network connectedness between natural gas

markets, uncertainty and stock markets. Energy Economics 95, 105001.
Gronwald, M., Ketterer, J., Trück, S., 2011. The relationship between carbon, commodity and financial markets: A copula analysis. Economic record 87, 105-124.
Hammoudeh, S., Ajmi, A.N., Mokni, K., 2020. Relationship between green bonds and financial and environmental variables: A novel time-varying causality. Energy Economics 92, 104941.
Hammoudeh, S., Lahiani, A., Nguyen, D.K., Sousa, R.M., 2015. An empirical analysis of energy cost pass-through to CO2 emission prices. Energy Economics 49, 149-156.
Huynh, T.L.D., Hille, E., Nasir, M.A., 2020. Diversification in the age of the 4th industrial revolution: The role of artificial intelligence, green bonds and cryptocurrencies. Technological Forecasting and Social Change 159, 120188.
Jarque, C.M., Bera, A.K., 1980. Efficient tests for normality, homoscedasticity and serial independence of regression residuals. Economics letters 6, 255-259.
Ji, Q., Xia, T., Liu, F., Xu, J.-H., 2019. The information spillover between carbon price and power sector returns: Evidence from the major European electricity companies. Journal of Cleaner Production 208, 1178-1187.
Ji, Q., Zhang, D., Geng, J.-b., 2018. Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets. Journal of Cleaner Production 198, 972-978.
Jin, J., Han, L., Wu, L., Zeng, H., 2020a. The hedging effect of green bonds on carbon market risk. International Review of Financial Analysis 71, 101509.
Jin, J., Han, L., Wu, L., Zeng, H., 2020b. The hedging effectiveness of global sectors in emerging and developed stock markets. International Review of Economics & Finance 66, 92-117.
Joëts, M., Mignon, V., Razafindrabe, T., 2017. Does the volatility of commodity prices reflect macroeconomic uncertainty? Energy Economics 68, 313-326.
Keppler, J.H., Mansanet-Bataller, M., 2010. Causalities between CO2, electricity, and other energy variables during phase I and phase II of the EU ETS. Energy Policy 38, 3329-3341.
Koenker, R., Bassett Jr, G., 1978. Regression quantiles. Econometrica: journal of the Econometric Society, 33-50.
Kroner, K.F., Ng, V.K., 1998. Modeling asymmetric comovements of asset returns. The review of financial studies 11, 817-844.
Kroner, K.F., Sultan, J., 1993. Time-varying distributions and dynamic hedging with foreign currency futures. Journal of financial and quantitative analysis 28, 535-551.
Lahiani, A., Mefteh-Wali, S., Vasbieva, D.G., 2021. The safe-haven property of precious metal commodities in the COVID-19 era. Resources Policy 74, 102340.
Lahiani, A., Miloudi, A., Benkraiem, R., Shahbaz, M., 2017. Another look on the relationships between oil prices and energy prices. Energy Policy 102, 318-331.
McInerney, C., Bunn, D.W., 2019. Expansion of the investor base for the energy transition. Energy Policy 129, 1240-1244.
Mensah, J.T., 2014. Carbon emissions, energy consumption and output: A threshold analysis on the causal dynamics in emerging African economies. Energy Policy 70, 172-182.
Mensi, W., Hammoudeh, S., Nguyen, D.K., Kang, S.H., 2016. Global financial crisis and spillover effects among the US and BRICS stock markets. International Review of Economics & Finance 42, 257-276.
Mensi, W., Rehman, M.U., Vo, X.V., 2020. Spillovers and co-movements between precious

