The effect of emissions tradings on the relationship between fossil fuel prices and renewable energy stock prices

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Abstract

In this study, we analyze the relationship between the price of carbon-intensive fuel and the stock prices of renewable energy companies, incorporating the price of carbon in the European Union emission trading system (EU ETS). Specifically, we employ wavelet methods to reconstruct time series with specific levels of persistence, reducing noise, trend, and seasonal components. Using these wavelet-adjusted series, we conduct a regression analysis that considers exogenous factors that may influence the demand for electricity and emission allowances. Subsequently, we estimate vector autoregressive models and obtain a connectedness measure and impulse response functions. The results consistently imply that increases in coal prices have (counterintuitively) a negative effect on renewable energy stock prices. Moreover, we show that this can be explained by a negative relationship between coal and carbon prices and a positive relationship between carbon prices and renewable energy stock prices. Our study contributes to the literature by uncovering the negative relationship between the price of carbon-intensive fuel and renewable energy stock prices by applying a suitable filtering procedure.

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1 Introduction

Developing renewable energy sources (RES) has emerged as the primary way to address concerns regarding climate change, cope with the depletion of fossil fuel resources, and establish a sustainable global energy system. A wide range of policies have been implemented to promote development in the renewable energy sector; however, renewable energy firms must be profitable to attract investment and maximize the effect of renewable energy policies. Emission trading sheds light on this by encouraging the environmental efficiency of RES (Anke and Möst, 2021; Jaraitė and Di Maria, 2012). The European emission trading system (EU ETS), part of the EU's policies to combat climate change, is a market-based mechanism designed to help achieve greenhouse gas emissions reduction targets. Under this cap-and-trade system, companies are required to buy emission allowances (EUAs) in an amount corresponding to their annual carbon emissions. A binding emission cap provides a significant price signal for the value of carbon abatement, especially for the electric power sector, which accounts for a significant part of total EU carbon emissions and therefore plays a prominent role in emission trading. To meet emission targets or to reduce the cost of relying on carbon-based fuels, the options available to power generators are fuel switching in the short run and/or investment in renewable energy technologies in the long run (Bruninx et al., 2020; Delarue and Van den Bergh, 2016; Chen and Tseng, 2008). Improvements in the economic feasibility of RES based on carbon pricing not only provide an effective method to reach emission reduction targets but also increase the profitability of renewable energy firms.

Higher fossil fuel prices are often seen as an incentive for the power sector to use RES (Kumar et al., 2012; Apergis and Payne, 2014). However, emission trading schemes obscure the logical relationships between carbon-intensive fuel and renewable energy stock prices. For example, when carbon-intensive fuel prices increase, there is an incentive for power plants to use low carbon fuel rather than carbon-intensive fuel, which reduces the demand for emission allowance, placing downward pressure on allowance prices (Aatola et al., 2013; Batten et al., 2021; Weigt et al., 2013).

The profits of renewable energy companies, which remain low, are closely related to allowance prices (Guo et al., 2020). Therefore, higher prices for carbon-intensive fuel have both a positive influence (owing to renewable energy penetration) and a negative influence (owing to decreased demand for allowances) on renewable energy stock prices. Thus, analyzing the relationship between carbon-intensive fuel prices and renewable energy stock prices allows for a richer understanding of how carbon pricing affects the expansion of RES.

In this study, we investigate the dependent relationship between a renewable energy index and the price of coal, the most carbon-intensive fuel, by considering the price of carbon. Focusing on the EU ETS Phase III, our empirical study uses European data for the period from January 2013 to December 2019. As a representative index of the European renewable energy sector, we consider the European renewable energy index (ERIX). For the price of carbon, we use the EUA futures price, which has been actively traded since the start of the EU ETS. Using a continuous wavelet transform, we first obtain information about dynamic correlations and lead-lag relationships across different time scales. The wavelet coherence and phase relationships indicate that the prices of coal and carbon are negatively correlated, the price of carbon and ERIX are positively correlated, and the price of coal and ERIX are negatively correlated at some time scales. In particular, we find significant wavelet power spectrums and wavelet coherences at the intermediate and long-term time scales. To reduce noise, trend, and seasonal components and reconstruct time series with specific time scales of interest, we apply a discrete wavelet transform and obtain denoised and detrended series, namely wavelet-adjusted series. Using these wavelet-adjusted series, we perform regression and vector autoregressive (VAR) analyses to examine the causality and direction of influence.

In our regression analyses, we estimate ordinary least squares (OLS) and as well as cointegrating regressions for robustness. To consider exogenous factors that may influence the demand for electricity and allowances, we construct a set of control variables including the prices of electricity, crude oil, a stock market index, a risk-free rate, average temperatures, and dummy variables representing extreme temperature and policy changes (Alberola et al., 2008; Alberola and Chevallier, 2009; Fan et al., 2017). The regression results imply that the coal price has a negative effect on the carbon price, the carbon price has a positive effect on the ERIX, and the coal price has a negative effect on the ERIX. These results are statistically and economically significant, and robust to controls for exogenous shocks. Utilizing estimates from our VAR analyses we obtain the connectedness measure from Diebold and Yilmaz (2009, 2012, 2014, herinafter DY) and impulse response functions. In a VAR system consisting of prices for coal, carbon, and ERIX, the net directional connectedness indicates that coal prices are a net transmitter of spillover while the carbon price and ERIX are net receivers. Finally, from the impulse response functions we find that the carbon price responds negatively to coal price shocks, ERIX responds positively to carbon price shocks, and finally, ERIX responds negatively to coal price shocks. In addition, we calculate the dark spread (i.e., the profit a coal-fired power plant generates from selling a unit of electricity) to capture the influence of coal price variations on power generation (Batten et al., 2021; Keppler and Mansanet-Bataller, 2010). Our findings are generally consistent even when the dark spread is used instead of the coal price.

This study contributes to the literature on the relationships among prices for fuel, carbon, and renewable energy stocks as follows. Although previous studies present evidence on the relationship between the EU ETS and the electric power sector, few consider how the ETS influences the way in which renewable energy stock prices depend on the price of carbon-intensive fuel (see Section 2 for further details). To fill this gap, we thoroughly investigate the relationships among the prices of coal and carbon, and the renewable energy index. Specifically, using wavelets we provide solid evidence of the negative relationship between ERIX and the price of carbon-intensive fuel. The analysis based on wavelets provides a better understanding of the dynamic dependence across different time scales (Hamdi et al., 2019; Jammazi and Aloui, 2010; Jiang and Yoon, 2020; Reboredo et al., 2017). The wavelet analysis shows that the original time series contains various levels of persistence, and based on wavelet decomposition we disentangle the components and reconstruct the time series. Using the wavelet-adjusted series we unveil significant relationships that are not explicitly seen in the original series and show that the results are robust across different specifications and estimation methods.

The remainder of the present study is presented as follows. In Section 2, existing studies on the power sector, ETS, and renewable energy development are briefly reviewed. Section 3 and 4 present the methodology and data used in this study, respectively. In Section 5, we discuss our empirical results. Finally, Section 6 concludes the study.

2 The power sector, emission trading system, and renewable energy development

The EU ETS, the oldest and the largest carbon market in the world, covers more than half of total carbon emissions produced in Europe. The electric power sector plays a prominent role in the EU ETS; as of 2019, the sector accounts for approximately 62% of total emissions in the EU ETS and its annual emission reduction is the largest across all sectors (Nissen et al., 2020). The electric power sector is a major target of policymakers who want to reduce carbon emissions and increase the use of RES because of the flexibility it offers in the choice of fuels. A significant number of European power plants are multi-fired plants in which inter-fuel substitution can occur quickly and easily (Söderholm, 2001). Each power plant determines the optimal fuel mix based on the profit margin from those fuels. The dark spread, defined as the profit a coal-fired power plant earns from selling a unit of electricity, is given by

$$Dark\ spread = P_E - \frac{P_c \times \eta_c}{E_c}, \tag{1}$$

where P_E and P_c are prices of electricity and coal, respectively; and η_c is a conversion factor; and E_c is the plant's efficiency of coal-fired generation. The spark spread is defined similarly for a gas-fired power plant. The EU ETS participants must submit allowances in proportion to their carbon emissions, which increases the cost of power generation, especially for high carbon fuels.[1] Taking carbon costs into consideration, dark and spark spreads must be corrected by the

[1]For coal-fired power generation, fuel costs account for 40% of total costs, and an allowance price of €20 increases total costs by roughly 40%. In contrast, an allowance price of €20 only increases the total cost of gas-fired power generation by 20% (Graus and Worrell, 2009).

allowance price; these are referred to as "clean" dark and spark spreads (see Abadie and Chamorro (2008) for more details). To meet emission targets or to cope with an increase in carbon or fuel prices, the short-term option available for power generation is fuel switching, namely, the use of low carbon fuels rather than a carbon-intensive fuel, while investing in clean energy technologies can be a longer-term solution. Carbon pricing under the EU ETS encourages the phase-out of fossil fuels and investment in low-carbon technologies that are capable of increasing renewable energy penetration (Cullen and Mansur, 2017; Fell and Linn, 2013; Rogge and Hoffmann, 2010). Anke and Möst (2021) examine the effect of the EU ETS on the growth of RES and show that higher carbon prices and coal phase-outs increase power prices as well as the economic feasibility of RES. Jaraitė and Di Maria (2012) measure environmental efficiency and show that the emission trading system increases environmental efficiency and encourages the technological development of RES but that an oversupply of EUA negatively affects the benefits of the policy.

