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RESEARCH ARTICLE

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Examining the interactions of carbon, electricity, and natural gas markets

Abstract This paper analyzes the relationship between the carbon, electricity and natural gas markets in Europe. To identify the origin and paths of price transmission among these markets, we employ the Diebold Yilmaz spillover approach. To investigate the multiscale response to price signals, we use the time-varying parameter stochastic volatility vector autoregression system. The results provide evidence that the market for natural gas plays a significant role in setting carbon prices, which are negative in the short-term and positive in the medium term. These effects can, however, be negated by the Russia–Ukraine conflict, and the resulting market for natural gas does not exert any such shocks on the electricity market. Since the conflict, the electricity market has become a major price transmitter and has produced short-term positive but medium-term negative effects on the carbon market. Our results suggest that short- and medium-term policies should focus on avoiding price distortions and stabilizing markets.

Keywords carbon market, natural gas market, electricity market, response mechanism, price transmission

1 Introduction

As regions respond to climate change, governments have actively promoted the deployment of carbon markets to mitigate carbon emissions (Meyer and Schwarze, 2019; Zhou et al., 2022, 2023). The European Union Emissions Trading System (EU ETS) is the best example of a worldwide activity and contains an extensive scope, diverse market structures, and impressive impacts on CO_2 emissions. Carbon emission costs are applied to the power industry through the EU ETS, which allows or auctions carbon emission allowances to promote the utilization of efficient energy (Wang and Zhou, 2020, 2022). Currently, the clean energy source within the power industry that is widely used is natural gas (Wang and Yang, 2023). However, the price of natural gas is not certain, and fluctuations may affect the cost of power generation and hence electricity tariffs. Furthermore, electric and natural energy use are significant in energy use, where natural gas consumption is 500 billion m^3, whereas electricity generation is 4032.5 TWh (BP, 2022; Yang et al., 2022). These markets experience oscillations that determine the movement of the carbon market (Lin and Jia, 2019; Lin and Xu, 2021; Batten et al., 2021). Similarly, a change in the stoke price of carbon can also influence productive and economic activities through a fuel-switching effect (Mosquera-López and Nursimulu, 2019; Duan et al., 2021; Wu et al., 2023a). Hence, the interactions of the carbon, electricity, and natural gas markets facilitate the flow of price flax from one market to the other, which complicates the processes of signalization and response.

Recently, the Russia–Ukraine conflict has led to supply–demand discrepancies and hence instabilities in the natural gas market (Qiao et al., 2023). Such fluctuations can quickly spill over to other related markets, and can be disastrous in the sense that they destabilize the market. This is referred to as the ripple effect on the carbon, natural gas and electricity markets (Uribe et al., 2022; Chen et al., 2023). Under such circumstances, subsequent changes in demand for carbon allowances and the consumption of natural gas and electricity can be initiated, which add to the complexity of the interactions among these markets. The transmission mechanisms and sources of price variability need to be established in addition to the mechanisms through which markets respond to shocks to identify knock-on effects due to unexpected

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shocks. Such an understanding can assist in the capture of price signals and likely future trends in these three markets.

There has been an increasing trend in the literature on the subject of price transmission across several energy markets, including carbon, electricity and natural gas. The objective is to determine the function of each market and the channel vectors pointing at price transmission (Chuliá et al., 2019; Wu et al., 2023b; Ha et al., 2024). Some scholars have focused on establishing the relationships that exist between the natural gas and carbon markets. These studies have also shown that the natural gas market acts as a price transmitter, while the carbon market is a price receiver (Tan et al., 2020; Chen et al., 2024).

As a result of the Russia–Ukraine conflict, several authors have analyzed the effects of this conflict on price transmission. They reported that the Russia–Ukraine conflict can shift the dynamics and ways through which cost signals are relayed (Fang and Shao, 2022; Vellachami et al., 2023; Wang et al., 2023). Nevertheless, there is still a lack of research on reactions to price signals resulting from the Russia–Ukraine conflict. How this conflict is related to the response mechanism of the three markets is unknown. This knowledge would be useful in determining how shock-proof these markets are and in predicting trends in the market in light of shocks that are hard to anticipate.

Numerous studies have focused on the interactions among the carbon, electricity, and natural gas markets, taking into account nonlinear and quantile dependence (Tan and Wang, 2017; Chevallier et al., 2019; Duan et al., 2021). The interconnectivity of these markets depends on different conditions prevailing in the markets. For instance, Tan and Wang (2017) applied the quantile regression method to show that the natural gas market can exert a positive influence on the carbon market. However, this impact strongly depends on the volatility of the carbon markets. Through the use of Quantile-on-Quantile regression analysis, Duan et al. (2021) concluded that there was a negative effect of the natural gas market on the carbon market and that there was asymmetry between the two markets. However, the literature has neglected the dynamics and multiscale interdependency of these markets, such that the policies are reactive to changes in the markets rather than proactive in shaping the markets' decisions (Gong et al., 2021; Qiao et al., 2023). According to the cap-and-trade principle, enterprises modify short-term and long-term political and regulatory expectations of energy consumption and carbon allowance demand (Zhu et al., 2019; Dai et al., 2021). As a result, the calculations revealed the existence of a set of heterogeneous short- and long-term reactions in the carbon, electricity, and natural gas markets. To overcome the above limitation of constant interaction, we recommend the use of time-varying parameter-stochastic volatility-vector autoregression (TVP-VAR) to capture the dynamics of these interdependencies and their multiscale properties. In addition, this makes it possible to study the effects of external disturbances on the relationships among the three markets.

This paper seeks to address the following issues: (1) What are the characteristics of the price transmission and response mechanism of the carbon, electricity, and natural gas markets? (2) What are the response mechanisms of the carbon, electricity, and natural gas markets for different horizons? (3) How does the Russia–Ukraine conflict change the response mechanism of the three markets? This study provides information that is relevant to the literature. First, it expands the focus of the activity to the sources and channels of the price signals. It studies the changes over time of the carbon-electricity-natural gas response mechanism and contains specifics about the ripple effect sources and each market's response. Second, as opposed to previous studies focusing on the impact of extreme events on price transmission, this paper also analyses the reactions of the carbon, electricity, and natural gas markets at various time horizons. This is done to reflect the general direction of the answers during critical incidents and reveal short-term, mid-term, and long-term discrepancies. The results may prove useful in detecting carbon price signals and defining hedge and safe-haven assets by investment time-frequency in conditions of high uncertainty. Finally, after the Russia–Ukraine conflict, the electricity market is more responsive to carbon market signals than the natural gas market is. The reactions of the carbon market to the electricity market are greater in the medium-term than in the short term. The interaction between the market of natural gas and the market of carbon is characterized by short-term negative effects and medium-term positive effects due to the Russia–Ukraine conflict. However, external shocks do not have a strong impact on how the electricity market responds to the natural gas market; therefore, the natural gas price can be used to forecast electricity prices efficiently. In light of these different and often heterogeneous responses across various time horizons, policy changes are required for market players to implement at the right time.

The remainder of this paper is organized as follows: Section 2 provides data description and methodology for examining spillover effects. Section 3 introduces the results. Section 4 summarizes the results and provides policy implications for market participants.

2 Data and methodology

2.1 Time-varying parameter vector autoregressive model

The structural vector autoregression (SVAR) model has limitations in regard to capturing relationships that may have structural breaks. To address this issue, Primiceri (2005) proposed a TVP-VAR model, which was further optimized by Nakajima (2011). This methodology allows for the variation of parameters and stochastic volatility over time, enabling a more accurate estimation of short-term and long-term interactions in the carbon, electricity, and natural gas markets. By considering simultaneous, nonlinear, and time-varying relationships between variables, as well as the heteroscedasticity of shocks, this approach takes into account the effects of external shocks such as the COVID-19 pandemic and the Russia–Ukraine conflict. Consequently, this model has advantages in examining spillover effects among variables.

