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Electricity market crisis in Europe and cross border price effects: A quantile return connectedness analysis

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ABSTRACT

As the interconnection of the European electricity markets and integration of renewables progresses, there is little known about interconnectedness across them at times of market turbulence. The electricity crisis of 2021 and 2023 were significant events that can also provide lessons in the behaviour of integrated markets with high renewables under stress. Despite the impacts of the COVID-19 pandemic and the Russia-Ukraine war on the European energy market, little is known about their effects on the transmission of risks between the electricity markets. We employ the quantile connectedness approach to quantify the return connectedness between eleven key European markets, as well as the natural gas and carbon markets. We then examine the effect of the two crises on the interconnectedness. We find significant return interconnectedness, driven by spillover effects, among the markets. Analysis of connectedness across quantiles shows that the spillover effects are much stronger at tail ends of conditional distribution. Moreover, our results reveal opposite effects from crises on market interconnectedness. While the COVID-19 pandemic reduced the interconnectedness, the Russia-Ukraine war intensified the return shock transmission. Finally, we find that the natural gas and carbon markets are net recipients of return shocks across the quantiles.

1. Introduction

The attainment of the net-zero policy targets by 2050 has hastened the need for electricity markets in the European Union (EU), as well as globally, to facilitate the transition to clean energy while ensuring energy security and affordability. A key strategy to achieve this in the EU is to establish an integrated electricity market as a cost-effective way to achieve these objectives.[1] In a fully integrated market there are no barriers to cross-border electricity trade and electricity produced in one country can be delivered to consumers in another one. As a result, wholesale and retail competition intensifies, thereby encouraging companies to invest in innovative and cost-saving technologies. Such investments might cause electricity prices to progressively decrease, become more stable, and converge among member countries, thus leading to improved efficiency, higher welfare, and (or) diversified energy sources (Böckers and Heimeshoff, 2014; Newbery et al., 2016; Batalla-Bejerano et al., 2019). Estimates from the EC suggest that the potential welfare gain of fully integrated electricity markets could range between EUR 16 billion to EUR 43 billion annually by 2030.

A large strand of literature has investigated the extent to which electricity prices in the EU are integrated (e.g., Bower, 2002; Zachmann, 2005; Robinson, 2007a; Robinson, 2007b; Robinson, 2008; Zachmann, 2008; Nitsche et al., 2010; Böckers and Heimeshoff, 2014; Ouriachi and Spataru, 2015; de Menezes and Houllier, 2016; Telatar and Yaşar, 2020; Ciferri et al., 2020; Saez et al., 2019; Cassetta et al., 2022; Cassetta et al., 2022). Most of these studies agree that there remain large heterogeneities in electricity prices across the Member Countries (MCs), which is a concern for decision-makers (ACER, 2021). However, it remains to be examined how the external shocks in the electricity market propagate into price differences. A better understanding of how price shocks are transmitted is extremely important for designing energy, climate, and environmental policies of the EU.

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[1] https://energy.ec.europa.eu/topics/markets-and-consumers/market-legislation/electricity-market-design_en

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In this paper, we contribute to the literature by investigating the dynamic transmission of return shocks[2] between electricity prices in eleven European countries, including four Nordic countries (Norway, Finland, Denmark, Sweden), the United Kingdom, and six EU member states (France, Germany, Italy, Netherlands, Spain, and Poland), together with two principal components of costs of electricity generation and price determinants in Europe, namely, natural gas and carbon prices.

The inclusion of natural gas and carbon prices in the analysis is motivated by at least three reasons. First, despite substantial efforts to decarbonise European electricity systems, natural gas remains the most important source of energy for electricity generation in Europe. In 2020, the share of natural gas in power generation in Europe was largest, standing at 21.3% (see Fig. 1), followed by nuclear (20.9%) and hydro (17.2%). Second, extant literature suggests that natural gas and carbon prices would have significant impacts on electricity price setting and volatility. Given the crucial role of natural gas for electricity generation, Zakeri et al. (2023) find that natural gas is the most critical factor determining electricity price setting in Europe. In addition, various studies such as Kim et al. (2010), Wild et al. (2015), and Wong and Zhang (2022) have documented the pass-through effect of carbon prices on electricity prices. Lastly, as most natural gas is imported to Europe, the significant reliance on natural gas as key energy source makes European electricity prices vulnerable to geopolitical risks and international natural gas price volatility.

In addition, conducting an in-depth exploration into the repercussions of the COVID-19 outbreak and the Russia-Ukraine war stands as a valuable contribution of our study toward comprehending the dynamics of liberalized electricity markets when confronted with external shocks. The COVID-19 pandemic represented a positive demand shock, altering consumption patterns and market behaviours, while the Russia-Ukraine conflict served as a negative supply shock, disrupting the regular flow of energy resources. These instances are noteworthy examples of the challenges faced by contemporary electricity markets in times of unexpected events. Furthermore, an insightful exploration into the implications of tail risks associated with rare events, such as pandemics and geopolitical crises, holds significant relevance for energy policy. As the energy sector undergoes transformation, enhancing sectoral resilience and fortifying power systems against unforeseen disruptions become imperative goals. By delving into the transmission of return shocks during extreme market conditions, policymakers can develop strategies that bolster the adaptability and robustness of the energy sector, contributing to a more secure and sustainable energy market.

To this end, our research objectives centre around addressing the following crucial questions:

(*i*) Magnitude of return connectedness: What is the extent of return connectedness between EU electricity, natural gas, and carbon markets? This investigation seeks to quantify the magnitude of interdependence among the markets.

(*ii*) Identification of net transmitters and recipients: Which markets within the network act as net transmitters or recipients of return shocks? Identifying these pivotal players is important to understand the flow of shocks and the specific roles each market plays in transmitting or absorbing shocks within the network.

(*iii*) Variation of the return connectedness by quantiles: Does the return interconnectedness exhibits variations across different quantiles? This inquiry delves into the nuanced aspects of the connectedness dynamics, exploring whether the level of spillover effects vary under extreme market conditions.

(*iv*) Impacts of recent crises: What are the repercussions of recent energy crises arising from the COVID-19 pandemic and the Russia-Ukraine war, on the interconnectedness? Understanding how extraordinary events affect market interconnectedness is pivotal to anticipate and address potential systematic risk and disruptions in the market.

To examine return connectedness in the electricity markets, we employ daily returns of wholesale electricity prices in eleven European countries, the natural gas prices of the Trading Hub Europe (THE), and the European Union Allowances (EUA) carbon prices from January 02, 2012, to December 12, 2022. First, we apply the connectedness framework of Diebold and Yilmaz (2012) to compute the mean-based return connectedness between electricity, natural gas, and EUA carbon prices. To further shed light on connectedness dynamics during extremely volatile market conditions, we use a quantile connectedness approach developed by Ando et al. (2022). The quantile-based measures of connectedness are necessary because mean-based measures may not be appropriate for measuring connectedness in crisis periods, especially at the tails of the return distributions. Previous studies have shown the potential volatility in electricity and gas markets (e.g., Escribano et al., 2011; Huisman and Mahieu, 2003; Hailemariam and Smyth, 2019). However, by focusing on extreme shocks in the tails, we gain a better understanding of how electricity, natural gas, and carbon prices are connected under rare conditions.

Our analyses deliver several significant findings. First, our empirical results show that the electricity prices, natural gas, and EUA are connected much stronger in the tails of the distribution compared to the central portion. The total connectedness index of the network increases from 40.6% at the mean of the return distribution to 81.5% (81.5%) at the upper (lower) quantiles. As expected, the main contribution to system connectedness is from the electricity sector. Notably, cross-market connectedness between natural gas or EUA with the European electricity markets is much more pronounced at the tails of the return distribution. In normal conditions (i.e., at the conditional mean), the cross-market spillover index between European electricity and natural gas and that between European electricity and EUA are 1.1% and 0.7%, respectively. Though, at the lower (upper) quantiles, these measures increase remarkably to 6.1% and 5.9% (5.8% and 6.0%). Our findings reveal that the EU electricity markets are more vulnerable to changes in EUA and natural gas prices during extreme fluctuations. Furthermore, the connectedness indices at various quantiles are symmetric, indicating that electricity market participants tend to equitably respond to extremely negative or positive return shocks of EUA and natural gas.

Second, return shock spillover from natural gas and EUA to electricity prices varies across European countries. In normal market conditions, Italy and Denmark experience the greatest and smallest effect of natural gas prices, respectively. Meanwhile, at the extreme conditions, the UK is most affected by return shocks from natural gas, while Germany is least affected. Pertaining to the role of EUA, Italian prices bear the greatest effect of EUA in both normal and extreme market conditions, while France is relatively independent from the EUA prices. In the group-level analysis, Nordic countries show less dependence on natural gas prices compared to other countries. This finding holds regardless of the quantile of return distribution used to compute the connectedness indices.

Most importantly, we present a comprehensive analysis of the effects of the COVID-19 pandemic and the Russia-Ukraine war on the return interconnectedness of selected markets, focusing on the middle, lower, and upper quantiles of the return distribution. At the aggregate level, we find that the COVID-19 pandemic had a negative impact on the total connectedness index at the middle and lower tails, indicating a reduction in the integration of the EU electricity market. The Russia-Ukraine war, on the other hand, exerted a significantly positive effect on the interconnectedness at the middle and lower tails, suggesting that the war fuelled the transmission of average and extremely negative return shocks between the markets.

The heterogeneous effects of the two recent crises on the

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[2] We define asset returns as daily changes in the logarithmic prices of the asset. Return shock refers to an effect of an exogenous shock that cause change in the asset return. Besides, following Diebold and Yilmaz (2014), we use the term “spillover” and “connectedness” interchangeably.

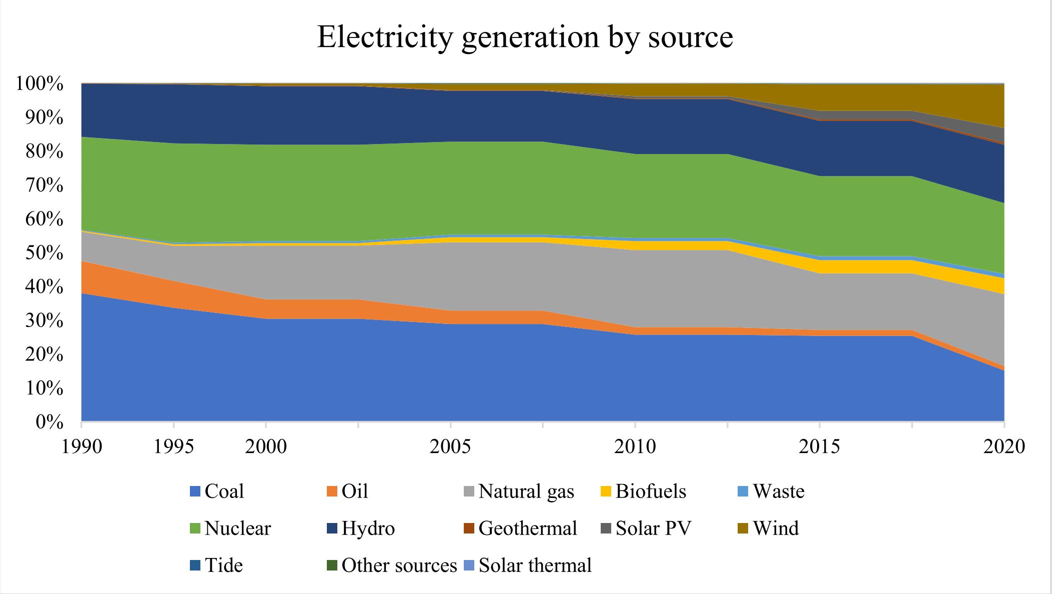

Fig. 1. Electricity generation by source in Europe.
Note: This figure shows the energy mix in Europe with data sourced from the International Energy Association's website.

interconnectedness might be attributed to their inherent differences. The COVID-19 pandemic is a demand shock to the EU electricity market as Prol and Sungmin (2020) find that COVID-19-related containment measures reduced electricity demand by 3–12% in 5 months following the outbreak. Besides, the effects of the pandemic were heterogeneous across European countries as Bahmanyar et al. (2020) documents that electricity consumption during the pandemic reflects the heterogeneity in peoples' activities across EU countries due to various containment measures applied. This heterogeneity could lead to more variations in electricity prices across European countries during the pandemic, as shown by the decreasing effect of COVID-19 on the interconnectedness. Contrary to COVID-19, the Russia-Ukraine war restraints natural gas supply, and induces substantial volatility in the energy commodity markets (Fang and Shao, 2022). As natural gas is an important input for electricity generation for most countries, a shock to natural gas prices could be perceived alike in most European electricity markets, leading to a higher level of interdependence during the war period.

Our study makes several contributions to the literature. Firstly, it is the first attempt to investigate the transmission of return shocks between European electricity, natural gas, and carbon markets. Prior studies on the integration of the EU electricity market mostly focus on the co-integration of contemporaneous energy prices among MCs (e.g., Bower, 2002; Böckers and Heimeshoff, 2014; Ouriachi and Spataru, 2015; de Menezes and Houllier, 2016; Ciferri et al., 2020; Saez et al., 2019; Cassetta et al., 2022; Cassetta et al., 2022; among others) and the obstacles to integrating energy market (e.g., Glachant and Ruester, 2014; Grossi et al., 2018; Pepermans, 2019). We aim to fill the gap in the literature by exploring the lead-lag relationship among European markets, considering the significant variations in electricity prices and market design among the Member States (Osińska et al., 2022). Second, besides focusing on the interaction among European markets, we add insights into the interconnectedness between two important energy sources (i.e., natural gas and EUA) and electricity prices. We contribute to the extant literature on shock transmission between energy commodities and electricity markets (e.g., Naeem et al., 2020; Moutinho et al., 2011; Kolos and Ronn, 2008). Finally, since the extant literature have rarely discussed the determinants of the interconnectedness, our study provides a thorough investigation of its drivers with a focus on the recent crises caused by the COVID-19 pandemic and the Russia-Ukraine war. The analysis, at the aggregate level and country level, reveals several financial and macroeconomic drivers of the return connectedness measures not only at the conditional median but also at the lower and upper tails. Most importantly, we find that COVID-19 and the Russia-Ukraine war affect the market interconnectedness in opposite directions, emphasizing their distinct impacts on European energy markets. Therefore, this paper contributes to an emerging strand of literature that examines the consequences of the pandemic and the war on energy and electricity markets (e.g., Werth et al., 2021; Prol and Sungmin, 2020; Korosteleva, 2022; Nerlinger and Utz, 2022; Abdullah et al., 2023; Naeem and Arfaoui, 2023; among others).

In addition to the key contributions highlighted earlier, our paper diverges from previous studies on the interconnectedness of electricity markets, such as those by Apergis et al. (2017), Do et al. (2020a, 2020b), Han et al. (2020), Naeem et al. (2020, 2022), and Ma et al. (2022). While these studies predominantly employed the mean-based connectedness framework proposed by Diebold and Yilmaz (2009, 2012); Diebold and Yılmaz (2014) or Baruník and Křehlík's (2018) frequency connectedness approach, our methodology takes a different route. We estimate return connectedness measures under extreme circumstances, introducing a nuanced perspective that enhances our contribution to the existing literature. This approach provides valuable insights into the dynamics of interconnectedness, particularly in the context of highly volatile market conditions.

The remainder of the paper proceeds as follows. Section 2 presents the methodology used. Section 3 describes the data and offers descriptive analysis. Section 4 reports and discusses the empirical findings. Finally, we discuss policy implications and conclude the paper in section 5.

2. Methodologies

We utilize the quantile connectedness framework of Ando et al. (2022) to compute the return connectedness between natural gas, EUA, and electricity markets. This approach first employs quantile regression to estimate a vector autoregressive (VAR) model at a specific conditional quantile. Then, we apply the approach of Diebold and Yilmaz (2012) to measure the connectedness indices. Specifically, suppose that we have a VAR (p)[3] model including *13* assets.[4] At τthconditional quantile, we can estimate the VAR model using equation-by-equation quantile regression as below:

$$\omega_t = \Lambda_{0(\tau)} + \sum_{\ell=1}^{p} \Lambda_{\ell(\tau)} \omega_{t-\ell} + e_{t(\tau)} \tag{1}$$

where $\tau \in (0, 1)$ is a given quantile index, ω_t denotes the 13×1 return vector for the 13 selected markets, $\Lambda_{0(\tau)}$ represents the 13×1 vector of intercepts and $e_{t(\tau)}$ indicates the 13×1 vector residual at τthquantile. $\Lambda_{\ell(\tau)}$ is the ℓth 13×13 autoregressive parameter matrix at τthquantile.

We rewrite Eq. (1) as follows,

$$\omega_{st} = \Lambda_{s(\tau)}^{\top} \kappa_t + e_{jt(\tau)} \tag{2}$$

where $s = 1, 2..., 13$ and κ_t denotes $(13p + 1) \times 1$ coefficient vector including the constant; $\Lambda_{s(\tau)}$ is the corresponding estimated parameters at τthquantile. The residuals in Eq. (2) follow the conditional quantile restriction, $Q_t\left(e_{st(\tau)} \middle| z_t\right) = 0$. Based on Koenker and Xiao (2006), the conditional quantile function of ω_{st} atτthis denoted by Q_τ and Q_τ is expressed as,

$$Q_\tau(\omega_{st} | \kappa_t) = \Lambda_{s(\tau)}^{\top} \kappa_t \tag{3}$$

Koenker and Hallock (2001), the autoregressive coefficients $\Lambda_{j(\tau)}$ at quantile τ, is attained through resolving the problem,

$$\min_{\Lambda_{s(\tau)}} \sum_{t=1}^{T} \left(\tau - \boldsymbol{L}\left[\omega_{st} \leq \Lambda_{s(\tau)}{}_{s(\tau)}^{\top} z_t\right]\right)\left(\omega_{st} - \Lambda_{s(\tau)}^{\top} \kappa_t\right) \tag{4}$$

where $\boldsymbol{L}[\bullet]$ denotes the indicative function, being 1 if $\omega_{st} \leq \Lambda_{s(\tau)}^{\top} \kappa_t$ and 0 otherwise; T indicates the number of observations.

Note, Eq. (1) can be expressed as an infinite moving average form as,

$$\omega_t = \pi_{(\tau)} + \sum_{k=1}^{\infty} \mathrm{B}_{k(\tau)} e_{t-k(\tau)} \tag{5}$$

where $\pi(\tau)$ and $\mathrm{B}_k(\tau)$ are determined as,

$$\pi_{(\tau)} = \left(L_m - \Lambda_{1(\tau)} - \ldots - \Lambda_{p(\tau)}\right)^{-1} \Lambda_{0(\tau)}$$

$$\mathrm{B}_{k(\tau)} = \begin{cases} 0 \text{ for } k < 0; \\ L_m \text{ for } k = 0; \\ \Lambda_{1(\tau)} \mathrm{B}_{k-1(\tau)} + \ldots + \Lambda_{p(\tau)} \mathrm{B}_{k-p(\tau)} \text{ for } k > 0 \end{cases}$$

Following Diebold and Yilmaz (2012), the generalized forecast error variance decomposition (GFEVD) of the ith variable, due to shocks of other variables for a forecast horizon H at τth quantile, can be computed as,

$$\theta_{ij(\tau)}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \mathrm{B}_{h(\tau)} \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} e_i' \mathrm{B}_{h(\tau)} \Sigma \mathrm{B}_{h(\tau)}' e_i} \tag{6}$$

where $\theta_{ij(\tau)}(H)$ is the contribution of asset j to the variation of h-step-ahead forecast error of asset i at quantile τ; σ_{jj} is the jth diagonal value of Σ; Σ indicates the variance matrix of residuals; and e_i represents the selection vector, which equals 1 for the ith element and 0 otherwise. We normalize $\theta_{ij(\tau)}(H)$ using the following formula,

$$\widetilde{\theta}_{ij(\tau)}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{m} \theta_{ij}(H)} \tag{7}$$

Based on the GFEVD, we calculate five connectedness indices at each quantile. First, the pairwise spillover index (PSI) between asset i and asset j is computed as,

$$PSI_{ij(\tau)}(H) = \left(\widetilde{\theta}_{ij(\tau)}(H) + \widetilde{\theta}_{ji(\tau)}(H)\right) \Big/ 2 \tag{8}$$

By definition, $PSI_{ij(\tau)}(H)$ shows the average connectedness between asset i and asset j. Second, the total connectedness index (TCI) at τth quantile is:

$$TCI(\tau) = \frac{\sum_{i,j=1;i \neq j}^{m} \widetilde{\theta}_{ij(\tau)}(H)}{13} \times 100 \tag{9}$$

The net spillover index (NSI)[5] of asset i at τth quantile can be estimated as,

$$NSI_{i(\tau)} = \vartheta_{.i(\tau)} - \vartheta_{i.(\tau)} \tag{10}$$

where $\vartheta_{i.(\tau)}$ is the spillover effects that i receives from all other assets at τth quantile and $\vartheta_{i.(\tau)} = \frac{\sum_{j=1;i \neq j}^{m} \widetilde{\theta}_{ij(\tau)}}{13} \times 100$; $\vartheta_{.i(\tau)}$ is the spillover effects that i transmits to all other assets at τth quantile and $\vartheta_{.i(\tau)} = \frac{\sum_{j=1;i \neq j}^{m} \widetilde{\theta}_{ji(\tau)}}{13} \times 100$.