The entire supply of EUA depends on the overall emissions reduction target set by the European Commission, and an individual firm's supply is determined by allocations of the total cap to each firm. However, changes in external circumstances including fuel price, weather events, and economic conditions influence electricity production and energy needs, thereby affecting demand for allowances. Owing to inflexible supplies and the full auctioning applied to the electricity sector, carbon prices become more sensitive to demand-side factors. The seminal study by Alberola et al. (2008) examines price drivers and structural breaks in EUA prices during Phase I. Using OLS, these authors find the primary drivers of carbon prices to be energy prices and unexpected temperature changes. They also identify two structural changes related to the disclosure of verified emissions (in April 2006) and the announcement of the allocation plan (in October 2006). Chevallier (2009) finds that carbon futures prices are influenced by power plants' fuel-switching behavior rather than the macroeconomic environment. Creti et al. (2012) find that oil prices, an equity index, and the switching price (the difference between clean dark and spark spreads) are key components of EUA prices during Phase II. Numerous studies identify various key components including energy prices, macroeconomic conditions, and weather events (see Benz and Trück, 2009; Bunn and Fezzi, 2007;

Mansanet-Bataller et al., 2007; Christiansen et al., 2005; Hintermann, 2010; Peri and Baldi, 2011; Lutz et al., 2013).

When a stringent emission cap is in place, the EUA supply is unresponsive to various exogenous factors such as renewable energy promotions. In particular, renewable energy policies have little impact on further emission reduction because they simply displace carbon emissions from the electricity power sector to other sectors within the ETS (Delarue and Van den Bergh, 2016; Sijm, 2005; Van den Bergh et al., 2013). De Perthuis and Trotignon (2014) point out weaknesses in the EU ETS and argue the necessity of dynamic supply management. They identify three causes of EUA price declines over the period from 2008 to 2013: an oversupply of allowances, overlapping regulations (e.g., renewable energy policies), and a demand shock caused by the global financial crisis. In the EU ETS, low EUA prices resulting from inflexible emission caps have triggered discussions about a policy supplement. For example, Richstein et al. (2015) argue that the carbon price can be decoupled from renewable energy policy by adjusting the emission cap according to renewable energy policies. Schäfer (2019) develops a unilateral flexible cap based on emission intensity that eliminates demand-side effects such as overlapping regulations. He shows that the combination of an intensity-based cap and an absolute cap is advantageous in the German power sector. To adjust the EU ETS, the European Commission increased the linear reduction factor and introduced a market stability reserve (MSR) that allows allowances to be cancelled.[2] However, Bruninx et al. (2019) demonstrate that the current MSR would suffer from problems of overlapping regulations and could even increase the uncertainty of cumulative emissions. Bruninx et al. (2020) examine the impact of the MSR on EUA and electricity prices, focusing on short-term fuel switching and long-term investment in power plants. Based on a sensitivity analysis, they demonstrate that the effect of the MSR is highly dependent on other energy policies, including coal phase-outs and renewable energy promotion.

Changes in regulations or policies greatly affect both supply and demand for EUAs. For example, the disclosure of verified emissions and a subsequent announcement regarding the allocation

[2]During 2014 to 2016, the allocation and auctioning of 800 million EUAs was postponed (backloading) but failed to prevent price drops. The MSR absorbs part of the excess EUAs.

plan induced structural breaks in the EUA prices (Alberola et al., 2008; Benz and Trück, 2009; Chevallier et al., 2009; Conrad et al., 2012; Hitzemann et al., 2010; Lepone et al., 2011; Mansanet-Bataller and Pardo, 2009). Alberola and Chevallier (2009) show that the low EUA prices during Phase I can be explained not only by oversupply but also by banking restrictions in place between Phase I and Phase II. The impact of policy adjustments on EUA prices is well organized in Fan et al. (2017). The aforementioned authors categorize 50 events into six categories and measure the abnormal returns of EUA spot and futures prices around the dates of the events. They conclude that newly announced events related to the supply and demand of allowance (e.g., caps, free allocations, and auction events) tended to have a significant influence on the return.

Fundamentally, an increase in fossil fuel prices or coal-phase out increases the economic feasibility, and thereby encourages the expansion of RES (Anke and Möst, 2021; Jaraitė and Di Maria, 2012). In an early study, Kumar et al. (2012) examine the relationship among oil, carbon, and clean energy stock prices during EU ETS Phase I using a VAR framework and conclude there is a positive relationship between oil and clean energy stock prices because of energy substitution. Apergis and Payne (2014) examine the drivers of renewable energy consumption in seven Central American countries and find that long-run elasticity estimates between coal prices, oil prices, real GDP per capita, and carbon emissions per capita are significant and positive. However, the existence of emission allowance complicates the logical relationships between fuel prices and the economics of RES because prices of carbon-intensive fuels and allowance prices are negatively correlated. If coal prices increase (or the dark spread decreases), power generators would convert from using coal to using natural gas in the short run, and would increase the use of RES in the long run.[3] The substitution from carbon-intensive fuel(s) to low- or zero-carbon fuel(s) decreases the demand for, and therefore lowers the price of allowances. Keppler and Mansanet-Bataller (2010) show that coal and natural gas prices affect EUA futures prices through dark and spark spreads, and that the dark spread is positively correlated with EUA prices. Aatola et al. (2013) suggest an equilibrium model to identify the price drivers of EUA, focusing on Germany's electricity sector. Their model

[3] Pettersson et al. (2012) provide some evidence for the existence of price-induced fuel switching behavior between coal and gas in the short-run based on a generalized Leontief model.

implies that higher costs for a more-polluting input (e.g., coal) lead to greater use of a less-polluting input (e.g., natural gas), resulting in a decrease in permit prices in the equilibrium. Their results suggest the significant and negative effect of a coal price shock on EUA prices using a regression and VAR analysis using data from 2005 to 2010. Weigt et al. (2013) estimate the effect of RES deployment on the demand for EUA and show that the availability of RES significantly reduces CO_2 emissions, which decreases the demand for EUA. Batten et al. (2021) investigate the key components of carbon prices, focusing on energy prices and weather conditions. They discover that coal, gas, and electricity prices have significant relationships with EUA prices during Phase III. In particular, a coal price shock has a negative impact on EUA prices because the coal price increase causes fuel switching from coal to natural gas, which puts downward pressure on EUA demand. Similarly, the price of natural gas and the dark spread are positively correlated with the price of EUA. With respect to weather conditions, unanticipated temperature changes, rather than the temperature level, impacts EUA prices.

Existing studies focus primarily on pairwise relationships among fuel, carbon, and renewable energy markets. In this study, we investigate how changes in the price of carbon-intensive fuel (e.g., coal) influence the stock prices of renewable energy firms involved in the ETS. The renewable energy stock prices represent the market's expectation of future growth in the renewable energy sector. Thus, without the ETS, coal and renewable energy stock prices would have a positive relationship owing to renewable energy penetration. With the ETS, we must take into account the price of carbon. The price of carbon and renewable energy stock prices are positively correlated because a high carbon price not only encourages the development of renewable energy technologies, it directly affects renewable energy firms' profits because renewable energy subsidies and emission allowances still account for a considerable portion of these firms' revenue. Considering the negative effect of high coal prices on carbon prices, we expect a negative correlation between the price of coal and renewable energy stock prices. Between these two counteracting effects, we expect renewable energy stock prices to react negatively to coal price shocks because the change in carbon prices due to renewable energy penetration plays a more important role than the renewable energy penetration itself. This study contributes to the literature by analyzing coal, carbon, and renewable energy stock markets together, discovering a negative relationship between coal and renewable energy stock prices in the ETS.

It is noteworthy that these relationships characterize the dynamics of coal, carbon, and renewable energy stock markets from a long-term perspective. Accounting for persistence heterogeneity, we apply wavelet methodologies to analyze dynamic correlations and lead-lag relationships across time scales, and to reduce noise, trends, and seasonal components and focus on specific levels of persistence. Wavelet methodology is widely used in multiscale analysis and in denoising time series. For example, econometricians apply wavelet methodology for beta decomposition and to study multiscale systematic risk (Bandi and Tamoni, 2020; Boons and Tamoni, 2015; Gençay et al., 2003, 2005; Kang et al., 2017; Xyngis, 2017). They use wavelets for multiresolution factor analysis and obtain scale-wise factor loadings. The seminal work of Ortu et al. (2013) decomposes consumption growth and representative financial ratios by their level of persistence in the presence of persistence heterogeneity. They demonstrate that specific levels of persistence in consumption growth can be predicted by the same degree of persistence in the price-dividend ratio. Fosten (2019) decomposes emissions and economic cycles at different time scales and shows that emissions and economic activity are significantly linked at frequencies of around one to three years, a relationship that may not be discovered without an appropriate filter. Bandi et al. (2019) provide the theoretical background of scale-specific predictability in multiresolution analysis and Donoho and Johnstone (1994, 1995), Fan and Wang (2007), and Zhang et al. (2016) show that wavelet methodology can successfully remove the microstructural noise in time series.