The basic SVAR can be written as follows:

$$\boldsymbol{A}y_t = F_1 y_{t-1} + \cdots + F_s y_{t-s} + \mu_t,\ t = s+1,\ldots,n, \tag{1}$$

where y_t is a $K\times 1$-dimensional column vector and where $\boldsymbol{A}, F_1 \ldots, F_s$ is a $K\times K$ coefficient matrix. Moreover, μ_t represents a $K\times 1$ structural shock and $\mu_t \sim (0,\Sigma\Sigma)$, where

$$\boldsymbol{\Sigma} = \begin{pmatrix} \theta_1 & 0 & \ldots & 0 \\ 0 & \theta_2 & \cdots & 0 \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \theta_K \end{pmatrix}. \tag{2}$$

$\boldsymbol{A}$ is a lower triangular matrix,

$$A = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{21} & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{K1} & \alpha_{K2} & \cdots & 1 \end{pmatrix}. \tag{3}$$

Equation (1) can be written more simply as:

$$\boldsymbol{Y}_t = \boldsymbol{B}_1 \boldsymbol{Y}_{t-1} + \cdots + \boldsymbol{B}_s \boldsymbol{Y}_{t-s} + A^{-1}\Sigma\varepsilon_t,\ t = s+1,\ldots,n, \tag{4}$$

where $B_i = A^{-1}F_i\ i = 1,\ldots,s$, and $\varepsilon_t \sim N(0, I_K)$. Equation (4) can be rewritten as:

$$\boldsymbol{y}_t = \boldsymbol{X}_t\boldsymbol{\beta} + A_t^{-1}\Sigma\varepsilon_t,\ t = s+1,\ldots,n. \tag{5}$$

$\boldsymbol{\beta}$ is a $K^2 s\times 1$ column vector. TVP-VAR can be simplified to:

$$y_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t,\ t = s+1,\ldots,n, \tag{6}$$

where β_t, A_t^{-1}, and Σ_t are the time-varying variables. To reduce the estimated parameters, the elements not equal to 0 or 1 of matrix A_t in Eq. (6) are stacked into a row vector: $\boldsymbol{\alpha}_t = (\alpha_{21}, \alpha_{31}, \alpha_{32}, \alpha_{41}, \ldots, \alpha_{K,K-1})'$ and $\boldsymbol{h}_t = (h_{1t}, \ldots, h_{Kt})'$, $h_{gt} = \ln\sigma_{jt}^2$, $j = 1,2,\ldots,\boldsymbol{K}, t = \boldsymbol{s}+1, \boldsymbol{s}+2,\ldots,n$.

The parameters to be estimated are assumed to follow a random walk process:

$$\begin{aligned} \boldsymbol{\beta}_{t+1} &= \boldsymbol{\beta}_t + \mu_{\beta t}, \\ \boldsymbol{\alpha}_{t+1} &= \boldsymbol{\alpha}_t + \mu_{\alpha t}, \\ \boldsymbol{h}_{t+1} &= \boldsymbol{h}_t + \mu_{ht}, \end{aligned} \quad \begin{pmatrix} \varepsilon_t \\ \mu_{\beta t} \\ \mu_{\alpha t} \\ \mu_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_\alpha & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix}\right), \tag{7}$$

where Σ_β, Σ_α, and Σ_h are diagonal matrixes that assume the initial values: $\beta_{s+1} \sim N(\mu_{\beta 0}, \Sigma_{\beta 0})$, $\alpha_{s+1} \sim N(\mu_{\alpha 0}, \Sigma_{\alpha 0})$, and $\mathrm{h}_{s+1} \sim N(\mu_{h0}, \Sigma_{h0})$.

Nakajima (2011) employed a Markov chain Monte Carlo (MCMC) model based on the Bayesian framework to estimate the TVP-VAR. The MCMC process was iterated 50,000 times, with the initial 5,000 iterations treated as a burn-in sample.

2.2 Time-varying spillover index model

We utilized the spillover index based on TVP-VAR (Antonakakis et al., 2020), which combines the approaches of Diebold and Yılmaz (2009, 2012, and 2014) and Koop and Korobilis (2014). This spillover index overcomes the limitations of window sizes in the VAR-based spillover index, as they can affect empirical results. To calculate the generalized forecast error variance decomposition (GFEVD) (Koop et al., 1996; Pesaran and Shin, 1998), we had to transform the TVP-VAR model into a TVP-VMA (time-varying moving average) model on the basis of Wold's representation theorem:

$$y_t = \sum_{h=0}^{\infty} A_{h,t}\varepsilon_{t-i}, \tag{8}$$

where $A_0 = I_K$, $\varepsilon_t \sim N(0, \Sigma_t)$. The H-step of GFEVD, which reflects the shock effects of series j on series i, can be written as follows:

$$\varphi_{ij,t}^{\text{gen}}(H) = \frac{\sum_{h=0}^{H-1}(e_i' A_{ht}\Sigma_t \boldsymbol{e}_j)^2}{\left(\boldsymbol{e}_j'\Sigma_t\boldsymbol{e}_j\right)\sum_{h=0}^{H-1}(\boldsymbol{e}_i' A_{ht}\Sigma_t A_{ht}'\boldsymbol{e}_i)}, \tag{9}$$

$$\mathrm{G}SOT_{ij,t} = \frac{\varphi_{ij,t}^{\text{gen}}(H)}{\sum_{j=1}^{K}\varphi_{ij,t}^{\text{gen}}(H)}, \tag{10}$$

where e_i is a $K\times 1$ dimension zero vector with unity at position i. $\sum_{j=1}^{K}\varphi_{ij,t}^{\text{gen}}(H) \neq 1$, so Diebold and Yilmaz (2009, 2012 and 2014) normalized it to unity by the row sum to scale GFEVD by $gSOT_{ij,t}$. The total directional connectedness of one variable from and to all the other variables can be defined as:

$$S_{i\leftarrow\cdot,t}^{\text{gen,from}} = \sum_{j=1,i\neq j}^{K} gSOT_{ij,t}, \tag{11}$$

$$S_{i\rightarrow\cdot,t}^{\text{gen,to}} = \sum_{j=1,i\neq j}^{K} gSOT_{ji,t}. \tag{12}$$

The net total directional connectedness of series i can be computed as $S_{i,t}^{\text{gen,net}} = S_{i\rightarrow\cdot,t}^{\text{gen,to}} - S_{i\leftarrow\cdot,t}^{\text{gen,from}}$. If $S_{i,t}^{\text{gen,net}} > 0$ or

$S_{i,t}^{\text{gen,net}} < 0$, then series i is a net transmitter or receiver, respectively, of shock effects. The total connectedness index (TCI) is defined as the average total directional connectedness:

$$gSOI_t = \frac{1}{K}\sum_{i=1}^{K} S_{i\leftarrow \cdot,t}^{\text{gen,from}} = \frac{1}{K}\sum_{i=1}^{K} S_{i\rightarrow \cdot,t}^{\text{gen,to}}. \tag{13}$$

A high TCI value indicates a high level of risk.

2.3 Data and descriptive statistics

To explore the dynamics of the electricity–carbon–natural gas nexus, we analyzed weekly continuous data from June 1, 2012, to June 24, 2022. This period corresponds to Phase III of the EU ETS, during which several reforms were implemented to promote carbon efficiency. As part of this effort, the EU decided to strengthen the EU ETS by introducing a market stability reserve in Phase III, resulting in a surge in carbon prices (Bruninx et al., 2020). Additionally, major crises such as the COVID-19 pandemic and the Russia–Ukraine conflict caused significant fluctuations in the three markets.

For the carbon market variable, we obtained weekly future prices of the Intercontinental Exchange European Union Allowance (EUA) from the WIND database. Intercontinental exchange Dutch title transfer facility natural gas futures (GAS) were used to represent the natural gas market. The electricity market was represented by Phelix Electricity Baseload futures prices (ELEC), which were sourced from Bloomberg. Figure 1 illustrates the dynamics of natural gas futures prices, EU carbon allowance futures prices, and electricity futures prices.

