Energy Reports 12 (2024) 2845–2854

Contents lists available at ScienceDirect

Energy Reports

journal homepage: www.elsevier.com/locate/egyr

Research paper

Carbon emission allowances and Nordic electricity markets: Linkages and hedging analysis

Joonas Vaissalo [a], Anupam Dutta [b,*], Elie Bouri [c], Nehme Azoury [d]

[a] Global Sustainability Function of Hiab, Helsinki, Finland
[b] School of Accounting and Finance, University of Vaasa, Finland
[c] School of Business, Lebanese American University, Lebanon
[d] USEK Business School, Holy Spirit University of Kaslik, Lebanon

ARTICLE INFO

Keywords:
European Union allowances (EUA)
EU ETS
Nordic electricity market
Return and volatility spillovers
Hedging effectiveness
DCC-GARCH
COVID-19 outbreak

ABSTRACT

Unlike previous studies which tend to consider only return linkages between European emission allowances and electricity markets, this paper examines return and volatility linkages between the two markets and importantly conducts a hedging analysis. Using a dynamic conditional correlation model and daily price data covering European emission allowances and Nord Pool electricity markets from 28th January 2009–22 th February 2022, which comprise the second and third phases of the European emission allowances trading system, the main results are summarized as follows: Firstly, volatility and returns flow from the Nordic electricity market to the European emission market, with no evidence of a feedback effect, suggesting that rapid changes in demand for electricity may have forced producers to ramp up carbon-intensive facilities. Secondly, the conditional dynamic correlation between the two markets is weak but varies with time, and its sensitivity to crisis periods is noted. Thirdly, the hedging analysis indicates that Nordic electricity market participants can lower their downside risk by including carbon emission allowances in their portfolios, as evidenced by the effectiveness of hedging returns of the Nordic electricity markets with European allowances, irrespective of the COVID-19 sub-periods.

1. Introduction

Greenhouse gas emissions, especially carbon dioxide (CO_2), are the main driver of global warming and changing climate (Luo and Wu, 2016), threating society, the global financial system, and the global economy.[1] To tackle this threat, organizations and governments across the globe joined forces in 1997 to establish the Kyoto protocol based on the United Nations framework convention on climate change (UNFCCC),[2] which led to the introduction of the European Union (EU) emission trading scheme (ETS) in 2005. Based on the 'cap and trade' principle, the EU ETS provides incentives to meet the goals set in the Kyoto protocol. Operators buy or receive emissions allowances, which are traded on the market. Under the cap, participants are able to trade CO_2 emission allowances freely, meaning the price of allowances to emit carbon dioxide is determined by market forces (European Commission, 2015). The EU ETS sets a maximum cap on greenhouse gas emissions emitted by participating corporations and facilities, which is decreased annually with the target of carbon neutrality by the year 2050. Interestingly, the EU ETS constitutes the largest single market for CO_2 emission allowances, called European Union allowances (EUA), representing more than 80 % of the market value of global carbon.

The European electricity sector is one of the largest participants in the EU ETS, exerting an influence on the equilibrium of EUA supply and demand. Utilities make decisions regarding their need for emission

* Corresponding author.
E-mail addresses: joonas.vaissalo@hiab.com (J. Vaissalo), adutta@uwasa.fi (A. Dutta), elie.elbouri@lau.edu.lb (E. Bouri), nehmeazoury@usek.edu.lb (N. Azoury).

[1] Some studies consider climate change indices and media coverage of the pandemic (Polat et al., 2023), and adaptation funding and CO_2 emissions (Djoundourian et al., 2022), whereas others consider the environmental movement (Djoundourian, 2011), climate change challenges (Djoundourian, 2021), environmental policy objectives (Hilmi et al., 2021), and emission taxes (Marrouch and Sinclair-Desgagné, 2012), bearing in mind that monetary policies are affected by a changing financial environment (Shahin and El-Achkar, 2017). Related studies consider digital transformation for sustainable societies (Tarhini et al. 2022), policy insight into carbon capture (Gowd et al., 2023), energy transition in advanced economies (Hu et al., 2022; Sinha et al., 2023), sustainability practices (Nader et al., 2022) and sustainability issues (Ali et al., 2023; Dai et al., 2023; Nwani et al., 2023; Quito et al., 2023).

[2] The initial goal of the Kyoto protocol was to decrease the amount of greenhouse gases emitted on average by 5.2 % compared to the year 1990 (UNFCCC, 2003).

https://doi.org/10.1016/j.egyr.2024.08.072
Received 27 January 2023; Received in revised form 28 May 2024; Accepted 26 August 2024
Available online 4 September 2024

allowances and buying strategies based on their power production mix, which ultimately has a major influence on how EUA prices evolve in both the long and short term (World Bank, 2012). Accordingly, our first motivation is that the power production mix in Europe's Nordic areas relies heavily on carbon-free methods, which makes it interesting to study its return and volatility dynamics with emission trading and the resulting hedging implications for economic actors. The second motivation concerns the occurrence of crisis periods such as COVID-19 and the war in Ukraine, which might affect EUA prices (Berrisch et al., 2023) but are not full covered in previous studies of the EUA-electricity nexus (Castagneto-Gissey, 2014; Zhu et al., 2017, 2019; Wen et al., 2017; Moutinho et al., 2022). In this regard, Dutta et al. (2019) and Lin and Zhang (2022) study the forecast of EUA prices and highlight the importance of structural changes. This further motivates our analysis of the return and volatility spillovers between EUA and electricity prices and the hedging analysis over a rich period covering the COVID-19 outbreak and war in Ukraine.

The existing literature on the link between EUA and electricity markets is narrow compared to that on EUA and fossil fuels such as crude oil and coal (see, Gong et al., 2021; Aslam et al., 2023).[3] Notably, very few studies focus on the price and return dynamics between electricity and EUA markets (Hammoudeh et al., 2014; Huisman and Kiliç, 2015; Wen et al., 2017; Zhu et al., 2017; Qiao et al., 2023).[4]

The purpose of this paper is to examine the return and volatility relationship between EUA and Nordic electricity markets and conduct a dynamic hedging analysis. Data used are daily covering EU ETS allowance prices and electricity prices from the Nordic electricity exchange, also referred to as Nord Pool. Our sample period is July 2009 to June 2023, including most of Phase II, Phase III, and the first 3 years of Phase IV.

Accordingly, we formulate the following null hypothesis:

H_0. : There exists no significant relationship between EU ETS and Nordic electricity markets.

The following alternative hypotheses are derived:

H_1. : There exists significant volatility spillovers between EU ETS and Nordic electricity markets.

H_2. : There exists significant return spillovers between EU ETS and Nordic electricity markets.

H_3. : The correlation between EU ETS and Nordic electricity prices is significant and time-varying.

H_4. : There is effective hedging between EU ETS and Nordic electricity markets.

Methodologically, we use the dynamic conditional correlation generalized conditional heteroscedastic (DCC-GARCH) model originally proposed by Engle (2002). The DCC-GARCH model enables non-constant conditional correlation matrices, with which analysis of time-varying relationships is possible. This accounts for correlation clustering, reflecting the fact that correlation is more likely to be high today if it was high yesterday (see, Basher and Sadorsky, 2016; Saeed et al., 2020; Gustafsson et al., 2022). Additionally, the DCC-GARCH model produces parameters that allow for the investigation of return and volatility cross-effects between the two markets under study. Notably, it takes into account important features of time series such leptokurtic returns and volatility clustering. The latter indicates that volatility is not constant and a shock occurring today can affect the volatility tomorrow, which requires a GARCH-based model capable of dealing with conditional heteroscedasticity (see, Chevallier, 2012; Saeed et al., 2020; Gustafsson et al., 2022).