In the field of energy economics, the wavelet method has been widely used to analyze relationships among energy and financial markets. A number of studies analyze the significant dependence of stock prices on oil price shocks using wavelet methods. Jammazi and Aloui (2010) combine Markov-switching VAR and wavelet method to analyze the effect of oil price shocks on stock market returns in the United Kingdom (UK), France, and Japan. Using wavelet denoised series, they show the significant impact of oil price shocks on the stock market returns. Hamdi et al. (2019) examine the relationship between oil price volatility and sectoral index returns in the Gulf Cooperation Council countries using quantile regressions. They apply wavelet denoising with soft-thresholding and discover an interdependence between oil price volatility and all sectors except energy and transportation. Jiang and Yoon (2020) study the dependence between oil prices and the stock market indices of oil-importing and oil-exporting countries across different time scales, uncovering feedback relationships between oil prices and stock market indices at specific time scales. Liu (2017) explores co-movements between oil price returns and stock returns in the UK's oil and gas industries and finds a significant long-term dependency that is not observed in the original series. Reboredo et al. (2017) analyze co-movements and causal relationships between oil prices and renewable energy stock prices at different time scales. Their empirical results indicate that the dependence between oil and renewable energy stock prices is weak in the short run but strengthens as the time scale increases.

Similar to the study of Reboredo et al. (2017), co-movement and causal relationships over different time scales have been examined by combining the wavelet method and a VAR framework. Tiwari et al. (2020) analyze causal relationships and spillover effects between fuel prices and prices of food, industrial inputs, agricultural materials, and metals using wavelet coherence, phase-differences, and spillover indices. Tiwari et al. (2018) examine co-movements and causal relationships between oil prices and agricultural commodities using wavelet coherence, phase-differences, and multiple cross-correlations. Based on wavelet coherence and a Toda–Yamamoto analysis, Pal and Mitra (2017) show that the price of crude oil leads world food prices in a long-term time scale. Yang (2019) examines causal relationship and connectedness between oil prices and economic policy uncertainty using a DY spillover index. Combining a time-varying parameter VAR and stochastic volatility models, Urom et al. (2021) employ time-varying correlation and a spillover index to investigate dependence and connectedness among the crude oil market, global financial markets, and regional green energy stock markets. Khalfaoui et al. (2015), Boubaker and Raza (2017), and Yahya et al. (2021) analyze the scale-wise features of mean and volatility spillovers among oil and equity markets by combining VAR and various GARCH-type models. In addition, Mensi et al.

(2017) and Yahya et al. (2019) use wavelet-based copula frameworks and Storhas et al. (2020) propose a symbolic wavelet transfer entropy to study lead-lag relationships between the price of oil and other variables.

3 Methodology

3.1 Continuous wavelets

A wavelet is created from a real-valued and square-integrable function called a mother wavelet ψ. Location (ξ) and scale (ϑ) parameters are two key components of a wavelet; the location parameter ξ determines its exact position and the scale parameter ϑ decides the wavelet's stretch. A higher scale value indicates a less compact wavelet, which translates into a lower frequency and vice versa. Using location and scale parameters, a wavelet can be presented as

$$\psi_{\xi,\vartheta}(t) = \frac{1}{\sqrt{\vartheta}}\psi\left(\frac{t-\xi}{\vartheta}\right), \tag{2}$$

where $\frac{1}{\sqrt{\vartheta}}$ rescales the wavelet to have a unit variance. The Morel wavelet of Goupillaud et al. (1984) is widely used in the field of economics and finance, as given by the following:

$$\psi(t) = \pi^{-\frac{1}{4}}e^{iw_0 t}e^{-\frac{1}{2}t^2}, \tag{3}$$

where $e^{iw_0 t}$ and $e^{-\frac{1}{2}t^2}$ are a complex sinusoid and a Gaussian envelope with a variance of one, respectively, and $\pi^{-\frac{1}{4}}$ is a normalization constant. We set $\omega_0 = 6$ following prior studies.

Let $y(t)$ be a time series with a finite length. Based on Eq.(2), the continuous wavelet transformation can be presented as a function of location and scale parameters, defined as

$$W_y(\xi,\vartheta) = \frac{1}{\sqrt{\vartheta}}\int_{-\infty}^{\infty} y(t)\psi^{\star}\left(\frac{t-\xi}{\vartheta}\right)dt, \tag{4}$$

where $\star$ denotes complex conjugate. To measure the amplitude of specific time series, we calculate the wavelet power spectrum $|W_y(\xi,\vartheta)|^2$, indicating the variance contribution at each time scale.

Using continuous wavelet transformation, the covariance between two time series in the time-frequency domain, namely the cross-wavelet transform, can be calculated as follows:

$$W_{yx}(\xi, \vartheta) = W_y(\xi, \vartheta) W_x^{\star}(\xi, \vartheta), \tag{5}$$

where $W_y(\xi, \vartheta)$ and $W_x(\xi, \vartheta)$ are continuous wavelet transforms of $y(t)$ and $x(t)$, respectively. Similar to the wavelet power spectrum, the cross-wavelet power spectrum assesses the covariance contribution for a particular time and frequency. As suggested by Torrence and Compo (1998), the squared wavelet coherence captures the intensity of the interdependence in the time and frequency domain, given by

$$K_{yx}^2(\xi, \vartheta) = \frac{|\kappa\left(\vartheta^{-1} W_{yx}(\xi, \vartheta)\right)|^2}{\kappa(\vartheta^{-1}|W_y(\xi, \vartheta)|^2)\kappa(\vartheta^{-1}|W_x(\xi, \vartheta)|^2)}, \tag{6}$$

where κ is a smoothing parameter. The squared wavelet coherence has a value between 0 and 1, where a higher (lower) value denotes a stronger (weaker) dependence. Its statistical significance can be obtained using a Monte Carlo method. However, the squared wavelet coherence has a limitation in capturing the sign of correlation and the lead-lag relationship. The wavelet coherence phase difference of Torrence and Compo (1998) can supplement this, defined as

$$\phi_{yx}(\xi, \vartheta) = \tan^{-1}\left(\frac{\mathbb{I}\{\kappa\left(\vartheta^{-1} W_{yx}(\xi, \vartheta)\right)\}}{\mathbb{R}\{\kappa\left(\vartheta^{-1} W_{yx}(\xi, \vartheta)\right)\}}\right), \tag{7}$$

where $\mathbb{I}\{\cdot\}$ and $\mathbb{R}\{\cdot\}$ are the imaginary and real part operators, respectively. Phase relationships between variables are often illustrated by an arrow; a right (left) arrow denotes in- (out-of) phase and an upward (downward) arrow implies that the first (second) series leads another.

3.2 Discrete wavelets

A time-series $y(t)$ can be decomposed into several subseries based on time scales using a discrete wavelet transform, presented as

$$y(t) = \sum_k s_{J,k}\varphi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t), \tag{8}$$

where φ is a father wavelet for the low frequency part of the time series and ψ is a mother wavelet for the high frequency part. Wavelet transform coefficients, that is, $s_{J,k}, d_{J,k}, \ldots, d_{1,k}$, measure how much a given wavelet function accounts for the total system. From Eq.(8), the J-th level multiresolution representation of $y(t)$ can be obtained as

$$y(t) = D_J(t) + D_{J-1}(t) + \cdots + D_1(t) + S_J(t), \tag{9}$$

where $D_j(t)$ denotes the variation corresponding to the time scale 2^j and $S_J(t)$ contains a J-th level smoothing component. In this study, we use maximum overlap discrete wavelet transform with the multiresolution level $J = 10$ in consideration of the data length (1826 days). For daily data, D_j roughly corresponds to a 2^j-day scale shock. For example, Fig.1 visualizes D_1, D_4, and D_7 components of ERIX that correspond to 2- to 4-day, 16- to 32-day, and 128- to 256-day scale shocks, respectively. We find that as the time scale increases, the wavelength and amplitude of the wave increase, indicating a lower frequency variation.

[Fig.1 inserted about here]

3.3 Granger causality, impulse response, and connectedness

A VAR model of order p can be presented as follows (by omitting the constant):

$$\boldsymbol{y}_t = \Pi_1\boldsymbol{y}_{t-1} + \Pi_2\boldsymbol{y}_{t-2} + \cdots + \Pi_p\boldsymbol{y}_{t-p} + \epsilon_t^v, \tag{10}$$

where $\boldsymbol{y}$ is a $k \times 1$ vector of endogenous variables and Π is a $k \times k$ coefficient matrix. To examine the system, we perform a Granger causality test, impulse response analysis, and forecasting error variance decomposition using the VAR estimates. First, we test the null hypothesis that the variable j does not cause i, expressed as $H_0^g : \Pi_1(i,j) = \Pi_2(i,j) = \cdots = \Pi_p(i,j) = 0$, where $\Pi(i,j)$ denotes the (i,j) element of the matrix Π. Second, we investigate the response of variable i when a shock to variable j is observed. If the invertability condition is satisfied, the vector moving average representation (i.e., VMA(∞)) can be obtained from Eq.(10) as follows:

$$\boldsymbol{y}_t = \sum_{q=0}^{\infty} \Psi_q \epsilon_{t-q}^v, \Psi_q = \Omega_1 \Psi_{q-1} + \Omega_2 \Psi_{q-2} + \cdots + \Omega_p \Psi_{q-p}, \Psi_0 = I_k, \tag{11}$$

where I_k is a $k \times k$ identity matrix. In the vector moving average representation, endogenous variables are expressed in terms of ϵ_t^v. Accordingly, $\Psi_l(i,j)$ captures the response of variable i when ϵ_j^v increased by one unit with time lag l. Finally, we measure the spillover effect among endogenous variables. DY propose a connectedness measure based on the generalized forecasting error variance decomposition of Koop et al. (1996) and Pesaran and Shin (1998). The contribution of variable j to the H-step ahead forecast error variance of variable i is given by

$$\Xi_{ij}^H = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma_\epsilon e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma_\epsilon \Psi_h' e_i)}, \tag{12}$$

where e_i is a selection vector where the i-th element equals one and zero elsewhere, Σ_ϵ and σ_{jj} are the covariance matrix of ϵ^v and its j-th diagonal element, respectively. DY define the pairwise direction connectedness as Ξ_{ij}^H and *net* pairwise directional connectedness as $\Xi_{ij}^H - \Xi_{ji}^H$. Furthermore, they calculate the total directional connectedness *from others to i* ($\Xi_{i \leftarrow \bullet}^H = \sum_{q=1, q \neq i}^k \Xi_{iq}^H$), total directional connectedness *from i to others* ($\Xi_{i \rightarrow \bullet}^H = \sum_{q=1, q \neq i}^k \Xi_{qi}^H$), and *net* total directional connecteness *from i* ($\Xi_{i \rightarrow \bullet}^H - \Xi_{i \leftarrow \bullet}^H$). The directional connectedness allows us to determine whether a variable is a transmitter or a receiver of spillover in the system.