As the TCI encompasses the spillover effects within eleven European electricity markets, we further estimate two connectedness indices that primarily measure the return connectedness between the European electricity markets with natural gas and EUA. The first is the cross-market spillover index between European electricity markets and natural gas market ($\mathrm{CSI}_{\text{Gas-Electricity}}$), which is calculated as,

$$CSI_{Gas-Electricity(\tau)}(H) = \sum_{i=1}^{11} \left(PSI_{i,Gas(\tau)}(H)\right) \Big/ 11 \tag{11}$$

where $PSI_{i,Gas(\tau)}$ is the pairwise spillover index between electricity market i and the natural gas market. Similarly, the cross-market spillover index European electricity markets and EUA ($\mathrm{CSI}_{\text{EUA-Electricity}}$) is defined as,

$$CSI_{EUA-Electricity(\tau)}(H) = \sum_{i=1}^{11} \left(PSI_{i,EUA(\tau)}(H)\right) \Big/ 11 \tag{12}$$

where $PSI_{i,EUA(\tau)}$ is the pairwise spillover index between electricity market i and EUA.

3. Data and preliminary analysis

3.1. Sample and data

We use daily baseload electricity price[6] data of eleven European countries including Denmark (DNK), Finland (FIN), Norway (NOR), Sweden (SWD), France (FRA), Germany (GER), Italy (ITA), Netherlands (NTH), Spain (SPN), the United Kingdom (UK), and Poland (PLN). The use of baseload price as reference for European electricity markets is motivated by the fact that the European Commission considers baseload electricity price as a key reference price in its quarterly report on European electricity markets.[7] In addition, baseload prices have been used in several studies that investigate the price dynamics of European electricity markets (e.g., Redl et al., 2009; Kalantzis and Milonas, 2010; Huisman and Kilic, 2013; Moreno and Díaz, 2019; among others).

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[3] p is the lag order, which is determined based on the Akaike Information Criteria (AIC).

[4] Including natural gas, EUA, and 11 electricity markets.

[5] It is defined as the change between the total return shocks sent to and those obtained from all other assets at τth quantile.

[6] Baseload electricity prices are calculated by power exchanges from the day-ahead market prices for the lowest demand periods (i.e., midnight).

[7] Baseload price is used as the key price in quarterly report on European electricity markets by the European Commission. For instance, please see:https://energy.ec.europa.eu/system/files/2021-10/quarterly_report_on_european_electricity_markets_q2_2021_final.pdf

Daily electricity price data are sourced from Thomson Reuters DataStream. Following de Menezes and Houllier (2016), we choose the electricity prices from the following power exchanges: Nordpool for the Nordic countries (i.e., Denmark, Finland, Norway, Sweden, APX for the Netherlands and the UK, EPEX for France and Germany, IPEX for Italy; OMEL for Spain. For Poland, we use price data from POLPX. Electricity price is quoted as EUR per MWh for all countries except for Norway (NOK per MWh) and Poland (Zloty per MWh). We use daily exchange rates from DataStream to convert electricity prices in Norway and Poland to EUR per MWh. Our data are collected for the period between January 02, 2012, to December 31, 2022. This sample period covers two recent crises in the European energy markets, including the COVID-19 pandemic and the Russia-Ukraine war.

To proxy for the European natural gas market, we use the price series of the EEX GAS Price Reference EGIX index for the German market (thereafter, EGIX). This index was constructed by the European Energy Exchange as the arithmetic mean of the daily volume weighted average prices of all trades of the largest nationwide gas hub in Germany – the Trading Hub Europe (THE).[8] The unit of the index is EUR per MMBtu. Finally, to proxy for carbon price in Europe, we follow Chevallier (2011) and Lutz et al. (2013) and employ the European Union Allowances (EUA) futures price, which is originally from the European Climate Exchange (ECX). Following Chevallier (2011), we do not use carbon spot prices in this paper since the data has not been available since 2007 between Phases I and II of the EU Emissions Trading Scheme. The unit of EUA is EUR per ton of CO_2. The data on both natural gas and EUA prices are also sourced from DataStream.

The daily returns[9] of the selected markets are plotted in Fig. 2. Natural gas and EUA exhibit substantially lower return range fluctuations than electricity prices. The natural gas market experienced significant volatility during the period 2020–2022, characterised by the COVID-19 pandemic and the start of the Russia-Ukraine war.

3.2. Descriptive statistics

Table 1 summarizes key statistics for the selected return series. Daily average returns are positive for natural gas and EUA, with EUA exhibiting a notably higher average return (0.04% compared to GAS's 0.02%). Daily average returns for electricity prices vary across countries, with positive returns observed in Denmark, Finland, Norway, Italy, and Poland, while negative returns are seen in Sweden, France, Germany, Netherlands, Spain, and the UK. France has the lowest daily average return of −0.06%. Additionally, return variance reveals that natural gas and EUA are less volatile than electricity prices, which inherently exhibit high volatility in European wholesale markets. Nordic countries, particularly Denmark, show higher price volatility, while Italy and Poland demonstrate the lowest volatility.

Table 1 also indicates positive skewness for GAS (1.09) and negative skewness for EUA (−0.93), suggesting common extreme positive returns for natural gas and more extreme negative return shocks for EUA. Skewness varies among European markets, with significant differences observed. In addition, each market is prone to frequent occurrences of extreme returns, as suggested by its kurtosis value of above 3. This leptokurtic distribution indicates the necessity to adopt the quantile connectedness approach when investigating the return shock transmission between natural gas, EUA, and electricity markets. Diagnostic tests in the last four columns of Table 1 confirm non-normality, stationarity, and autocorrelation in the return series of selected markets. Jarque-Bera statistics reject normal distribution, Elliott-Rothenberg-Stock (ERS) tests confirm stationarity, and Ljung-Box Q statistics indicate significant autocorrelation up to 10 and 20 lags.

The pairwise correlation matrix in Fig. 3 shows positive return correlations between natural gas and each electricity market, albeit relatively low (below 0.1). EUA exhibits both positive and negative correlations with selected electricity markets. Correlation coefficients among European electricity markets differ substantially. Natural gas has the highest return correlation with the UK electricity market (0.08), while the pairs of GER and FRA (0.59), and GER and DNK (0.59) show the highest return correlations between European electricity markets. The contemporaneous linkage between GAS and EUA is mild, with a correlation coefficient of 0.08.

4. Empirical results and discussion

This section examines four different perspectives of the return shock transmission between European electricity prices, EUA, and natural gas. Subsection 4.1 discusses return connectedness at the conditional mean and conditional median. Subsection 4.2 computes connectedness measures at the lower and upper quantiles of the return distribution. Subsection 4.3 displays and discusses the evolution of the connectedness measures over time. Lastly, subsection 4.4 investigates the effect of COVID-19 and the Russia-Ukraine war on the interconnectedness indices.

4.1. Return connectedness at the conditional mean and median

We first utilize the mean-based connectedness framework of Diebold and Yilmaz (2012) to calculate the return spillover effects of the system at the conditional mean. Then, the quantile connectedness approach by Ando et al. (2022) is applied to estimate the return connectedness measures at the conditional median (quantile $\tau = 0.5$ or middle quantile). The results of the connectedness measures at the conditional mean and median are reported in Table 2 Panels A and B, respectively. The results show a remarkable likeness across different connectedness measures at the conditional mean and median. To illustrate, in Panel A, the Total Connectedness Index (TCI) stands at 40.6%, which is relatively close to the TCI reported in Panel B (38.5%).

In addition to this similarity, further important findings are noticeable from the table. **First**, the relatively high connectedness in the system is largely attributable to within-sector return spillover effects among the European electricity markets. The results indicate that the return shock transmission tends to be stronger among the Nordic markets. For instance, as evidenced in the fourth row of Panel A, the Finnish market was considerably affected by the volatility of prices in Denmark (9.1%), Norway (8.9%), and Sweden (12.2%). By contrast, price volatility in other countries only mildly influences the Finnish prices. The significant interdependency among the Nordic markets is consistent with Amundsen and Bergman (2006), who documented substantial integration among the Nordic markets. It is noteworthy that Nordic markets are the oldest and most integrated regional market in Europe (Meeus and Belmans, 2008). The Nordic countries began with market integration in 1995 by the establishment of Norwegian power exchange. Its day-ahead wholesale auction trading system then expanded to Sweden in 1996, Finland in 1998 and Denmark in 2000.

Among the EU countries, Spain, Sweden, and the UK are least dependent on shocks from other markets as indicated by the low values numbers in the "*From*" column of both panels. The relatively high independence of electricity prices in Spain can be explained by the fact the country is considered an "energy island" in Europe with low interconnection capacity with the neighbouring countries (Abadie and Chamorro, 2021). According to Abadie and Chamorro (2021), the

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[8] THE was established in October 2021 by the merger of two largest natural gas hubs in Germany, namely, NetConnect Germany (NCG) and GASPOOL (GPL).

[9] Based on the price data, daily return is measured by the change between the natural logarithm of the price of day *t* and the price of day *t-1* times 100%.

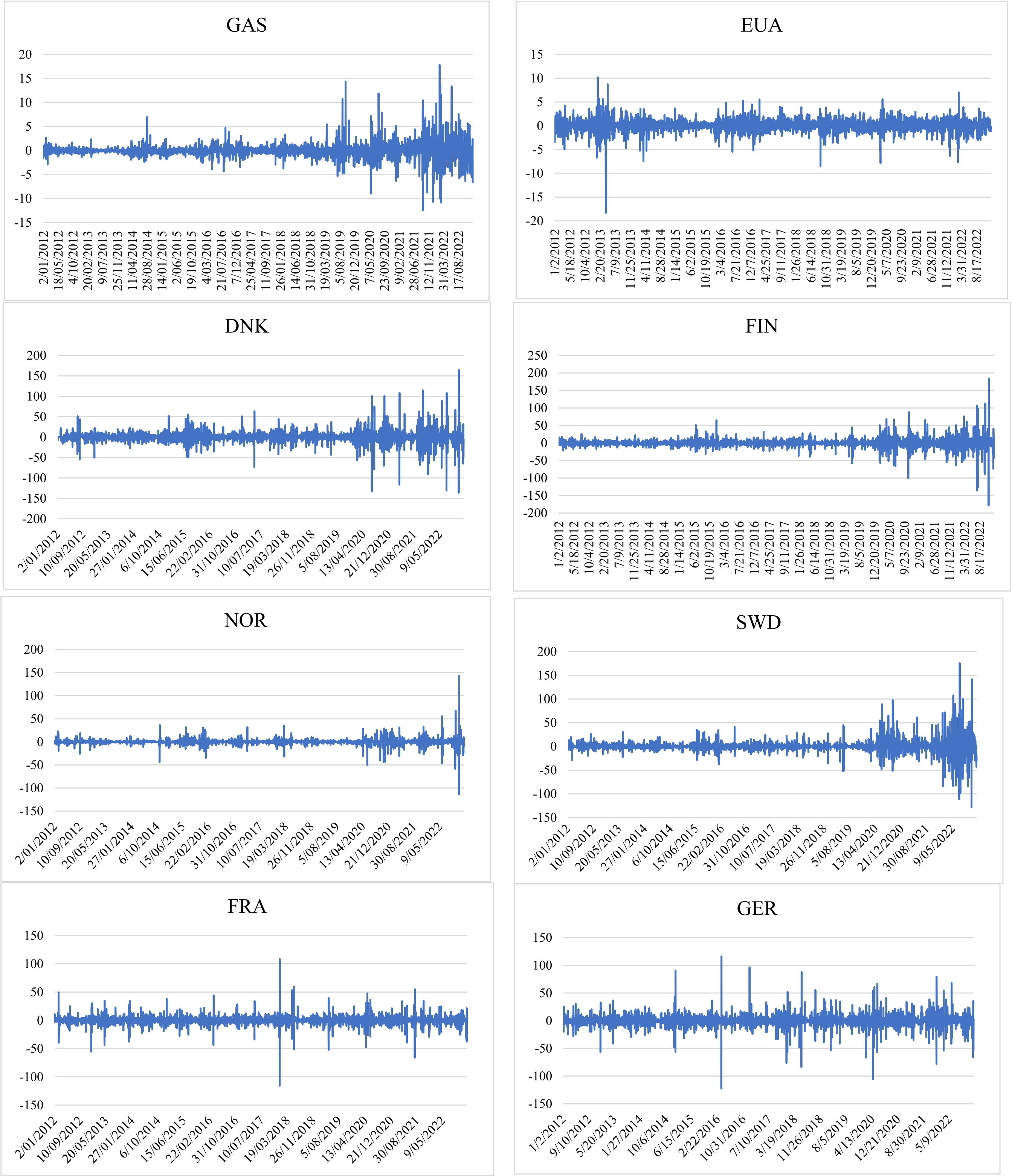

Fig. 2. Return series.
Note: This figure shows the time-varying return series for each sample asset during the research period between January 02, 2012, to December 31, 2022.

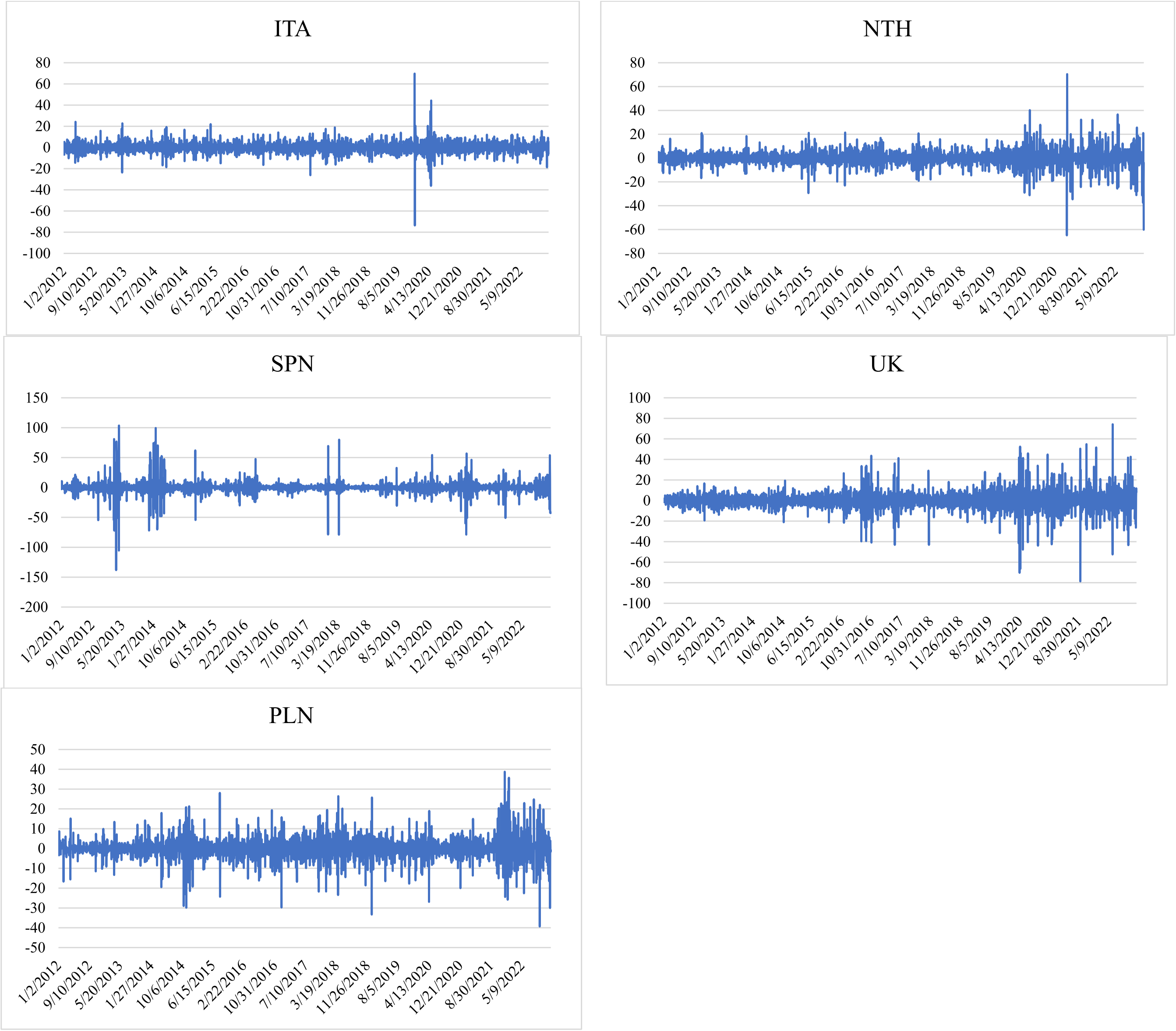

Fig. 2. (*continued*).

Table 1
Descriptive statistics and diagnostic tests.

	Mean	Variance	Skewness	Kurtosis	JB	ERS	LB-Q(10)	LB-Q(20)
GAS	0.02	2.67	1.09	19.77	47,314.9***	−24.9***	22.4***	719.3***
EUA	0.04	2.01	−0.93	13.72	22,934.1***	−23.8***	11.7***	86.2***
DNK	0.02	200.23	0.38	20.66	51,084.6***	−16.9***	240.8***	327.5***
FIN	0.00	159.38	0.34	34.19	139,813.1***	−15.1***	137.1***	159.0***
NOR	0.03	42.91	3.28	91.66	1,009,709.7***	−15.4***	36.6***	32.6***
SWD	−0.05	168.01	1.68	30.53	112,828.4***	−18.3***	143.8***	332.7***
FRA	−0.06	57.62	−0.22	12.27	18,013.8***	−3.1*	145.9***	455.2***
GER	−0.05	140.49	−0.13	19.25	44,331.8***	−13.7***	233.0***	385.9***
ITA	0.00	26.91	0.07	30.00	107,645.1***	−8.7***	298.6***	787.4***
NTH	0.00	38.13	0.05	14.20	24,115.6***	−28.9***	152.2***	102.4***
SPN	−0.05	113.13	−0.51	30.48	111,190.0***	−6.7***	213.0***	544.1***
UK	−0.04	69.38	−0.27	11.71	16,444.0***	−19.1***	302.7***	325.0***
PLN	0.05	28.44	0.00	7.17	6155.2***	−8.2***	188.7***	339.5***

Note: This table reports the descriptive statistics of daily return series of European electricity prices, natural gas, and EUA between January 02, 2012, to December 31, 2022. LB-Q(10) and LB-Q(20) represent the Ljung-Box Q-statistics up to the 10th and 20th order autocorrelation. Jarque-Bera statistics indicate the test for the normality of sample data. ERS test represent the Elliott et al. (1992) unit root test. *** denotes the cases where the null hypothesis of no autocorrelation (for LB Q test), and normal distribution (for JB test), and a presence of a unit root (for ERS test) is rejected at the 1% significance level.