We contribute to the academic literature on the relationship between carbon emission allowances and Nordic electricity markets in several ways. Firstly, the existing literature considers the volatility of EUA returns (Villar-Rubio et al., 2023) and its tail risk (Fang and Cao, 2021), but remains silent and very thin regarding the volatility dynamics between electricity and EUA markets during crisis periods such as the COVID-19 outbreak.[5] Castagneto-Gissey (2014) investigates the volatility transmission from EUA prices to various European electricity forward prices using a GARCH-based approach, revealing that EUA volatility has positive and significant effects on electricity volatility in France, Germany, and especially Nordic countries, indicating that the most significant factor affecting the electricity volatility during EU ETS Phase II is EUA volatility. However, Castagneto-Gissey (2014) does not account for turbulent periods nor conduct a hedging analysis. Therefore, in this current paper, unlike previous studies (Wen et al., 2017; Zhu et al., 2017, 2019; Moutinho et al., 2022; Qiao et al., 2023), we investigate the return, volatility, and time-varying conditional correlation relationship between EUA and Nordic electricity and examine the hedging effectiveness under crisis periods. Secondly, our analysis adds to previous studies focusing on the portfolio and risk implications. Fang and Cao (2021) consider the modeling of the risk of carbon emission allowances prices in Europe and China using value-at-risk and expected shortfall measures, indicating that downside risk in China is larger than that in Europe. Villar-Rubio et al. (2023) study the volatility of EUA returns and make inferences about volatility prediction using univariate GARCH models. However, these studies lack an analysis of the returns and volatility linkages between EUA and electricity markets and a hedging analysis using an updated sample period covering the market instability experienced since the COVID-19 outbreak and war in Ukraine. Thirdly, our sample period is relatively long (July 2009 to June 2023), including most of Phase II, Phase III, and the first 3 years of Phase IV. This also allows us to contribute to the literature (Castagneto-Gissey, 2014) by extending the reach of current research into energy and emission markets to unstable periods such as the COVID-19 outbreak and war in Ukraine.

Our key findings suggest that volatility and returns flow only from the Nordic electricity market to the European emission market. No evidence of information or return flows in the opposite direction is found. This could be due to Nordic countries developing their production mixes to include more carbon-free generation. Thus, EUA prices have no impact on the region's electricity price formation. Furthermore, electricity's volatility could affect EUA volatility as rapid changes in demand for electricity may force producers to ramp up carbon-intensive facilities. Finally, the hedging analysis proves that Nordic electricity market participants can lower their downside risk by including carbon emissions assets in their portfolios.

[3] On a related front, the literature considers the relationship between EUA and stock market indices (e.g., Jiménez-Rodríguez, 2019). In an interesting study, Köten (2018) focuses on advanced numerical and experimental studies of compression ignition (CI) engine emissions.

[4] For example, Zhu et al. (2017) consider the Granger causal flows between EUA and electricity markets during 2005–2016, indicating that causality is not necessarily seen across time-scales although the effect of the carbon market on the electricity market is weakening. Notably, they do not consider the entirety of Phase III or any parts of Phase IV, and importantly, do not conduct any hedging analysis for portfolio and risk managers in the EUA and electricity markets. Wen et al. (2017) focus on Phase II and part of Phase III using copulas and indicate that, of the four energy commodities, coal is the most useful to reduce carbon risk, whereas electricity is the least. Qiao et al. (2023) consider the relationships between carbon, fossil energy and electricity markets using a time-varying parameter VAR and impulse response functions. They indicate that the spillover effects across the three markets are characterized by lag and periodicity. Furthermore, in the short term, higher carbon prices are negatively related to electricity prices.

[5] Other studies consider economic worries in response to the pandemic (e.g. Bou-Hamad et al., 2022) and the political economy of health in conflict during the pandemic (e.g. Fouad et al., 2022).

Our above analysis provides important and useful information for market operators and corporate managers responsible for managing risk and hedging market exposure during stable and turbulent periods. Given the recent shift to greener energy and environmentally friendly businesses, our results are useful for socially responsible and eco-friendly investors who intend to decarbonize their portfolios by holding alternative (green) energy assets.

2. Literature review

Over the past decade, the academic literature on the carbon market has received a growing amount of interest from scholars, policymakers and investors, especially studies regarding return and volatility dynamics between EU ETS and commodity or stock markets.

2.1. Studies on EU ETS

The EU is engaged in reducing CO_2 emissions through the EU ETS. It has progressed from Phase I (2005–2007), which acted as the trial or learning phase before the full adoption of the Kyoto protocol, to Phase II (2008 – 2012), which worked jointly with the Kyoto protocol, to Phase III (2013–2020), under which carbon emissions were set to be reduced by 20 %. Currently, it is in Phase IV (2021–2030), under which the sectors covered by the EU ETS are required, before the end of 2030, to reduce their carbon emissions by 43 % compared to 2005 levels.

Early studies on EUA prices include Oberndorfer (2009) and Veith et al. (2009), both of which analyse only Phase I of the EU ETS. Employing a multifactor framework including firm specific EUA effects, Oberndorfer (2009) finds a significant positive correlation between EUA price changes and the stock performance of European electricity firms, and argues that the relation is time- and country-specific. Veith et al. (2009) also report a somewhat counterintuitive positive correlation between EUA price and electricity producers. According to both studies, the root cause of the positive correlation is the over-allocation of free emission allowances during the trial period. Zhu et al. (2017) examine the Granger causal relationship between EUA and electricity markets during 2005–2016, showing evidence that causality is not necessarily seen across time-scales although the effect of the carbon market on the electricity market is weakening. Further investigations of return linkages are carried out by Oestreich and Tsiakas (2015) and Tian et al. (2016), who extend the study period to Phase II of emission trading. Oestreich and Tsiakas (2015) explain the positive correlation between German stock returns and EUA with excess abnormal returns, i.e. carbon premium. Tian et al. (2016) use panel data regressions and indicate that the two main drivers of the EUA market which impact electricity producers are carbon intensity of production and overall market volatility. Zhu et al. (2019) conduct a multiscale analysis to study the drivers of carbon prices and find that electricity prices and stock market index play a positive role, especially in the short term, whereas coal prices play a negative role in the medium and long term. Moutinho et al. (2022) examine the long-term relationships between the prices of energy commodities, carbon prices, and wholesale electricity prices in the Iberian market using 2018 daily data and Markov-switching regression models. Overall, they show that coal and natural gas prices have a moderate impact on electricity prices. Berrisch et al. (2023) model the volatility and dependence of EUA and energy markets (natural gas, coal, and crude oil) using a GARCH-based approach combined with copulas. They assess the forecasting performance using an out-of-sample analysis.

Targets to limit global warming have introduced a rising demand for renewable energy sources. The supply of renewable energy is variable, making the grid less flexible while increasing the uncertainty of the energy supply. The reduced reliability of the energy grid introduces a demand for additional market participants with different bidding strategies. Increasing carbon prices further affect the bidding strategies of these new participants. In recent literature, scholars explore how aggregators operate and how carbon pricing impacts their strategies. Coelho et al. (2021) propose a bidding strategy for aggregators operating with multi-energy systems and examine how carbon prices affect operators following the proposed strategy. According to their results, an aggregator which follows the proposed network secure bidding strategy, the authors suggest, sees an increase in costs following an increase in carbon emission pricing. However, the increase does not impact its bidding before the price for a tonne of emitted carbon reaches €200.

Besides the electricity power sector, the academic literature on EUA considers the stock market at the aggregate and sectoral levels (Demailly and Quirion, 2008; Chan et al., 2013; Meleo, 2014; Moreno and Silva, 2015; Jiménez-Rodríguez, 2019). The literature also considers the possible effects of commodities on the electricity markets because electricity and heat are often produced using energy commodities (see, Creti et al., 2012; Kumar et al., 2012; Aatola et al., 2013; Dutta, 2017; Dutta et al., 2018).

In a related strand of literature, Fang and Cao (2021) compare carbon emission allowances in Europe and China by modeling extreme risks using value-at-risk and expected shortfall measures. They show that the downside risk in China is larger than in Europe and that the relationship between upside carbon emission allowances prices in both countries varies across periods and across the two risk measures. Villar-Rubio et al. (2023) model the volatility of EUA returns by applying an asymmetric GARCH model and make inferences about volatility prediction. Dai et al. (2022) provide evidence supporting the significant effect of economic policy uncertainty, both European and global, on the long-term volatility of EUA prices. Bouri et al. (2023) consider the directional predictability from climate risks to the returns and volatility of energy assets and green bonds, including EUA prices. Their results show that predictability is significant during some periods and under some market conditions and volatility states. Notably, the predictability of volatility is positive for brown energy and EUA.