The graph clearly shows that before 2021, natural gas futures prices remained below 30 EUR/MWh. However, during the energy crisis in 2021, these prices sharply increased to 130 EUR/MWh by December 2021. Owing to the ongoing Russia–Ukraine conflict, natural gas prices have subsequently remained high. In March 2022, they reached nearly 200 EUR/MWh.

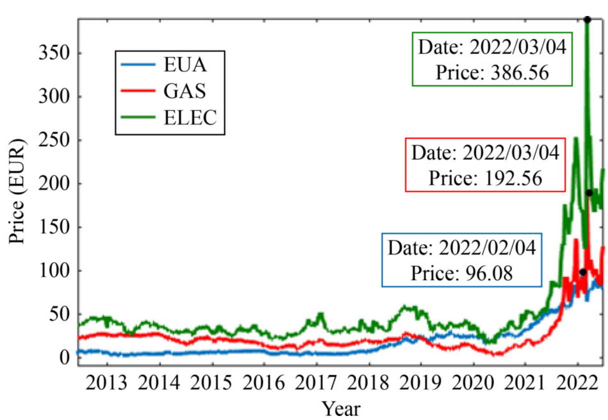

Fig. 1 Dynamics of GAS, EUA, and ELEC.

The EU ETS was established in 2005 and entered Phase III in 2013. However, carbon prices remained low, not exceeding 10 EUR/ton CO_2. From 2018 to 2019, there was an upward trend in carbon allowance prices, with values exceeding 20 EUR/ton CO_2. The COVID-19 pandemic, however, has led to a downward trend in carbon prices. In February 2022, there was another increase in carbon allowance prices, reaching a peak at 96 EUR/ton CO_2. From 2013–July 2015, electricity prices gradually declined, falling to as low as 25 EUR/MWh before gradually rising again. The COVID-19 pandemic has had an impact on electricity prices, as they gradually decreased from 40 EUR/MWh to 16 EUR/MWh in April 2020. The price of electricity subsequently increased in June 2020, exceeding 50 EUR/MWh in January 2021 and reaching 250 EUR/MWh by December 2021. Although a slight decrease was observed in January and February 2022, electricity prices increased to 400 EUR/MWh in March 2022 due to the Russia–Ukraine conflict. In May 2022, electricity prices decreased to 180 EUR/MWh.

The spillover of returns can reflect the transmission of information across the carbon, electricity, and natural gas markets (Gong et al., 2023). The continuously compounded returns of the three variables can be computed as $\ln P_t - \ln P_{t-1}$. The descriptive statistics for the returns of the carbon, natural gas, and electricity markets are shown in Table 1. The standard deviation indicates that ELEC is riskier than EUA and GAS are. Positive skewness values suggest that GAS and ELEC are positively skewed, whereas EUA is negatively skewed. The Jarque-Bera test confirms that EUA, GAS, and ELEC do not follow a normal distribution. To ensure the stationarity of the time series and apply the TVP-VAR model, the ADF test is used, which shows that the return series for the three variables are stationary.

Table 1 Descriptive statistics of EUA, GAS, and ELEC

Statistics	EUA	GAS	ELEC
Mean	0.0049	0.0032	0.0033
Median	0.0073	−0.0021	−0.0019
Maximum	0.2324	0.7126	1.0645
Minimum	−0.4129	−0.6338	−0.3233
Std. Dev.	0.0694	0.0844	0.0935
Skewness	−0.9688	0.7109	3.2312
Kurtosis	8.1283	20.8160	36.1585
Jarque–Bera	656.162	6974.280	24917.290
Probability	0.0000	0.0000	0.0000
ADF	−22.514***	−19.007***	−24.241***

Notes: a) *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. b) ADF is the augmented Dickey–Fuller test used to test the unit root (Fuller, 1979).

3 Results

3.1 Static spillovers across carbon, electricity, and natural gas markets

The average connectedness results are presented in Table 2. The “TO” column shows the total spillover effects from one specific market to all other markets, whereas the “FROM” row indicates the total spillover effects received from all other markets in one specific market. The “NET” row represents the difference between “TO” and “FROM.” Each market’s contribution to the forecast error variance is indicated by the rows, while the columns show the effect of a specific market on all other markets individually. The diagonal element reveals that the volatility of a particular market is influenced by its own shocks, whereas the off-diagonal elements describe the contribution of this market to the returns of other markets (FROM) and the contribution of other markets to this market’s returns (TO). In summary, the TCI is equal to 29.80%, indicating that, on average, 29.80% of the forecast error variance within this network can be explained by the spillover effects from all other markets. The GAS acts as the spillover transmitter with a net contribution of 3.83%, whereas the EUA and ELEC are spillover receivers with net values of −2.67% and −1.16%, respectively. This result is consistent with the findings of Man et al. (2024), who also identified the carbon market as the net receiver. The results suggest that the carbon return is more sensitive to spillovers from the natural gas return. The EUA has the lowest return spillover (14.05%) to other markets, whereas GAS has the highest return spillover (25.15%) to other markets. Furthermore, GAS contributes more to ELEC (15.50%) than to EUA (9.66%), indicating that GAS is more susceptible to the volatility of EUA.

Figure 2 illustrates the price transmission network of GAS, EUA, and ELEC. The blue nodes represent the net transmitters, whereas the yellow nodes denote the net receivers. The thickness of the directional arrows indicates the intensity of the net-pairwise spillovers. The EUA receives shocks from the GAS and ELEC, making it the net receiver. ELEC received the shock from GAS and transmitted it to EUA. Conversely, the GAS acted as the net transmitter, transmitting shocks to the EUA and ELEC. The largest directional price transmission occurs between GAS and ELEC, indicating that the natural gas market plays a significant role in fluctuations in the electricity market.

Table 2 Average dynamic connectedness

	EUA	GAS	ELEC	FROM
EUA	83.28	9.66	7.06	16.72
GAS	8.01	78.67	13.32	21.33
ELEC	6.05	15.50	78.45	21.55
TO	14.06	25.16	20.38	TCI
NET	−2.67	3.83	−1.16	29.80

3.2 Dynamic spillover across the carbon, electricity, and natural gas markets

3.2.1 Dynamic total spillovers

Figure 3 shows the intertemporal evolution of the total spillover index. Notably, the values of the total spillover index varied considerably between 7% and 50% across the sample periods. During early 2013, the total spillover index oscillated at a very high level, peaking at approximately 34%. This high level can be attributed to the new phase of the EU ETS, where the free carbon allowances of the power sector were cancelled and power enterprises participated more actively in carbon trading. However, the total spillover index reached a trough in 2015. It peaked in 2020, which can be attributed to the COVID-19 pandemic. Additionally, the most significant spike was observed in 2022, when the Russia–Ukraine conflict broke out. These results indicate that the increasing spillover index is responsive to external shocks. In particular, the rise in the connectedness among the carbon, natural gas, and electricity markets during major events highlights the contagion effects in these markets.

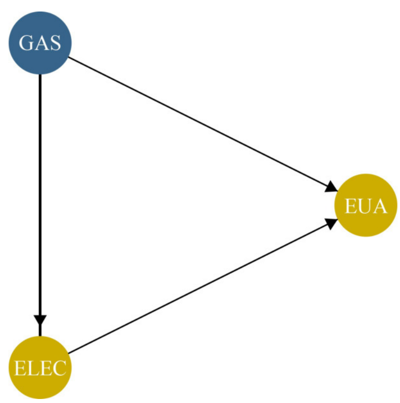

Fig. 2 Network of price transmissions of GAS, EUA, and ELEC.