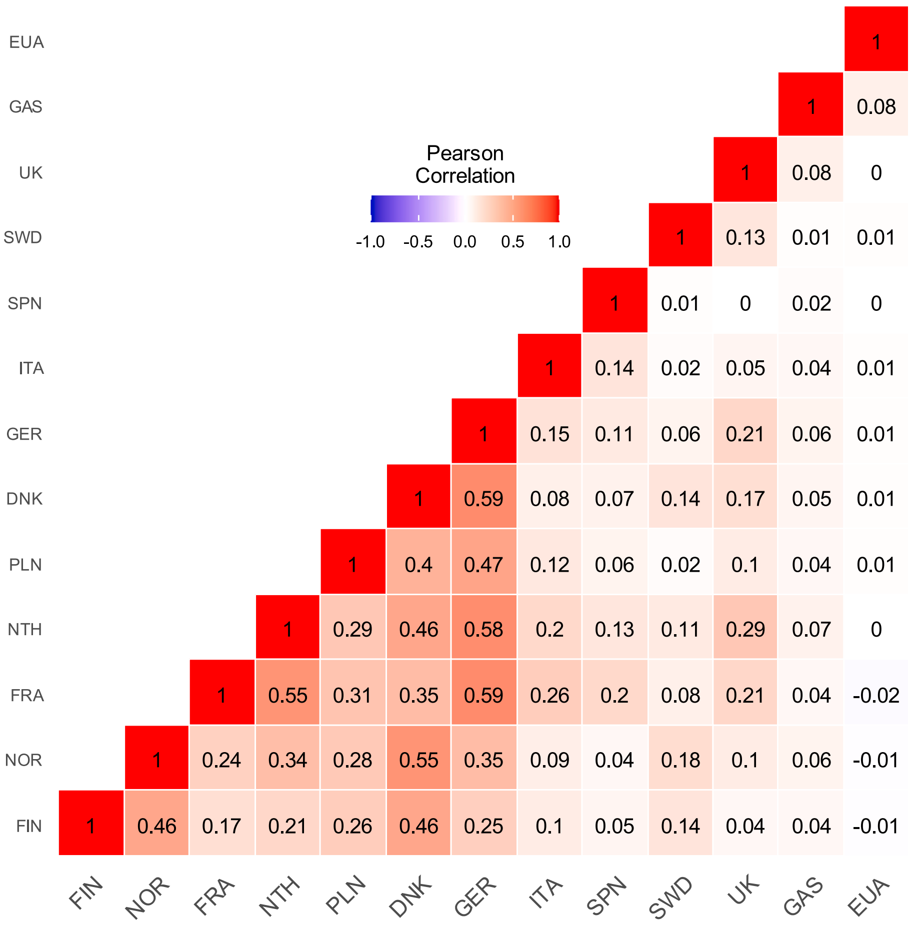

Fig. 3. Correlation matrix.
Note: This graph shows the matrix of pair-wise Pearson correlation coefficients among the sample assets. The sample is from January 02, 2012, to December 31, 2022.

interconnection ratio[10] of Spain was only 2.8% in 2019, which is far below the EU goal of 10% for 2020 and the minimum of 15% for 2030. The low dependence of the UK electricity prices on other countries could be the result of Brexit. After Brexit, the UK officially left the European Internal Energy Market (IEM) on 1st January 2021. Consequently, trading through electricity interconnectors between the EU and Great Britain is no longer conducted through existing single market tools, such as EU market coupling, as these are reversed for the EU countries.[11] Lastly, Sweden has been consistently one of the most important power exporters in Europe. For instance, in 2022, Sweden exported 33 TWh to other nations, making it the number one exporter in Europe. The dominant exporter role of Sweden as could explain partly why electricity prices in Sweden are less dependent on energy prices in other European countries.

Second, the return shock transmission from (to) the natural gas market to (from) European electricity markets is low at both conditional mean and median. In detail, the "*From*" column of Table 2 Panel A (Panel B) indicates that natural gas is modestly influenced by other markets, with 16.9% (14.7%) of its return variations justified by past fluctuations of other markets' returns. Of which, past variations of EUA accounts for 4.7% (3.9%) and the rest 12.2% (10.8%) from past fluctuations of European electricity markets.[12] Further, variations in electricity prices in the UK and Norway exert the greatest impacts on the gas market with contributions of 1.7% (1.7%) and 1.4% (1.2%), respectively. The significant impacts of energy markets in the UK and Norway on the gas market could be due to the leading role of both countries as largest gas producing countries in Europe.[13] Conversely, changes in gas return account for <2% of the variation of each electricity market except for Italy (ITA), as shown in the first column of both panels. The higher impact of the natural gas market on Italian electricity prices is due to the country's dependence on gas as a key energy source. For instance, as of 2021, natural gas accounts for 43.7% of the energy mix of Italy, the highest proportion among the selected European countries (see Appendix A1). In summary, the cross-market spillover indices between gas and electricity markets ($CSI_{Gas\text{-}Electricity}$) at the conditional mean and middle quantile are 1.1 and 0.9, respectively. These indicate that, on average, past return variations in the gas market affect 1.1% (0.9%) of return fluctuation of an EU electricity market and vice versa.

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[10] Computed as the sum of the import capacities divided by the installed generation capacity.

[11] Please see more on the impacts of Brexit on European energy markets in: https://www.europarl.europa.eu/RegData/etudes/BRIE/2023/749801/EPRS_BRI(2023)749801_EN.pdf

[12] 4.7% is the proportion that past variation of EUA contributes to fluctuations of GAS as numbered in the first row of the second column (EUA) in Table 1 Panel A. The sum of other entries in the first row (except for the first and second items) indicates the contributions of past variations in electricity price returns of eleven EU countries to return fluctuations of natural gas, which equals 12.17%. Alternatively, it equals the difference between "From" of GAS (16.87%) minus 4.7%.

[13] Norway, the UK and the Netherlands have been the three largest gas oil producing countries in Europe in 2022. Source: https://www.offshore-technology.com/data-insights/top-ten-natural-gas-producing-fields-in-europe/

Table 2
Connectedness table at the conditional mean and median.

Panel A. At the conditional mean

	GAS	EUA	DNK	FIN	NOR	SWD	FRA	GER	ITA	NTH	SPN	UK	PLN	*From*
GAS	83.1	4.7	1.1	0.8	1.4	1.0	1.1	0.9	1.3	1.0	1.0	1.7	0.9	*16.9*
EUA	4.3	86.7	0.9	1.3	0.7	1.2	0.7	0.7	0.7	0.8	0.8	0.6	0.7	*13.3*
DNK	0.6	0.5	37.3	6.6	8.6	9.4	5.1	14.7	0.9	6.6	0.7	1.6	7.5	*62.7*
FIN	0.6	0.7	9.1	52.9	8.9	12.2	2.2	3.6	1.3	2.0	0.8	1.8	4.1	*47.1*
NOR	0.8	0.5	10.9	8.0	47.9	12.0	3.1	5.5	1.0	4.3	0.8	1.9	3.4	*52.1*
SWD	1.0	0.7	4.8	4.0	5.1	72.7	2.1	2.1	1.0	2.3	0.8	1.8	1.5	*27.3*
FRA	1.0	0.4	5.7	1.5	2.6	2.9	43.3	14.8	4.8	11.7	3.8	2.5	5.1	*56.7*
GER	0.7	0.3	14.7	2.4	4.3	4.0	12.5	36.0	1.6	10.7	1.4	2.1	9.4	*64.0*
ITA	2.3	0.8	1.3	1.3	1.4	1.4	6.6	2.9	70.9	3.0	3.3	1.8	3.1	*29.1*
NTH	0.9	0.5	7.4	1.7	4.3	3.8	12.1	13.2	2.0	44.9	1.5	3.7	4.1	*55.1*
SPN	1.6	0.7	1.1	1.0	1.2	1.1	5.8	2.5	3.6	2.5	75.7	1.2	2.0	*24.3*
UK	1.5	0.7	2.7	1.1	2.2	2.5	4.0	4.0	1.2	5.8	1.1	71.6	1.6	*28.4*
PLN	0.6	0.5	9.7	3.5	3.8	3.6	5.9	12.4	2.3	4.7	2.1	1.4	49.4	*50.6*
To	*15.8*	*10.7*	*69.4*	*33.3*	*44.5*	*55.0*	*61.1*	*77.5*	*21.7*	*55.4*	*18.0*	*22.0*	*43.3*	
NSI	**−1.1**	**−2.6**	**6.7**	**−13.8**	**−7.6**	**27.8**	**4.4**	**13.4**	**−7.4**	**0.2**	**−6.3**	**−6.4**	**−7.3**	
TCI	**40.6**													
CSI$_{\text{Gas-Electricity}}$	**1.1**													
CSI$_{\text{EUA-Electricity}}$	**0.7**													

Panel B. At the conditional median

	GAS	EUA	DNK	FIN	NOR	SWD	FRA	GER	ITA	NTH	SPN	UK	PLN	*From*
GAS	85.3	3.9	1.1	0.9	1.2	1.2	0.8	0.9	1.0	0.8	0.7	1.7	0.6	*14.7*
EUA	4.1	87.6	0.8	1.3	0.7	1.3	0.5	0.6	0.7	0.6	0.6	0.6	0.6	*12.4*
DNK	0.4	0.4	38.5	6.4	8.3	11.0	4.8	14.4	0.7	6.1	0.6	1.3	7.1	*61.5*
FIN	0.5	0.5	8.8	54.0	8.5	13.8	2.0	3.3	1.1	1.8	0.7	1.4	3.7	*46.0*
NOR	0.6	0.3	10.6	7.9	51.9	10.4	2.8	5.4	0.9	4.2	0.7	1.1	3.4	*48.1*
SWD	0.6	0.4	4.1	3.6	4.7	77.9	1.7	1.6	0.7	1.7	0.6	1.5	0.9	*22.1*
FRA	0.9	0.3	5.6	1.5	2.4	2.4	45.2	14.7	4.7	11.3	3.7	2.3	5.0	*54.9*
GER	0.4	0.4	14.8	2.2	4.1	3.7	12.6	37.7	1.5	10.3	1.2	1.9	9.2	*62.3*
ITA	2.3	0.8	1.3	1.2	1.4	1.5	6.4	3.0	71.7	2.7	3.2	1.8	2.8	*28.3*
NTH	0.8	0.4	7.1	1.7	4.2	3.4	11.8	12.8	1.9	47.1	1.4	3.6	3.7	*52.9*
SPN	1.1	0.5	0.9	0.9	1.0	0.9	5.7	2.3	3.2	2.5	78.6	0.8	1.7	*21.4*
UK	1.6	0.7	2.5	0.9	1.9	2.1	3.9	3.8	1.1	5.5	1.1	73.4	1.5	*26.6*
PLN	0.4	0.4	9.4	3.4	3.8	3.2	5.9	12.3	2.2	4.4	2.0	1.3	51.2	*48.8*
To	*13.7*	*8.9*	*67.0*	*32.0*	*42.3*	*54.9*	*58.9*	*74.9*	*19.7*	*51.9*	*16.4*	*19.2*	*40.0*	
NSI	**−1.0**	**−3.5**	**5.5**	**−14.0**	**−5.7**	**32.8**	**4.0**	**12.6**	**−8.6**	**−1.0**	**−5.0**	**−7.4**	**−8.8**	
TCI	**38.5**													
CSI$_{\text{Gas-Electricity}}$	**0.9**													
CSI$_{\text{EUA-Electricity}}$	**0.6**													

Note: Panel A reports the average connectedness indexes across the sample assets, estimated based on mean-based connectedness framework of Diebold and Yilmaz (2012). Panel B presents the average connectedness indexes estimated based on the quantile VAR at the quantile $\tau = 0.5$. NSI denotes Net Spillover Index. TCI indicates Total Connectedness Index. CSI represents Cross-market Spillover Index.

Third, Table 2 points out the direction and magnitude of the return spillover between EUA and European electricity markets. Carbon prices, measured by EUA, affect electricity prices via supply as fossil-fuel electricity generation tends to be low when carbon price is high (Mosquera-López and Nursimulu, 2019). In addition, according Daskalakis et al. (2015), increased volatility in carbon price results in increased hedging costs for power producers, leading to more volatile electricity prices. In the opposite direction, demand and supply of electricity can also influence carbon price. For instance, Thema et al. (2013) suggests that electricity demand reduction policies (i.e., energy efficiency policies) will reduce carbon price. Van den Bergh et al. (2013) find that the deployment of renewable energy sources has contributed to a reduction in EUA price between 2007 and 2010. Pertaining to the EUA-electricity price nexus, we find that EUA-electricity spillover effects are weak at both the conditional mean and median, evidenced by the cross-market spillover indices between EUA and EU electricity market (CSI$_{\text{EUA-Electricity}}$) standing at 0.7 and 0.6, respectively. These figures further imply that, compared to natural gas, EUA is less interrelated with European electricity markets. The low connectedness between EUA and European electricity prices is consistent with the growing contributions of renewable energy sources in the energy mix of European countries. According to the European Council, the share of renewables in electricity generation has more than doubled since 2004, from >15% in 2004 to nearly 40% in 2022.[14]

Fourth, the net spillover indexes (NSI) of natural gas and EUA are negative, standing at −1.1 and − 2.6 at the conditional mean and − 1.0 and − 3.5 at the conditional median, respectively. These negative figures indicate that both gas and EUA are net recipients of shocks in the network, implying that they receive more shocks from electricity markets than they transmit to.

Finally, the net transmitters of return shocks are DNK, SWD, FRA, and GER while the net receivers are FIN, NOR, ITA, NTH, SPN, UK, and PLN. The net-transmitter role of FRA and GER can be explained by their economic importance in the EU as Germany and France are the largest and second-largest electricity consumers in Europe, respectively. Additionally, the net-diffuser role of DNK and SWD can be partly justified by their highest volatility of prices (Table 1).

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[14] Source: https://www.consilium.europa.eu/en/infographics/how-is-eu-electricity-produced-and-sold/

4.2. Return connectedness at the tails

In Tables 3 and 4, we present the tail connectedness measures, computed at the lower quantile ($\tau = 0.1$) and upper quantile ($\tau = 0.9$), respectively. At both lower and upper quantiles, the TCIs are significantly higher than those computed at the conditional mean and median. In Tables 3 and 4, the TCI has a value of 81.5% and 81.5%, respectively, compared to 38.5% at the conditional median (i.e, middle quantile or $\tau = 0.5$). Furthermore, the cross-market spillover indices (CSI) of gas or EUA with European markets are noticeably higher at the tails. The $CSI_{\text{Gas-Electricity}}$ rises dramatically from 0.9% at the conditional median to 6.1% at the lower tail and 5.8% at the upper tail. Similarly, the $CSI_{\text{EUA-Electricity}}$ increases tenfold from 0.6% at the middle quantiles to 5.9% and 6.0% at the lower and upper tails, respectively. These results suggest that gas and EUA are more connected with European electricity markets in extremely negative and positive shocks. Concerning the net spillover effect, we observe that gas and EUA continue to be net receivers of shocks, evidenced by their net spillover index (NSI) at the lower (upper) tail of −5.7% (−12.1%) and − 9.9% (−9.0%), respectively.

Fig. 4 shows the connectedness network between European electricity prices, EUA, and natural gas across different quantiles. Fig. 4a, b, and c display the network at the conditional median, lower tail, and upper tail, correspondingly. The node's size indicates the degree of the net return spillover effects of each asset in the network. The node's colour implies whether the considered asset is a net transmitter (green) or net recipient (yellow) of shocks. Lastly, the magnitude of pairwise spillover between two assets is denoted by the width of the arrow edge (in purple).

At the conditional median, (i.e., Fig. 4a), Sweden (SWD), Germany (GER), France (FRA), and Denmark (DNK) act as net transmitters of return shocks whereas natural gas (GAS), carbon prices (EUA), and other countries' markets play the role of net receivers. Notably, of the net transmitters, SWD is the strongest diffuser of return shocks, followed by GER. Conversely, Finland (FIN) and the UK (UK) are the most significant return shock absorbers. The width of the arrow edge suggests strong transmission of return shocks between German and French markets and between German and Denmark markets.

Fig. 4b, displays the connectedness network of the system at the lower quantile. It is evident that there are significant changes in the role of each market when they experience extremely negative shocks. First, more countries become net shock transmitters at the lower tail. For instance, compared to Fig. 4a, the UK (UK), Netherlands (NTH), and Poland (PLN) play the role of net diffusers of shocks instead of net recipients. Moreover, NTH and DNK are the largest transmitters of extremely negative shocks. In addition, Spain (SPN), GAS, and EUA are the most important net recipients of return shocks at the lower tail.

In Fig. 4c, we plot the connectedness network at the upper quantile. Compared to Fig. 4b, the British market's role (UK) has switched from net diffuser to net recipient of shocks. Conversely, the Finnish market (FIN) plays the role of net shock diffuser instead of net shock recipient as in Fig. 4b. In terms of significance, similar to Fig. 4b, the Netherlands (NTH) and Denmark (DNK) remain the largest net transmitters of extremely positive shocks, followed by Germany (GER) and France (FRA). In the same vein, Spain remains the largest net absorber of shocks at the upper tail, followed by natural gas (GAS) and EUA.

In addition to these notable observations, Fig. 4 shows a greater interrelationship of European electricity markets with natural gas and EUA markets at the lower and upper quantiles than at the conditional median. Specifically, in Fig. 4a, the arrows connecting GAS (or EUA) with European electricity markets have a slim edge, indicating very low levels of interconnectedness. By contrast, in Fig. 4b and Fig. 4c, these arrows become substantially thicker, implying considerable interdependency between European electricity markets, EUA, and natural gas. The visualization of higher interdependence at the lower and upper tails corroborates our prior results shown in Tables 3 and 4.

In Fig. 5, we increase the number of quantiles used to estimate the TCI and display the variations in the TCI of the network across different quantiles. The fluctuations of the TCI across various quantiles emphasize that the return spillover effects are intensified at both tails, reaffirming that the strength of shock transmission increases with both extremely negative and positive shocks. In addition, the TCI in Fig. 5 exhibits a symmetrical shape at the lower and upper quantiles, implying that negative or positive shocks are evenly significant in driving the transmission of return shocks within the system.

4.3. Return connectedness measures over time

In previous subsections, the connectedness network between European electricity market, EUA, and natural gas has been analysed from a static basis. This subsection will investigate the time evolution of the connectedness indices by implementing a rolling analysis. We employ a *10*-step forecasting horizon and a constant 200-day window length to compute different connectedness measures of the system.

The dynamic TCI at the conditional mean and at various quantiles (i.e, median, lower, and upper quantiles) is shown in Fig. 6. We observe that the TCIs at the conditional mean and median chart an analogous pattern. Moreover, they display large variations over time, fluctuating between 25% and 51%. Starting in October 2012 at about 31%, the TCIs experienced a short uptrend until October 2013 when they started to decrease. The downward trend starting in October 2013 lasted about two years and terminated in the end of October 2015, reaching a low level of 25%. The indices then recovered quickly between November 2015 and May 2016. The sharp increase in the TCIs during this period reflected the increased integration of electricity markets in Europe following the market coupling of 15 European countries in 2014. This market coupling added the Baltic States, the UK, and Poland to the Market Coupling in Western Europe and the Nordic countries. Furthermore, in 2015, the Italian market started coupling its borders with France. Since 2016, the Multi-Regional Coupling (MRC) with 19 European countries is established (including the 11 sample countries) and covers about 85% of European electricity consumption.[15] After a swift correction in late 2016 and early 2017, the indices plateaued between February 2017 and September 2018. After that, the uptrend in the TCI resumed and the indices reached a new high in January 2019. During this time, the increase in the TCI would stem from heightened risks in energy markets, sparkled by Fed's successive monetary tightening.[16] After an abrupt surge of the indices in February 2020 admitting the start of the COVID pandemic, the indices retreated until July 2020 when they started to rise again. After reaching high levels at the end of 2020, the indices pulled back in early 2021. This period coincided with the decoupling of the UK electricity market from the European Internal Energy Market since January 2021. The decline in the TCI in early 2021 could reflect the impact of this decoupling that made electricity prices in the UK less integrated with those of other European countries. Since mid-February 2021, the uptrend in the TCI has resumed. The indices attained their highest points in June 2021 and experienced a sharp correction afterward. The tension in the Russia-Ukraine relationship in November 2021 coincides with the rise of indices in late 2021. The indices spiked in late February 2022 when the Russia-Ukraine war started on February 24, 2022. The effect of the war seems long-lasting as the indices remained high despite experiencing minor fluctuations afterward.