2.2. Volatility dynamics between EUA and financial markets

Besides returns, scholars focus on the volatility dynamics between EUA prices and other financial markets, yet the literature remains scarce. Tian et al. (2016) study the existence of volatility linkages between carbon markets and the stock prices of electricity companies with a multivariate DCC-GARCH model. The results of the analysis suggest that the model including dynamic conditional correlations is an appropriate fit for the data, as correlations are volatile during the whole second phase of emission trading. However, the stage including Phase I fails to yield any significant results regarding EUA price returns. The results from Phase II show positive and significant effects considering past variability and volatility spillovers for both EUA price returns and returns from electricity stocks. Dutta et al. (2018) use a bivariate VAR-GARCH model to demonstrate the volatility linkages between clean energy stocks and emission trading. Notably, Phase I is excluded from the sample period as carbon prices are close to zero at the end of the trading phase. Evidence from the VAR-GARCH analysis suggests that volatility transmission from the emission market to European clean energy stocks exists. Additionally, the authors fail to find significant volatility linkages between EUA and the US market. This indicates that

the effect is market-specific.[6]

The literature also considers the interrelations of electricity and carbon allowances. Daslakis and Markellos (2009) examine the connection between the carbon spot market and electricity risk premia. By regressing realized percentage risk premia against logarithmic EUA returns, they detect a positive connection between EUA returns and electricity risk premia, suggesting that the connection is based on carbon market uncertainties and the trading of initially allocated free allowances. Keppler and Mansanet-Bataller (2010) use a Granger causality framework and argue that electricity prices affect carbon allowances through spreads between the sum of electricity production and carbon price, and the spot price of electricity. Using a GARCH model, Castagneto-Gissey (2014) find significant volatility spillovers from carbon prices to electricity price volatility in France, Germany, and particularly, the Nordic region.

2.3. Related studies of hedging effectiveness

Some studies examine the hedging effectiveness of EUA and electricity markets separately. Reboredo (2013) examines EUA-oil portfolios and shows evidence of the diversification benefits and hedging effectiveness of EUA for crude oil. Balcilar et al. (2016) focus on the risk transmission between energy and carbon markets and indicate hedging strategies for carbon risk, although it exhibits some instability across periods and market conditions. Wen et al. (2017) use copulas and highlight the risk reduction in a portfolio combining energy commodity futures (crude oil, coal, natural gas, and electricity) and carbon emission allowances. Notably, they show that coal is the most attractive for reducing carbon risk, whereas electricity is the least attractive. Hanly et al. (2018) study the efficacy of financial futures to hedge the risk of electricity markets, while highlighting the efficiency of energy futures markets. Souhir et al. (2019) argue that risk and hedging strategies in the Nord Pool electricity market can be achieved by considering sectoral stock markets. Jin et al. (2020) examine the hedging effect of green bonds on the carbon market and highlight their hedging ability during crisis periods.

Based on the above review of the literature on the relationship between EU ETS and other financial markets, it is clear that previous studies lack a comprehensive analysis of both return and volatility linkages between EUA and electricity markets and the portfolio implications, using an updated sample period covering the market instability under the COVID-19 outbreak and war in Ukraine. In fact, the end of Phase III saw the rise of the COVID-19 pandemic that severely affected global economic activity and increased uncertainty in financial markets. Notably, the second year of Phase IV (2021–2030) saw the Russia-Ukraine war, during which energy prices increased substantially under the heightened geopolitical risk and EUA prices experienced a large spike and increased variability. Thus, analysing the return and volatility dynamics between EUA and electricity markets and the time-varying correlation during tranquil and turbulent periods to ultimately make inferences regarding hedging possibilities before and after crisis periods should be useful to investors, portfolio and risk managers, and policymakers concerned with energy transition and portfolio decarbonization.

[6] Methodologically, GARCH-based models are often used to describe the volatility dynamics and risk spillovers between EUA and certain commodities. Chevallier (2012) compares results from three GARCH family models and indicates that the DCC-GARCH is the most efficient in modeling time-varying correlations between emission allowances and energy commodities. The results indicate significant co-movements between EUA, gas and crude oil. Dhamija et al. (2018) study the effects of coal, natural gas and crude oil using a BEKK-GARCH model and identify significant effects from gas and oil to EUA markets, but no evidence of a volatility relationship between coal and EUA. Furthermore, the applied BEKK-GARCH model is unable to identify any long-term effects. However, the findings of Dhamija et al. (2018) regarding the effect of crude oil on EUA are contractionary to Reboredo (2014), who finds a significant interrelationship between crude oil and EU ETS markets.

3. Data and methodology

3.1. Data description and preliminary analysis

We use European emission allowances prices, traded on the European Energy Exchange (EEX), and Nordic electricity average prices, collected from DataStream at the daily frequency. The sample period is 1st July 2009–30 th June 2023, based on price data availability. The sample yields a total of 3558 daily observations, covering EUA trading Phase II and Phase III and a short period of the currently ongoing Phase IV (2021–2030), under which the sectors covered by the EU ETS are required, before the end of 2030, to reduce their carbon emissions by 43 % compared to 2005 levels. Following Dutta (2019), the entire first trading phase and the first days of the second phase are left out of the scope of the study, as the price of EUA was practically zero due to interphase banking restrictions of allowances.

Fig. 1 illustrates the time evolution of European emission and Nordic electricity prices over the sample period. From early 2017, the EUA prices see a rising trend due to a tightening cap and the implementation of new operationalities such as the market stability reserve. They surge to almost 30 €/tCO_2 before declining back to below 20 €/tCO_2 around February-March 2020, potentially due to the abrupt emergence of the COVID-19 pandemic. After that, they experience a spike towards 96 €/tCO_2. Nordic electricity prices exhibit strong volatility, seasonality, and extreme prices, although they increase after the pandemic period. Volatile price behavior is possibly due to the special characteristics of electricity such as high seasonality and non-storability.

Studying volatility connections and time-varying return correlations between emission and electricity prices in a GARCH-family model necessitates the use of returns series. Thus, we use the logarithmic returns of the prices in each market.

Fig. 2 illustrates the logarithmic returns for both Nordic electricity and EUA over the sample period. Both logarithmic return series exhibit extreme values and volatility clustering, suggesting that a period of high volatility is likely to be followed by another period of high volatility and periods of low volatility are likely to be followed by low volatility periods.

Table 1 shows the summary statistics of both Nordic electricity returns and EUS returns. The means of both return series are close to zero. Nordic electricity returns are more volatile than EUA returns. The distribution of EUA returns is negatively skewed, while Nordic electricity returns are positively skewed. High values of kurtosis point to a leptokurtic distribution. The non-normality of both return distributions is verified by Jarque-Bera tests. The augmented Dickey-Fuller and Philips-Perron tests confirm the stationarity of both return series. Finally, the results of the autoregressive conditional heteroscedasticity - Lagrange multiplier (ARCH-LM) test of Engle (1982) show the significance of the ARCH effect in the squared residuals of EUA and electricity returns up to 10 lags, suggesting the appropriateness of using a GARCH-based model to deal with this conditional heteroscedasticity in the return series.

3.2. Methodology

3.2.1. The DCC-GARCH model

In this paper, we examine return and volatility spillovers and study the time-varying correlation between the carbon emission allowances and electricity markets under study using the DCC-GARCH model (Engle, 2002) in its bivariate framework (Dutta, 2019). As argued by Chevallier (2012), the superiority of DCC-GARCH modeling in the context of crude oil, gas and carbon prices is recognized. Furthermore, Tian et al. (2016) highlight the appropriateness of the DCC-GARCH framework is in the context of EU ETS and electricity stock prices.

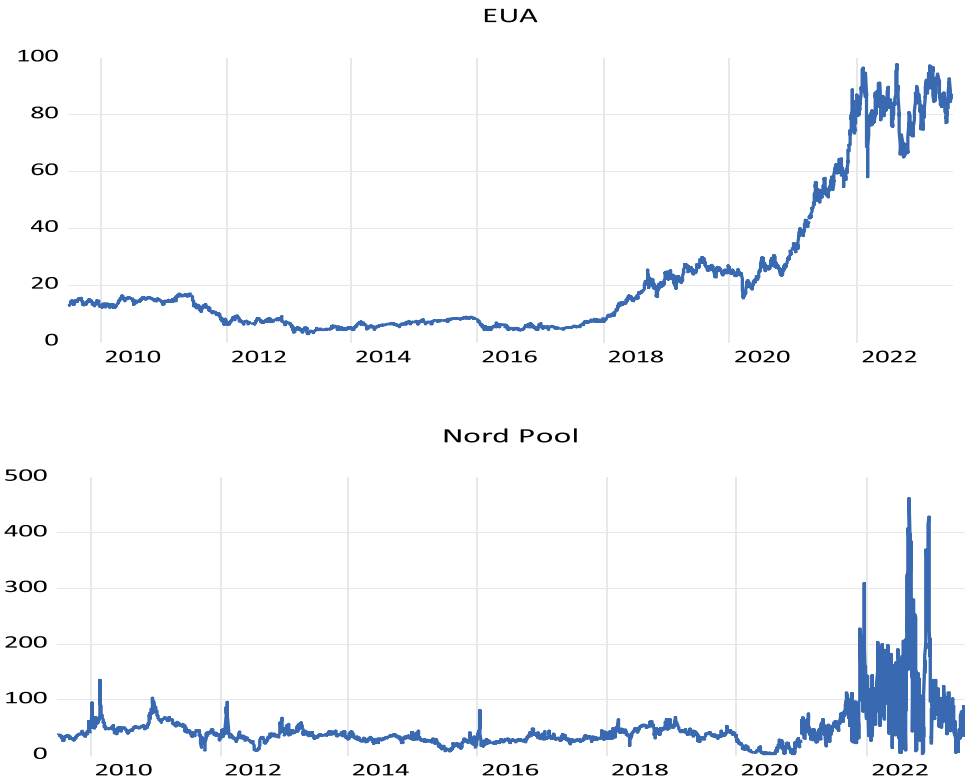

Fig. 1. Price evolution of EUA and Nordic electricity markets.