4 Data

To examine the dynamics among coal, carbon, and renewable energy stock prices, we focus on the European markets during EU ETS Phase III.[4] The variables considered are the prices of coal, carbon, and the renewable energy stock index as well as control variables including the prices of electricity, crude oil, a stock market index, the risk-free rate, and weather conditions. The dynamics among the prices of coal, carbon, and renewable energy stocks are strongly influenced by exogenous factors such as macroeconomic activities and weather conditions (Bel and Joseph, 2015; Chevallier, 2009; Declercq et al., 2011). For example, electricity is the end product of electricity-generating firms, and therefore, when growing demand for electricity raises the price, firms would generate more electricity, leading to an increase in demand for both fuel and allowances. Here, the prices of electricity, fuels, and allowances are positively related in the short run. Our control variables not only capture economic fluctuations but also the overall movements of fossil fuel prices and stock markets which would affect the demand for electricity and allowances.

We collect daily data for the period from January 1, 2013, to December 31, 2019 (1,826 days) from the following sources. For the price of carbon, we primarily use EUA futures data owing to the trading volume and continuity of prices of those contracts (Chevallier, 2009, 2011; Cretí and Joëts, 2017). We obtain EUA futures prices from the Intercontinental Exchange where those contracts have actively traded since the beginning of the EU ETS. To represent the stock prices of European renewable energy firms, we use the ERIX, which consists of Europe's representative clean energy generation companies. Coal prices (COAL) are CIR ARA forward prices, crude oil prices (OIL) are Intercontinental Brent crude oil futures, and electricity prices (ELEC) are German baseload electricity forward prices. We note that changes in coal prices affect coal-firing through the dark spread; therefore, it is the dark spread rather than the price of coal itself that drives fuel substitution. The dark spread (DSPR) is calculated following Eq.(1), using $\eta = 0.143$ and

[4] The analysis for Phase III (2013-2020) provides a better understanding of the overall relationships involving EUA. The EU ETS suffered from an oversupply problem during Phase I and II. Having learned from those trial periods, the EU ETS introduced various stabilizing policies in Phase III. Moreover, auctioning became the primary rule of allocation, especially for the power sector. Therefore, the determinants of demand for EUA are expected to have more influence on the price of EUA in Phase III.

$E_c = 0.350$ by referring to the International Energy Agency. For robustness, we report results for both coal prices and the DSPR. Instead of using the switching price, we use the price of coal and the DSPR because the switching price was found to be not useful in improving the explanatory power of the model and it causes a full rank problem (Batten et al., 2021). For the stock market index and the risk-free rate, we use the Euro STOXX 50 index (STOXX) and an average of 10-year government bond rates in the Euro area. Finally, weather data are defined as temperatures in major German cities that are due to the country's geographical location and contribute to Europe's electricity sector (Batten et al., 2021). We calculate the average temperature and as well as dummy variables for extremely high and low temperatures to capture unexpected temperature changes (Alberola et al., 2008; Keppler and Mansanet-Bataller, 2010; Mansanet-Bataller et al., 2007).

Table 1 shows descriptive statistics for the raw data (Panel A) and daily returns (Panel B). The average EUA futures price was €10.02 during the sample period, which is significantly lower than the price of €24.48 at the end of the period, on December 31, 2019. The average daily return of ERIX (0.10%) is three times greater than that of the STOXX 50 (0.03%), which indicates that renewable energy stock prices have increased rapidly, possibly because of government and private sector policies that reflect growing environmental concerns. Compared to these stock returns, EUA prices generated a higher average return over the period (0.14%) but a lower median (0.00%) and higher standard deviation (2.80%). This indicates that the EUA return was more volatile than stock returns over the sample period. The row labeled "*Corr. with ERIX*" ("*Corr. with EUA*") shows the Pearson correlation coefficient between ERIX (EUA) and each variable. In line with our expectations, we find that ERIX and EUA prices are positively correlated and that the DSPR is positively correlated with both ERIX and the price of EUA. The price of coal has small positive correlations with both ERIX and the price of EUA. This may indicate that positive short-run relationships driven by the demand for electricity are more dominant than negative relationships driven by the ETS. Fig.2 illustrates the evolution in ERIX, EUA and coal prices, and the DSPR over the sample period. Both ERIX and the EUA price appear to be upward-trending, which indicate the stabilization of the EU ETS and growth in RES. Visual inspection of Fig.2 also shows that ERIX often depends more on the EUA price than the coal price. For example, in 2013, 2015, and early 2019, the coal price collapses but ERIX does not decline and even increases along with the EUA prices. During the third quarter of 2019, the coal price increases but both ERIX and the EUA price decrease. Nonetheless, these findings provide only weak support for the negative relationships between coal and renewable energy stock prices. Thus, we conclude that there is a positive relationship between ERIX and EUA prices whereas the negative relationship between the coal price and ERIX (or between the coal and EUA prices) is not apparent in the original data.

[**Table 1 inserted about here**]

[**Fig.2 inserted about here**]

5 Empirical results

5.1 Continuous wavelet analysis

Fig.3 displays the results from the continuous wavelet power spectrum of ERIX, EUA prices, coal prices, and the DSPR, where the horizontal and vertical axes indicate time and frequency, respectively. The warmer color denotes a higher wavelet power and the thick black contour indicates significance at the 5% level. The thin black contour designates the cone of influence and the shaded area signifies the area where the results might be distorted because of the edge effect. The time scale decompositions in Fig.3 indicate that wavelet power is generally greater at intermediate and lower frequencies than at higher frequencies. For example, ERIX and EUA price respond strongly to shocks on scales greater than 32 days whereas coal prices and DSPR react to shocks on scales greater than 16 days. We observe that the power significantly increased for EUA prices after mid-2018, implying that price variations in EUA have recently increased. In addition, there is high power in coal prices at scales up to one year, indicating seasonal and long-term trend components.

[**Fig.3 inserted about here**]

Fig.4 presents wavelet coherence and phase-differences for four pairs of variables: ERIX and EUA prices, ERIX and coal prices, EUA and coal prices, and EUA prices and the DSPR. The arrow represents relative phase relationships; the right (left) arrow signifies in (out-of) phase and the up (down) arrow indicates that the first (second) series leads another series. Information on the wavelet coherence and phase-differences support our predictions. Specifically, we find that the EUA price leads ERIX and that they are in phase (↘) with significant wavelet coherence from 2015 to 2017 over 32- to 128-day scales. The price of coal also leads ERIX and that they had a negative relationship (↙) during 2018 over 50- to 100-day scales and from 2016 to 2017 over 128- to 256-day scales with significant wavelet coherence. EUA and coal prices, which might have a negative relationship, are also generally in anti-phase. However, in some time periods and frequencies, we observe positive relationships among coal prices, EUA prices, and ERIX. For example, ERIX and coal prices are in phase during the last quarter of 2017 over 32- to 64-day scales. EUA and coal prices are in phase during the last quarter of 2016 over 16- to 64-day scales and in the last quarter of 2018 over 64-to 100-day scales. Fig.2 also indicates that their original time series also move together during those periods. This may be related to the co-movement of coal prices, EUA prices, and ERIX driven by a demand shock for electricity. Finally, for EUA prices and the DSPR, we find that although the lead-lag relationship is unclear, the two are in phase with significant wavelet coherence during 2018 and in the first quarter of 2019 over 16- to 128-day scales.

[Fig.4 inserted about here]

5.2 Regression analysis for wavelet-adjusted series

The empirical results of the continuous wavelet analysis show that ERIX, carbon prices, and coal prices have significant relationships over intermediate and long-term time scales that reveal the dynamics of the energy transition that is occurring in the power sector. This implies there is significant information that could be extracted at specific levels of persistence and that other components (e.g., noise and seasonal components) can obscure the actual nature of these relationships. In this regard, the discrete wavelet transform can be seen as a way to reconstruct time series with specific time scales of interest (Hamdi et al., 2019; Jammazi and Aloui, 2010; Ortu et al., 2013; Pal and Mitra, 2017). In particular, we decompose the time series of ERIX, EUA prices, coal prices, and the DSPR as well as for the price of Brent crude oil, the STOXX 50 index, and electricity prices into different time scales using discrete wavelets. Subsequently, for each variable we remove the variation in time scales of less than 16 days (representing the noise component) and greater than 256 days (representing seasonal and trend components) and calculate the sum of the variations in the remaining time scales ranging from 16 to 256 days. These reconstructed series, referred to as wavelet-adjusted series, emphasize intermediate and long-run variations by reducing the noise, seasonal, and trend components.[5] Table 2 shows descriptive statistics for and Fig.5 displays plots of these wavelet-adjusted series. The pairwise correlation coefficients among wavelet-adjusted series as shown in Table 2 are in line with our predictions. For instance, ERIX and EUA have a high positive correlation of 0.82. The wavelet-adjusted EUA and COAL are negatively correlated (-0.18), which is in contrast to the positive correlation (0.09) observed in their original time series. The wavelet-adjusted ERIX and COAL are also negatively correlated (-0.35), in contrast to the positive correlation (0.12) seen in their original series. Tests for stationarity, including the augmented Dickey–Fuller unit root (Dickey and Fuller, 1979; ADF), Phillips-Perron (Phillips and Perron, 1988; PP), and Kwiatkowski–Phillips–Schmidt–Shin (Kwiatkowski et al., 1992; KPSS) tests, are also presented in Table 2. The results of all three tests indicate that all wavelet-adjusted series are stationary.