Fig. 6 also illustrates the TCI at the upper and lower quantiles. Three noteworthy observations regarding its temporal fluctuations are evident from the figure. Firstly, in contrast to the TCI at the conditional mean and median, the TCIs at both tails exhibit a narrower range of variation,

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[15] For a chronology of market coupling in Europe, see https://www.next-kraftwerke.com/knowledge/market-coupling

[16] From March 2018 to August 2019, the U.S. Federal Reserve (Fed) has risen its target rates five consecutive times.

Table 3
Connectedness table at the lower quantile.

	GAS	EUA	DNK	FIN	NOR	SWD	FRA	GER	ITA	NTH	SPN	UK	PLN	*From*
GAS	21.5	8.2	6.5	6.6	5.5	6.0	6.2	5.8	7.0	7.0	5.6	7.6	6.7	*78.5*
EUA	8.3	21.5	6.5	6.7	5.8	6.5	5.8	5.8	7.1	6.7	5.7	6.7	7.0	*78.5*
DNK	5.6	5.3	14.8	8.3	7.9	8.2	7.2	9.5	5.8	8.3	4.6	6.6	8.0	*85.2*
FIN	6.0	5.6	8.9	17.1	8.2	8.8	6.5	6.7	6.5	6.8	4.9	6.7	7.5	*82.9*
NOR	5.3	5.1	9.1	8.4	18.2	8.7	6.6	7.0	5.9	7.6	4.6	6.5	6.9	*81.8*
SWD	5.9	5.9	7.6	7.8	7.4	21.4	6.4	6.1	6.3	7.0	4.9	6.9	6.5	*78.6*
FRA	5.6	4.9	7.3	6.1	6.1	6.6	15.9	9.4	7.7	9.5	6.4	6.8	7.8	*84.1*
GER	5.0	4.8	10.0	6.5	6.6	6.4	9.5	15.8	6.1	9.4	4.7	6.4	8.9	*84.3*
ITA	6.8	6.1	6.2	6.8	5.9	6.0	8.2	6.5	19.4	7.5	6.4	6.7	7.6	*80.6*
NTH	5.8	5.3	8.2	6.2	6.7	6.5	9.1	9.0	6.6	16.2	5.2	7.6	7.6	*83.8*
SPN	6.2	5.9	6.1	6.0	5.4	5.8	8.1	6.2	7.9	7.0	22.7	5.9	6.8	*77.3*
UK	6.8	6.0	7.2	6.2	6.2	6.3	7.1	7.0	6.5	8.7	5.0	20.1	6.9	*79.9*
PLN	5.7	5.6	8.8	7.2	6.6	6.4	7.8	9.1	7.0	8.1	5.3	6.4	16.0	*84.0*
To	*72.8*	*68.7*	*92.5*	*82.7*	*78.2*	*82.0*	*88.3*	*88.4*	*80.3*	*93.7*	*63.2*	*80.8*	*87.9*	
NSI	**−5.7**	**−9.9**	**7.2**	**−0.1**	**−3.5**	**3.4**	**4.2**	**4.1**	**−0.3**	**9.9**	**−14.1**	**0.9**	**3.9**	
TCI	**81.5**													
CSI$_{\text{Gas-Electricity}}$	**6.1**													
CSI$_{\text{EUA-Electricity}}$	**5.9**													

Note: This table reports the average return connectedness indexes across the sample assets, estimated based on the quantile VAR at the lower quantile τ = 0.1. NSI denotes Net Spillover Index. TCI indicates Total Connectedness Index. CSI represents Cross-market Spillover Index.

Table 4
Connectedness table at the upper quantile.

	GAS	EUA	DNK	FIN	NOR	SWD	FRA	GER	ITA	NTH	SPN	UK	PLN	*From*
GAS	21.8	8.3	6.3	6.4	5.6	6.3	6.2	6.0	6.7	7.0	5.5	7.4	6.5	*78.2*
EUA	7.8	21.5	6.4	6.6	5.7	6.9	6.1	5.9	7.0	6.8	5.8	6.9	6.7	*78.5*
DNK	5.1	5.1	15.4	8.2	8.2	7.8	7.3	9.9	5.6	8.3	4.6	6.4	8.2	*84.6*
FIN	5.4	5.6	8.9	17.6	8.4	8.0	6.7	7.1	6.6	6.9	5.1	6.3	7.4	*82.4*
NOR	4.7	5.2	9.5	8.6	17.6	8.7	6.7	7.4	5.9	7.7	4.8	6.4	6.9	*82.4*
SWD	5.6	6.5	7.8	7.8	7.3	19.2	6.7	6.5	6.7	7.3	5.0	7.1	6.6	*80.8*
FRA	4.9	4.7	7.7	6.3	5.8	6.2	16.6	10.1	7.6	9.7	6.3	6.7	7.6	*83.4*
GER	4.7	4.7	10.4	6.4	6.6	6.0	9.8	16.3	5.9	9.4	4.9	6.2	8.8	*83.7*
ITA	5.7	6.2	6.2	6.7	5.9	6.4	8.4	6.7	19.6	7.6	6.7	6.8	7.3	*80.4*
NTH	5.5	5.2	8.1	6.3	6.8	6.7	9.3	9.2	6.8	15.9	5.5	7.5	7.3	*84.1*
SPN	5.6	6.2	6.2	6.2	5.4	5.8	8.1	6.3	8.0	7.1	22.4	6.1	6.8	*77.6*
UK	6.1	6.0	7.2	6.0	6.2	6.7	7.6	7.1	6.8	8.5	5.4	19.7	6.7	*80.3*
PLN	5.2	5.6	9.0	7.2	6.7	6.3	7.9	9.2	6.7	7.8	5.5	6.3	16.7	*83.3*
To	*66.1*	*69.5*	*93.5*	*82.6*	*78.4*	*81.8*	*90.7*	*91.1*	*80.2*	*93.9*	*65.1*	*80.0*	*86.8*	
NSI	**−12.1**	**−9.0**	**8.9**	**0.2**	**−3.9**	**1.0**	**7.4**	**7.4**	**−0.3**	**9.8**	**−12.5**	**−0.3**	**3.5**	
TCI	**81.5**													
CSI$_{\text{Gas-Electricity}}$	**5.8**													
CSI$_{\text{EUA-Electricity}}$	**6.0**													

Note: This table reports the average return connectedness indexes across the sample assets, estimated based on the quantile VAR at the lower quantile τ = 0.9. NSI denotes Net Spillover Index. TCI indicates Total Connectedness Index. CSI represents Cross-market Spillover Index.

hovering between 77% and 85% throughout the sample period. Second, though exhibiting limited variations, the TCIs at the lower and upper quantiles consistently surpass the TCIs at the conditional mean and median. This observation reinforces our earlier conclusion that across all market situations, the carbon, gas, and electricity markets exhibit greater sensitivity to extreme shocks compared to normal shocks. Third, although there are dissimilarities in the short-term fluctuations between the TCI at the upper and lower quantiles, the TCIs at both tails demonstrate a relatively common trend in the long-run.[17] This provides additional support to our prior finding that both extremely negative and positive shocks are evenly crucial in driving the return connectedness of the selected assets.

Fig. 7 displays the dynamic cross-market spillover index between gas and electricity markets (CSI$_{\text{Gas-Electricity}}$). It showcases the index at the conditional mean and median as well as at the upper and lower quantiles. Similar to Fig. 6, we find that the CSI$_{\text{Gas-Electricity}}$ at the lower and upper tails are substantially higher than at the conditional mean and median throughout the research period. This observation reinstates that the transmission of extremely negative and positive return shocks between gas and electricity markets is more severe than the spillover of average shocks. In addition, we observe that the CSI$_{\text{Gas-Electricity}}$ at the lower and upper quantiles exhibits strong fluctuations, which is contrary to the findings of TCI in Fig. 6. Finally, the CSI$_{\text{Gas-Electricity}}$ at the conditional mean and median stabilized at the low level (below 2%) during most of the sample period, including the COVID-19 pandemic. The indices, however, rose sharply by October 2021 when the Russia-Ukraine relationship became tense and hit the highest values during the war. While the connectedness between gas and electricity markets reduced since June 2022, they were still much higher than in the pre-war period.

Fig. 8 shows the movement of the cross-market spillover index between EUA and electricity markets (CSI$_{\text{EUA-Electricity}}$) at the conditional mean and across various quantiles over the sample period. In line with the results in Fig. 6 and Fig. 7, we find that CSI$_{\text{EUA-Electricity}}$ at the lower and upper quantiles is considerably higher than at the conditional mean and median. In addition, while the indices at the conditional mean and mean move closely with each other, the CSIs at the lower and upper tails are less connected. In particular, the differences were noticeable after

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[17] The correlation coefficient between the TCIs at the upper and lower quantiles is 0.50.

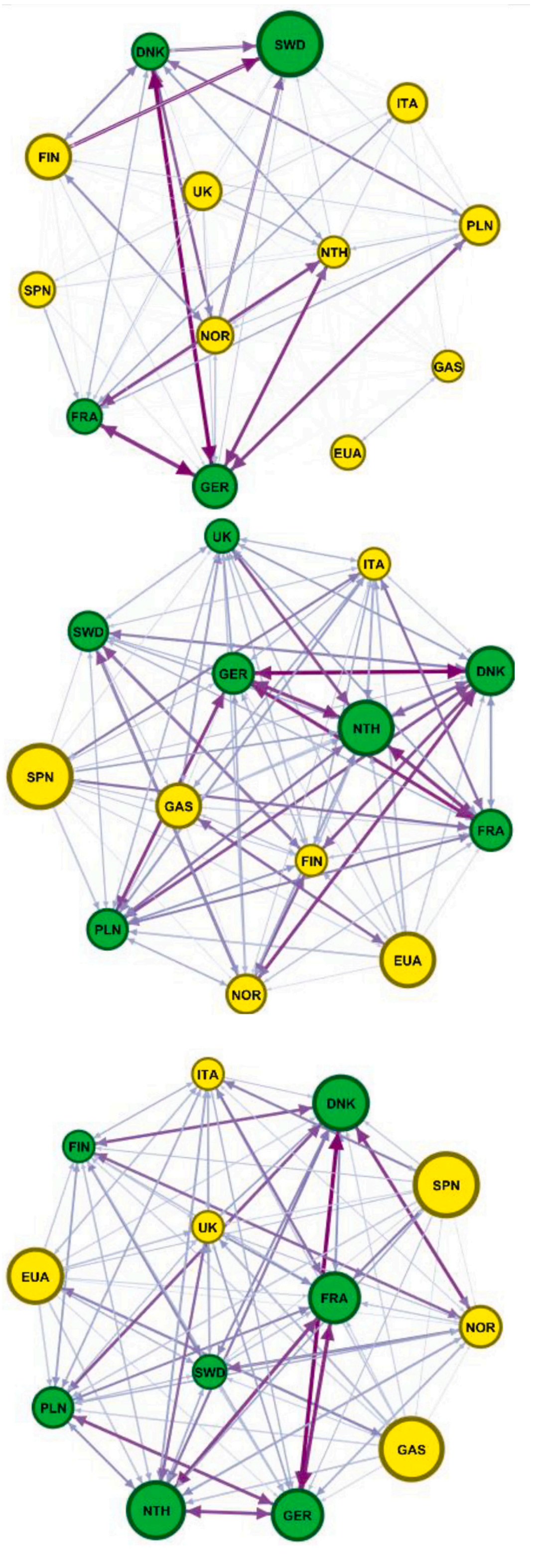

Fig. 4. Network connectedness at various quantiles.

Note: These graphs illustrate the network connectedness across the selected assets. Fig. 4a, b, c describes the network connectedness at middle quantile ($\tau = 0.5$), at lower quantile ($\tau = 0.1$) and at upper quantile ($\tau = 0.9$), respectively. The node colour represents the role of net transmitter (green)/ receiver (yellow) of return shocks. The node size is determined by the magnitude of the net return spillover of each asset. The thickness of the arrow edge indicates the strength of pairwise directional spillover. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the early stage of the COVID-19 pandemic in March 2020. The $\text{CSI}_{\text{EUA-Electricity}}$ at the conditional mean (median) reached its highest value in July 2019, which is different from the $\text{CSI}_{\text{Gas-Electricity}}$ in Fig. 7. Finally, the CSIs at the conditional mean and median were quite calm during the COVID-19 pandemic and the Russia-Ukraine war. By contrast, the CSIs at the lower and upper tails fluctuated strongly during these periods.

Fig. 9 plots the dynamic net spillover index (NSI) of natural gas. First, as shown in Fig. 9, the NSIs were below the zero threshold during most of the study period, indicating that the energy commodity market is primarily a net recipient of shocks. Second, there were remarkable increases in the indices since the end of 2019. Notably, the NSI of natural gas at the conditional mean (blue line) rose robustly since the onset of the COVID-19 pandemic in 2020 and stayed above zero for most of 2020. Intriguingly, all NSIs except the NSI at the upper quantile (yellow line) were mostly in the positive zone from the end 2021 until the end of the sample period. These observations suggest that while gas is a net receiver of shocks, the energy commodity is a net diffuser during periods of market crises such as COVID-19 and the Russia-Ukraine war.

Fig. 10 displays the net spillover (NSI) index of EUA over time. Throughout most of the sample period, the NSIs exhibit negative values, indicating the carbon market is mostly a net absorber of shocks. The dynamic NSIs at the conditional mean and across quantiles mostly stay negative during the study period, suggesting that the carbon market is consistently a net recipient of shocks. Furthermore, the NSIs at lower and upper tails are prone to be more negative and experience higher volatility than those at the conditional mean and median. Remarkably, they attained their lowest levels during the start of Russia-Ukraine war in 2022, implying the carbon market receives substantially extreme shocks from gas and electricity markets during this period.

4.4. Determinants of the connectedness indices: The impact of the crises

4.4.1. Analysis at the aggregate level

Given the significant variations and volatility observed in the quantile connectedness measures, it is crucial for investors to monitor and balance their portfolios based on these key drivers. Furthermore, considering the effects of recent crises such as COVID-19 and the Russia-Ukraine war on the European economy and energy markets, we also examine the impact of these events on the connectedness indices.

To uncover the factors influencing the connectedness indices, we employ the model as follows,

$$Connectedness_t = \beta + \gamma X_{t-1} + \alpha_1 COVID + \alpha_2 WAR + \varepsilon_t \tag{13}$$

where $Connectedness_t$ is either the dynamic total connectedness index (TCI), the cross-market spillover index between gas and electricity markets ($\text{CSI}_{\text{Gas-Electricity}}$) or the cross-market spillover index between EUA and electricity markets ($\text{CSI}_{\text{EUA-Electricity}}$), which are computed at the conditional median, upper quantile, and lower quantile; β denotes the intercept; ε_t represents the error term; and X_{t-1} demonstrates a vector of six control variables.

The control variables include daily frequency of (1) the implied volatility of the crude oil market measured by the CBOE[18] Crude Oil Volatility Index (*OVX*); (2) the expected volatility of the Dow Jones EuroStoxx 50 Index (*VSTOXX*); (3) the European term spread proxied by the discrepancy between the yield of Germany 10-year Treasury note and that of the 2-year Treasury note (*TERMSPR*); (4) the Economic Policy Uncertainty (*EPU*) index, as defined by Baker et al. (2016); (5) the index of global geopolitical risk (*GOPRX*), developed by Caldara and Iacoviello (2022); (6) a dummy variable (*WINTER*), which equals 1 for data recorded in November, December, January, or February and 0 for data recorded in other months. To account for the impacts of COVID-19, we followed Güler et al. (2022) and include the dummy variable *COVID*,

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[18] Chicago Board Options Exchange (CBOE).

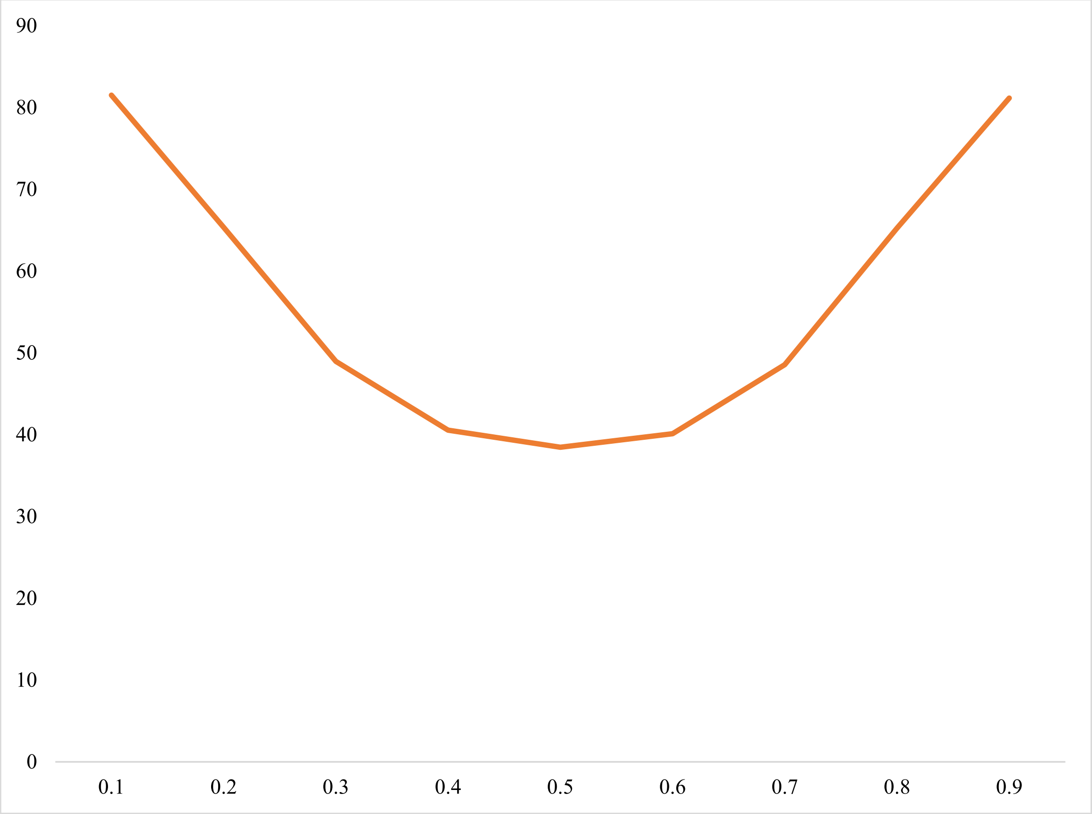

Fig. 5. TCI across quantiles.
Note: This figure shows the Total Connectedness Index (TCI) of the system across different quantiles.