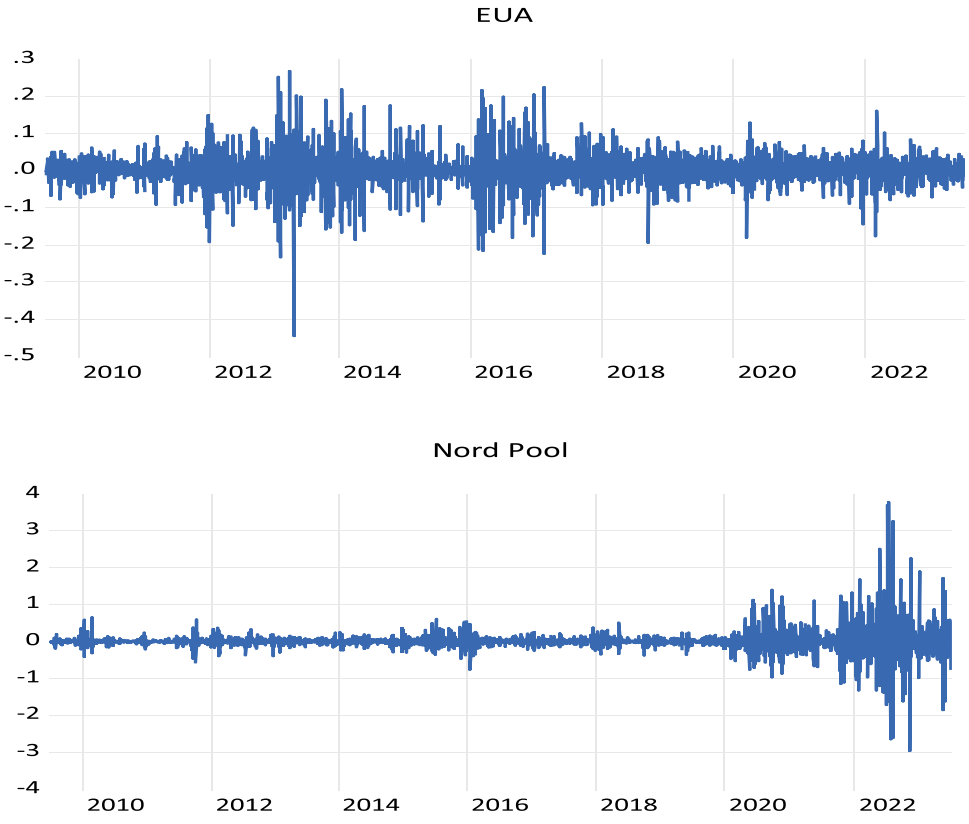

Fig. 2. Logarithmic returns of EUA and Nordic electricity.

Table 1
Summary and stationarity test statistics of logarithmic returns.

Indices	Mean	Standard deviation	Skewness	Kurtosis	Jarque-Bera	ADF	PP	ARCH test
EUA	0.0005	0.0411	−0.931	12.670	13,928.600***	−49.810***	−74.220***	29.390***
Nord Pool	−0.0001	0.2738	1.510	48.390	30,682.110***	−16.170***	−127.290***	102.580***

Notes: This table shows the summary statistics for returns. *** indicates statistical significance at the 1 % level.

The mean and volatility equations are the building blocks of the DCC-GARCH model used in this paper, starting with the mean equations of the bivariate framework, given by:

$$r_t = L + \tau r_{t-1} + \varepsilon_t \tag{1}$$

$$\varepsilon_t = H_t^{\frac{1}{2}} z_t \tag{2}$$

where, r_t is a vector of EUA and Nordic electricity prices returns, L is a vector of fixed parameters, τ is a matrix including coefficients representing the lagged returns of EUA and Nordic electricity prices, and ε_t represents a vector of residual terms.

H_t is a matrix including conditional volatilities of EUA and electricity returns, and z_t represents a sequence of independently and identically distributed random vectors. The conditional covariance matrix of r_t is represented by H_t as follows:

$$H_t = D_t R_t D_t \tag{3}$$

$$D_t = diag(\sqrt{h_t^c}, \sqrt{h_t^e}) \tag{4}$$

$$R_t = diag(Q_t)^{-1} Q_t diag(Q_t)^{-1} \tag{5}$$

where, D_t is a diagonal matrix with time-varying standard deviations on the diagonal. The correlation matrix, R_t, varies over time.

In a univariate GARCH(1,1) model, the elements of H_t are represented by:

$$\mathrm{h}_{\mathrm{i,t}} = \omega_{\mathrm{i}} + a\varepsilon_{\mathrm{i,t-1}}^2 + \mathrm{b_i h_{i,t-1}} \tag{6}$$

$$Q_t = (1 - \theta_1 - \theta_2)\overline{Q} + \theta_1 z_{t-1} z'_{t-1} + \theta_2 Q_{t-1} \tag{7}$$

Eq. (7) illustrates the construction of a time-varying covariance matrix denoted as Q_t, where θ_1 and θ_2 are non-negative scalar parameters which are demeaned to fulfill the condition $\theta_1 + \theta_2 < 1$, and $\overline{Q}$ is the unconditional matrix of standardized residuals z_t ($z_t = \varepsilon_t / \sqrt{h_t}$). The condition represents the mean-reverting process, ensuring that correlation is reverting back to long-term average after a shock affecting the returns. If $\alpha + \beta = 0$, then the model is reduced to the constant conditional correlation model. Parameters α and β measure the impacts from past shocks and past dynamic conditional correlations on current conditional correlations between EUA and electricity returns.

The conditional volatilities of EUA and electricity returns are represented by h_t^c and h_t^e, respectively.

$$h_t^c = d_c^2 + \beta_{c1}^2 h_{t-1}^c + \beta_{c2}^2 h_{t-1}^e + \alpha_{c1}^2 \varepsilon_{c\ ,t-1}^2 + \alpha_{c2}^2 \varepsilon_{e\ ,t-1}^2, \tag{8}$$

$$h_t^e = d_e^2 + \beta_{e1}^2 h_{t-1}^c + \beta_{e2}^2 h_{t-1}^e + \alpha_{e1}^2 \varepsilon_{c\ ,t-1}^2 + \alpha_{e2}^2 \varepsilon_{e\ ,t-1}^2. \tag{9}$$

where, β measures the own and cross-market effect of conditional variance on current EUA and electricity volatility, and α captures the corresponding own and cross-market impacts of past shocks and news on EUA and electricity volatility. The null hypothesis is that the coefficients α_{c2}^2, α_{e1}^2, β_{c2}^2 and β_{e1}^2 are insignificant and there is no spillover effect of volatility from EUA to electricity or electricity to EUA.