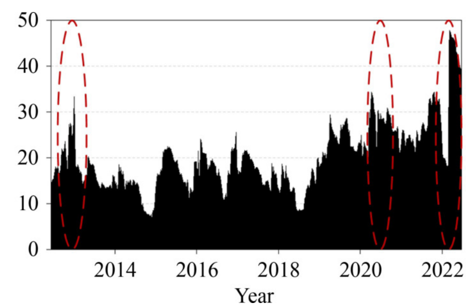

Fig. 3 Dynamic total spillover index.

3.2.2 Dynamic net spillovers

This paper examines both the dynamics of the total spillover index and the changing role of a specific market. Figure 4 presents the time-varying net total directional spillover, which was used to investigate whether the roles of the three markets remained consistent throughout the sample periods. Importantly, positive (negative) values indicate the net transmitting (receiving) role. Consequently, the GAS acted as the net transmitter for almost the entire duration of the sample period. In particular, in 2013, the net positive spillover index was greater than that in the other periods, which can be attributed to the removal of free carbon allowances for the power sector in Phase III of the EU ETS. Unlike GAS, the general roles of EUA and ELEC were unclear throughout the entire sample. At the beginning of 2013, the ELEC acted as a significant net shock transmitter, whereas the EUA functioned as a net shock receiver. These results suggest that the power sectors increased their demand for natural gas to reduce carbon emissions. The COVID-19 pandemic has altered the roles of the three markets. GAS and ELEC have transitioned from being net transmitters to receivers, whereas EUA has shifted from a net receiver to a net transmitter, indicating that the carbon market has become a source of risk. However, the net spillover of the carbon market is declining, which aligns with the findings of Jiang et al. (2023). In 2021, with global economic recovery, natural gas prices experienced a significant surge. GAS became a major net shock transmitter, whereas ELEC and EUA served as net shock receivers. Toward the end of 2021, EUA acted as the net shock transmitter, whereas GAS and ELEC functioned as net shock receivers. This may be due to a shortage in the natural gas supply, leading enterprises to resort to using more fossil fuels and consequently increasing the demand for carbon allowances. The Russia–Ukraine conflict caused ELEC and GAS to transition from being receivers to being transmitters, whereas EUA transitioned from being transmitters to being receivers. Additionally, the net spillover index of ELEC exceeded that of GAS during the Russia–Ukraine conflict, indicating that the electricity market played a dominant role as a shock transmitter.

We conducted an analysis of the time-varying net pairwise directional spillovers among the carbon, electricity, and natural gas markets, as depicted in Fig. 5. In the statements that follow, a positive value indicates that the former market has greater effects on the latter. The net pairwise spillover index between GAS and EUA, as well as between GAS and ELEC, exhibited fluctuations ranging between −20% and 20%. The net pairwise spillover index between EUA and ELEC fluctuated between −60% and 20%. In 2013, EUA served as the net recipient of shocks from GAS and ELEC, whereas GAS acted as the net transmitter of shocks to EUA and ELEC. ELEC acted as the net transmitter of shocks to the EUA but served as the net recipient of shocks from the GAS. During the COVID-19 pandemic, EUA emerged as the net transmitter of shocks to ELEC, and ELEC became the net transmitter of shocks to GAS. During the Russia–Ukraine conflict, the EUA played the role of the net transmitter of shocks to GAS and ELEC. The GAS, on the other hand, acted as the net transmitter of shocks to the ELEC throughout the

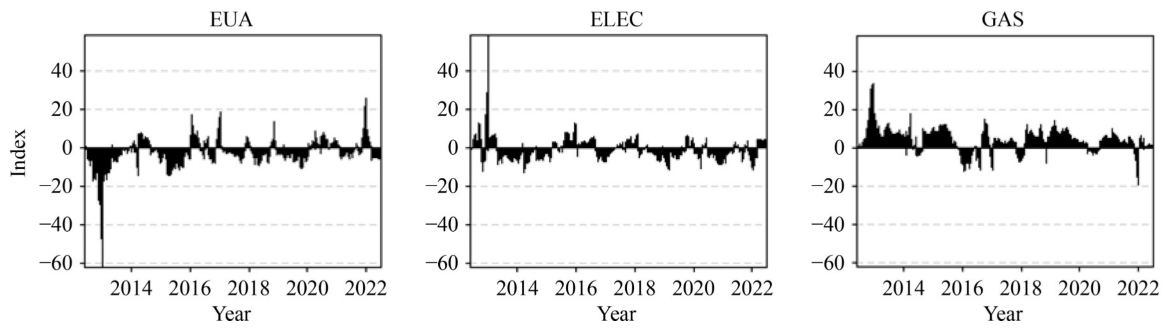

Fig. 4 Time-varying net total directional spillovers.

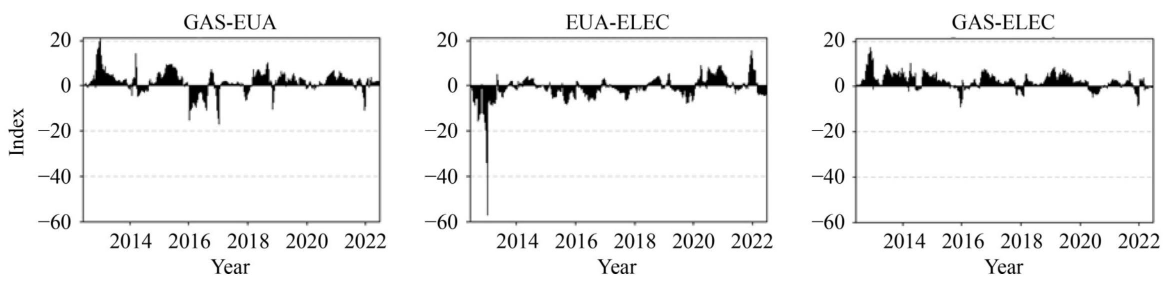

Fig. 5 Time-varying net pairwise directional spillovers.

sample period, indicating the dominant risk source of the natural gas market for the electricity market.

Figure 6 shows the total pairwise spillovers among the carbon, electricity, and natural gas markets. The total pairwise spillover between GAS and ELEC exceeds that between GAS and EUA, as well as between ELEC and EUA, indicating the increasing reliance on natural gas for power generation. Notably, there was a significant increase in total spillovers between EUA and ELEC, as well as between GAS and ELEC, during the COVID-19 pandemic. However, the weak spillovers between GAS and EUA during the same period suggest the potential for diversification opportunities to be exploited. This might be attributed to enterprises curtailing production due to the economic recession, which Europe has sought to counteract by accelerating its energy transition. Consequently, a strong spillover effect between GAS and ELEC was observed during the COVID-19 pandemic. Since the onset of the pandemic, the total pairwise spillovers between GAS and EUA, as well as between EUA and ELEC, have remained robust. This can be attributed to the EU's proactive measures in advancing its energy transition since 2020. In contrast, there was a decline in the spillover between GAS and ELEC. This decline can be attributed to enterprises increasing their demand for alternative energy sources to replace the costlier natural gas.

3.3 Response mechanism of the carbon, electricity, and natural gas markets

We utilized the TVP-VAR model to examine the dynamic spillover effects among the carbon market, natural gas market, and electricity market. This model allows us to incorporate the directions and magnitudes of these spillovers. Additionally, we employed specific time point impulse responses to analyze the effects of external shocks on the nexus of these markets. The selection of the optimal lag order for the TVP-VAR model was based on the Akaike information criterion (AIC), with a lag order of 2 chosen.