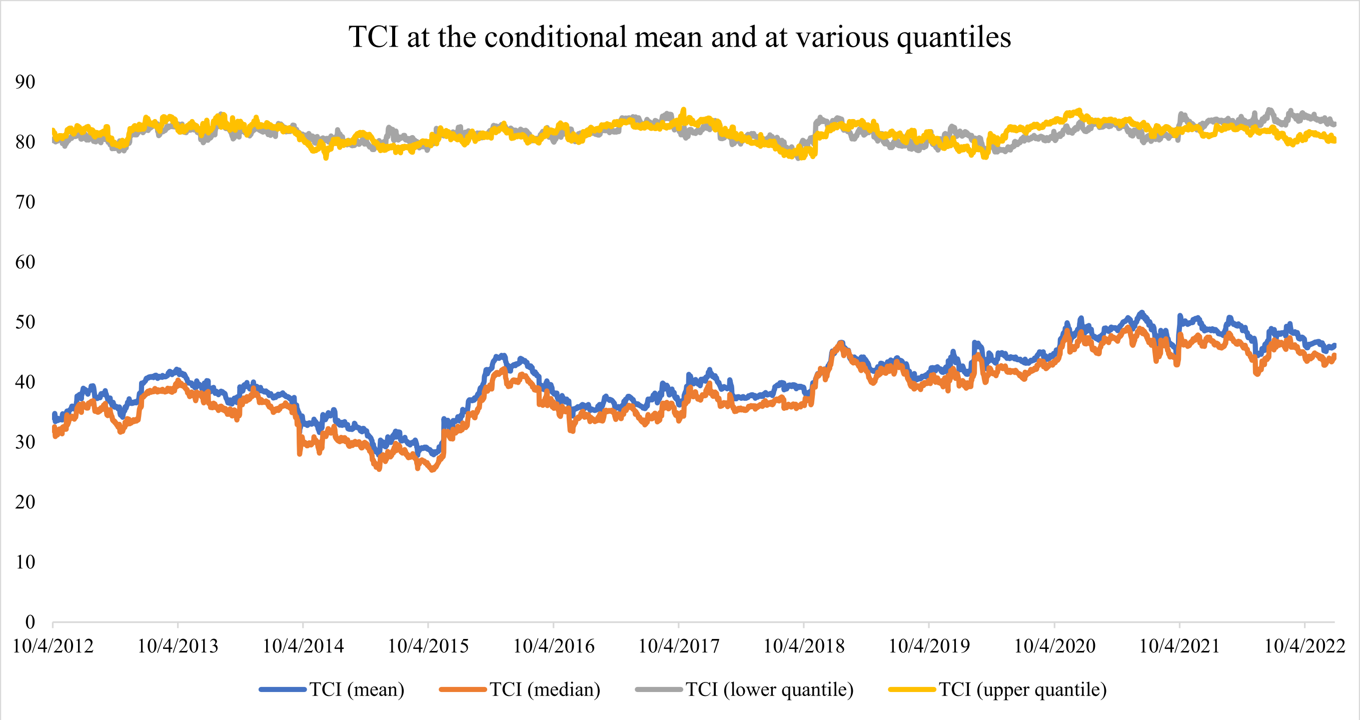

Fig. 6. Dynamic total connectedness index (TCI) at the conditional mean and at various quantiles.
Note: This figure shows the time-varying Total Connectedness Index (TCI) at the conditional mean and at various quantiles, during the research period.

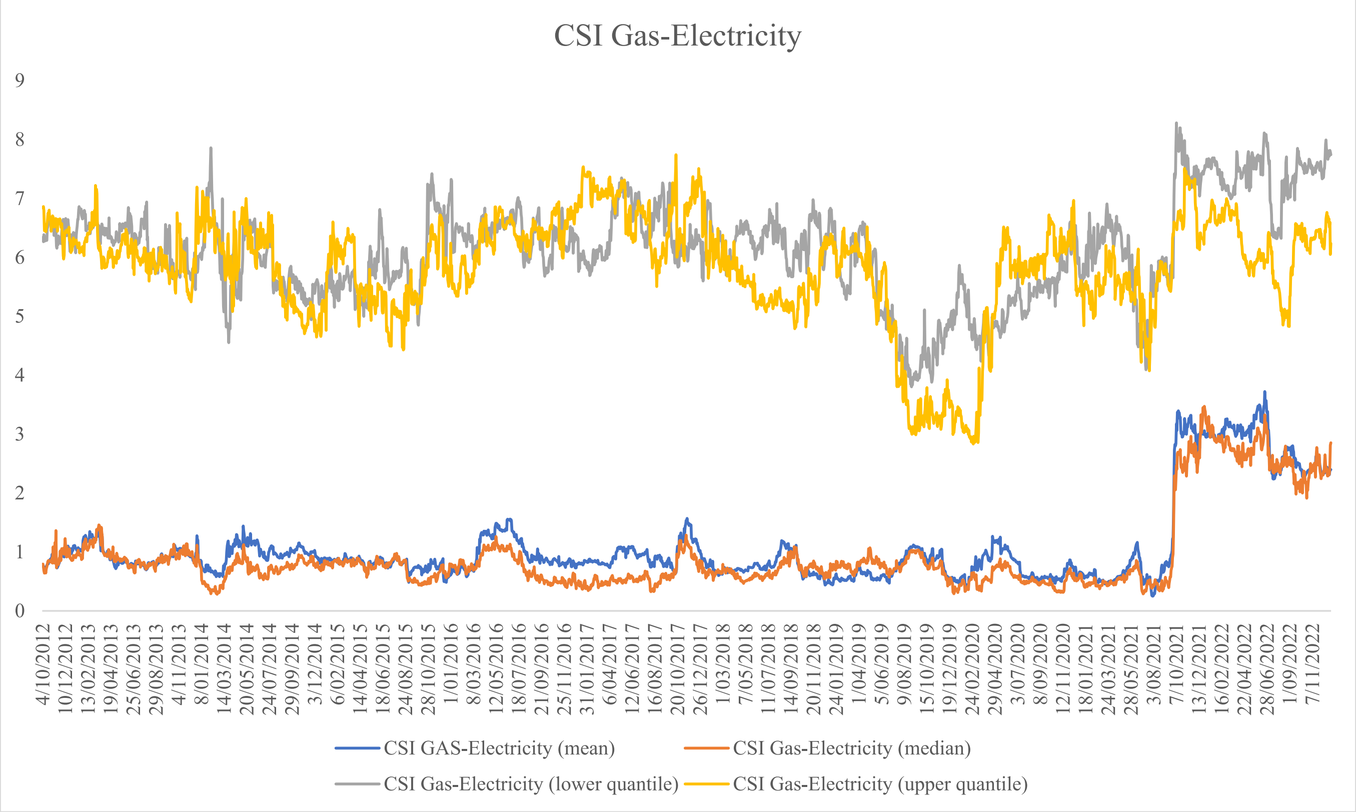

Fig. 7. Dynamic $\mathrm{CSI}_{\text{Gas-Electricity}}$ at the conditional mean and at various quantiles.
Note: This figure shows the time-varying Cross-market Spillover Index (CSI) between electricity and natural gas markets at the conditional mean and at various quantiles, during the research period.

which equals 1 if the data is between January 1st, 2020 and September 30th, 2020 and 0 otherwise. Following Güler et al. (2022), this period could have significant impact on European electricity markets as it includes both the outbreak of the pandemic in Europe and the time when strict containment measures were applied to suppress the outbreak. Finally, considering the impact of the Russia-Ukraine war, we include the variable *WAR*. It is set to 1 for data recorded between February 24th, 2022 and December 30th, 2022, and 0 otherwise.

The control variables identified in the literature are factors that can influence volatility of energy commodities and electricity markets, as well as their interconnectedness. First, *OVX* not only reflects expected volatility in the oil market but is also considered a barometer of energy market uncertainty (Dutta et al., 2020). As *OVX* levels rise, uncertainty in energy markets is forecasted to rise. Zhang et al. (2023) show that *OVX* increases the interconnectedness among clean energy, electricity, and energy metal markets. Second, *VSTOXX* is used to account for the systematic risk in the stock market, which is deemed a driving force of gas market volatility. Chen et al. (2021) find a positive impact of stock market volatility on the fluctuations of gas prices. Ding (2021) finds both negative and positive correlation between gas price volatility and stock market volatility. Thirdly, we employ *TERMSPR*, or yield curve slope, a widely considered an important barometer of the economy. Particularly, positive term spreads typically indicate economic growth, whereas negative readings presage economic slowdown or recession. As demand for electricity and economic growth are highly interrelated (e.g., Stern, 1993; Lorde et al., 2010; Gurgul and Lach, 2012; among others), expectations of economic slowdown or expansion can influence electricity demand, price, and their fluctuations. According to Karali and Ramirez (2014), energy commodities become volatile as the term spread narrows.

The next control variable is the economic policy uncertainty index (*EPU*). As the daily data of EPU in Europe is not available, we employ the daily U.S. EPU to proxy for the economic policy uncertainty of the sample countries. This replacement is supported by studies that reveal that the U.S. EPU has a critical role in shaping volatility and risk transmission in European markets (e.g., Krol, 2014; Bernal et al., 2016; Mei et al., 2018). Kang and Yoon (2019) find strong connectedness between country-level connectedness indices, including the U.S. EPU and European EPU. Earlier studies indicate substantial interconnections between the gas market and EPU (e.g., Geng et al., 2021; Scarcioffolo and Etienne, 2021; and Dash and Maitra, 2021). Additionally, EPU is positively correlated with the spillover effects in financial markets as shown in Adekoya et al. (2021) and Youssef et al. (2021). Another control variable, *GOPRX*, is used by Caldara and Iacoviello (2022) to capture risks caused by global geopolitical tensions. According to Victor et al. (2006), Liang et al. (2021), and Su et al. (2023), *GOPRX* is priced in the gas market. Furthermore, Gong and Xu (2022) find that *GOPRX* significantly amplifies the interconnectedness between different commodities. We expect that both *EPU* and *GOPRX* exert a positive effect on the interconnectedness between European electricity markets, EUA, and natural gas. Lastly, the indicative variable, *WINTER*, captures the seasonality of the European gas market (Martínez and Torró, 2015) and electricity markets (Kan et al., 2021; Taylor, 2010).

We first estimate Eq. (13) using TCI as the dependent variable and employ OLS estimation and report the corresponding results in Table 5. The *t*-statistics are corrected for heteroscedasticity based on Newey and West's (1987) robust standard errors. Table 5 reveals several important findings. Firstly, we find that across all models, the adjusted R^2 is significant, varying from 13% in Column (1) (i.e., TCI at upper tail) to 40% in Column (1) (i.e., TCI at the middle quantile). Moreover, the robust *F*-statistics support the appropriateness of the independent variables used to explain the fluctuations in the TCI. Secondly, impacts of all control

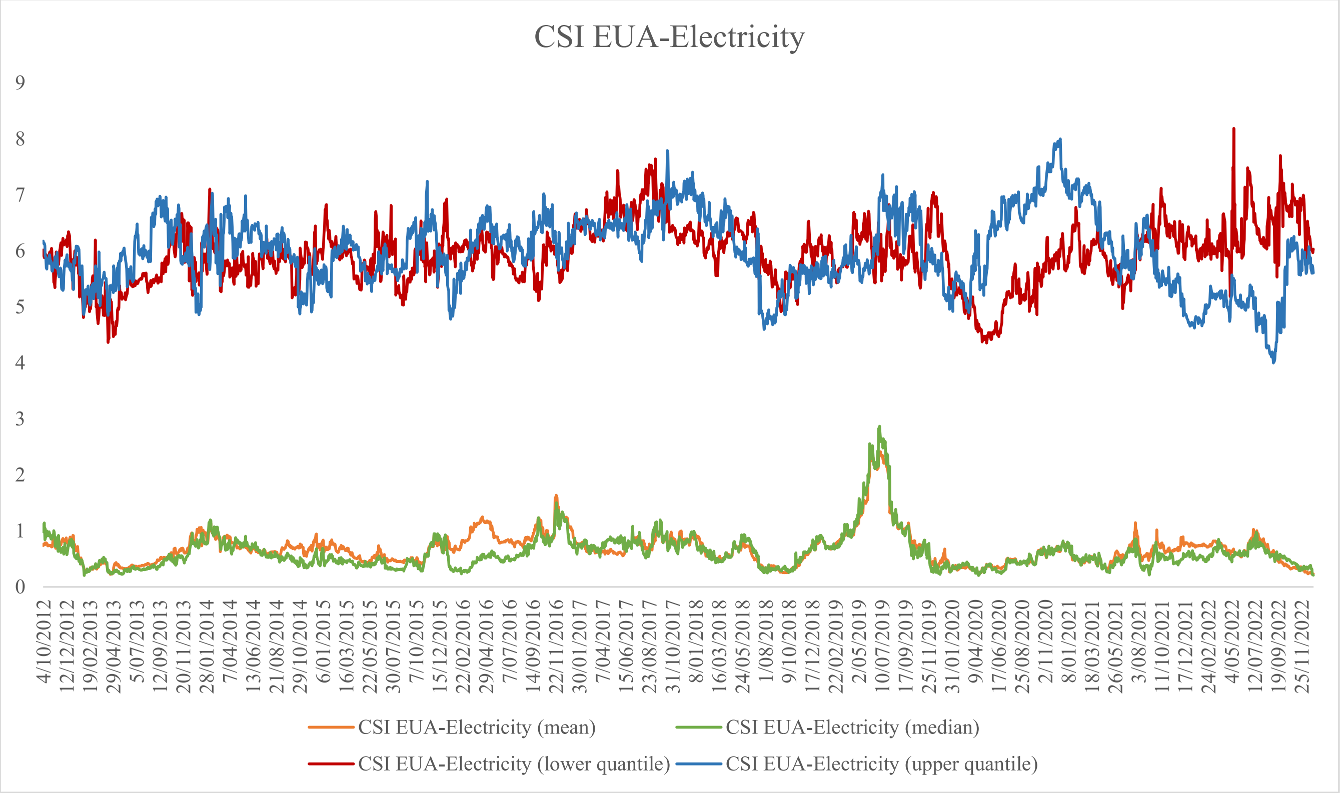

Fig. 8. Dynamic $\text{CSI}_{\text{EUAs-Electricity}}$ at the conditional mean and at various quantiles.
Note: This figure shows the time-varying Cross-market Spillover Index (CSI) between electricity and EUA markets at the conditional mean and at various quantiles, during the research period.

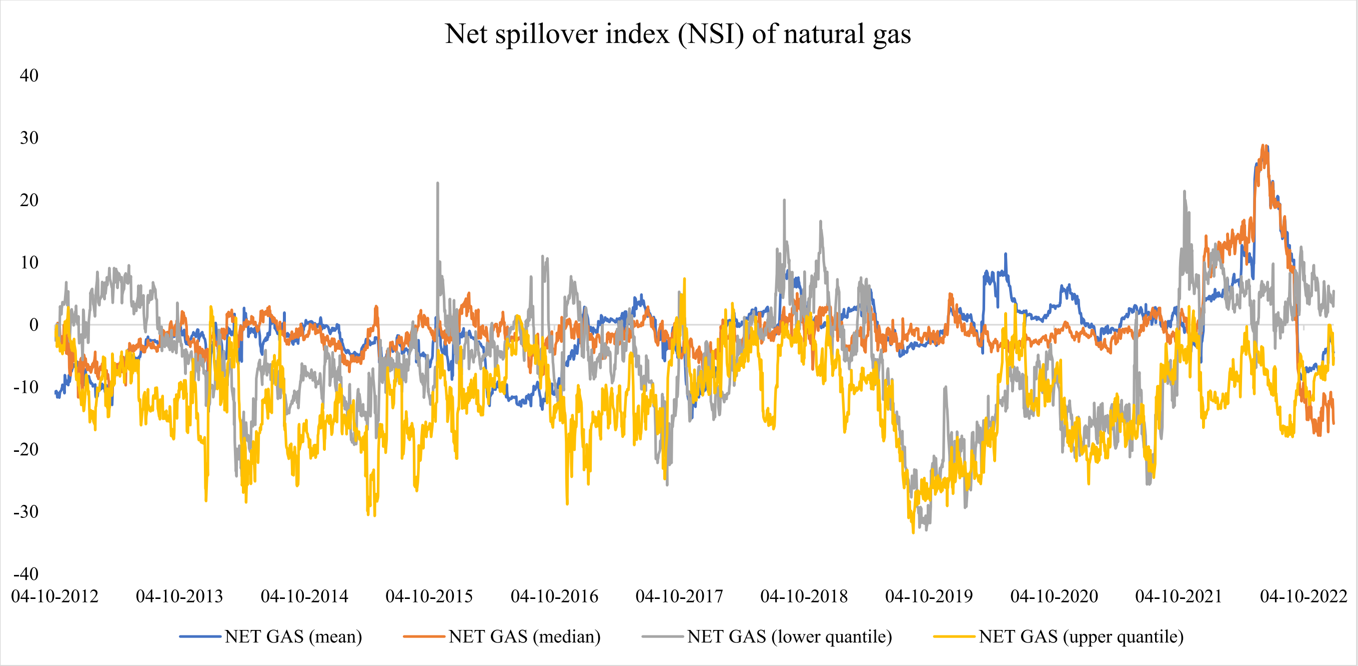

Fig. 9. Dynamic net spillover index (NSI) of natural gas across quantiles.
Note: This figure shows the time-varying Net spillover index (NSI) of natural gas at the conditional mean and at various quantiles, during the research period.

variables except *EPU* are heterogeneous across various quantiles. This strong heterogeneity underlines the necessity to explore the determinants of return spillover effects across quantiles. Specifically, as shown in Table 5, expected volatility of the crude oil market (*OVX*) only significantly affects the TCI at the middle quantile, whereas its effect on the index at the upper and lower tails is insignificant. Surprisingly, the results show that the expected volatility of the European stock market (*VSTOXX*) exerts a negative and significant impact on the index at the

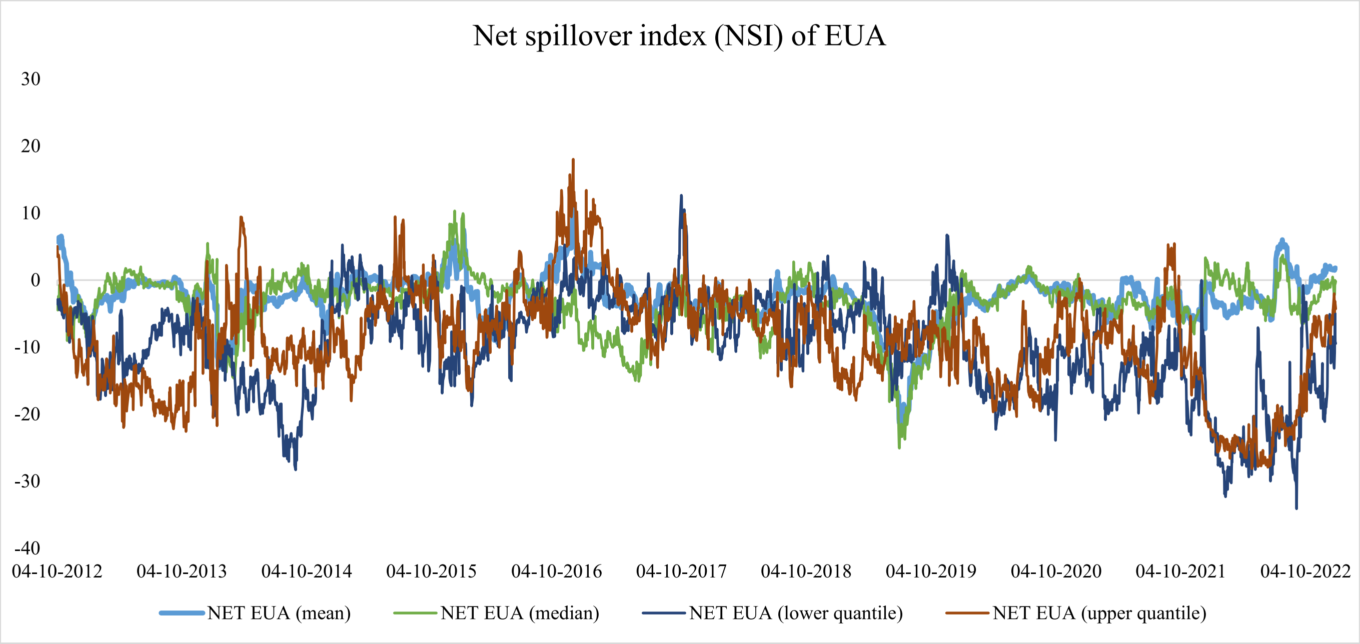

Fig. 10. Dynamic net spillover index of European Emission Allowances (EUA) across quantiles.
Note: This figure shows the time-varying Net spillover index (NSI) of EUA at the conditional mean and at various quantiles, during the research period.

Table 5
Determinants of total connectedness index (TCI).