The conditional covariance between EUA and electricity returns is given by:

$$h_t^{ce'} = Q_t * \left(\sqrt{h_t^c} * \sqrt{h_t^e}\right) \Big/ \left(\sqrt{Q_t^c} * \sqrt{Q_t^e}\right) \tag{10}$$

The dynamic conditional correlation is given by:

$$\rho_{c,e,t} = \frac{q_{c,e,t}}{\sqrt{q_{c,c,t} q_{e,e,t}}} \tag{11}$$

3.2.2. Hedging effectiveness

Based on the time-varying conditional correlation, we assess possible hedging benefits between the two markets. Specifically, we investigate whether including EUA in a portfolio with Nordic electricity reduces the risk in the combination portfolio. Thus, a hedging effectiveness (HE) analysis is conducted, with a higher value of HE indicating more efficient risk reduction. Following Ku et al. (2007), HE is computed as:

$$HE = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}} \tag{12}$$

where $Var_{unhedged}$ includes the variance of the unhedged portfolio including only Nordic electricity, and Var_{hedged} defines the corresponding variation in the combined portfolio including both Nordic electricity and EUA. Var_{hedged} is given as:

$$Var_{hedged} = (\omega_t^{ce})^2 h_t^c + (1 - (\omega_t^{ce})^2) h_t^e + 2\omega_t^{ce}(1 - \omega_t^{ce}) h_t^{ce} \tag{13}$$

where h_t^c and h_t^e are the conditional volatilities of EUA and Nordic electricity price returns, defined in Eqs. (8) and (9). h_t^{ce} represents the conditional covariance between the two markets. Furthermore, ω_t^{ce} denotes the optimal weight of EUA in a portfolio combining EUA and electricity investments, as shown by:

$$\omega_t^{ce} = \frac{h_t^c - h_t^{ce}}{h_t^c - 2h_t^{ce} + h_t^e} \tag{14}$$

4. Empirical results

The estimated results of the DCC-GARCH model are presented in Table 2[7]. We focus on the significance, sign, and magnitude of possible return and volatility spillovers between the EU ETS and Nordic electricity markets as well as the time-varying correlation between them.

4.1. DCC-GARCH estimation

4.1.1. Mean and variance equations

Table 2 gives the estimation results from the DCC-GARCH model. Notably, r_{t-1}^e measures the return of the electricity market at time t-1 and r_{t-1}^c captures the effect of returns from the European emission trading scheme. The error terms ε_{t-1}^e and ε_{t-1}^c measure the effect of shocks and surprising news on electricity and emission markets, respectively. Finally, h_{t-1}^e measures the effect of conditional variance of electricity returns while h_{t-1}^c captures the conditional variance of the corresponding sample from emission markets.

An examination of the mean equations reveals that past emission allowance returns have a significant impact on current electricity returns and vice-versa, implying a bidirectional return spillover between

[7] RATS statistical software is used in data analysis and model estimation.

Table 2
Results of the DCC-GARCH model.

	Nord Pool	EUA
Mean equation		
ret−1	0.1983***	0.1081***
	(0.00)	*(0.00)*
rct−1	0.3370***	0.0535***
	(0.00)	*(0.00)*
constant	−0.0060*** (0.00)	0.0099***
		(0.00)
Variance equation		
εet−1	0.2335***	0.1760***
	(0.00)	*(0.00)*
εct−1	0.0022***	0.3130***
	(0.00)	*(0.00)*
het−1	*0.9621***	0.0200***
	(0.00)	*(0.00)*
hct−1	−0.0001 (0.37)	0.7296***
		(0.00)
constant	0.0030***	0.0001***
	(0.00)	(0.00)
DCC parameters		
θ_1	0.1255***	
	(0.00)	
θ_2	0.4083***	
	(0.00)	
AIC	14.12	
LL	9639.01	

Notes: This table includes the results for the DCC-GARCH model, including the mean equation, the variance equation, and the DCC equation, including some diagnostics tests. Values in parentheses are p-values. *** indicates statistical significance at the 1 % level. r^e_{t-1} measures the return of the electricity market at time t-1 and r^c_{t-1} includes the effect of returns from EU ETS. ε^e_{t-1} and ε^c_{t-1} measure the effect of shocks and surprising news on electricity and emission markets, respectively. h^e_{t-1} measures the effect of conditional variance of electricity returns while h^c_{t-1} includes the conditional variance of the corresponding sample from the emission market.

these markets. Therefore, H_2 is accepted given the significant return linkages detected between the returns of EUA and electricity markets. Further inspection suggests that the EUA market return is influenced by its own past value, which is also the case for the electricity market. Therefore, past EUA (electricity) returns can be used to predict emission (electricity) returns. This finding extends the previous literature (e.g., Zhu et al., 2019; Gong et al., 2021; Aslam et al., 2023; Qiao et al., 2023) in several aspects. Firstly, while Zhu et al. (2019) and Qiao et al. (2023) show a significant impact of electricity prices on EUA returns, we report a bidirectional linkage between these two markets. Proper knowledge of such cross-effects is crucial for asset pricing, portfolio optimization, and policy formulation. Secondly, unlike earlier studies, we show that the EUA market can be a key driver of the Nord Pool market. Thus, variations in carbon prices are likely to affect the cost of power generation. Accordingly, investors, for instance, can build on our results to predict the price variations of the Nord Pool market using the information on carbon prices and vice-versa. Policymakers, should focus on the dynamic changes of the EUA market given that carbon prices are increasingly important for developing active strategies for the electricity market.

The variance equations in Table 2 present own and cross-asset volatility effects between emission allowances and Nordic electricity markets. Own past volatility and shocks have a positive and significant effect on Nordic electricity returns. However, past values of EUA news and volatility do not have a statistically significant impact on the current volatility of the Nordic electricity market. Thus, there exists no volatility spillovers from the European emission allowance market to the Nordic electricity market. This result contradicts the evidence of Castagneto--Gissey (2014), who identifies significant volatility transmission from carbon prices to continental European, and especially Nordic, electricity prices. This difference could be due to different observation periods or the evolution of markets during recent years, given that we use a longer and updated sample period. In fact, Castagneto-Gissey's (2014) sample covers only the second emission trading phase whereas this paper considers data from the second and third phases. Moreover, the volatility of primary fuels used in electricity production is found to have an impact on the volatility of electricity. Furthermore, the volatility of coal is a main driver of electricity's volatility (Castagneto-Gissy, 2014; Berrisch et al., 2023). During recent years, countries operating in the Nord Pool market region have decreased the carbon intensity of their energy production. This increase in sustainable energy production could mitigate the impact of European emission trading on the Nordic electricity markets.

Moreover, for the current volatility of European emission allowances, own past variance and shocks are found to have a significant impact similar to electricity price volatility. Contrary to the results of the electricity variance equation, a significant volatility flow from Nordic electricity markets to emission markets exists according to the estimation results. Past shocks in electricity markets are found to have a negative impact on carbon market volatility while the effect of electricity's past volatility is positive. Thus, H_1 is rejected, because of the significant volatility spillover from electricity to EUA markets. As mentioned, electricity markets are highly volatile and the magnitude of the rapid price swings is large. Electricity market volatility might affect EUA demand as producers move towards the right in the merit order curve. In other words, as demand for electricity and heating increases utilities ramp up emission intensive production facilities. This could be the driver behind volatility spillovers from electricity markets to EU ETS. Finally, the DCC-parameter θ_b is found to be significant while the sum of the two parameters is below 1, which indicates that the correlation between assets is dynamic and time-varying by nature. This is somewhat in line with previous studies showing that the correlation between EUA and energy prices is not stable over time (see, Aslam et al., 2023; Berrisch et al. 2023) or the linkages across carbon, fossil energy and electricity markets vary over time (see, Qiao et al., 2023).

4.1.2. Time-varying correlation

The DCC-GARCH model enables exploration of how correlations between assets evolve through time. Table 3 shows the summary statistics of the time-varying conditional correlations between Nordic electricity returns and European emission allowances returns over the sample period. We note that the mean correlation between the two markets is positive, but low, suggesting that on average an increase in emission prices is associated with a small increase in Nordic electricity prices. This result is in line with previous findings (e.g., Castagneto--Gissey, 2014; Huisman & Kilic, 2015), suggesting that carbon prices pass through to electricity prices. However, power production mix and carbon intensity of production are proven to impact the degree to which EUA prices pass through to electricity prices (Tian et al., 2016). Given that hydropower and renewable production are dominant in Nordic countries, the magnitude of the correlation is very low. Fig. 3 illustrates how the correlation evolves over the observation period. Notably, the DCC correlation varies over time, switching between positive and negative values often and exhibiting some large values from time to time. Taken together, the results of the correlation between the electricity and EUA markets implies that H_3 is accepted.

The magnitudes of negative correlation swings are not necessarily equal to those of positive correlation swings. The EU ETS trading period changes at the beginning of 2013 which, according to the estimation, causes extreme spikes in the DCC correlation. The key changes made to

Table 3
Summary statistics of time-varying correlation.

