The effect of emissions trading on the relationship between fossil fuel and renewable energy companies

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Outline

- Introduction
- Data and methodology
- Empirical results
- Conclusion

1. Introduction

Introduction

- Developing renewable energy sources (RES) has emerged as the primary way to address concerns regarding climate change and establish a sustainable global energy system.
- Emission trading sheds light on this by encouraging the environmental efficiency of RES (Anke and Möst, 2021; Jaraitė and Di Maria, 2012).
- The European Union emission trading system (EU ETS) is a market-based mechanism designed to help achieving greenhouse gas emissions reduction targets.

Introduction

- Under this cap-and-trade system, companies are required to buy emission allowances (EUAs) in an amount corresponding to their annual carbon emissions.
- Accordingly, price of carbon has considered in their decision-making process.
- Studies show that carbon risk affects firms' stock return (Bolton and Kacperczyk, 2021), tail risks (Ilhan et al., 2021), capital structure (Nguyen and Phan, 2020), and acquisition decisions (Bose et al., 2021).

Introduction

- The electric power sector is a major target of environmental policies because of their contribution to total emission and the flexibility in the choice of fuels.
- In response to the binding emission cap, the possible options 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).

Introduction

- 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).
- Increase of carbon-intensive fuel prices reduces the demand for emission allowance, placing downward pressure on allowance prices (Aatola et al., 2013; Batten et al., 2020; Weigt et al., 2013).
- The prices of renewable energy stocks are closely related to allowance prices (Guo et al., 2020).

Introduction

- Higher prices for carbon-intensive fuel have both positive and negative influences on renewable energy stock prices.

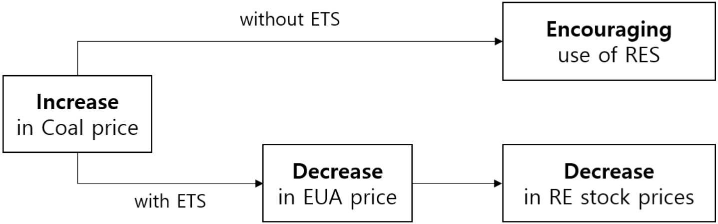

Figure. The relationship between coal and renewable energy stock prices

Introduction

- In this study, we investigate the dependent relationship between prices of European renewable energy stocks and coal, by considering the price of carbon.
- The results consistently imply that increases in coal prices have a negative effect on renewable energy stock prices.
- Our findings allow for a richer understanding of the effect of emission tradings and provide policy implications.

2. Data and methodology

Data

- Data period is from January 1, 2013, to December 31, 2019 (1826 days) corresponding to the EU ETS Phase III.

- European renewable energy index (ERIX): Representative renewable energy stock price index in Europe (see Appendix in Page 34).

- European emission allowance (EUA): Emission allowance traded in EU ETS.

- The dark spread, defined as the profit a coal-fired power plant earns from selling a unit of electricity, is given by

$$Dark\ spread = P_E - \frac{P_c \times \eta_c}{E_c}.$$

Data

Table. 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

Methodology - Wavelet Analysis

- We employ wavelet methods to reconstruct time series with specific levels of persistence, reducing noise, trend, and seasonal components.
- Wavelet-based decomposition is widely used for the multiscale analysis (Ortu et al., 2013; Xyngis, 2017; Kang et al., 2017) or denoising (Donoho and Johnstone, 1994, 1995; Zhang et al., 2016) of financial time-series.
- Many studies in the field of energy economics adopt wavelet decomposition to reconstruct time series with specific levels of persistence, reducing noise, trend, and seasonal components (Fosten, 2019; Hamdi et al., 2019; Reboredo et al., 2017).

Methodology - CWT

- The continuous wavelet transformation (CWT) of $y(t)$ can be presented as

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

where ψ is a wavelet and $\star$ denotes complex conjugate.

- The cross-wavelet transform can be calculated as follows:

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

Methodology - CWT

- The squared wavelet coherence captures the intensity of the interdependence, given by

$$K^2_{yx}(\xi,\vartheta) = \frac{|\kappa\left(\vartheta^{-1}W_{yx}(\xi,\vartheta)\right)|^2}{\kappa(\vartheta^{-1}|W_y(\xi,\vartheta)|^2)\kappa(\vartheta^{-1}|W_x(\xi,\vartheta)|^2)}.$$

- The wavelet coherence phase difference captures the sign of correlation and the lead-lag relationships, defined as

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

Empirical results - CWT

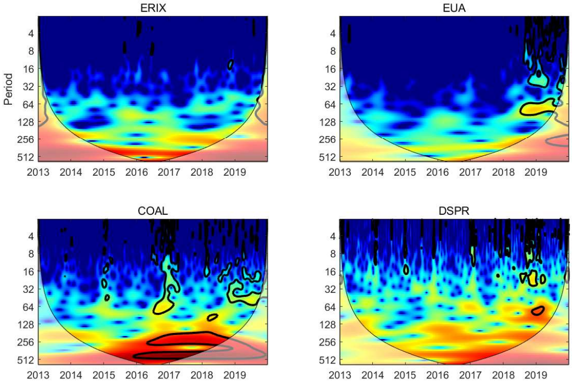

Figure. Wavelet power spectrum of ERIX, EUA, COAL, and DSPR

Notes. The thick black contour indicates significance at the 5% level. The hotter color illustrates higher power.