	TCI (median)	TCI (lower tail)	TCI (upper tail)
	(1)	(2)	(3)
OVX	−1.51***	−0.09	−0.10
	(−2.93)	(−0.47)	(−0.75)
VSTOXX	−0.09***	−0.003	−0.03***
	(−3.27)	(−0.43)	(−3.51)
TERMSPR	−3.85***	0.31	0.37
	(−4.33)	(1.01)	(1.58)
EPU	7.27***	0.49***	1.96***
	(11.76)	(2.97)	(10.57)
GOPR	0.80	1.13***	−0.15
	(0.92)	(5.20)	(−0.65)
WINTER	−0.04	0.42***	−0.04
	(−0.10)	(3.95)	(−0.32)
COVID	−2.18***	−1.37***	−1.12***
	(−3.93)	(−7.54)	(−3.65)
WAR	6.07***	2.48***	−0.42
	(4.77)	(5.44)	(−1.31)
Intercept	27.97***	77.96***	78.52***
	(10.95)	(136.8)	(130.7)
N. Obs.	2672	2672	2672
Adj. R-squared	0.40	0.25	0.13
F-statistics	227.78***	115.05***	50.23***

Note: This table presents the regression results of Eq. (13) to investigate the effects of COVID-19 and the Russia-Ukraine war on the Total Connectedness Index (TCI) among European electricity prices, natural gas, and EUA. Eq. (13) is estimated using OLS estimation with t-statistics computed using Newey and West's (1987) robust standard errors. ***, **, and * indicate statistical significance at 10%, 5%, and 1% level, respectively.

middle and upper quantiles. However, it does not influence the TCI at the lower quantile. This finding aligns with previous research by Creti et al. (2013), which suggests that volatility correlations between stock and electricity markets are often negative due to the distinctive fundamental of the electricity market. The impact of term spread (*TERMSPR*) is also noteworthy. In particular, the coefficient of *TERMSPR* (−3.85) is negative and highly significant in Column (1) but statistically insignificant in both Columns (2) and (3). These figures indicate that narrowing term spreads or worsening economic outlook intensifies the transmission of average return shocks among gas, EUA, and European electricity markets. Additionally, in Column (2), the coefficient estimates of *GOPRX* and *WINTER* are both statistically significant and positive, suggesting that the transmission of extremely negative shocks is more severe when geopolitical risk is heightened and during the winter period. The effects of *GOPRX* and *WINTER*, however, are muted regarding the index at the middle and upper quantiles. Lastly, Table 5 indicates a consistently positive effect of *EPU* on the total connectedness index across quantiles. This result emphasizes the critical role of economic policy uncertainty in intensifying the risk transmission in Eurozone markets and is consistent with evidence from Bernal et al. (2016) and Ma et al. (2022).

Table 5 show the effect of two recent crises, including the COVID-19 pandemic and the Russia-Ukraine war, on the total connectedness index. First, the results show that the coefficient of *COVID* is very consistent, negative, and statistically significant across all model specifications. This implies that interconnectedness among the markets is lower during the pandemic. This reduction is justifiable as the pandemic's effect on each electricity market was heterogeneous across European countries, depending on factors including but not limited to the intensity of the outbreak and the strictness of governments' measures to contain the outbreak. There are recent studies whose results support our argument (e.g, Bahmanyar et al., 2020; Halbrügge et al., 2021; Buechler et al., 2022; Werth et al., 2021; Prol and Sungmin, 2020; among others). Halbrügge et al. (2021) analyse the impacts of COVID-19 on 5 European countries' electricity markets (i.e., France, Germany, Spain, Italy, and Sweden) and find that while restrictions induced a substantial temporal decline in electricity consumption in Germany and Spain, their effects were unnoticeable in other countries. They attribute these variations to different approaches that European governments chose to fight the pandemic.[19] Using a sample of 58 countries, Buechler et al. (2022) examine variations in energy consumption during the pandemic and the drivers behind these. For European countries, they find that many countries in Southern Europe (e.g., Italy, Spain) experienced a large

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[19] For instance, the Swedish government applied an approach relied on citizens' own responsibility rather than deploying strict containing measures such country-wide lockdowns.

decrease in electricity consumption, while minimal change was observed in Sweden, Denmark, and Finland). In addition, they show that fluctuations in energy consumption during the pandemic depend largely on the change in daily mobility, severity of government restrictions, and intensity of the pandemic.

Second, Table 5 indicates that the Russia-Ukraine war exerts an intensifying effect on the TCI at the middle and lower tails while not affecting the TCI at the upper tail. This is consistent with several studies, which find that risk spillover effects among global financial markets was amplified during the war (e.g., Wang et al., 2022; Adekoya et al., 2022). Contrary to the COVID-19 pandemic, which mostly affects the demand for electricity, the war was a supply shock to most European countries and disrupted the supply of Russian gas – an important input for electricity generation in Europe. According to International Energy Agency (IEA), natural gas accounts for an average of 22% of the energy mix of the eleven European countries in our sample.[20] Consequently, the war, through its effects on the gas market, would cause fluctuations in electricity prices in the same direction in most or all selected electricity markets, leading to a higher interconnectedness and integration.

Besides investigating the effects of COVID-19 and the Russia-Ukraine war on the TCI, we also estimate the impacts of these crises on the cross-market spillover indices of the European electricity markets with the gas market ($\mathrm{CSI}_{\text{Gas-Electricity}}$) and carbon market ($\mathrm{CSI}_{\text{EUA-Electricity}}$). The estimations of Eq. (13) with dependent variables being $\mathrm{CSI}_{\text{Gas-Electricity}}$ and $\mathrm{CSI}_{\text{EUA-Electricity}}$ are shown in Table 6 Panels A and B, respectively. As shown in Panel A, the parameter estimate of *COVID* is broadly negative and statistically significant, irrespective of the quantile used to calculate $\mathrm{CSI}_{\text{Gas-Electricity}}$. This indicates that the pandemic contributes to reducing the transmission shocks between the gas and European electricity markets. This finding suggests the drivers of electricity and gas markets are less correlated during the pandemic. While the literature finds that COVID-19 had significant impacts on European electricity markets, little evidence is found on the impact of COVID-19 on gas volatility. Meher et al. (2020) finds that though the COVID-19 outbreak increased the volatility of crude oil, this leverage effect is not observed in the gas market. Ahmed and Sarkodie (2021) reveal that the intensity of the pandemic, measured by new deaths from COVID-19, has not affected the gas market. By contrast, as shown in Panel A, the Russia-Ukraine war imposes a leverage effect on the interconnectedness between the energy commodity and electricity markets. Fang and Shao (2022) find that the Russia-Ukraine tension substantially heightened the volatility risk of energy commodities including gas. In addition, as gas is an important input in the energy mix of Europe, the return shocks can be transmitted to electricity prices, intensifying their interconnectedness.

In Table 6 Panel B, the pandemic variable, *COVID*, is negatively and significantly correlated with the $\mathrm{CSI}_{\text{EUA-Electricity}}$ at the middle and lower quantiles, whereas its impact on the $\mathrm{CSI}_{\text{EUA-Electricity}}$ at the upper quantile is statistically insignificant. This indicates that COVID-19 reduces the interconnectedness between the European carbon and electricity markets. This finding is consistent with the effect of COVID-19 on the TCI and the $\mathrm{CSI}_{\text{Gas-Electricity}}$, documented previously in the study. According to Dong et al. (2022), while the outbreak of disease in March 2020 and the subsequent lockdown measures in European countries caused a sharp decrease in EUA price, its price gradually recovered thereafter.[21] In addition to bearing the impact of the pandemic, Dong et al. (2022) find that price volatility of EUA in 2020 was largely driven by the EU "green recovery plan" with a value of EUR 750 billion, passed by the European Commission in May 2020 with the aim to recover EU economy after COVID-19.[22] They further show that this plan is the main contributor to increase EUA price and reduce EUA volatility in the second half of 2020. This could explain the low return connectedness between EUA and electricity markets during the pandemic. Concerning the Russia-Ukraine war, Panel B shows that its effect on the $\mathrm{CSI}_{\text{EUA-Electricity}}$ is significantly positive at the middle and lower quantiles, but negative at the upper quantile. These results indicate that the war intensifies the transmission of average and extremely negative shocks between carbon and electricity markets while diminishing the spillover of their extremely positive shocks.

Finally, in both panels of Table 6, among control variables, the effects of economic policy uncertainty and geopolitical risk are mostly positive and statistically significant. These findings emphasize their role as key drivers of the connectedness of European electricity markets with the natural gas market and EUA.

4.4.2. *Heterogeneous impacts of COVID-19 and the war on Nordic electricity markets*

In this subsection, we explore the impacts of the two crises on the connectedness of electricity markets with gas and with EUA between Nordic countries and the rest of Europe. This exploration is motivated by studies that point out several distinct characteristics of Nordic electricity markets compared to other European countries (e.g., Amundsen and Bergman, 2006; Hellmer and Wårell, 2009; Hellström et al., 2012). First, compared to other countries, Nordic markets are less dependent on gas in their energy mix as shown in Appendix 2. Gas accounts for only 2.23% of the Swedish energy mix in 2021. Second, the Nordic electricity markets are expected to be less connected with EUA than other European countries as renewable energy has a larger share in the Nordic market. This difference translates to lower CO2 emissions in Nordic countries compared to other markets in our sample (see Appendix A3). Given the heterogeneities above, we expect that the pairwise spillover index between each electricity market and natural gas ($\mathrm{PSI}_{\text{Gas-Electricity}}$) and that between each electricity market and EUA ($\mathrm{PSI}_{\text{EUA-Electricity}}$) of Nordic markets are less affected by the COVID-19 pandemic and the Russia-Ukraine war than European countries.

To empirically investigate this hypothesis, we estimate the following equation:

$$\begin{aligned} PSI_{i,t} = {} & \beta + \gamma X_{t-1} + \alpha_1 COVID + \alpha_2 COVID \times Nordic + \delta_1 WAR \\ & + \delta_2 WAR \times Nordic + \delta_i + \epsilon_{i,t} \end{aligned} \tag{14}$$

where $PSI_{i,t}$ is either the $\mathrm{PSI}_{\text{Gas-Electricity}}$ or $\mathrm{PSI}_{\text{Gas-Electricity}}$ of country i at day t; X_{t-1}, *COVID*, and *WAR* are defined as the same as in Eq. (13); *Nordic* is an indicator variable, which equals to 1 if country i is a Nordic country (e.g., Denmark, Finland, Norway, Sweden) and zero otherwise; δ_i accounts for the country-fixed effects; and $\epsilon_{i,t}$ is the error term. The sum of α_1 and α_2 reflects the effect of COVID-19 on the interconnectedness of Nordic electricity markets with natural gas or EUA. In a similar vein, the sum of δ_1 and δ_2 indicates the effect of the Russia-Ukraine war. We expect the absolute value of the sum of α_1 and α_2 to be lower than the absolute value of α_1, implying that the $\mathrm{PSI}_{\text{Gas-Electricity}}$ of Nordic countries is less affected by the pandemic than other countries. Likewise, we hypothesize that the absolute value of the sum of $\delta_1$and δ_2 is less than the absolute value of δ_1.

We report the OLS regression results of Eq. (14), with standard errors corrected for heteroscedasticity, in Table 7. In Panel A, the dependent variable is the pairwise spillover between each electricity market and the gas market ($\mathrm{PSI}_{\text{Gas-Electricity}}$) at various quantiles. The $\mathrm{PSI}_{\text{Gas-Electricity}}$ of non-Nordic countries bears the negative impact of COVID-19 and the positive effect of the Russia-Ukraine war, as evidenced by the negative α_1 and positive δ_1 observed across quantiles. In addition, the estimates of α_2 and δ_2 are all statistically significant, implying that the effects of the two crises on the electricity-gas nexus vary considerably between the Nordic and other European markets. Specifically, the sum of α_1 and α_2 remains negative in all cases, indicating that COVID-19 exerts a negative impact on the $\mathrm{PSI}_{\text{Gas-Electricity}}$ of Nordic countries. However, the absolute value of the sum (0.30) is lower than that of α_1(0.53). This means that

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[20] Please see Appendices A1 and A2 for details.

[21] Dong et al. (2022) find similar results for the impact of COVID-19 on EUA.

[22] Please see the details of the plan at https://www.undrr.org/media/75031/download

Table 6
Determinants of cross-market spillover index (CSI).

Panel A. CSI$_{\text{Gas-Electricity}}$

	CSI$_{\text{Gas-Electricity}}$ (median)	CSI$_{\text{Gas-Electricity}}$ (lower tail)	CSI$_{\text{Gas-Electricity}}$ (upper tail)
	(1)	(2)	(3)
OVX	0.55***	0.37	−0.45
	(4.69)	(0.97)	(−1.22)
VSTOXX	0.02***	0.06***	0.05
	(4.02)	(2.73)	(1.44)
TERMSPR	−0.98***	1.21*	3.51***
	(−5.20)	(1.85)	(4.92)
EPU	0.31***	0.73**	2.22***
	(3.78)	(2.29)	(5.02)
GOPR	1.03***	2.77***	1.54***
	(5.93)	(6.38)	(3.11)
WINTER	0.11	0.76***	0.52*
	(1.52)	(3.28)	(1.81)
COVID	−0.87***	−3.51***	−3.42***
	(−7.75)	(−8.60)	(−3.75)
WAR	0.57*	4.12***	2.42**
	(1.75)	(4.09)	(2.45)
Intercept	−1.31***	14.37***	11.89***
	(−2.98)	(11.94)	(7.73)
N. Obs.	2672	2672	2672
Adj. R-squared	0.42	0.31	0.21
F-statistics	240.00***	153.10***	87.08***

Panel B. CSI$_{\text{EUA-Electricity}}$.

	CSI$_{\text{EUA-Electricity}}$ (median)	CSI$_{\text{EUA-Electricity}}$ (lower tail)	CSI$_{\text{EUA-Electricity}}$ (upper tail)
	(1)	(2)	(3)
OVX	−0.28***	−1.11***	−0.70**
	(−8.23)	(−3.61)	(−2.31)
VSTOXX	−0.016***	−0.04***	−0.08***
	(−4.49)	(−4.03)	(−6.36)
TERMSPR	0.27***	1.07**	0.13
	(3.87)	(2.18)	(0.26)
EPU	0.20***	−0.15	1.23***
	(4.24)	(−0.80)	(3.66)
GOPR	0.15***	1.74***	−1.74***
	(2.76)	(6.53)	(−4.26)
WINTER	−0.04	0.56***	−0.44*
	(−1.04)	(4.25)	(−1.93)
COVID	−0.38***	−3.05***	−0.33
	(−8.21)	(−11.23)	(−0.62)
WAR	0.39***	4.51***	−1.73*
	(5.02)	(5.73)	(−1.95)
Intercept	0.40***	20.40***	26.77***
	(3.63)	(31.42)	(27.05)
N. Obs.	2672	2672	2672
Adj. R-squared	0.17	0.34	0.17
F-statistics	68.44***	176.68***	68.77***

Note: This table presents the regression results of Eq. (13) to investigate the effects of COVID-19 and the Russia-Ukraine war on the Cross-market spillover index (CSI) between European electricity markets and natural gas market (CSI$_{\text{Gas-Electricity}}$) and that between European electricity markets and EUA (CSI$_{\text{EUA-Electricity}}$). Eq. (13) is estimated using OLS estimation with t-statistics computed using Newey and West's (1987) robust standard errors. ***, **, and * indicate statistical significance at 10%, 5%, and 1% level, respectively.

Table 7

Heterogeneous impacts of COVID-19 and the Ukrainian-Russian war between Nordic countries and the rest of Europe.

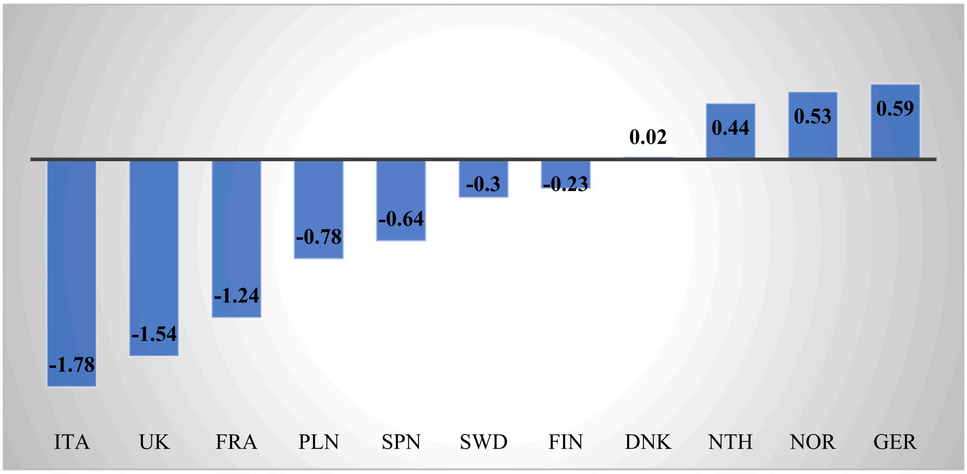
Panel A. PSI$_{\text{Gas-Electricity}}$

	PSI$_{\text{Gas-Electricity}}$ (median)	PSI$_{\text{Gas-Electricity}}$ (lower tail)	PSI$_{\text{Gas-Electricity}}$ (upper tail)
	(1)	(2)	(3)
OVX	0.29***	0.01***	−0.01***
	(15.24)	(3.69)	(−3.15)
VSTOXX	0.01***	0.003***	0.003***
	(9.18)	(13.63)	(9.94)
TERMSPR	−0.44***	0.08***	0.17***
	(−14.08)	(12.18)	(23.81)
EPU	0.09***	0.03***	0.12***
	(3.84)	(5.87)	(21.58)
GOPR	0.43***	0.11***	0.06***
	(12.51)	(16.00)	(8.47)
WINTER	0.07***	0.04***	0.01***
	(5.43)	(14.36)	(4.79)
α_1	−0.53***	−0.14***	−0.24***
	(−16.70)	(−25.29)	(−23.91)
α_2	0.23***	0.01*	0.11***
	(5.42)	(1.81)	(7.50)
δ_1	0.57***	0.28***	0.21***
	(10.39)	(29.15)	(19.94)
δ_2	−0.34***	−0.26***	−0.31***
	(−7.78)	(−41.07)	(−27.53)
N. Obs.	29,392	29,392	29,392
Adj. R-squared	0.09	0.13	0.14
Sum of α_1 and α_2	−0.30	−0.13	−0.13
Sum of $\delta_1$and δ_2	0.23	0.02	−0.10

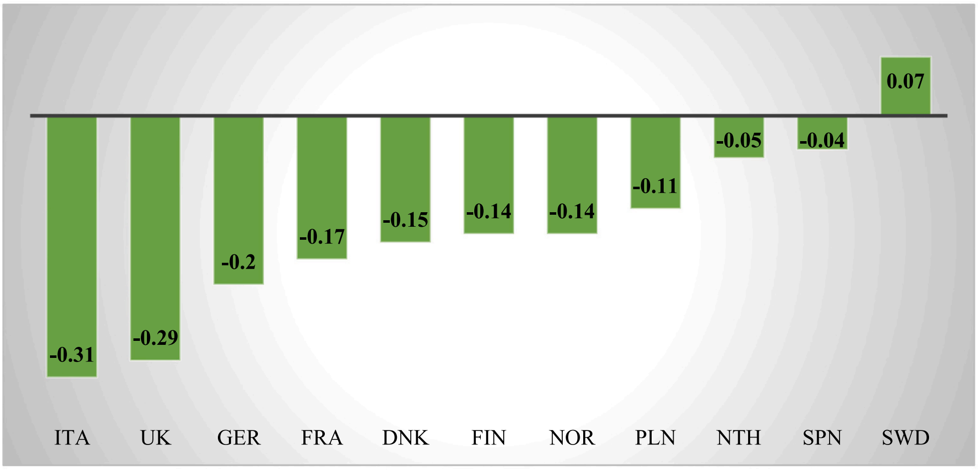
Panel B. PSI$_{\text{EUA-Electricity}}$

	PSI$_{\text{Gas-Electricity}}$ (median)	PSI$_{\text{Gas-Electricity}}$ (lower tail)	PSI$_{\text{Gas-Electricity}}$ (upper tail)
	(1)	(2)	(3)
OVX	−0.36***	−0.05***	−0.02***
	(−22.61)	(−14.13)	(−5.88)
VSTOXX	−0.02***	−0.002***	−0.003***
	(−17.46)	(−8.88)	(−21.70)
TERMSPR	0.46***	0.05***	−0.01
	(17.09)	(8.20)	(−1.32)
EPU	0.27***	−0.01**	0.05***
	(11.24)	(−2.25)	(11.57)
GOPR	0.14***	0.08***	−0.07***
	(4.52)	(12.45)	(−12.39)
WINTER	0.03***	0.03***	−0.02***
	(2.80)	(12.70)	(−8.32)
α_1	−0.57***	−0.16***	−0.03***
	(−21.39)	(−27.90)	(−5.31)
α_2	0.54***	0.05***	0.05***
	(15.06)	(6.67)	(6.77)
δ_1	0.86***	0.27***	−0.02*
	(19.12)	(33.15)	(−1.85)
δ_2	−0.57***	−0.22***	−0.27***
	(−14.85)	(−24.25)	(−17.39)
N. Obs.	29,392	29,392	29,392
Adj. R-squared	0.10	0.09	0.09
Sum of α_1 and α_2	−0.03	−0.11	0.02
Sum of $\delta_1$and δ_2	0.29	0.05	−0.29

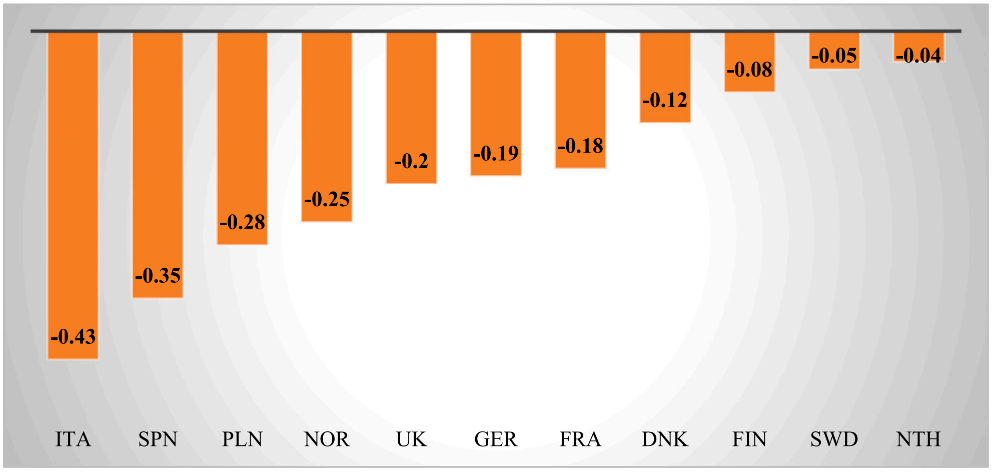
Note: This table presents the regression results of Eq. (14) to investigate the heterogeneous effects of COVID-19 and the Russia-Ukraine war on the Pairwise Spillover Index (PSI) of Nordic and non-Nordic countries. Eq. (13) is estimated using OLS estimation with t-statistics corrected for heteroscedasticity. ***, **, and * indicate statistical significance at 10%, 5%, and 1% level, respectively.