Minimum	Maximum	Mean	Standard deviation
−0.8815	0.9011	0.0.0230	0.1248

Note: This table reports the main summary statistics for the time-varying correlation between the two markets.

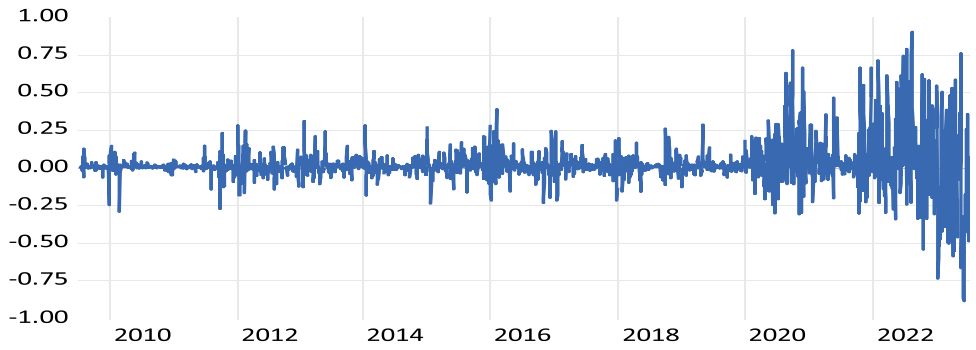

Fig. 3. Time-varying dynamic conditional correlation.

the EU ETS at the beginning of Phase III include the end of broad free allocation of allowances and reserving 30 million emission permits for the New Entrants Reserve (European Commission, 2021). Thus, the changes made to the emission trading scheme as the trading phase changed could cause the correlations to have extreme swings. Notably, both negative and positive spikes demonstrate values among the largest in magnitude in the observation period around the beginning of 2013. Thus, this dynamic nature has to be addressed when considering volatility modeling of electricity and carbon prices.

4.2. Results of hedging

Evidence that the mean correlation is positive yet very close to zero suggests possible hedging benefits in certain market circumstances. Therefore, we conduct a hedging analysis and present the results in Table 4. Note that, we examine the impact of the COVID-19 pandemic on the volatility estimates and hedging implications by conducting a subsample analysis, before and after the pandemic. The results given in Table 4 indicate that, for the full sample, the hedge ratio is 0.0131 and the hedging effectiveness amounts to 19.02 %. These numbers reveal that investors holding assets in the Nordic electricity sector can reduce their downside risk by considering EUA. Other entries indicate that the hedging effectiveness weakens during the COVID-19 pandemic period, which reflects the impact of the pandemic on the dynamics of financial markets, including carbon emission allowances (Aslam et al., 2023; Berrisch et al. 2023).

Overall, the results confirm that EUA is an effective instrument for decreasing the downside risk of Nordic electricity prices. Accordingly, H_4 is accepted. This does not fully concord with previous finding from Wen et al. (2017), which show a weak risk reduction resulting from combining EUA and electricity in the same portfolio. Possible reasons for this could be the longer sample period we consider covering recent phases of EU ETS and crisis periods such as COVID-19, and our reliance on a multivariate GARCH model unlike the copula used by Wen et al. (2017). Accordingly, it seems that the hedging ability of EUA does not decrease over time. However, the hedging is shaped by crisis periods such as the pandemic. Previous studies identify a hedging ability during crisis periods (e.g., Jin et al., 2020), although they show some instability in the portfolio implications during various market conditions (see, Balcilar et al., 2016).

Table 4
Results for optimal weight, hedge ratio, and hedging effectiveness.

	Optimal weight	Hedge ratio	Hedging effectiveness
Full sample period	0.18	0.0132	18.76 %
Before COVID−19	0.21	0.0219	21.76 %
After COVID−19	0.13	0.0032	12.03 %

4.3. Robustness check

Robust estimators, by definition, are not sensitive to atypical observations. With more robust estimators, one is able to draw more accurate conclusions and forecasts based on empirical results (Brooks, 2014). In this section, the robustness of the DCC-GARCH estimation results is tested with an asymmetric DCC-GARCH (ADCC-GARCH) model (Cappiello et al., 2006). This asymmetric model is able to take into account the magnitudes of effects with different signs (Villar-Rubio et al., 2023). Due to this capability, it is well suited for financial time series which are often non-linear by nature. In the asymmetric DCC-GARCH model, the time-varying conditional dependence formula Q_t is different from the symmetric model. It is formulated as:

$$Q_t = (1-\theta_1-\theta_2)\overline{Q} - \theta_3\overline{Z} + \theta_1 z_{t-1} z'_{t-1} + \theta_2 \quad Q_{t-1} \quad + \theta_3 \quad \xi_{t-1}\xi'_{t-1} \qquad (15)$$

where θ_3 captures the asymmetric effect; $\xi_t = I[z_t < 0] \otimes z_t$, with $\otimes$ being the Hadamard product, and $I[.]$ being a function that takes the value 1

Table 5
Results of the ADCC-GARCH model.

	Nord Pool	EUA
Mean equation		
ret−1	−0.1227*** (0.00)	−0.0003 (0.200)
rct−1	−0.0177 (0.53)	−0.1541*** (0.00)
constant	−0.0003 (0.75)	−0.0001 (0.95)
Variance equation		
εet−1	0.1330***	−0.0087** (0.04)
	(0.00)	
εct−1	−0.0001 (0.36)	0.0434***
		(0.00)
het−1	0.8267***	0.0214**
	(0.00)	*(0.03)*
hct−1	0.0002	0.9076***
	(0.38)	*(0.00)*
constant	0.0002***	0.0001***
	(0.00)	(0.00)
DCC parameters		
θ_1	0.0458***	
	(0.00)	
θ_2	0.8545***	
	(0.00)	
θ_3	0.1635***	
	(0.00)	
AIC	12.71	
LL	9646.38	

Notes: This table includes the results for the DCC-GARCH model, including the mean equation, the variance equation, the DCC equation, and some diagnostics tests. Values in parentheses are p-values. *** indicates statistical significance at the 1 % level. r^e_{t-1} measures the return of the electricity market at time t-1 and r^c_{t-1} includes effects of returns from EU ETS. ε^e_{t-1} and ε^c_{t-1} measure the effect of shocks and surprising news on electricity and emission markets, respectively. h^e_{t-1} measures the effect of conditional variance of electricity returns while h^c_{t-1} includes the conditional variance of the corresponding sample from the emission market.

Table 6
Results of hedging - robustness analysis based on ADCC-GARCH model.

	Optimal weight	Hedge ratio	Hedging effectiveness
Full sample period	0.17	0.0123	18.23 %
Before COVID−19	0.22	0.0223	20.61 %
After COVID−19	0.14	0.0042	12.86 %

when the residuals are negative and 0 otherwise. $\overline{Z}$ is the covariance matrix of $[E(\xi_t \xi_t^{'})]$.

Table 5 presents the estimation results of the ADCC-GARCH model. The estimates of the mean equations suggest no spillover effects between the two markets, which is inconsistent with that shown in Table 2. Further scrutiny indicates that the electricity price is influenced by its own lagged value, which is also the case for emission prices. Therefore, past electricity (EUA) returns can be used to predict current electricity (EUA) returns. Next, looking at the variance equations, we document a unidirectional volatility linkage running from the electricity market to the emission market. This finding is, however, in line with our earlier findings (see Table 2). Moreover, the coefficient θ_3 is found to be significant. This indicates that the correlation between the assets under study is asymmetric and thus reacts differently to positive and negative news shocks. In summary, we find consistent results for the volatility transmission linkage between the electricity and emission markets. Notably, the lower AIC and higher likelihood value for the asymmetric process indicate that the ADCC-GARCH model seems more significant than its symmetric counterpart (see Table 2).

Importantly, we re-conduct the hedging analysis based on the results of the ADCC-GARCH model and Table 6 provides evidence confirming the overall hedging ability of the carbon emission market for the Nordic electricity market. Consistent with the results shown in Table 4, the hedging effectiveness seems to weaken during the pandemic period.