3.3.1 Results based on Markov chain Monte Carlo (MCMC) simulation

The MCMC simulation was iterated a total of 50,000 times (M = 50,000). To ensure the stability and robustness of the results, we treated the initial 5,000 iterations as a burn-in sample. Table 3 shows the inefficiency factor values of $(\Sigma_\alpha)_1$ and $(\Sigma_\alpha)_2$ were computed to be 198.34 and 141.65, respectively. The inefficiency factor measures how well the MCMC chain mixes, and in this case, a factor of approximately 200 suggests that we obtain approximately 250 uncorrelated samples (M/200). This number of uncorrelated samples is considered sufficient for posterior inference. The convergence of the simulation results can be confirmed by assessing Geweke's CD statistics. If the sequence of the MCMC sampling is stationary, Geweke's CD statistics should converge in distribution to a standard normal. In our case, the values of Geweke's CD indicate that the simulation results are significant at the 95% confidence level. Therefore, we cannot reject the null hypothesis of convergence with the posterior distribution, confirming the reliability of the results. Figure 7 presents the estimation results of the sample autocorrelation, sample paths, and posterior distribution. The sample autocorrelation coefficient

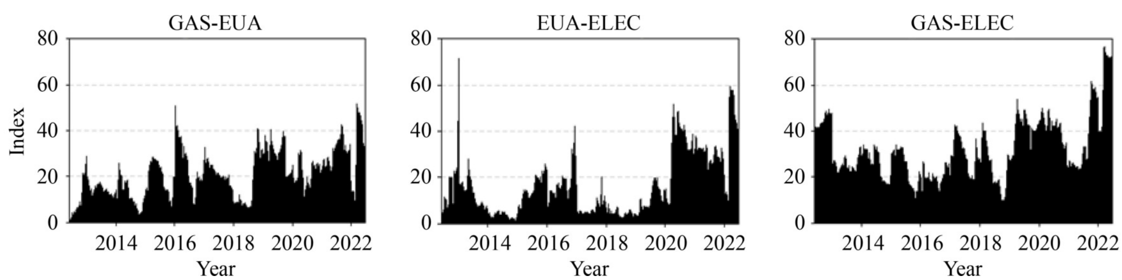

Fig. 6 Total pairwise spillover indices.

Table 3 Test results for stability and robustness

Parameter	Mean	Stdev.	95%L	95%U	Geweke's CD	Inefficiency factor
$(\Sigma_\beta)_1$	0.0023	0.0003	0.0018	0.0028	0.789	27.62
$(\Sigma_\beta)_2$	0.0023	0.0003	0.0018	0.0029	0.483	32.70
$(\Sigma_\alpha)_1$	0.0074	0.0029	0.0038	0.0148	0.003	198.34
$(\Sigma_\alpha)_2$	0.0055	0.0017	0.0033	0.0096	0.425	141.65
$(\Sigma_h)_1$	0.3043	0.0415	0.2312	0.3920	0.496	45.90
$(\Sigma_h)_2$	0.2528	0.0387	0.1804	0.3343	0.251	61.29

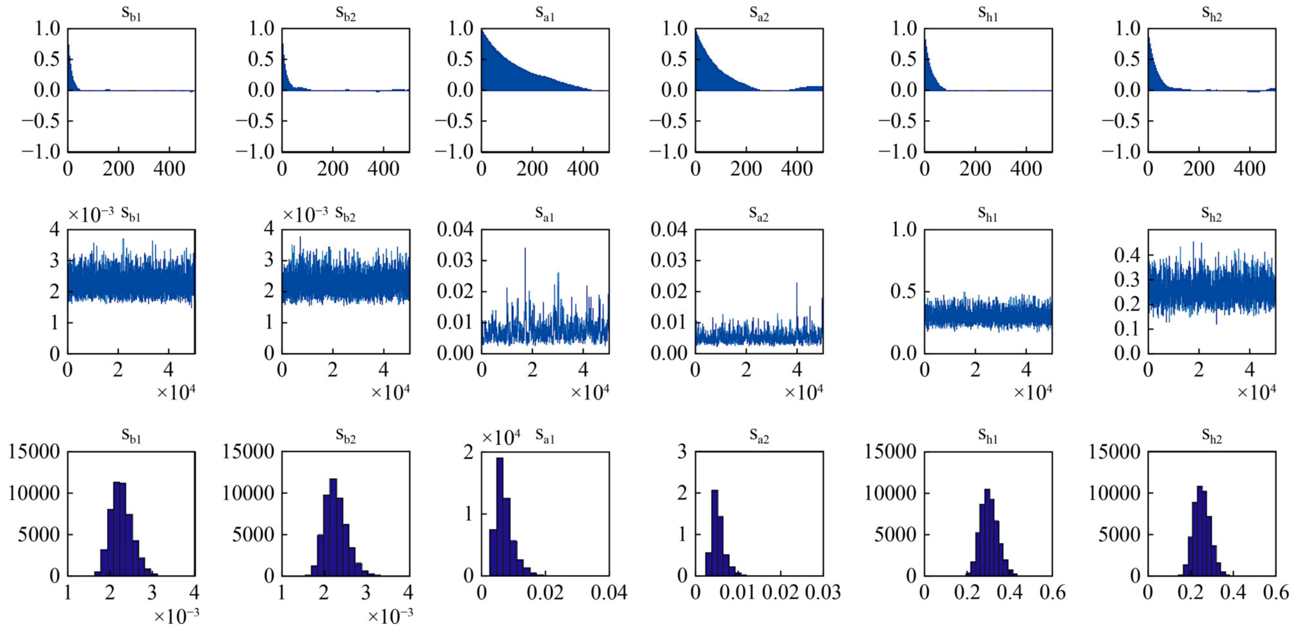

Fig. 7 Dynamic simulation paths of six parameters.

decreases dramatically to 0, indicating that the method effectively generates uncorrelated sample information. The fluctuations in the sample paths are relatively stable, providing further evidence for the effective simulation of the parameter distribution.

3.3.2 Simultaneous time-varying interactions among EUA, GAS, and ELEC

Figure 8 illustrates the interconnectedness between EUA, GAS, and ELEC. Figure 8(a) shows that an increase in GAS results in a positive effect on EUA. This could be attributed to the rise in production costs for enterprises caused by escalating natural gas prices. To mitigate these costs, enterprises shift to coal, which has lower costs but higher carbon emissions. Consequently, there is an increased demand for carbon allowances and a subsequent rise in carbon prices. The diminishing positive effects over time can be attributed to the growing use of clean energy as a substitute for natural gas. During the COVID-19 pandemic, the positive effects of GAS on EUA further weakened as enterprises reduced production and demand for natural gas due to exorbitant prices. Similarly, during the Russia–Ukraine conflict, the positive effects of GAS on EUA were minimal.

Figure 8(b) shows that an increase in the GAS yields an increase in the ELEC. This can be attributed to natural gas being a significant fuel source in the EU power system. Rising natural gas prices lead to increased electricity generation costs, thereby increasing the price of electricity. The positive simultaneous effect of the European carbon market on the electricity market is shown in Fig. 8(c), corroborating the findings of Andrianesis et al. (2021). From 2012 to 2014, the positive effects of EUA on ELEC declined. However, subsequently, EUA had stronger effects on ELEC. This can be explained by the adoption of more stringent approaches to allocating carbon allowances by the European Commission. Consequently, the supply of carbon credit decreased, resulting in increased positive effects. Following the outbreak of the Russia–Ukraine conflict, the positive effects of the carbon market on the electricity market remained high.

3.3.3 Time-varying impulse responses for different horizons

An equal-interval impulse response function was employed to analyze the spillover effects among the natural gas market, carbon market, and electricity market at varying lag periods. Specifically, we analyzed the one-week ahead (short-term), two-week ahead (medium term), and three-week ahead (long-term) periods. Figures 9–11 present the evolving nexus among GAS, EUA, and ELEC at these different time horizons.

Figure 9 illustrates the dynamic relationship between the EUA and the GAS. In the short-term, GAS had weak and negative effects on EUA before 2016, but these negative effects increased after 2016. This can be attributed to the increasing proportion of natural gas in energy consumption. However, the negative effects decreased during the COVID-19 pandemic because of reduced production by enterprises aiming to reduce costs.