Empirical results - CWT

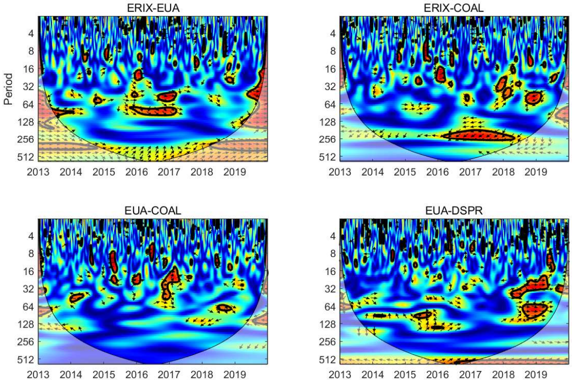

Figure. Wavelet coherence and phase plots

Notes. The right (left) arrow signifies in (out-of) phase and the up (down) arrow implies the first (second) series leads another series.

Methodology - DWT

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

$$\begin{aligned} y(t) &= \sum_k s_{J,k}\varphi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t) \\ &= S_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_1(t). \end{aligned}$$

- For daily data (1826 days), D_j roughly corresponds to a 2^j-day scale shock.

Methodology - DWT

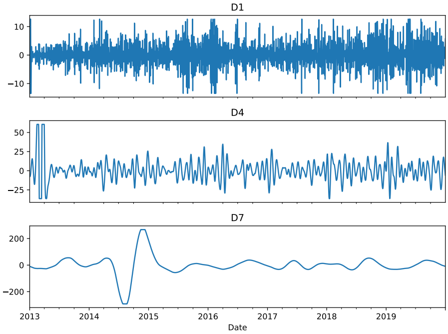

Figure. Plot of wavelet decomposed series for ERIX

- Figure visualizes components of ERIX that correspond to 2- to 4-day, 16- to 32-day, and 128- to 256-day scale shocks.

Wavelet-adjusted series

- We employ DWT to reconstruct time series with specific levels of persistence, reducing noise, trend, and seasonal components.

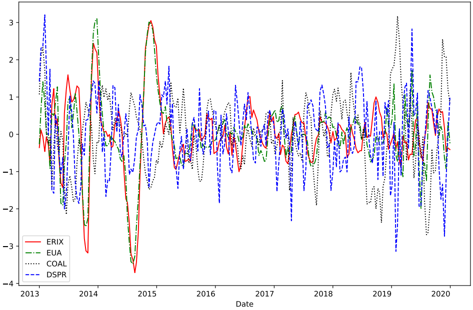

Figure. Wavelet-adjusted ERIX, EUA, COAL, and DSPR

Notes. For each variable we calculate the sum of the variations in the remaining time scales ranging from 16 to 256 days.

Wavelet-adjusted series

Table. Descriptive statistics 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

3. Empirical results

Empirical results - Regression analysis

- Using the wavelet-adjusted series, we perform following three regressions:

$$
\begin{aligned}
&\text{(R1)} \quad EUA_{t+1} = \alpha_1 + \beta_{1,F} Fuel_t + \boldsymbol{\beta}_1 \mathbf{X}_t + \epsilon_{1,t}, \\
&\text{(R2)} \quad ERIX_{t+1} = \alpha_2 + \beta_E EUA_t + \boldsymbol{\beta}_2 \mathbf{X}_t + \epsilon_{2,t}, \\
&\text{(R3)} \quad ERIX_{t+1} = \alpha_3 + \beta_{2,F} Fuel_t + \boldsymbol{\beta}_3 \mathbf{X}_t + \epsilon_{3,t}.
\end{aligned}
$$

- Coal price ($COAL$) and dark spread ($DSPR$) can be proxies for the fuel price.
- Year dummies, policy dummies, and time series regression methodologies are employed.

Empirical results - Regression analysis

Table. 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

Empirical results - Regression analysis

Table. 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

Empirical results - VAR

- To examine the VAR system, we perform a Granger causality test, impulse response analysis, and forecasting error variance decomposition.

- The vector moving average representation of a VAR model can be obtained as follows:

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

- $\Psi_l(i,j)$ captures the response of variable i when ϵ^v_j increased by one unit with time lag l.