5. Conclusion and discussion

In light of the important participation of the European electricity sector in the EU carbon emission trading scheme, in this study we examine the return and volatility relationship between Nordic electricity and carbon emission allowances markets and conduct a hedging analysis. The methods employed in this study include the dynamic conditional correlation model and a time-varying hedging analysis. The results are summarized as follows: Firstly, there is evidence of a unidirectional flow of returns and volatility from Nordic electricity to European emission markets. Past returns of electricity prices influence both current own and EUA returns, which suggests that Nordic electricity prices can be used to predict the evolution of carbon prices. Past volatility shocks in the electricity market have a significant impact on the volatility of carbon emission allowances. This finding might be driven by our extended sample period, during which Nordic countries have moved towards more sustainable energy production, which could have lowered the exposure of electricity markets to swings in carbon prices. Secondly, there is a weak conditional correlation between the returns of carbon emission allowances and the returns of the Nordic electricity market, which vary over time and exhibit some seasonality. The variability in the conditional correlation tends to cluster during periods corresponding to changes in the European Union's environmental policies. For example, as the third EUA trading phase, including new operationalities to the trading scheme, began in early 2013, we note some extreme values and variability in the dynamic conditional correlation between the markets. However, the lowest dynamic conditional correlation values are noted after the change of trading phase, suggesting that a changing environmental policy could divert price movements. Thirdly, given the weak correlation and evidence that the magnitude of negative values is higher than that of positive values, the hedging effectiveness analysis shows evidence that operators in the Nordic electricity market can reduce their downside risk by adding the carbon emission allowances asset to their portfolios. Our main results are robust to the choice of the dynamic conditional correlation model and the potential presence of asymmetric effects in that correlation. Interestingly, the results of the hedging analysis remain robust to considering the asymmetric effect.

Overall, we provide new evidence regarding the volatility dynamics in electricity and carbon emission markets and the hedging implications. The focus on the third emission trading phase in the empirical analysis provides fresh evidence of the continuously evolving EUA market. Evidence of significant volatility flow from Nordic electricity to European emission allowances matters not only for market participants searching for the most efficient ways to mitigate their emissions in light of the evolving European emissions markets, but also for socially responsible and eco-friendly investors who seek sustainability and ways to diversify the downside risk of their portfolios. Accordingly, investors can combine investments from both markets to reduce overall risk and thus benefit from hedging, bearing in mind that crisis periods such as the pandemic slightly reduce the hedging effectiveness of the carbon emissions market. This points to the potential utility of applying a dynamic hedging analysis to better exploit the benefits of hedging Nordic electricity prices with European emission allowances during crisis periods.

Our above analysis and findings offer incentives for future studies of the relationship between carbon and electricity assets including various countries and regions. This is based on the rationale that the carbon intensity of production could differ across countries and regions or exhibit different correlation dynamics and thus portfolio implications. On a related front, future studies could consider a more in-depth analysis of the asymmetric effects between carbon and electricity markets, revealed by the robustness analysis. On the methodological front, future studies could apply copula-based models, capturing tail-dependence.

CRediT authorship contribution statement

Nehme Azoury: Visualization, Writing – original draft, Writing – review & editing. **Joonas Vaissalo:** Data curation, Formal analysis, Methodology, Writing – original draft. **Anupam Dutta:** Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Elie Bouri:** Methodology, Supervision, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

My coauthors and I certify that there is no conflict of interest.

Data availability

Data will be made available on request.

References

Aatola, P., Ollikainen, M., Toppinen, A., 2013. Price determination in the EU ETS market: Theory and econometric analysis with market fundamentals. Energy Econ. 36, 380–395.
Ali, E.B., Gyamfi, B.A., Bekun, F.V., Ozturk, I., Nketiah, P., 2023. An empirical assessment of the tripartite nexus between environmental pollution, economic growth, and agricultural production in Sub-Saharan African countries. Environ. Sci. Pollut. Res. 30 (27), 71007–71024.
Aslam, F., Ali, I., Amjad, F., Ali, H., Irfan, I., 2023. On the inner dynamics between Fossil fuels and the carbon market: a combination of seasonal-trend decomposition and multifractal cross-correlation analysis. Environ. Sci. Pollut. Res. 30 (10), 25873–25891.
Balcilar, M., Demirer, R., Hammoudeh, S., Nguyen, D.K., 2016. Risk spillovers across the energy and carbon markets and hedging strategies for carbon risk. Energy Econ. 54, 159–172.
Basher, A.S., Sadorsky, P., 2016. Hedging emerging market stock prices with oil, gold, VIX, and bonds: a comparison between DCC, ADCC and GO-GARCH. Energy Econ. 54, 235e247.
Berrisch, J., Pappert, S., Ziel, F., Arsova, A., 2023. Modeling volatility and dependence of European carbon and energy prices. Financ. Res. Lett. 52, 103503.
Bou-Hamad, I., Hoteit, R., Harajli, D., Reykowska, D., 2022. Personal economic worries in response to COVID-19 pandemic: a cross sectional study. Front. Psychol. 13, 871209.