According to Baur and McDermott (2010) , an asset that has a negative relationship with other assets during normal periods can be considered a hedge. During extreme periods, this negative interaction signifies safe

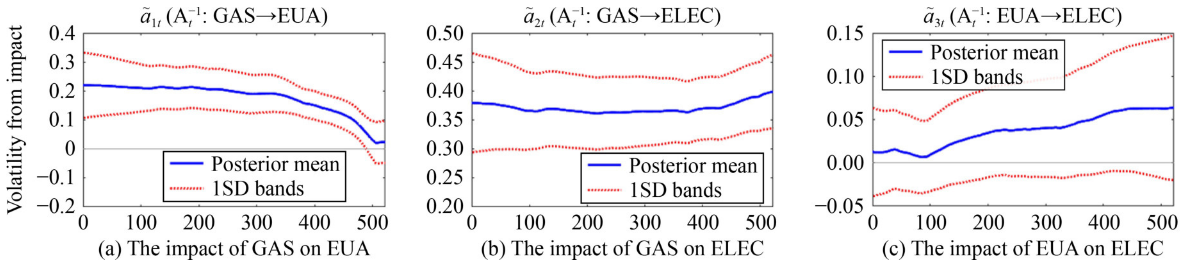

Fig. 8 The simultaneous connectedness between EUA, gas, and electricity.

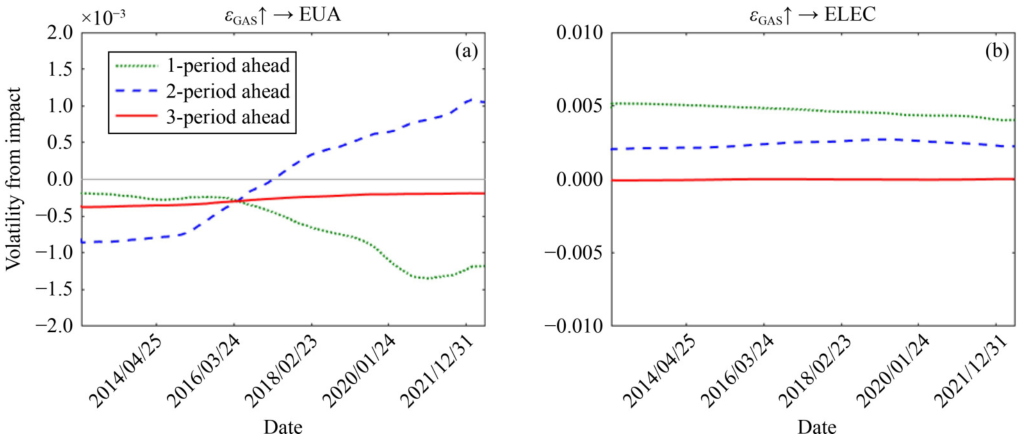

Fig. 9 Equal-interval impulse responses of EUA (a) and ELEC (b) to the GAS.

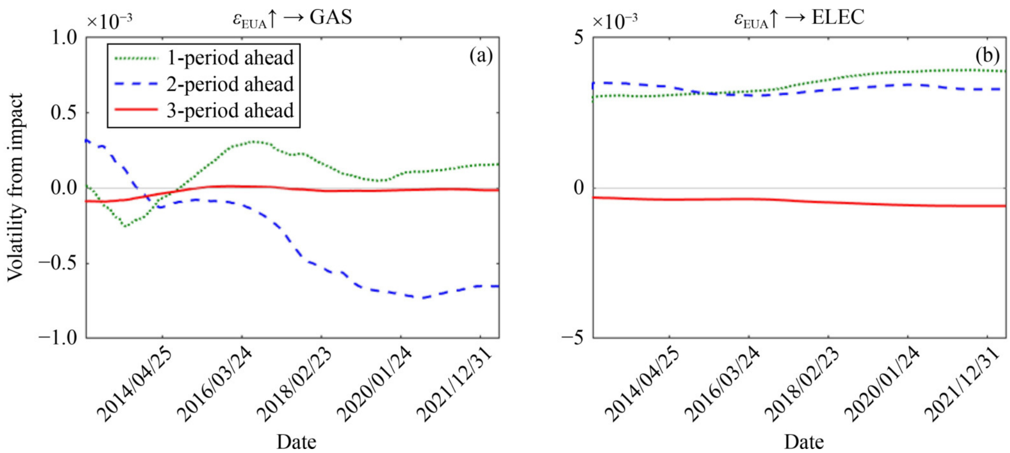

Fig. 10 Equal-interval impulse responses of GAS (a) and ELEC (b) to EUA.

haven properties. In the medium term, GAS initially had a negative influence on EUA, but the negative effects became positive after 2017. These positive effects showed an increasing trend, particularly during the Russia–Ukraine conflict, and remained high. This was due to rising natural gas prices, which led enterprises to adjust their production strategies and increase their demand for fossil energy. In contrast to the short- and medium-term effects, GAS had long-term negative effects on EUA due to restrained production. This suggests that carbon futures can serve as both short-term and long-term hedges and safe havens for natural gas futures.

With respect to the response of ELEC prices to GAS, GAS had a positive influence on ELEC in the short and medium terms. The positive effects remained stable during these time horizons. This can be attributed to the significant share of natural gas in power generation, which results in higher costs and increased electricity prices. The effects of GAS on ELEC varied across different time horizons. The relatively consistent effects of GAS on ELEC indicated the predictive ability of the natural gas market for the electricity market. By comparing the reactions of EUA and ELEC to shocks from GAS, it is evident that GAS had a stronger effect on ELEC.

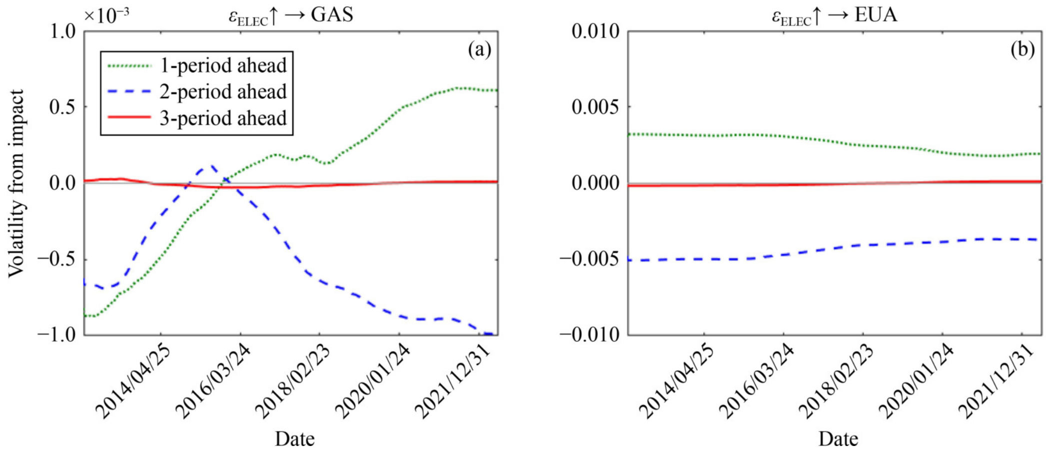

Fig. 11 Equal-interval impulse responses of GAS (a) and EUA (b) to ELEC.

There is a clear difference in the impact of the EUA on the GAS direction before and after 2014, as demonstrated in Fig. 10. Prior to 2014, EUA had a short-term negative effect on GAS. However, in the subsequent period, EUA positively influenced GAS, which can be attributed to the lower carbon prices during the initial phase of Phase III. As a result, this led to increased use of fossil energy by enterprises, causing negative effects. The positive effects observed can be linked to the implementation of stricter carbon reduction policies, which increased carbon prices. In the medium term before 2014, EUA had a positive impact on GAS, but this effect showed a decreasing trend. However, since then, EUA has progressively had more negative effects on GAS, likely due to the growing utilization of clean energy as a substitute for natural gas. From 2020 onward, the negative effects remained significant in the medium term, which can be attributed to the adverse economic conditions resulting from the pandemic and the Russia–Ukraine conflict. Consequently, enterprises have either curtailed production or opted for cheaper energy sources to reduce costs.