Empirical results - VAR

- Diebold and Yilmaz (2009, 2012, 2014, herinafter DY) propose a connectedness measure based on the generalized forecasting error variance decomposition.
- The contribution of variable j to the H-step ahead forecast error variance of variable i is given by

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

Empirical results - VAR

- In the connected matrix, cell (i, j) represents the pairwise direction connectedness from i to j (Ξ_{ij}^{H}). We can calculate *net* pairwise directional connectedness $(\Xi_{ij}^{H} - \Xi_{ji}^{H})$.

- To determine whether a variable is a transmitter or a receiver of spillover in the system, we calculate total directional connectedness *from i to others* $(\Xi_{i\to\bullet}^{H} = \sum_{q=1,q\neq i}^{k} \Xi_{qi}^{H})$, and *net* total directional connecteness *from i* $(\Xi_{i\to\bullet}^{H} - \Xi_{i\leftarrow\bullet}^{H})$.

Empirical results - VAR

Table. Connectedness table

	ERIX	EUA	COAL	From others
Panel (a) Connectedness (%)				
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 others	9.50	10.83	4.81	25.14
Panel (b) Net directional connectedness (%)				
ERIX		0.80	0.31	1.11
EUA			1.26	0.46
COAL				-1.57

	ERIX	EUA	DSPR	From others
Panel (a) Connectedness (%)				
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 others	9.31	11.60	1.69	22.60
Panel (b) Net directional connectedness (%)				
ERIX		1.14	-0.09	1.05
EUA			0.03	-1.11
DSPR				0.06

Empirical results - VAR

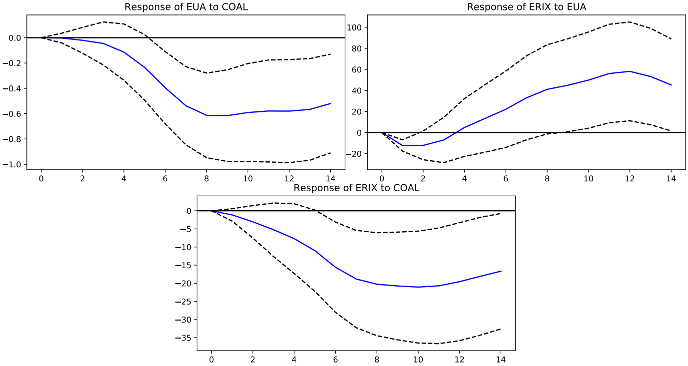

Figure. IRF of VAR model for ERIX, EUA, COAL

Empirical results - VAR

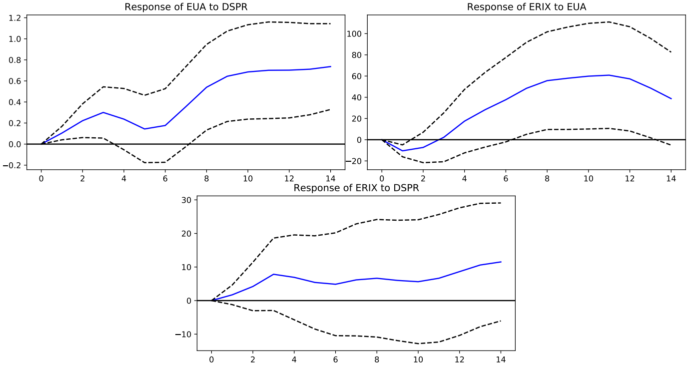

Figure. IRF of VAR model for ERIX, EUA, DSPR

4. Conclusion

Conclusion

- It is believed that higher fossil fuel prices force to accelerate technological developments of RES.
- By applying a suitable filtering procedure, we observe a negative relationship between the price of carbon-intensive fuel and the prices of RE stocks in the ETS.
- Our findings have implications for both researchers and policymakers who wish to examine the effect of ETS in promoting the development of RES.

Appendix. ERIX components

TOP COMPONENTS

Name	Country	Weight (%)
MEYER BURGER TECHNOLOGY AG	CH	6.25%
SCATEC SOLAR ASA	NO	5.50%
SOLARIA ENERGIA Y MEDIO AMBI	ES	5.49%
SMA SOLAR TECHNOLOGY AG	DE	4.87%
ALBIOMA SA	FR	4.72%
NORDEX SE	DE	4.56%
VESTAS WIND SYSTEMS A/S	DK	20.28%
ORSTED A/S	DK	18.96%
SIEMENS GAMESA RENEWABLE ENE	ES	18.21%
VERBUND AG	AT	11.15%

SECTOR BREAKDOWN

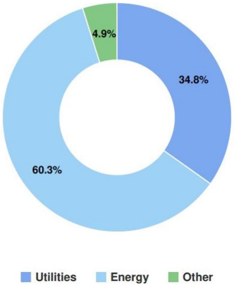

Figure. ERIX components (2020.09.30)

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