[**Table 2 inserted about here**]

[**Fig.5 inserted about here**]

Using the wavelet-adjusted series, we perform three regressions that measure the dependence of carbon prices on fuel prices (R1), ERIX on the price of carbon (R2), and ERIX on fuel prices (R3) as follows:

(R1) $EUA_{t+1} = \alpha_1 + \beta_{1,F} Fuel_t + \boldsymbol{\beta}_{1,c} \boldsymbol{X}_t + \epsilon_{1,t}$,

[5] Hereafter, ERIX, EUA, COAL, DSPR, BRENT, STOXX, and ELEC represent their corresponding wavelet-adjusted series.

(R2) $ERIX_{t+1} = \alpha_2 + \beta_{2,E} EUA_t + \boldsymbol{\beta}_{2,c} \boldsymbol{X}_t + \epsilon_{2,t}$,

(R3) $ERIX_{t+1} = \alpha_3 + \beta_{3,F} Fuel_t + \boldsymbol{\beta}_{3,c} \boldsymbol{X}_t + \epsilon_{3,t}$,

where $Fuel_t$ represents fuel prices (i.e., COAL or DSPR) and $\boldsymbol{X}_t$ represents the set of control variables including wavelet-adjusted BRENT, STOXX, and ELEC as well as the 10-year government bond yield, average temperature, and dummy variables for extreme temperatures. Note that we collect one out of every eight data points (a total of 228 out of 1,826 data points) to mitigate the serial correlation of the wavelet-adjusted series. The variables are standardized to have a mean zero and a standard deviation of one.

Table 3 shows the results of the regression analysis with EUA as the dependent variable and fuel prices (represented by either COAL or DSPR) as the key independent variable (R1). The row labeled "*COAL*" shows the results of the regression using COAL, and the row labeled "*DSPR*" presents the regression using DSPR. The OLS estimation results presented in the first column indicate that increases in carbon-intensive fuel costs decrease the allowance price; COAL has a negative coefficient of -0.062 (t-stat = -2.64) and DSPR has a positive coefficient of 0.127 (t-stat = 3.08), indicating that the negative effect of coal price shocks on the price of EUA is statistically and economically significant. This illustrates that when the coal price increases but the price of electricity does not also go up, the DSPR decreases and the power company has less incentive to generate "dirty" electricity; thus, the company will need fewer allowances, pushing the price of those allowances down. Moreover, we consider the effect of regulation and policy changes on the supply and demand for emission allowances. The EU ETS made announcements of the introduction of MSR on April 1, 2015, and November 9, 2017, which significantly affected EUA prices (Bruninx et al., 2020; Schäfer, 2019). In addition, various annual events such as the allocation and submission of allowances play prominent roles in explaining EUA price variations. In Column 2 of Table 3, we include two policy dummies and seven year dummies as explanatory variables and obtain consistent results.

[Table 3 inserted about here]

Serial correlation and endogeneity problems often cause biases in OLS estimates from time series regressions. To account for these problems, we supplement our analyses with fully-modified OLS (FMOLS; Phillips and Hansen, 1990), dynamic OLS (DOLS; Stock and Watson, 1993), and canonical cointegrtating regressions (CCR; Park, 1992). These methods are commonly used in energy economics to estimate the cointegration coefficients among variables and adjust for asymptotic endogeneity and serial correlation (Apergis and Payne, 2014; Bilgili et al., 2016; Creti et al., 2012; Dong et al., 2018). Columns 3, 4, and 5 of Table 3 present the FMOLS, CCR, and DOLS estimations, respectively. In line with the OLS estimation results, an increase in the price of coal has a negative effect, and an increase in DSPR has a positive effect on the EUA price. The estimated coefficients in both cases are significant at the 1% level. Untabulated results show that cointegration coefficients are not significant and the findings are consistent for various trend specifications because wavelet-adjusted series are stationary, and thus, there are no cointegration relationships among variables.

Table 4 presents regression estimates of the effect of EUA on ERIX (R2) and fuel prices on ERIX (R3). The row labeled "*EUA*" stands for the results of regressions with ERIX as the dependent variable and EUA as the key independent variable. "*COAL*" displays the impact of COAL on ERIX, and "*DSPR*" demonstrates that of DSPR on ERIX. Focusing on EUA, the results in our study are in line with prior studies that reveal a positive relationship between EUA prices and ERIX; the OLS coefficient here is 0.249 with a t-statistic of 5.22. The regressions of ERIX on EUA have larger R^2 values and larger absolute coefficients than the other regression models, which indicates the strong dependence of ERIX on the price of these allowances. We also find that ERIX reacts negatively to coal price shocks. Focusing on the OLS estimates, COAL has a negative coefficient of -0.049 (t-stat = -4.20) and DSPR has a positive coefficient of 0.157 (t-stat = 5.15). All estimated coefficients are significant at the 1% level. This is consistent with our prediction that when the price of coal increases (decreases), the negative (positive) effect of a lower (higher) EUA price is greater than the positive (negative) effect of energy substitution.

[Table 4 inserted about here]

5.3 VAR analysis for wavelet-adjusted series

The regression analyses provide robust results regarding the impact of coal prices on carbon prices and ERIX. Here, we further analyze the dynamic relationships among the prices of coal, carbon, and renewable energy stocks using VAR models. A VAR model allows us to address the potential endogeneity problem and validate the robustness of the previous results. We estimate two trivariate VAR models; one comprising ERIX, EUA, and COAL and the other using ERIX, EUA, and DSPR. We apply the Schwarz criterion to determine the optimal lag length, and the chosen lag length is 8 for both VAR models. Both VAR models can be considered stationary because we use the stationary wavelet-adjusted series.

In the first step, we illustrate the spillover dynamics based on the DY connectedness measure described in Section 3.3. Table 5 shows connectedness matrix among ERIX, EUA, and COAL (Panel A) and ERIX, EUA, and DSPR (Panel B). The table presents the DY spillover from the column variable to the row variable, while the diagonal values denote their own contributions. The column labeled "*From*" stands for total spillover from the other variables to each variable and the row labeled "*To*" denotes total spillover from each variable to the other variables. We observe that the total connectedness values in the VAR systems are 25.14% for COAL and 22.60% for DSPR, implying moderate spillover effects among these markets. The pairwise connectedness from EUA to ERIX is greater than for other pairs, which indicates that EUA shocks largely account for variations in ERIX. The net pairwise directional connectedness ($\Xi_{ij}^{H} - \Xi_{ji}^{H}$) and the net total directional conneteness to others ($\Xi_{i\to\bullet}^{H} - \Xi_{i\leftarrow\bullet}^{H}$) are also calculated to examine the net direction of spillovers. Focusing on the VAR model for ERIX, EUA, and COAL (Panel A), we discover positive net pairwise connectednesses from COAL to EUA (1.26%), EUA to ERIX (0.80%), and COAL to ERIX (0.31%). Accordingly, the net total connectednesses from ERIX (-1.11%) and EUA (-0.46%) to the system are negative while the net total connectedness from COAL (1.57%) is positive, meaning that COAL is a net transmitter of spillover and EUA and ERIX are net receivers in the system. In addition, untabulated Granger causality test results indicate that COAL Granger-causes both EUA and ERIX, while EUA Granger-causes ERIX. These findings provide evidence that coal price shocks are transmitted to ERIX through EUA prices. By contrast, in Panel (b), the variance contributions of DSPR to EUA and ERIX are smaller than that of COAL. The net total connectednesses for EUA (1.11%) and ERIX (-1.05%) imply that they are a net transmitter and receiver, respectively, while the net effect of DSPR (-0.06%) is ambiguous. This may be due to the simultaneous relationship between EUA and DSPR, which is driven by the price of electricity.

[**Table 5 inserted about here**]

Finally, using impulse response analyses we examine the impact of unexpected shocks in one variable on the other variables over time. The impulse response functions are shown in Table 6 and Fig.6. The first three columns in Table 6 and in Panel (a) of Fig.6 present the results from the VAR model for ERIX, EUA, and COAL. Consistent with previous results, we find that (i) EUA reacts negatively to a shock to COAL, (ii) ERIX reacts positively to a shock to EUA, and finally, (iii) ERIX reacts negatively to a shock to COAL. The impulse response functions are statistically significant over some periods, and the direction of the impact is consistent with our predictions. The last three columns in Table 6 and Panel (b) of Fig.6 show the results of the VAR model using ERIX, EUA, and DSPR. We observe that EUA responds positively to a shock to DSPR, and ERIX responds positively to a shock to EUA; these impulse response functions are also significant over some periods. While a shock to DSPR causes a positive impact on ERIX, the effect is not significant. This may imply that a change in the price of electricity partially offsets the negative effect of a coal price shock to renewable energy stock prices.