Figure 10 illustrates the positive effects of EUA on ELEC in the short and medium terms. This can be explained by the increased demand for electricity as a whole. The rise in carbon prices has prompted enterprises to adopt cleaner energy sources for power generation, thus leading to an increase in electricity prices. The positive effects in the medium term have remained relatively stable, indicating the predictive nature of carbon prices on electricity prices. However, the long-term impact of positive shock effects from EUA on ELEC has resulted in negative effects. This can be attributed to the substitution between cleaner energy and fossil energy for power generation, as enterprises seek to reduce costs (Csereklyei and Stern, 2018). Additionally, the positive effects observed in the short and medium terms outweigh the negative effects in the long-term.

In the short-term, the effects of ELEC on GAS remained negative until 2016, as shown in Fig. 11. However, after 2016, there was a positive upward trend in the effects of electricity on natural gas. This can be attributed to the implementation of the Paris Agreement in 2016, which aimed to reduce emissions and encouraged enterprises to proactively adopt cleaner energy sources, leading to an increased demand for natural gas. Over time, the positive effects of electricity on natural gas have continued to increase, indicating a growing demand for natural gas as part of the energy transition.

On the other hand, since 2016, the negative effects of electricity on natural gas have increased in the medium term. This can be explained by the development of renewable energy sources that serve as substitutes for natural gas. Enterprises have scaled back production and reduced electricity demand to minimize losses during the pandemic, which has amplified the negative effects of electricity on natural gas. Additionally, during the Russia–Ukraine conflict, the electricity market became a net transmitter to the natural gas market. However, the negative effects in the medium term were not enough to offset the positive effects caused by the natural gas shortage, resulting in high natural gas prices.

In terms of EUA, Fig. 11 shows that electricity has had a positive influence on EUA in the short-term. However, this positive effect has shown a downward trend. In the medium term, electricity can have a negative effect on EUAs, possibly due to the increased demand for clean energy in power generation. The negative effects of electricity on EUA indicate that carbon futures serve as a good hedging tool for electricity futures during the sample periods and provide a medium-term safe haven during major crises.

3.3.4 Specific time point impulse responses

The starting time points chosen were 2013-01-04 to represent the beginning of Phase III of the EU ETS, 2020-03-13 to represent the COVID-19 pandemic, and 2022-02-25 to represent the Russia–Ukraine conflict. During the

COVID-19 pandemic, strict lockdown measures were implemented to curb the spread of the virus, resulting in a 17% reduction in carbon emissions (Le Quéré et al., 2020). The lockdown measures also led to a decrease in energy demand and electricity consumption (Bruninx and Ovaere,2021). The date 2020-03-13 is considered the time point of the COVID-19 pandemic, according to the World Health Organization. Furthermore, Europe's reliance on Russian gas has contributed to the ongoing energy crisis, with natural gas prices continuing to rise since the fall of 2021. The Russian–Ukraine conflict, officially declared on February 24, 2022, further exacerbated the increase in natural gas prices. Hence, the date 2022-02-25 was chosen as the starting date of the Russia–Ukraine conflict.

Figure 12 illustrates the effects of GAS on EUA and ELEC before and during the COVID-19 pandemic, as well as during the Russia–Ukraine conflict. Initially, the rise in natural gas prices had a positive effect on carbon prices. Prior to the pandemic, GAS had a stronger positive influence on EUA than it did during the pandemic. This discrepancy may be attributed to the significant increase in natural gas prices during the Russia–Ukraine conflict, which resulted in reduced production and subsequently decreased demand for carbon allowances. During the second week, the ELEC continued to react positively to the shock caused by GAS. This could be due to natural gas being a critical fuel source for power generation. The substantial volatility in natural gas prices caused power generation companies to be unable to promptly adjust their production strategies, leading to increased power generation costs and prices. Throughout the three time periods, the positive effects of GAS on ELEC remained nearly unchanged, indicating that the COVID-19 pandemic and Russia–Ukraine conflict did not alter the spillover effects of natural gas on electricity.

Figure 13 shows that in the first period during the COVID-19 pandemic and the Russia–Ukraine conflict, EUA had a positive influence on GAS, but this influence was negative prior to the pandemic. During the two major crises, the most pronounced and statistically significant negative effects were observed around the second lag period. These results suggest that the effects of EUA on GAS are delayed. The negative response of GAS to EUA indicates the safe-haven nature of GAS for EUA. Additionally, the magnitudes of these responses were generally greater during the COVID-19 pandemic and Russia–Ukraine conflict than during the period prior to the pandemic. This can be attributed to production restrictions aimed at reducing costs. Furthermore, Fig. 13 shows that the positive effects of EUA on ELEC were more pronounced during the COVID-19 pandemic and the Russia–Ukraine conflict than they were before the pandemic. This can be attributed to the tightening of free

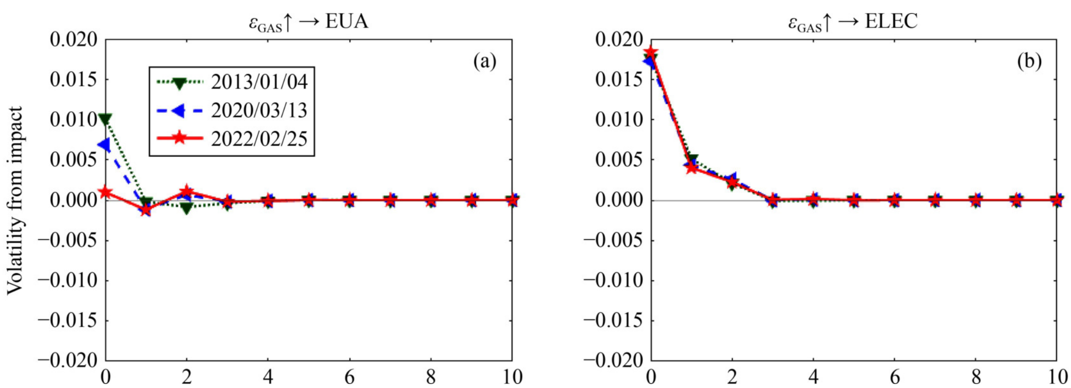

Fig. 12 Specific time point impulse responses of EUA (a) and ELEC (b) to GAS.

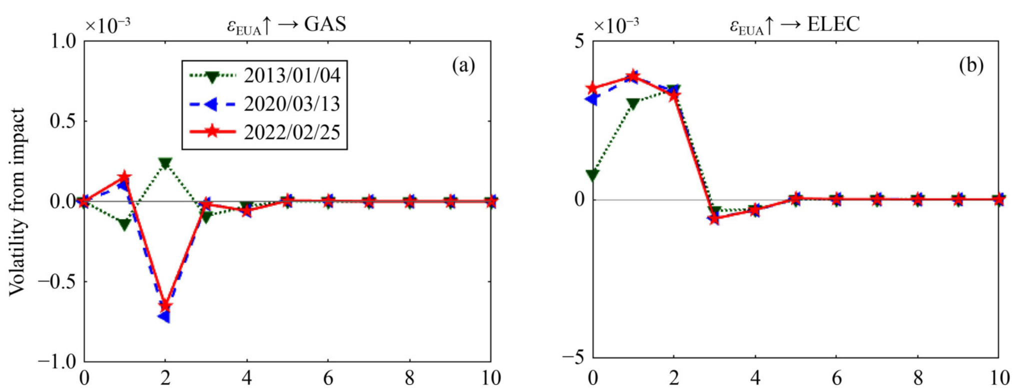

Fig. 13 Specific time point impulse responses of GAS (a) and ELEC (b) to EUA.

carbon allowances for the power sector, which prompted enterprises to adopt cleaner energy sources and increased power generation costs.