Bouri, E., Rognone, L., Sokhanvar, A., Wang, Z., 2023. From climate risk to the returns and volatility of energy assets and green bonds: a predictability analysis under various conditions. Technol. Forecast. Soc. Change 194, 122682.
Brooks, C., 2014. Introductory Econometrics for Finance, 3rd ed. Cambridge University Press.
Cappiello, L., Engle, R.F., Sheppard, K., 2006. Asymmetric dynamics in the correlations of global equity and bond returns. J. Financ. Econ. 4 (4), 537–572.
Castagneto-Gissey, G., 2014. How competitive are EU electricity markets? An assessment of ETS Phase II. Energy Policy 73, 278–297.
Chan, H.S., Li, S., Zhang, F., 2013. Firm competitiveness and the European Union emissions trading scheme. Energy Policy 63, 1056–1064.
Chevallier, J., 2012. Time-varying correlations in oil, gas and CO_2 prices: an application using BEKK, CCC and DCC-MGARCH models. Appl. Econ. 44 (32), 4257–4274.
Coelho, A., Iria, J., Soares, F., 2021. Network-secure bidding optimization of aggregators of multi-energy systems in electricity, gas, and carbon markets. Appl. Energy 301, 117460.
Creti, A., Jouvet, P., Mignon, V., 2012. Carbon price drivers: phase I versus phase II equilibrium? Energy Econ. 34, 327–334.
Dai, J., Ahmed, Z., Sinha, A., Pata, U.K., Alvarado, R., 2023. Sustainable green electricity, technological innovation, and ecological footprint: does democratic accountability moderate the nexus? Uti. Policy 82, 101541.
Dai, P.F., Xiong, X., Huynh, T.L.D., Wang, J., 2022. The impact of economic policy uncertainties on the volatility of European carbon market. J. Commod. Mark. 26, 100208.
Daskalakis, G., Markellos, R.N., 2009. Are electricity risk premia affected by emission allowance prices? Evidence from the EEX, Nord Pool and Powernext. Energy Policy 37, 2594–2604.
Demailly, D., Quirion, P., 2008. European emission trading scheme and competitiveness: A case study on the iron and steel industry. Energy Econ. 30, 2009–2027.
Dhamija, A.K., Yadav, S.S., Jain, P.K., 2018. Volatility spillover of energy markets into EUA markets under EU ETS: a multi-phase study. Environ. Econ. Policy Stud. 20, 561–591.
Djoundourian, S., 2011. Environmental movement in the Arab world. Environ., Dev. Sustain. 13 (4), 743–758. https://doi.org/10.1007/s10668-011-9287-7.
Djoundourian, S.S., 2021. Response of the Arab world to climate change challenges and the Paris agreement. Int. Environ. Agreem.: Polit., Law Econ. 21 (3), 469–491.
Djoundourian, S., Marrouch, W., Sayour, N., 2022. Adaptation funding and greenhouse gas emissions: Halo effect or complacency? Energy J. 43 (4), 215–230.
Dutta, A., 2017. Oil price uncertainty and clean energy stock returns: new evidence from crude oil volatility index. J. Clean. Prod. 164, 1157–1166.
Dutta, A., 2019. Impact of carbon emission trading on the European Union biodiesel feedstock market. Biomass Bioenergy 128, 105328.
Dutta, A., Bouri, E., Noor, M.H., 2018. Return and volatility linkages between CO_2 emission and clean energy stock prices. Energy 164, 803–810.
Dutta, A., Jalkh, N., Bouri, E., Dutta, P., 2019. Assessing the risk of the European union carbon emission allowance market: structural breaks and forecasting performance. Int. J. Manag. Financ. 16 (1), 49–60.
Engle, R., 1982. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of the U. K. Inflation. Econometrica 50, 987–1008.
Engle, R.F., 2002. Dynamic conditional correlation. A simple class of multivariate autoregressive conditional heteroskedasticity models. J. Bus. Econ. Stat. 20 (3), 339–350.
European Commission. (2015). EU ETS Handbook [Brochure]. https://ec.europa.eu/clima/sites/default/files/docs/ets_handbook_en.pdf.
European Commission. (2021). EU Emissions Trading System (EU ETS). https://ec.europa.eu/clima/policies/ets_en.
Fang, S., Cao, G., 2021. Modelling extreme risks for carbon emission allowances—evidence from European and Chinese carbon markets. J. Clean. Prod. 316, 128023.
Fouad, F.M., Soares, L., Diab, J.L., Abouzeid, A., 2022. The political economy of health in conflict: lessons learned from three states in the Eastern Mediterranean region during COVID-19. J. Glob. Health 12.
Gong, X., Shi, R., Xu, J., Lin, B., 2021. Analyzing spillover effects between carbon and fossil energy markets from a time-varying perspective. Appl. Energy 285, 116384.
Gowd, S.C., Ganeshan, P., Vigneswaran, V.S., Hossain, M.S., Kumar, D., Rajendran, K., Pugazhendhi, A., 2023. Economic perspectives and policy insights on carbon capture, storage, and utilization for sustainable development. Sci. Total Environ., 163656
Gustafsson, R., Dutta, A., Bouri, E., 2022. Are energy metals hedges or safe havens for clean energy stock returns? Energy 244, 122708.
Hammoudeh, S., Nguen, D.K., Sousa, R.M., 2014. Energy prices and CO2 emission allowance prices: a quantile regression approach. Energy Policy 8, 201–206.
Hanly, J., Morales, L., Cassells, D., 2018. The efficacy of financial futures as a hedging tool in electricity markets. Int. J. Financ. Econ. 23 (1), 29–40.
Hilmi, N., Djoundourian, S., Shahin, W., Safa, A., 2021. Does the ECB policy of quantitative easing impact environmental policy objectives? J. Econ. Policy Reform 1–13.
Hu, K., Sinha, A., Tan, Z., Shah, M.I., Abbas, S., 2022. Achieving energy transition in OECD economies: discovering the moderating roles of environmental governance. Renew. Sustain. Energy Rev. 168, 112808.
Huisman, R., Kiliç, M., 2015. Time variation in European carbon-pass-through rates in electricity futures prices. Energy Policy 86, 239–249.
Jiménez-Rodríguez, R., 2019. What happens to the relationship between EU allowances prices and stock market indices in Europe? Energy Econ. 81, 13–24.
Jin, J., Han, L., Wu, L., Zeng, H., 2020. The hedging effect of green bonds on carbon market risk. Int. Rev. Financ. Anal. 71, 101509.
Keppler, J., H, Mansanet-Bataller, M., 2010. Causalities between CO_2, electricity, and other energy variables during phase I and phase II of the EU ETS. Energy Policy 38, 3329–3341.
Köten, H., 2018. Advanced numerical and experimental studies on CI engine emissions. J. Therm. Eng. 4 (4), 2234–2247.
Ku, Y.H.H., Chen, H.C., Chen, K.H., 2007. On the application of the dynamic conditional correlation model in estimating optimal time-varying hedge ratios. Appl. Econ. Lett. 14, 503–509.
Kumar, S., Managi, S., Matsuda, A., 2012. Stock prices of clean energy firms, oil and carbon markets: a vector autoregressive analysis. Energy Econ. 34, 215–226.
Lin, B., Zhang, C., 2022. Forecasting carbon price in the European carbon market: the role of structural changes. Process Saf. Environ. Prot. 166, 341–354.
Luo, C., Wu, D., 2016. Environment and economic risk: an analysis of carbon emission market and portfolio management. Environ. Res. 149, 297–301.
Marrouch, W., Sinclair-Desgagné, B., 2012. Emission taxes when pollution depends on location. Environ. Dev. Econ. 17 (4), 433–443.
Meleo, L., 2014. On the determinants of industrial competitiveness: the European Union emission trading scheme and the Italian paper industry. Energy Policy 74, 535–546.
Moreno, B., da Silva, P., 2015. How do Spanish polluting sectors' stock market returns react to European Union allowances prices? A panel data approach. Energy 103, 240–250.
Moutinho, V., Oliveira, H., Mota, J., 2022. Examining the long term relationships between energy commodities prices and carbon prices on electricity prices using Markov switching regression. Energy Rep. 8, 589–594.
Nader, J., El-Khalil, R., Nassar, E., Hong, P., 2022. Pandemic planning, sustainability practices, and organizational performance: an empirical investigation of global manufacturing firms. Int. J. Prod. Econ. 246, 108419.
Nwani, C., Usman, O., Okere, K.I., Bekun, F.V., 2023. Technological pathways to decarbonisation and the role of renewable energy: a study of European countries using consumption-based metrics. Resour. Policy 83, 103738.
Oberndorfer, U., 2009. EU Emission Allowances and the stock market: evidence from the electricity industry. Ecol. Econ. 68, 1116–1126.
Oestreich, A.M., Tsiakas, I., 2015. Carbon emissions and stock returns: evidence from the EU Emissions Trading Scheme. J. Bank. Financ. 58, 294–308.
Polat, O., El Khoury, R., Alshater, M.M., Yoon, S.M., 2023. Media coverage of COVID-19 and its relationship with climate change indices: a dynamic connectedness analysis of four pandemic waves. J. Clim. Financ., 100010
Qiao, S., Dang, Y.J., Ren, Z.Y., Zhang, K.Q., 2023. The dynamic spillovers among carbon, fossil energy and electricity markets based on a TVP-VAR-SV method. Energy 266, 126344.
Quito, B., del Río, M.D.L.C., Álvarez-García, J., Bekun, F.V., 2023. Spatiotemporal influencing factors of energy efficiency in 43 European countries: a spatial econometric analysis. Renew. Sustain. Energy Rev. 182, 113340.
Reboredo, J.C., 2013. Modeling EU allowances and oil market interdependence. Implications for portfolio management. Energy Econ. 36, 471–480.
Reboredo, J.C., 2014. Volatility spillovers between the oil market and the European Union carbon emission market. Econ. Model. 36, 229–234.
Saeed, T., Bouri, E., Tran, D.K., 2020. Hedging strategies of green assets against dirty energy assets. Energies 12 (13), 3141.
Shahin, W., El-Achkar, E., 2017. Banking and Monetary Policies in a Changing Financial Environment. Routledge, UK.
Sinha, A., Bekiros, S., Hussain, N., Nguyen, D.K., Khan, S.A., 2023. How social imbalance and governance quality shape policy directives for energy transition in the OECD countries? Energy Econ. 120, 106642.
Souhir, B.A., Heni, B., Lotfi, B., 2019. Price risk and hedging strategies in Nord Pool electricity market evidence with sector indexes. Energy Econ. 80, 635–655.
Tarhini, A., Harfouche, A., De Marco, M., 2022. Artificial intelligence-based digital transformation for sustainable societies: the prevailing effect of COVID-19 crises. Pac. Asia J. Assoc. Inf. Syst. 14 (2), 1.
Tian, Y., Akimov, A., Roca, E., Wong, V., 2016. Does the carbon market help or hurt the stock price of electricity companies? Further evidence from the European context. J. Clean. Prod. 112, 1619–1626.
UNFCCC. (2003). Caring for climate. A guide to the Climate Change Convention and the Kyoto Protocol [Brochure]. https://unfccc.int/resource/docs/publications/caring_en.pdf.
Veith, S., Werner, J.R., Zimmerman, J., 2009. Capital market response to emission rights returns: evidence from the European power sector. Energy Econ. 31, 605–613.
Villar-Rubio, E., Huete-Morales, M.D., Galán-Valdivieso, F., 2023. Using EGARCH models to predict volatility in unconsolidated financial markets: the case of European carbon allowances. J. Environ. Stud. Sci. 1–10.
Wen, X., Bouri, E., Roubaud, D., 2017. Can energy commodity futures add value to the carbon emission market? Econ. Model. 62, 194–206.
World Bank. (2012). State and Trend of the Carbon Market 2012. https://openknowledge.worldbank.org/handle/10986/13336.
Zhu, B., Han, D., Chevallier, J., Wei, Y.M., 2017. Dynamic multiscale interactions between European carbon and electricity markets during 2005–2016. Energy Policy 107, 309–322.
Zhu, B., Ye, S., Han, D., Wang, P., He, K., Wei, Y.M., Xie, R., 2019. A multiscale analysis for carbon price drivers. Energy Econ. 78, 202–216.