[**Table 6 inserted about here**]

[**Fig.6 inserted about here**]

6 Conclusions

Higher fossil fuel prices are often seen as a force to accelerate technological developments of RES by strengthening the incentives to use alternative energy sources. However, the price of carbon should be considered carefully when analyzing the dynamics of the relationship between fuel prices and the stock prices of renewable energy companies involved in an emission trading system. In particular, when the price of carbon-intensive fuel increases (decreases), power plants use less (more) of that carbon-intensive fuel, which reduces (increases) the demand for emission allowances, which in turn puts downward (upward) pressure on the price of carbon. Given that the renewable energy stock prices are positively correlated with the price of carbon, a lower (higher) carbon price driven by a higher (lower) price for carbon-intensive fuel may cause the renewable energy stock prices to decrease (increase). If the price of carbon plays a more important role than the price of fuel in the variation of renewable energy stock prices, we observe a (perhaps counterintuitive) negative relationship between the price of carbon-intensive fuel and the prices of renewable energy stocks.

In this study, we investigate the relationship between ERIX, a representative renewable energy sector index, and the price of coal, incorporating the influence of the price of carbon in the EU ETS. Our empirical analysis, which uses various approaches based on wavelets, consistently indicates that changes in the price of coal negatively affect ERIX. Specifically, continuous wavelets provide information on dynamic correlations and lead-lag relationships for different time scales over time. Wavelet coherence and phase relationships show that coal and carbon prices are negatively correlated, the price of carbon and ERIX are positively correlated, and the price of coal and ERIX are negatively correlated over specific time scales and frequencies. Our results also indicate that the wavelet power spectrum and wavelet coherence are more significant at intermediate and lower frequencies than at higher frequencies. To focus on specific levels of persistence by reducing noise, trend, and seasonal components, we apply a discrete wavelet transform and obtain wavelet-adjusted series. Next, we perform regression and VAR analyses using the wavelet-adjusted series. The regression results imply that the price of coal has a negative effect on the price of carbon, the price of carbon has a positive effect on the ERIX, and the price of coal has a negative effect on ERIX. These results are statistically and economically significant, and robust to controls for exogenous shocks. From the VAR estimates, we derive the DY connectedness measure and impulse response functions. The results provide robust evidence of the negative response of carbon prices to coal price shocks, the positive response of the ERIX to carbon price shocks, and finally, a negative response of ERIX to coal price shocks. Our findings have implications for both researchers and policymakers who wish to examine the effect of ETS in promoting the development of RES.

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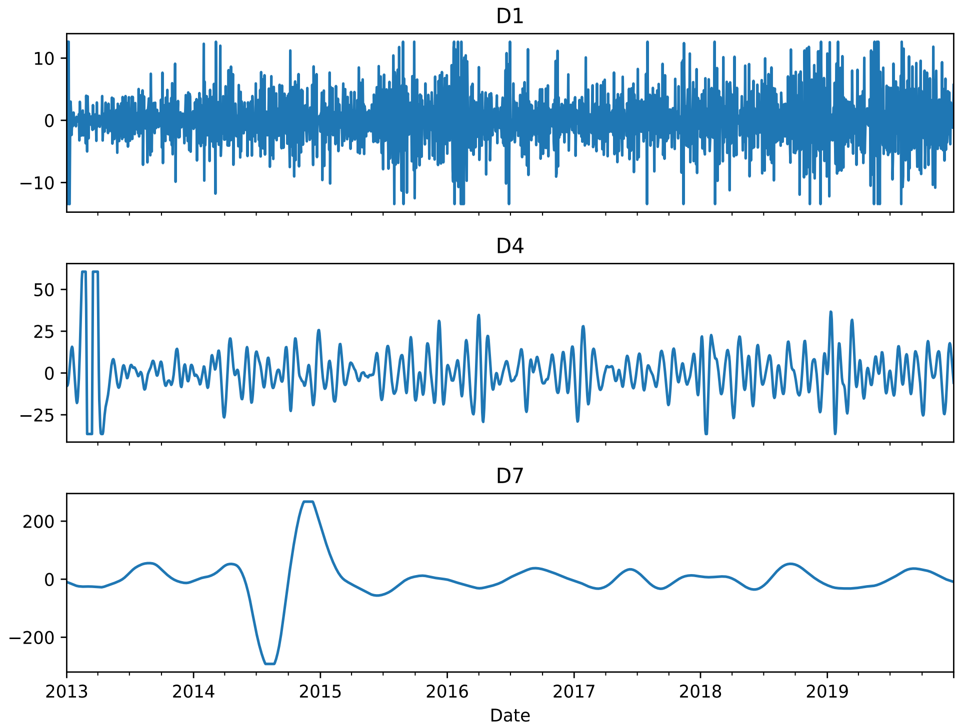

Figure 1. Plot of wavelet decomposed series for ERIX

Notes. The subfigures stand for the discrete wavelet coefficient correspond to time scales: D1 (2-4 days), D4 (16-32 days), and D7 (128-256 days), respectively.

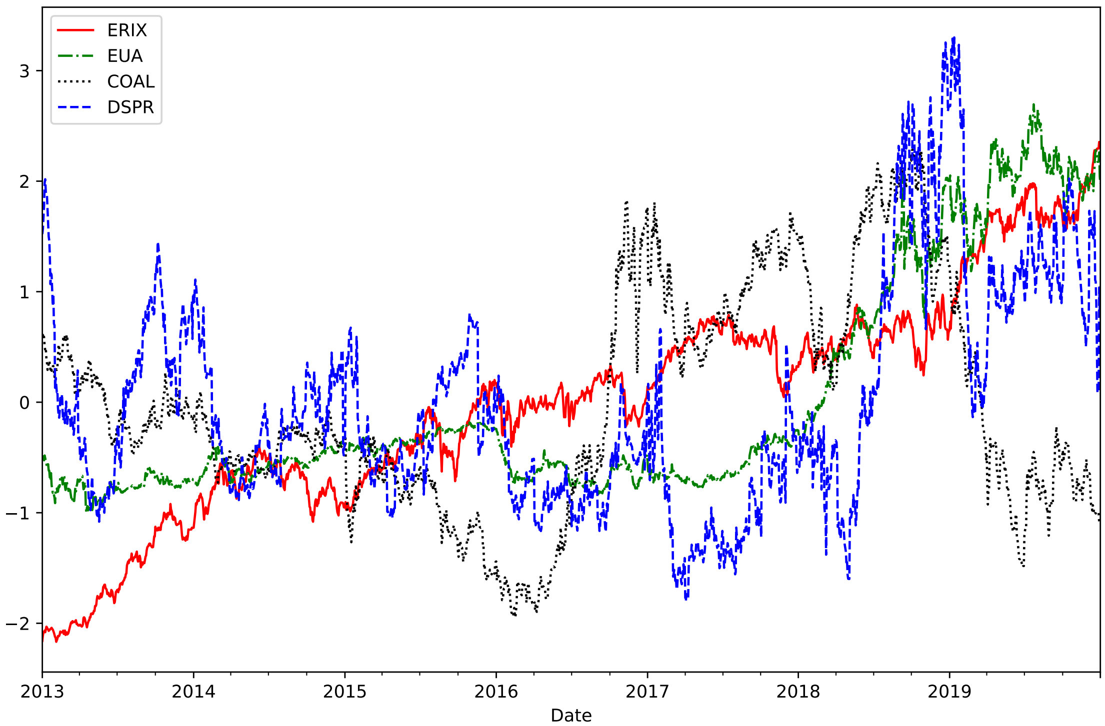

Figure 2. Daily ERIX, EUA price, coal price, and DSPR

Notes. The variables are standardized to mean zero and variance one for ease of comparison.

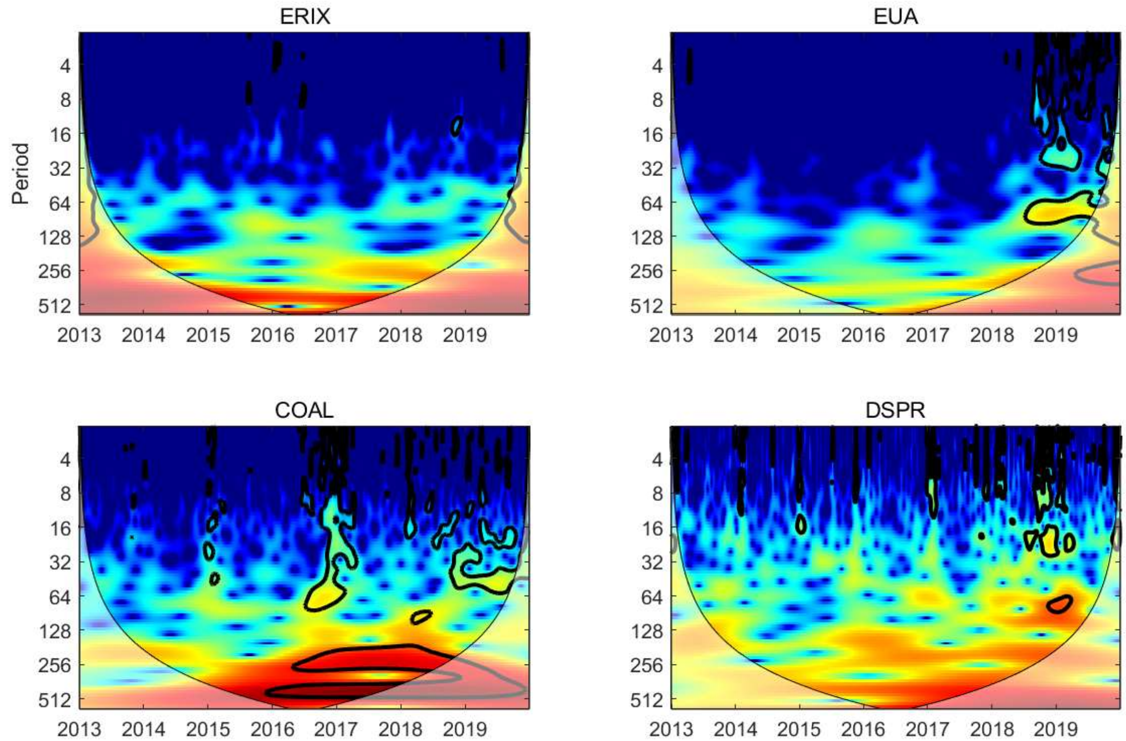

Figure 3. Wavelet power spectrum of ERIX, EUA, COAL, and DSPR

Notes. The thick black contour indicates significance at the 5% level. The thin black contour designates the cone of influence and the shaded area denotes the area where the results might be distorted because of the edge effect. Warmer colors indicate higher power.