metals and energy markets: Implications on portfolio management. Resources Policy 69, 101836.
Mensi, W., Sensoy, A., Aslan, A., Kang, S.H., 2019. High-frequency asymmetric volatility connectedness between Bitcoin and major precious metals markets. The North American Journal of Economics and Finance 50, 101031.
Mo, D., Gupta, R., Li, B., Singh, T., 2018. The macroeconomic determinants of commodity futures volatility: Evidence from Chinese and Indian markets. Economic Modelling 70, 543-560.
Montagnoli, A., De Vries, F.P., 2010. Carbon trading thickness and market efficiency. Energy Economics 32, 1331-1336.
Olson, E., Vivian, A., Wohar, M.E., 2017. Do commodities make effective hedges for equity investors? Research in International Business and Finance 42, 1274-1288.
Paramati, S.R., Alam, M.S., Apergis, N., 2018. The role of stock markets on environmental degradation: A comparative study of developed and emerging market economies across the globe. Emerging Markets Review 35, 19-30.
Pham, L., 2016. Is it risky to go green? A volatility analysis of the green bond market. Journal of Sustainable Finance & Investment 6, 263-291.
Reboredo, J.C., 2013. Modeling EU allowances and oil market interdependence. Implications for portfolio management. Energy Economics 36, 471-480.
Reboredo, J.C., Uddin, G.S., 2016. Do financial stress and policy uncertainty have an impact on the energy and metals markets? A quantile regression approach. International Review of Economics & Finance 43, 284-298.
Reinhart, C.M., Rogoff, K.S., 2008. Is the 2007 US sub-prime financial crisis so different? An international historical comparison. American Economic Review 98, 339-344.
Rigobon, R., Sack, B., 2003. Spillovers across US financial markets. National Bureau of Economic Research Cambridge, Mass., USA.
Shen, Y., Shi, X., Variam, H.M.P., 2018. Risk transmission mechanism between energy markets: A VAR for VaR approach. Energy Economics 75, 377-388.
Sousa, R., Aguiar-Conraria, L., Soares, M.J., 2014. Carbon financial markets: a time–frequency analysis of CO2 prices. Physica A: Statistical Mechanics and Its Applications 414, 118-127.
Tan, X., Sirichand, K., Vivian, A., Wang, X., 2020. How connected is the carbon market to energy and financial markets? A systematic analysis of spillovers and dynamics. Energy Economics 90, 104870.
Tan, X.-P., Wang, X.-Y., 2017. Dependence changes between the carbon price and its fundamentals: A quantile regression approach. Applied Energy 190, 306-325.
Tiwari, A.K., Abakah, E.J.A., Gabauer, D., Dwumfour, R.A., 2022. Dynamic spillover effects among green bond, renewable energy stocks and carbon markets during COVID-19 pandemic: Implications for hedging and investments strategies. Global Finance Journal 51, 100692.
Van der Hoeven, M., 2014. CO2 emissions from fuel combustion-highlights 2014. IEA (International Energy Agency), Paris, France.
Vardar, G., Coşkun, Y., Yelkenci, T., 2018. Shock transmission and volatility spillover in stock and commodity markets: evidence from advanced and emerging markets. Eurasian Economic Review 8, 231-288.
Wang, Y., Guo, Z., 2018. The dynamic spillover between carbon and energy markets: New

evidence. Energy 149, 24-33.
Wang, Z., Gao, X., An, H., Tang, R., Sun, Q., 2020. Identifying influential energy stocks based on spillover network. International Review of Financial Analysis 68, 101277.
Wara, M., 2007. Is the global carbon market working? Nature 445, 595-596.
Wu, R., Qin, Z., 2021. Assessing market efficiency and liquidity: Evidence from China's emissions trading scheme pilots. Science of The Total Environment 769, 144707.
Yavas, B.F., Dedi, L., 2016. An investigation of return and volatility linkages among equity markets: A study of selected European and emerging countries. Research in International Business and Finance 37, 583-596.
Zeng, S., Jia, J., Su, B., Jiang, C., Zeng, G., 2021. The volatility spillover effect of the European Union (EU) carbon financial market. Journal of Cleaner Production 282, 124394.
Zhang, Y.-J., Sun, Y.-F., 2016. The dynamic volatility spillover between European carbon trading market and fossil energy market. Journal of Cleaner Production 112, 2654-2663.