Figure 14 shows that during the COVID-19 pandemic and the Russia–Ukraine conflict, there was a positive influence of the increase in electricity prices on natural gas prices. This contrasts with the negative effects observed prior to the pandemic. Moreover, the negative responses of the natural gas market to the electricity market were stronger during the second period of the Russia–Ukraine conflict than during the other two periods. This suggests that the conflict has intensified the spillover from the electricity market to the natural gas market. Additionally, the negative effects observed in the second period were stronger than the positive effects observed in the first period.

With respect to the relationship between electricity and the EUA, the positive effects of electricity on the EUA were weaker under the shocks of the pandemic and the Russia–Ukraine conflict than in the period before the pandemic. However, electricity can have a negative effect on the EUA during the second period. The negative responses of the EUA to electricity before the COVID-19 pandemic were stronger than those in the other two periods. This result may be attributed to the fact that enterprises restricted production during the pandemic and the Russia–Ukraine conflict.

3.4 Robustness test

In terms of the robustness test, we conducted a sensitivity analysis by varying the forecasting horizons. Figure 15 displays the total spillover index based on 30- and 50-day forecasting horizons. The results show that the total spillover varies between 7% and 50%, which is consistent with the baseline results. This confirms the robustness of our findings.

4 Conclusions and implications

This paper has focused on the price transmission and response mechanism of carbon, electricity, and natural gas markets. The conclusions are as follows:

First, the Russia–Ukraine conflict has changed the price transmission and response mechanism of such markets. Therefore, with this conflict, there is an increase in the spillover effects among the three markets, showing contagion effects. Since the outbreak of the conflict, the carbon market has been a net receiver, whereas the natural gas and electricity markets are net transmitters. In this period, the influence of the natural gas market on the carbon market was weaker than that in other periods, whereas the influence of the electricity market on the carbon market was strong.

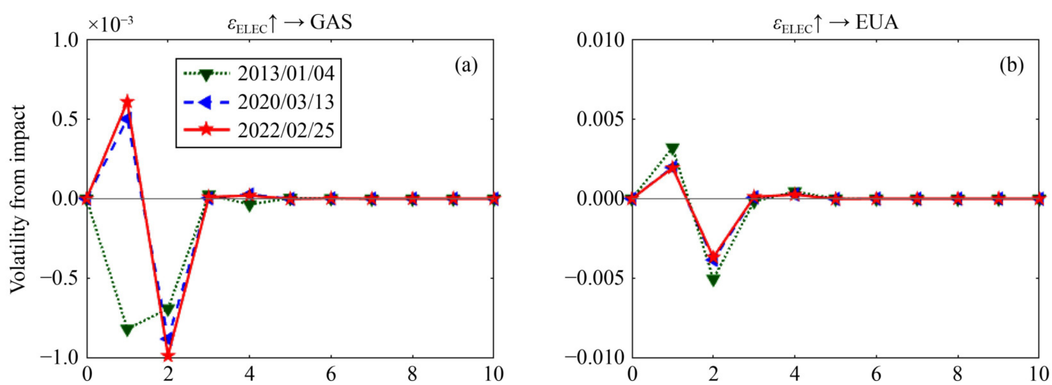

Fig. 14 Specific time point impulse responses of GAS (a) and EUA (b) to ELEC.

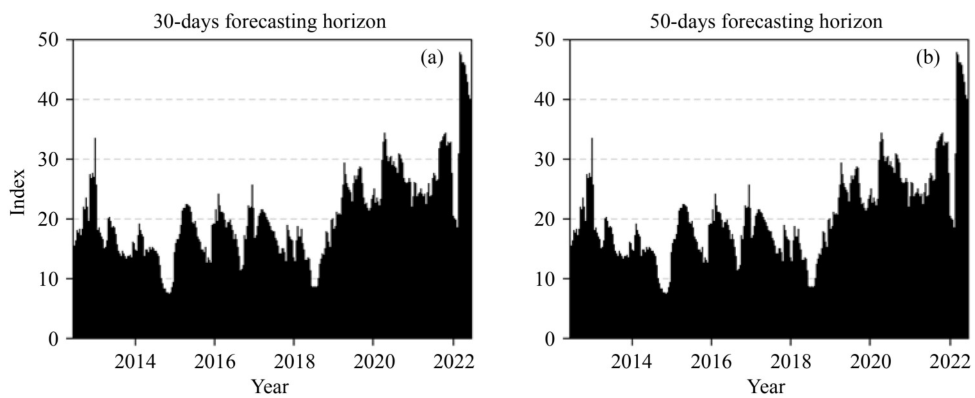

Fig. 15 Robustness test over 30-days (a) and 50-days (b) forecasting horizons.

Second, each market may generate different price signals for different time horizons. The impact of the carbon market on the electricity market was positive in the short and medium terms but negative in the long-term. The natural gas market reacted positively in the short-term but turned increasingly negative in the medium term to the carbon market. Similarly, the market for natural gas has had negative effects in the short run on the carbon market, which is considered to be positive in the medium run. Its response in the carbon market to the electricity market was positive at the short-term level but became negative at the medium-term level. In addition, in comparison with the natural gas market, the electricity market has a much stronger impact on the carbon market, which suggests that the main dependence of carbon price formation is on fluctuations in the electricity market and that the leading effects are medium-term.

Therefore, this paper proposes the following policy implications. First, the shock transmitter must be better supervised by decision-makers. In addition, adjustment policies should be issued in time to ensure that the carbon market operates smoothly. The natural gas market is the major shock transmitter in the carbon-electricity-natural gas system. Therefore, close attention must be paid to price distortions in the natural gas market. Moreover, policymakers should remain aware of changes in market conditions. In this context, the carbon and electricity markets should receive special care in situations where the transmitter of the shock changes. With stability in the interaction between the carbon and electricity markets, one could count the dynamics within the electricity market by the movements within the carbon market and vice versa. In the short and medium run, the sensitivity of the carbon market to the natural gas market is increasing, which highlights the increasing importance of the natural gas market in carbon price formation. Therefore, to prevent price distortions in the carbon market, the strengthening of short- and medium-term supervision by policymakers concerning the natural gas market is necessary.

Firms can shift their energy demand in response to a carbon signal, which is effective at different time horizons. Nevertheless, the prices of the natural gas and electricity markets due to the carbon signal vary over the short and medium run. More precisely, in carbon markets, fluctuations within the electricity market are more sensitive, with medium-term effects predominant over short-term effects. The findings tend to show that medium-term price signals for electricity are more important in predicting prices for carbon. Moreover, enterprises can adapt their energy consumption to the signals of carbon prices. If prices for carbon remain high, enterprises can temporarily reduce demand for natural gas, but in the medium term, demand will expand and lower production costs.

Dynamically, such an important change, owing to the impact it has on hedging strategies and portfolios at various time horizons, forces investors to dynamically adjust trading decisions and risk measurements. Investors should enhance their risk management skills and closely focus on the major crisis events that lead to increased linkages among the electricity, carbon, and natural gas markets. This weakens the benefits for portfolio diversification. Relatively weak total pairwise spillovers across the natural gas and carbon markets during the COVID-19 pandemic created opportunities for portfolio diversification with carbon and natural gas futures. The negative responses of the carbon market to the natural gas market in the short and long-terms reveal the hedging and safe haven properties of carbon futures for natural gas futures. It also reveals the negative impact of the electricity market on the carbon market in the medium run and therefore opens up the avenue of medium-run hedging and safe haven strategies using carbon futures for underlying electricity futures.

Finally, there are several limitations of this study, which, in the context of future research, need to be explored further. It is limited to the markets for carbon, electricity, and natural gas, so future research needs to cover the clean energy markets to provide a deeper understanding of the role that a carbon market plays in the energy transition. For example, since the expectations of energy consumption and carbon allowance demand may vary for different periods and under different market structures, such an analysis of short- and long-term price transmission under alternative market conditions would have great implications for government policy and regulatory development.

Competing Interests The authors declare that they have no competing interests.

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