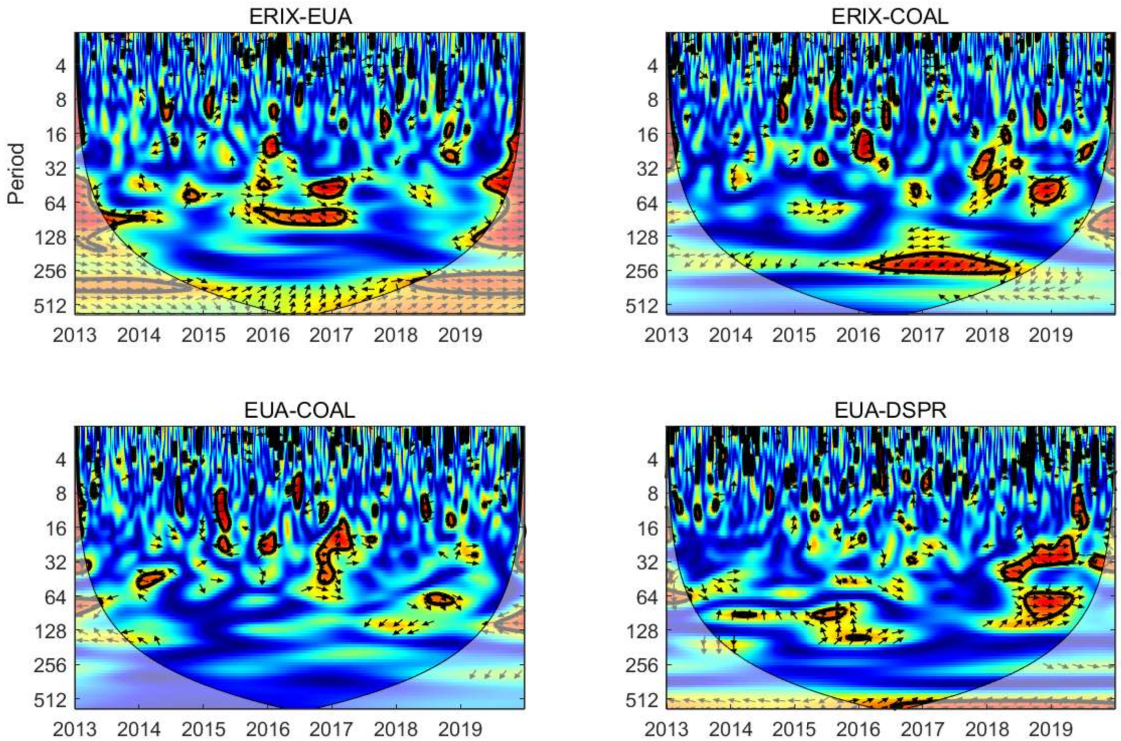

Figure 4. Wavelet coherence and phase plots

Notes. The thick black contour indicates significance at the 5% level. The thin black contour designates the cone of influence and the shaded area denotes the area where the results might be distorted because of the edge effect. The arrow represents the relative phase relationships; the right (left) arrow signifies in (out-of) phase, and the up (down) arrow implies the first (second) series leads another series. Warmer colors indicate a higher coherence level.

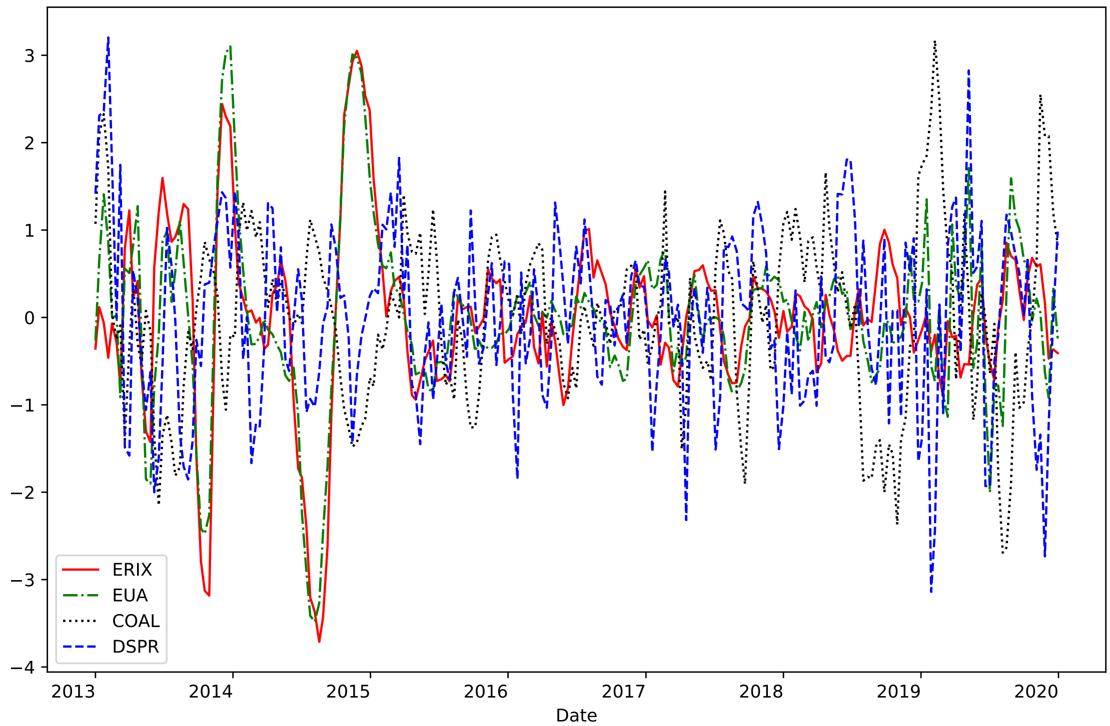

Figure 5. Wavelet-adjusted ERIX, EUA, COAL, and DSPR

Notes. Wavelet-adjusted series are reconstructed using discrete wavelet coefficients correspond to time scales: D4 (16-32 days), D5 (32-64 days), D6 (64-128 days), and D7 (128-256 days).