A. At the middle quantile

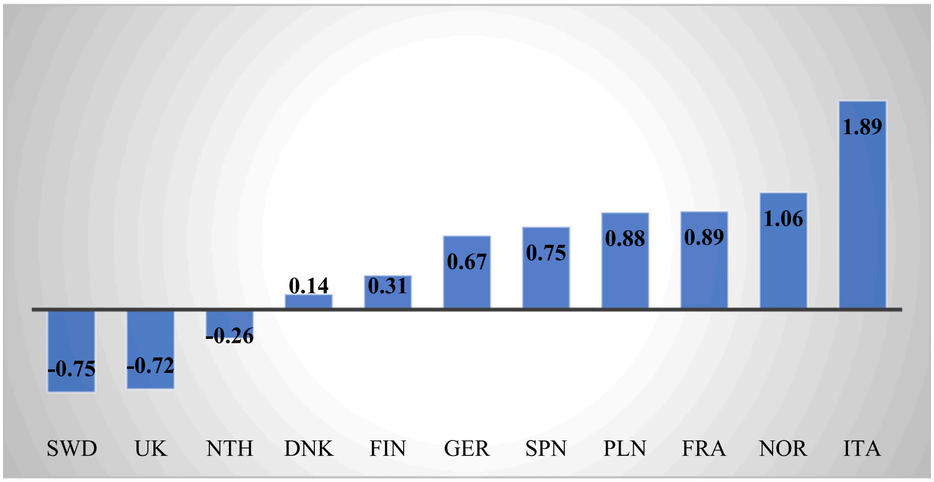


B. At the lower quantile

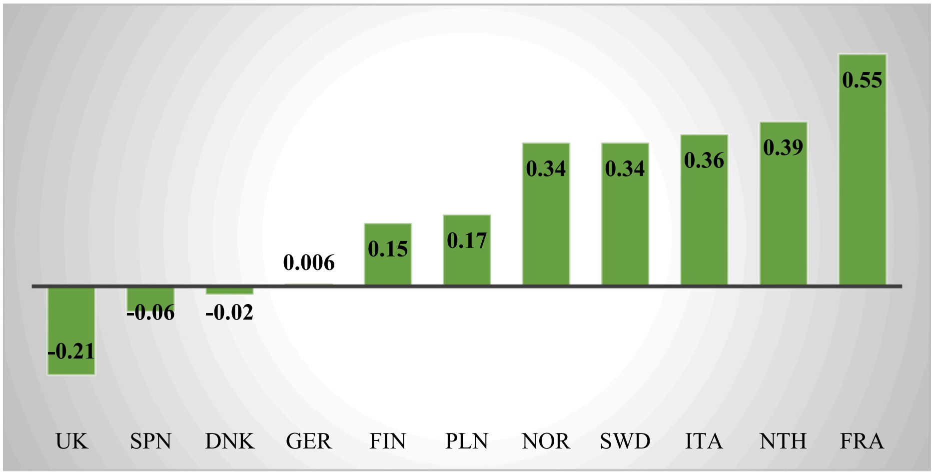


C. At the upper quantile

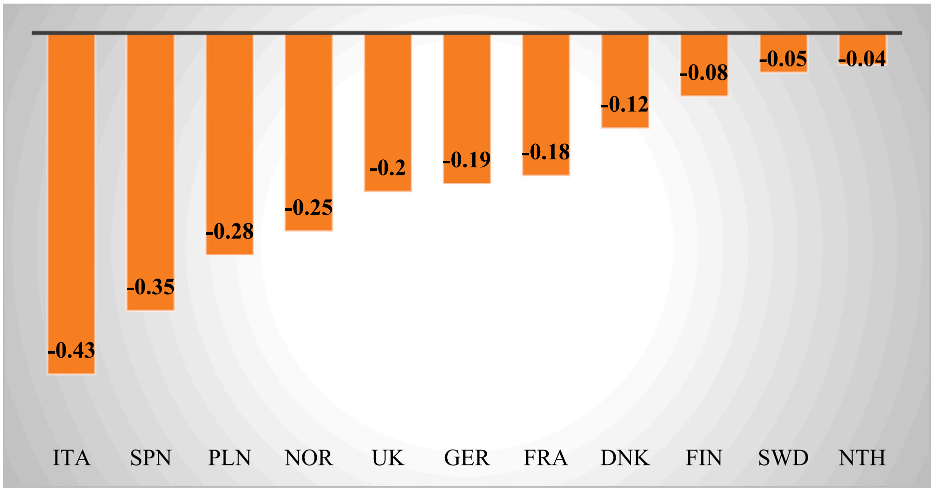
Fig. 11. Effect of COVID on $PSI_{Gas\text{-}Electricity}$ of Selected European Countries at Various Quantiles.
A. At the middle quantile.
B. At the lower quantile.
C. At the upper quantile.



A. At the middle quantile

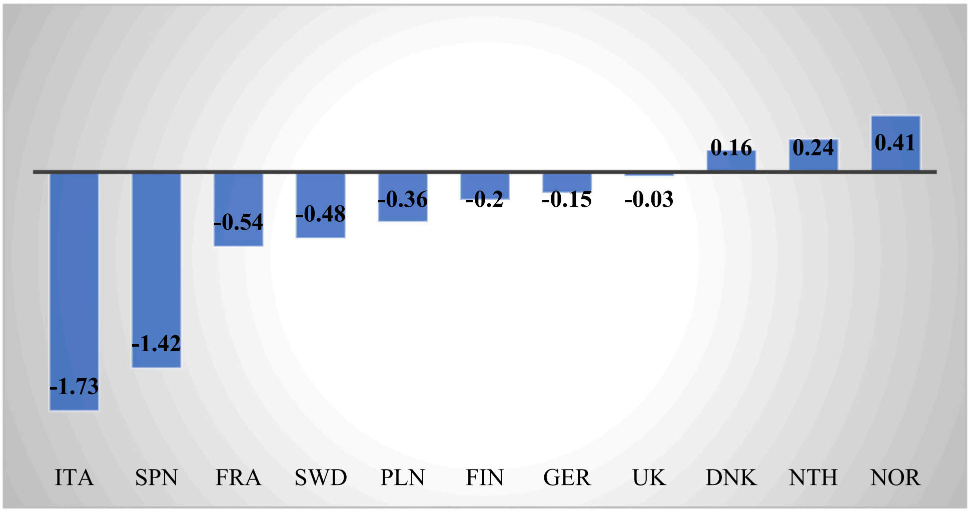


B. At the lower quantile

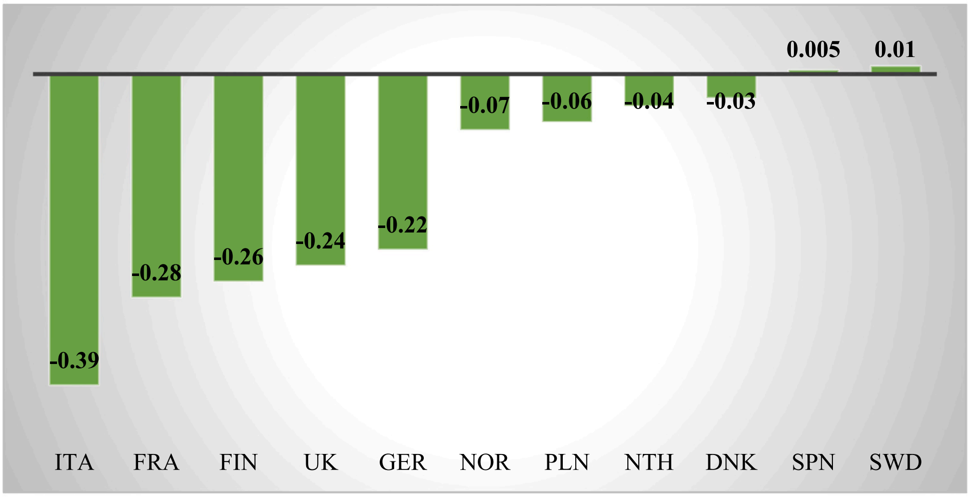


C. At the upper quantile

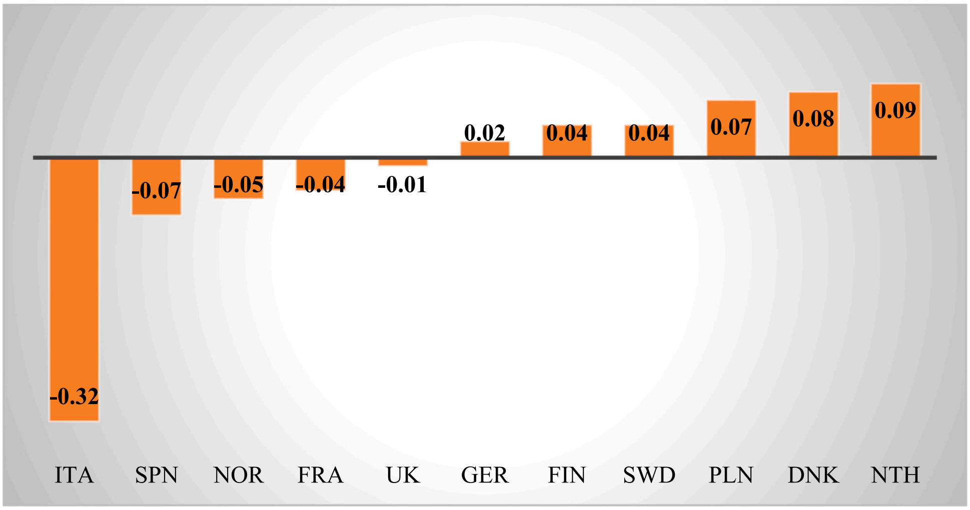
Fig. 12. Effect of WAR on $PSI_{Gas\text{-}Electricity}$ of Selected European Countries at Various Quantiles.
A. At the middle quantile.
B. At the lower quantile.
C. At the upper quantile.



A. At the middle quantile

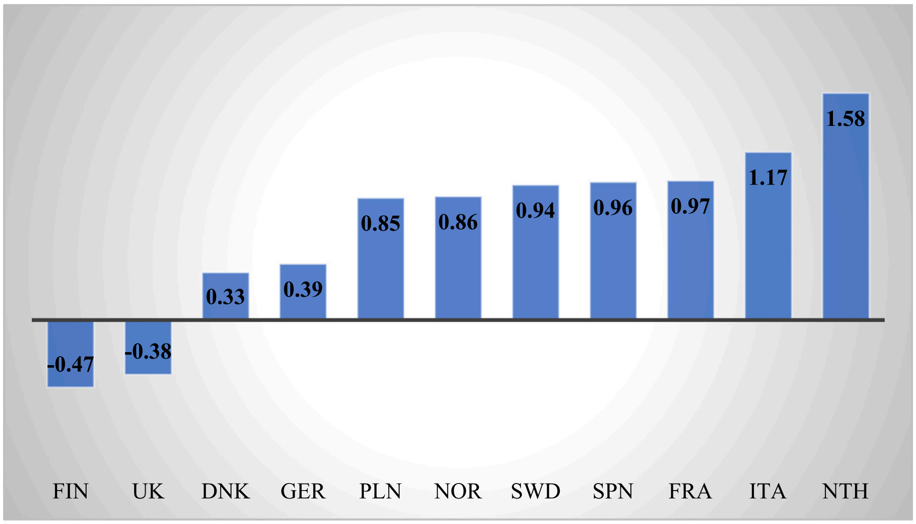


B. At the lower quantile

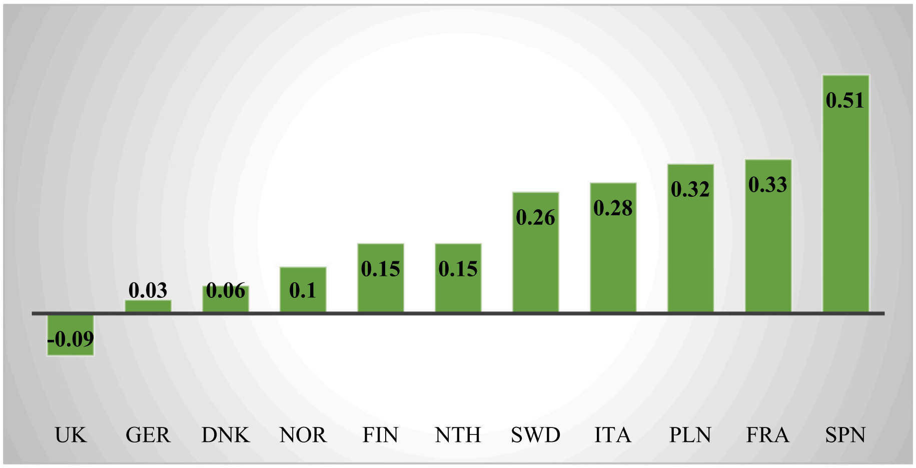


C. At the upper quantile

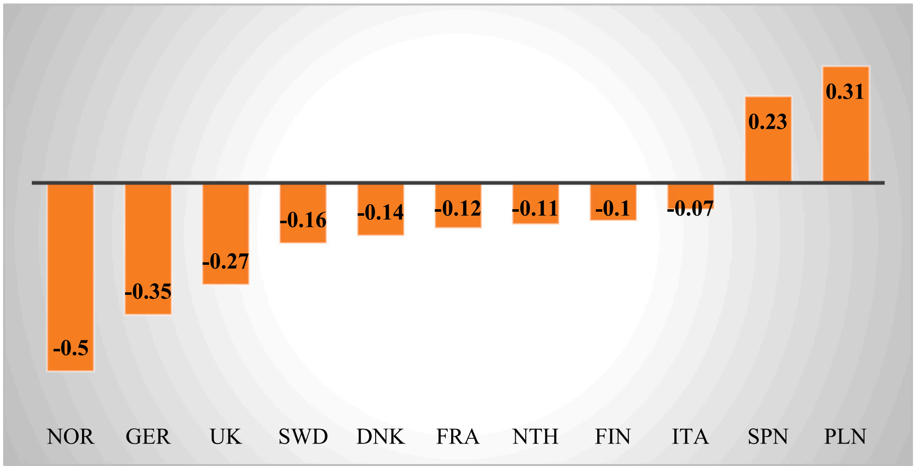
Fig. 13. Effect of COVID-19 on $PSI_{EUA\text{-}Electricity}$ of Selected European Countries at Various Quantiles.
A. At the middle quantile.
B. At the lower quantile.
C. At the upper quantile.



A. At the middle quantile



B. At the lower quantile



C. At the upper quantile

Fig. 14. Effect of War on $PSI_{EUA\text{-}Electricity}$ of Selected European Countries at Various Quantiles.
A. At the middle quantile.
B. At the lower quantile.
C. At the upper quantile.

the $\mathrm{PSI}_{\text{Gas-Electricity}}$ of Nordic markets is less vulnerable to COVID-19 shocks than other European countries, which is consistent with our expectations. Relatedly, the sum of δ_1 and δ_2 has lower absolute value than that of δ_1, lending further support to our hypothesis. It is noteworthy that in Column (3), the sum of $\delta_1$and δ_2 as a negative value, implying that the war has a reducing effect on the transmission of extremely positive shocks between gas and Nordic electricity markets. This reducing effect is contrary to the increasing impact of the war on the gas-electricity market nexus in other European countries as shown by the estimates of δ_1.

In Panel B, we report the results of Eq. (14) using $\mathrm{PSI}_{\text{EUA-Electricity}}$ as the dependent variable. Similar to Panel A, we observe the statistical significance of α_2 and δ_2 across model specifications, which highlights the differences between Nordic and non-Nordic countries in bearing the impact of COVID-19 and the Russia-Ukraine war. More importantly, the absolute value of the sum of α_1 and α_2 ($\delta_1$and δ_2) is lower than the absolute value of α_1 (δ_1) in most cases, reaffirming our conjecture.

4.4.3. *Country-level impacts of COVID-19 and the Russia-Ukraine war*

In this final analysis, we remove the variable *Nordic* and re-estimate Eq. (14) at the country level. In this way, we can add more insights into the heterogeneous impacts of the two crises. To conserve space, we report the estimates of α_1 and δ_1 of each country at various quantiles and corresponding *t*-statistics in Appendices A4 and A5. We display α_1 and $\delta_1$from the lowest to the highest in Figs. 11–14. In Figs. 11 and 12, α_1 and δ_1 measure the effects of the COVID-19 pandemic and the Russia-Ukraine war on the $\mathrm{PSI}_{\text{Gas-Electricity}}$ of each country, respectively. Likewise, Figs. 13 and 14 show their impacts on the $\mathrm{PSI}_{\text{EUA-Electricity}}$.

As observed in Fig. 11, the impact of COVID-19 on $\mathrm{PSI}_{\text{Gas-Electricity}}$ is mostly negative across countries and quantiles, which is consistent with our findings in Table 7. The negative effect of COVID-19 is most severe in Italy in all quantiles, indicating that the return nexus between the Italian electricity and gas markets are profoundly impacted by the pandemic. Other countries exhibit strong impacts of the pandemic across quantiles including the UK and France (at the middle quantile); the UK and Germany (at the lower quantile); and Spain and Poland (at the upper quantile). In Fig. 12, the effect of the war on the $\mathrm{PSI}_{\text{Gas-Electricity}}$ is strongest in Italy and Norway (at the middle quantile); France and Netherlands (at the lower quantile); and Italy and Spain (at the upper quantile). The severe impact of COVID-19 and the war on the electricity-gas nexus in Italy can be explained by the strong reliance of the country on gas. As shown in Appendix A2, gas accounts for 43.7% of the energy mix in Italy in 2021, which is the highest proportion across countries in the sample. In addition, as of 2021, most gas imports in Italy come from Russia (29.2%),[23] indicating the large impact of the war on the country's gas-electricity nexus.