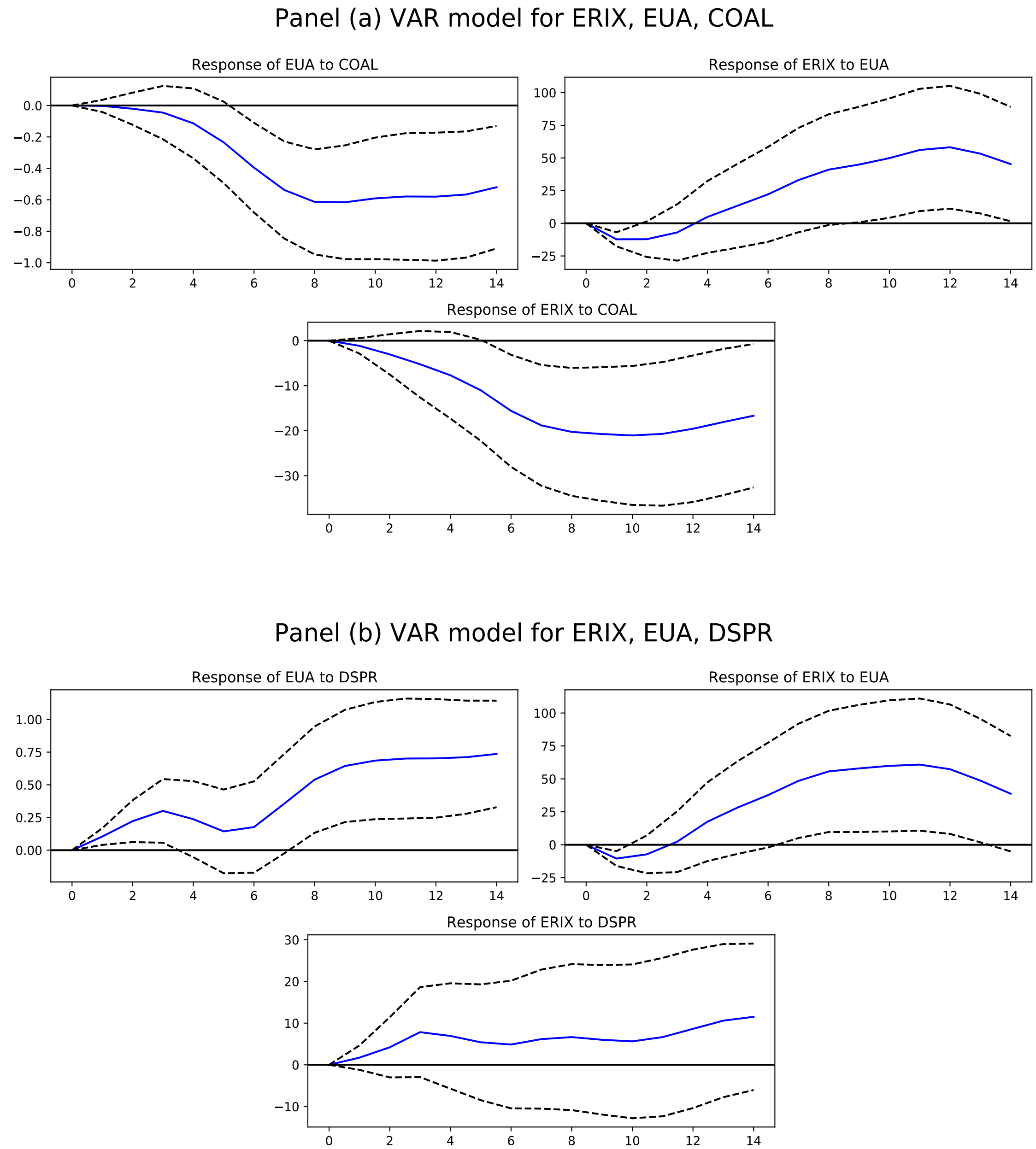

Figure 6. Impulse response functions

Notes. Subfigures in Panel (a) illustrate the impulse response functions of the VAR model consisting of ERIX, EUA, and COAL. Subfigures in Panel (b) stand for that of ERIX, EUA, and DSPR. Dashed lines denote 95% confidence intervals.

Table 1. Descriptive statistics of original series

Variable	ERIX	EUA	COAL	DSPR	BRENT	STOXX	ELEC
Panel (a) Raw data							
Mean	884.40	10.02	61.26	12.27	71.06	3242.88	36.59
Median	892.80	6.74	58.40	10.97	63.67	3264.32	35.35
Max	1515.31	29.78	88.87	31.96	118.90	3828.78	63.70
Min	303.59	2.72	37.74	1.52	27.88	2511.83	21.10
Std.dev	267.92	7.33	12.08	5.97	23.76	287.49	8.20
Skew	-0.02	1.30	0.34	0.91	0.59	-0.34	1.09
Kurt	-0.35	0.14	-0.69	0.49	-0.97	-0.69	1.44
Corr. with ERIX	-	0.77	0.12	0.26	-0.56	0.68	0.27
Corr. with EUA	-	-	0.09	0.70	-0.16	0.40	0.58
Panel (b) Return data							
Mean	0.10	0.14	-0.02	0.22	-0.02	0.03	0.02
Median	0.10	0.00	-0.04	0.02	0.00	0.03	0.00
Max	3.00	7.25	3.60	19.11	4.50	2.33	5.21
Min	-2.90	-6.84	-3.26	-15.83	-4.56	-2.40	-4.89
Std.dev	1.23	2.80	1.31	6.28	1.78	0.96	1.87
Skew	-0.09	0.04	0.22	0.35	-0.05	-0.10	0.15
Kurt	0.23	0.52	0.92	1.50	0.61	0.40	1.07
Corr. with ERIX	-	0.12	0.09	-0.01	0.17	0.67	0.05
Corr. with EUA	-	-	0.07	0.16	0.18	0.11	0.25

Table 2. Descriptive statistics and stationary test results of wavelet-adjusted series

Variable	ERIX	EUA	COAL	DSPR	BRENT	STOXX	ELEC
Mean	1.20	0.02	0.00	0.00	-0.04	0.90	0.01
Median	1.37	0.01	0.01	0.11	0.33	4.36	0.00
Max	277.31	5.25	12.26	6.12	19.46	418.24	7.71
Min	-334.84	-5.85	-10.42	-6.00	-17.62	-357.22	-5.65
Std.dev	90.53	1.69	3.87	1.91	6.68	125.01	2.19
Skew	-0.45	-0.04	0.02	-0.11	0.14	-0.01	0.20
Kurt	3.53	2.95	0.31	0.39	0.34	0.44	0.94
Corr. with ERIX	-	0.82	-0.35	0.04	-0.53	0.76	-0.20
Corr. with EUA	-	-	-0.18	0.26	-0.59	0.54	0.04
ADF	-4.24***	-5.55***	-5.81***	-7.40***	-7.26***	-5.43***	-6.25***
PP	-4.92***	-5.28***	-5.23***	-8.59***	-4.83***	-5.48***	-7.40***
KPSS	0.018	0.019	0.019	0.023	0.017	0.018	0.021

Notes. Wavelet-adjusted series are reconstructed using discrete wavelet coefficients correspond to time scales: D4 (16-32 days), D5 (32-64 days), D6 (64-128 days), and D7 (128-256 days). *** denotes significance at the 1% level. Rows labeled "*ADF*," "*PP*," and "*KPSS*" denote ADF, PP, and KPSS test results, respectively.

Table 3. The results of regression analysis for EUA

		(i) OLS	(ii) OLS	(iii) FMOLS	(iv) CCR	(v) DOLS
COAL	Coef.	-0.062***	-0.072***	-0.077***	-0.076***	-0.102***
		(-2.64)	(-2.85)	(-2.91)	(-2.66)	(-2.94)
	Adj-R^2	0.528	0.574	0.557	0.556	0.722
DSPR	Coef.	0.127**	0.111***	0.151***	0.161***	0.260***
		(3.08)	(3.08)	(3.08)	(2.79)	(3.58)
	Adj-R^2	0.547	0.585	0.568	0.567	0.742
Number of obs.		228	228	228	228	228
Control variables		O	O	O	O	O
Policy dummy		X	O	O	O	O
Year dummy		X	O	X	X	X
Long-run relationships		X	X	O	O	O

Notes. The table represents the estimated coefficient (t-statistic in parentheses) and adjusted R^2 from each regression. *** and ** denote significance at the 1% and 5% levels, respectively.

Table 4. The results of regression analysis for ERIX

		(i) OLS	(ii) OLS	(iii) FMOLS	(iv) CCR	(v) DOLS
EUA	Coef.	0.249***	0.247***	0.264***	0.267***	0.305***
		(5.22)	(4.80)	(6.71)	(6.33)	(6.78)
	Adj-R^2	0.682	0.691	0.680	0.679	0.907
COAL	Coef.	-0.049***	-0.050***	-0.058***	-0.056***	-0.057***
		(-4.20)	(-3.72)	(-3.61)	(-3.22)	(-2.92)
	Adj-R^2	0.637	0.650	0.641	0.640	0.854
DSPR	Coef.	0.157***	0.145***	0.177***	0.180***	0.201***
		(5.15)	(4.59)	(4.37)	(3.80)	(3.58)
	Adj-R^2	0.647	0.656	0.646	0.644	0.859
Number of obs.		228	228	228	228	228
Control variables		O	O	O	O	O
Policy dummy		X	O	O	O	O
Year dummy		X	O	X	X	X
Long-run relationships		X	X	O	O	O

Notes. The table represents the estimated coefficient (t-statistic in parentheses) and adjusted R^2 from each regression. *** denotes significance at the 1% level.

Table 5. Connectedness table

Panel (a) COAL				
	ERIX	EUA	COAL	From
ERIX	22.72	8.94	1.67	10.61
EUA	8.14	22.04	3.14	11.29
COAL	1.35	1.89	30.10	3.24
To	9.50	10.83	4.81	25.14
Panel (b) DSPR				
	ERIX	EUA	DSPR	From
ERIX	22.97	10.15	0.21	10.36
EUA	9.01	22.84	1.48	10.49
DSPR	0.30	1.45	31.59	1.75
To	9.31	11.60	1.69	22.60

Notes. This table presents the DY spillover from the column variable to the row variable. The diagonal values denote their own contribution. The column labeled "*From*" stands for total spillover from other variables to each variable and the row labeled "*To*" denotes total spillover from each variable to other variables.

Table 6. Impulse response functions

lag	COAL to EUA	EUA to ERIX	COAL to ERIX	DSPR to EUA	EUA to ERIX	DSPR to ERIX
1	0.00	**-12.25**	-1.14	**0.10**	**-10.47**	1.71
2	-0.02	-12.17	-3.04	**0.22**	-7.28	4.20
3	-0.05	-7.01	-5.23	**0.30**	2.30	7.84
4	-0.11	4.85	-7.68	0.24	17.49	6.92
5	-0.23	13.50	-11.01	0.14	28.30	5.41
6	**-0.40**	22.16	**-15.58**	0.18	37.71	4.86
7	**-0.54**	33.04	**-18.82**	0.36	**48.46**	6.17
8	**-0.61**	41.07	**-20.26**	**0.54**	**55.68**	6.65
9	**-0.62**	**44.96**	**-20.74**	**0.64**	**57.95**	6.01
10	**-0.59**	**49.87**	**-21.05**	**0.69**	**59.89**	5.63
11	**-0.58**	**56.11**	**-20.70**	**0.70**	**60.83**	6.65
12	**-0.58**	**58.16**	**-19.56**	**0.70**	**57.36**	8.63
13	**-0.57**	**53.30**	**-18.08**	**0.71**	**48.71**	10.60
14	**-0.52**	**45.31**	**-16.67**	**0.74**	38.73	11.52
15	**-0.44**	37.24	**-15.50**	**0.74**	29.60	11.72

Notes. Bold indicates significance at the 5% level.