In Fig. 13, the $\mathrm{PSI}_{\text{EUA-Electricity}}$ of Italy continues to suffer the most impacts from the COVID-19 pandemic, regardless of the quantile used to compute $\mathrm{PSI}_{\text{EUA-Electricity}}$. On the contrary, in Fig. 14, the effects of the war on $\mathrm{PSI}_{\text{EUA-Electricity}}$ are highest in the Netherlands (at the middle quantile), Spain (at the lower tail), and Norway (at the upper tail).

4.5. *Robustness tests*

To check the robustness of our findings, we conduct three additional empirical works. First, we re-estimate the time-varying TCI index using different VAR model specifications. Specifically, we change the H-step forecast head (*h*) from 10 to 5 and the rolling window (*n*) from 200 to 250 days. The TCIs at the conditional mean and across quantiles calculated using new model specifications are displayed in Appendix A6. As evidenced in the appendix, the time variations of these indices are very similar to those in Fig. 5, showing that our baseline findings are not affected by changing model specifications.

Besides, we use another proxy for the gas market, which is the reference gas price from the Title Transfer Facility (TTF) in the Netherlands (RFV), to compute the dynamic TCI. The results, displayed in Appendix A7, are very similar to our baseline results in Fig. 5. This closeness adds further credence to our main findings documented in the paper.[24]

Third, the estimation of Eq. (13) and Eq. (14) could be subject to endogeneity issue. While the control variables are deliberately chosen based on theoretical and empirical evidence to lessen the impact of omitted variables, it does not rule out the possibility of endogeneity. To address this issue, we conduct Granger causality test within a Vector Autoregressive (VAR) model to assess the impacts of *COVID* and *WAR* on key connectedness measures. The results of the test, presented in Appendix A8, are highly consistent with the statistically significant effects of these events on the connectedness measures shown in Tables 5 and 6, reaffirming their importance in driving spillover effects between energy markets.

Finally, in an additional analysis, we consider the connection between the selected markets using their return volatility series. The return volatility of the markets is measured by their squared absolute logarithm return. Then, we apply the mean-based connectedness framework of Diebold and Yilmaz (2012) to re-estimate the connectedness measures. The newly constructed connectedness measures are presented in Appendix A9. Overall, the average TCI has declined when volatility series are used, standing at 29.9%. However, the $\mathrm{CSI}_{\text{Gas-Electricity}}$ and $\mathrm{CSI}_{\text{EUA-Electricity}}$ are comparable to those computed using return series. In addition, as shown in Appendix A8, the most important net transmitters of shocks in the network at the conditional mean of the volatility distribution remain Sweden and Germany while Finland continues to be the most crucial net receiver of volatility shock.

5. Conclusion and policy implications

This paper provides an extensive analysis of the connectedness between European electricity, EUA, and natural gas markets. Specifically, we first adopt the Diebold and Yilmaz's (2012) connectedness approach to measure the magnitude and direction of the spillover effects among the markets at the conditional mean. Then, we apply the quantile connectedness framework of Ando et al. (2022) to quantify the transmission of extremely positive and negative shocks within the network. Our analysis is further augmented by a comprehensive investigation of the evolvement and the drivers of the connectedness indexes over time, focusing on the effects of recent global events including COVID-19 and the Russia-Ukraine war. The key insights conveyed by our empirical results can be summarized as below.

First, the European Union's persistent endeavours to create a unified internal electricity market have strengthened the interconnectedness between its markets over time. During the period covered by our research, the total connectedness index of the network has increased by roughly 42% from around 31 in October 2012 to roughly 44. Notably, there was a significant increase in the TCI in 2015 and 2016, which could be result of the market coupling of 15 European countries in 2014.

Second, our results reveal significant differences in the level of integration among individual electricity markets. A closer examination reveals a regional pattern in these differences where the Nordic and western European clusters of connectedness can be observed. From a resource-mix perspective, the Nordic markets are complementary and physically well-connected. As expected, they exhibit a high degree of

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[23] See the gross imports of natural gas in Italy in 2021 by country athttps://www.statista.com/statistics/787720/natural-gas-imports-by-country-of-origin-in-italy/

[24] Connectedness tables using the new model specifications, or the new gas proxy also yield similar results about the role of gas, EUA, and electricity markets as our baseline results in Tables 2, 3, and 4. These results are available upon request.

price return volatility connectedness, as evidenced in our results.

Third, our results show the role of individual markets in the network in transmitting return shocks. Among electricity markets, Sweden, Germany, France, and Denmark emerge as the most important net transmitter of average return shocks in the network whereas Finland, Norway, Italy, and Poland are net receivers. We also find that natural gas and EUA markets are net receivers of shocks from the electricity markets, i.e. both receive more return shocks from the electricity markets than they diffuse to the electricity markets.

Fourth, our analysis of the connectedness network also considers the transmission of extremely positive and negative return shocks. Using quantile connectedness framework of Ando et al. (2022), our results show that the total connectedness indices at lower and upper tails of the conditional distribution are significantly higher than those of mean or middle quantiles. Moreover, natural gas and EUA markets exhibit stronger connectedness with electricity markets at times of extreme negative or positive shocks, while they remain net receivers of return shocks. The results further indicate symmetrical effects of extremely positive and negative return shocks on the network connectedness. Our time-varying analysis also found additional insights. For instance, unlike the total connectedness indices at mean and median, these indices at lower and upper tails vary in a relatively narrow band and exhibit a similar pattern over time.

Fifth, pertaining to the effects of recent global events on the network connectedness, our results reveal heterogeneous impacts of the COVID-19 pandemic and the Russia-Ukraine war on the transmission of return shocks between markets. In particular, the overall effects of COVID-19 on measures of connectedness at the median, upper, and lower tails are negative and significant. By contrast, the effect of the Ukraine-Russia war on connectedness is positive and significant, with the upper tail of total connectedness being a notable exception.

Our results highlighted above provide valuable implications for policymakers and investors in energy sectors in Europe. First, the increasing trend in the TCI documented in the study indicates that the European Union's energy policies, focused on establishing an integrated energy market, has effectively strengthened the ties between its markets. The magnitude of the integration, measured by the TCI, however, can still be improved in the future, especially regarding the interconnection across different regions of the EU. For instance, our results show that Spain has the lowest interconnectedness with other markets, which is consistent with the fact that the country's level of interconnection is below the recommended figure of 10% of the installed capacity. As a result, the country should focus on improving its cross-border power interconnections in the future. This task would require a substantial amount of finance and creates both challenges and opportunities for investors in electricity markets in Europe.

Second, by exhaustively depicting the magnitude and the direction of the return shock transmission between the energy markets, our study helps policymakers and investors understand better the price dynamics of electricity markets and energy commodities. In particular, our study indicate which markets are the key transmitters and receivers of return shocks, which highlights the role of individual markets in transmitting spillover effects. Understanding the transmission dynamics of individual markets is crucial for policymakers to develop targeted interventions and risk management approaches to mitigate the effects of electricity price volatility on market participants. Furthermore, as both natural gas and emission allowance markets are net receivers of shocks, investors and traders in these markets should be aware of the return spillover effects derived from the electricity markets.

Third, as the connectedness measures at the upper and lower tails are substantially higher, policymakers and investors should closely monitor the potential impacts of spillover effects during extreme market conditions. Also, in these cases, the role of an individual market could change from net shock transmitter to net shock absorber and vice versa. Consequently, our analysis of quantile-based connectedness provides a more rounded picture of the shock transmission between the markets. Notably, a greater level of attention should be placed on Denmark and Netherlands electricity markets as they are the most important diffusers of both extremely negative and positive return shocks to the network.

Last but not least, it is crucial for policymakers and investors to recognize that market integration is influenced not only by the European Union's energy policies but also by external factors such as the emergence of common shocks, exemplified by recent global events such as the COVID-19 pandemic and the Russia-Ukraine war. More important, our analysis underscores the distinct effects of these two events on the network connectedness measures, depending on the demand-side or supply-side nature of the event. Considering these distinct effects, it becomes imperative for policymakers and investors to delve deeper into the nature of shocks, understanding their origins and characteristics. This understanding is essential for accurately assessing the potential impacts on market integration and for crafting adaptive strategies that can navigate the complexities introduced by both policy-driven and external shocks. As markets continue to evolve, this nuanced comprehension will enable policymakers to make informed decisions that contribute to the resilience, stability, and integration of European electricity markets.

CRediT authorship contribution statement

Hung Xuan Do: Supervision, Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Rabindra Nepal:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Son Duy Pham:** Writing – review & editing, Writing – original draft, Software, Formal analysis, Data curation, Conceptualization. **Tooraj Jamasb:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization.

Acknowledgment

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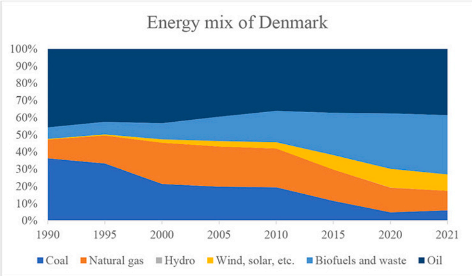
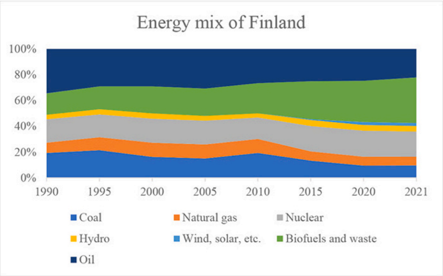
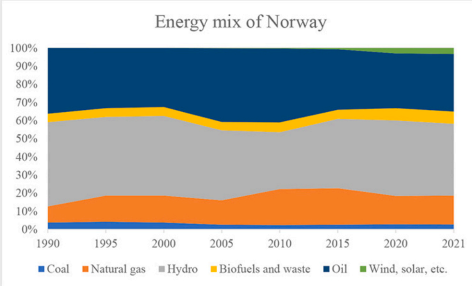
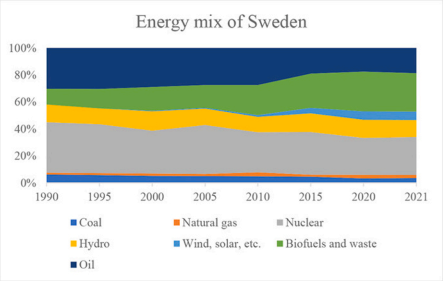
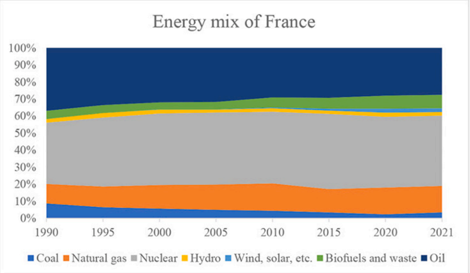
A.1. Energy Mix of Selected European Countries Over Time

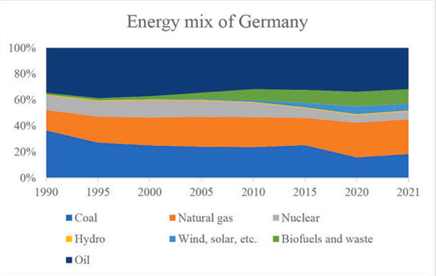

Energy mix of Denmark

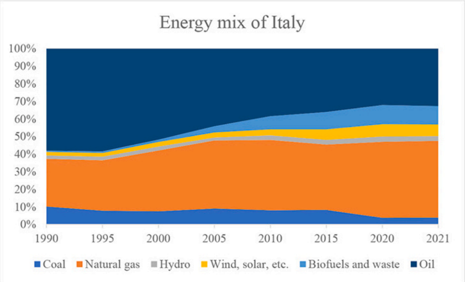

Energy mix of Finland

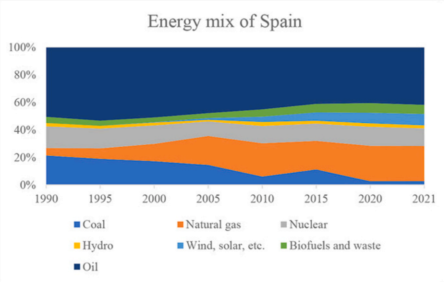

Energy mix of Norway

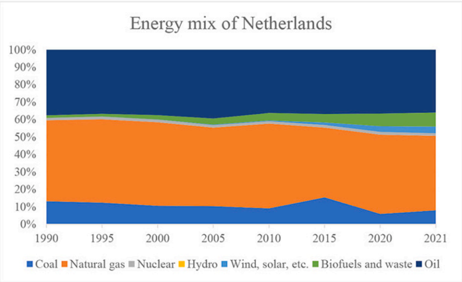

Energy mix of Sweden

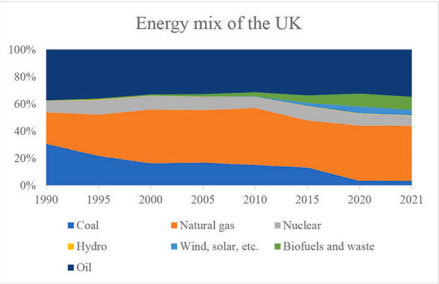

Energy mix of France

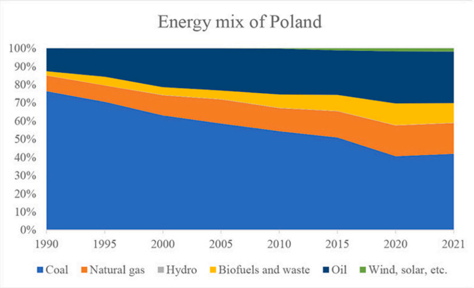

Energy mix of Germany


Energy mix of Italy


Energy mix of Spain

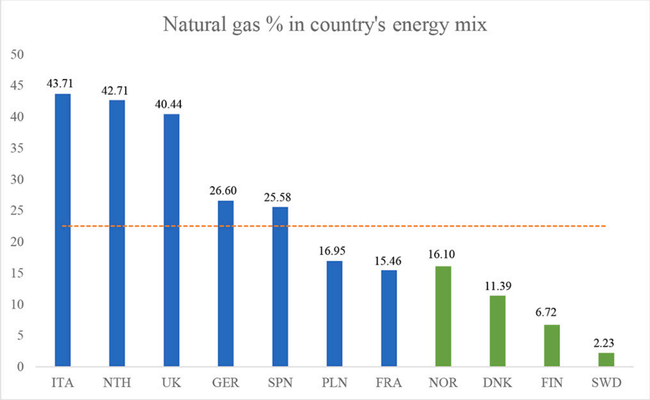

Energy mix of Netherlands


Energy mix of the UK


Energy mix of Poland

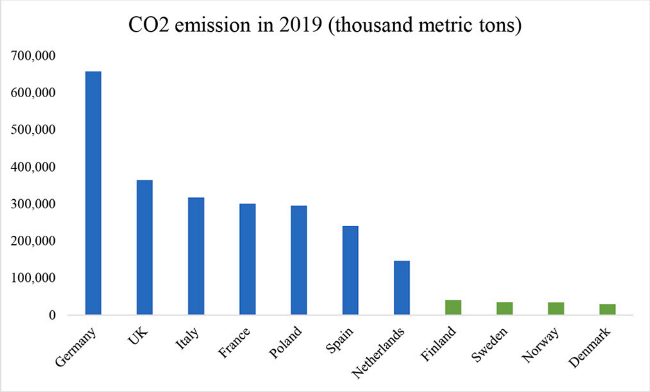
Note: This figure shows the energy mix of the selected countries with data sourced from the International Energy Association's website.

A.2. Role of Natural Gas in Energy Mix of Selected Countries



Note: This figure shows the contribution of natural gas (as percentage) to the energy mix of selected countries in 2021 with data sourced from the International Energy Association's website.

A.3. CO2 Emission by European Countries in 2019



Note: This figure shows the amount of CO2 emission in thousand metric tons of selected countries in 2019 with data sourced from Statista.

A.4. Effects of COVID-19 and the Russian-Ukrainian war on $PCI_{Gas\text{-}Electricity}$ at the country-level

Panel A. Impact of COVID-19

	DNK	FIN	NOR	SWD	FRA	GER	ITA	NTH	SPN	UK	PLN
α_1(middle)	0.02	–0.23***	0.53***	–0.30**	–1.24***	0.59***	–1.78***	0.44***	–0.64***	–1.54***	–0.78***
	(0.24)	(−3.25)	(7.71)	(−2.65)	(−17.96)	(7.11)	(−15.22)	(5.68)	(−9.80)	(−17.92)	(−10.05)
α_1(lower)	−0.15***	−0.14***	−0.14***	0.07***	−0.17***	−0.20***	−0.31***	−0.05***	−0.04***	−0.29***	−0.11***
	(−15.34)	(−10.44)	(−7.76)	(2.90)	(−11.95)	(−12.70)	(−20.29)	(−4.36)	(−3.00)	(−22.49)	(−10.40)
α_1(upper)	−0.12***	−0.08**	−0.25***	−0.05*	−0.18***	−0.19***	−0.43***	−0.04	−0.35***	−0.20***	−0.28***
	(−4.66)	(−2.58)	(−10.40)	(−1.81)	(−7.80)	(−5.75)	(−12.81)	(−1.25)	(−17.18)	(−13.29)	(−13.77)

Panel B. Impact of war

	DNK	FIN	NOR	SWD	FRA	GER	ITA	NTH	SPN	UK	PLN
δ_1(middle)	0.14	0.31***	1.06***	−0.75***	0.89***	0.67***	1.89***	−0.26**	0.75***	−0.72***	0.88***
	(1.44)	(3.22)	(10.03)	(−4.28)	(6.61)	(5.04)	(10.68)	(−2.54)	(4.58)	(−4.70)	(7.02)

(*continued on next page*)

(*continued*)

Panel B. Impact of war

	DNK	FIN	NOR	SWD	FRA	GER	ITA	NTH	SPN	UK	PLN
δ_1 (lower)	−0.02 (−1.18)	0.15*** (7.08)	0.34*** (6.92)	0.34*** (10.38)	0.55*** (15.00)	0.006 (0.30)	0.36*** (12.40)	0.39*** (13.16)	−0.06* (−1.88)	−0.21* ** (−8.57)	0.17*** (5.71)
δ_1 (upper)	−0.02 (−0.85)	0.08*** (3.28)	0.06 (1.09)	0.16*** (6.52)	0.15*** (5.78)	−0.10*** (−4.28)	0.24*** (9.23)	0.17*** (5.26)	0.05 (1.51)	−0.07*** (−4.10)	0.34*** (11.30)

Note: This table presents the estimates of coefficients, α_1 and δ_1, in Eq. (14) at the country-level regression using $PCI_{Gas\text{-}Electricity}$ as the dependent variable. ***, **, and * indicate statistical significance at 10%, 5%, and 1% level, respectively.

A.5. Effects of COVID-19 and the Russian-Ukrainian war on $PCI_{EUA\text{-}Electricity}$ at the country-level

Panel A. Impact of COVID-19

	DNK	FIN	NOR	SWD	FRA	GER	ITA	NTH	SPN	UK	PLN
α_1 (median)	0.16* (1.87)	– 0.20*** (−3.48)	0.41*** (5.55)	– 0.48*** (−5.16)	– 0.54*** (−8.53)	– 0.15** (−2.42)	– 1.73*** (−24.13)	0.24*** (3.94)	– 1.42*** (−18.53)	– 0.03*** (−0.53)	– 0.36*** (−5.49)
α_1 (lower)	−0.03*** (−2.76)	−0.26*** (−25.77)	−0.07*** (−3.85)	0.01 (0.65)	−0.28*** (−16.85)	−0.22*** (−15.33)	−0.39*** (−34.52)	−0.04*** (−4.55)	0.005 (0.34)	−0.24*** (−16.43)	−0.06*** (−9.13)
α_1 (upper)	0.08*** (6.02)	0.04*** (3.09)	−0.05*** (−4.82)	0.04** (2.08)	−0.04*** (−3.27)	0.02 (1.10)	−0.32*** (−14.88)	0.09*** (7.31)	−0.07*** (−4.55)	−0.01 (− 0.64)	0.07*** (6.33)

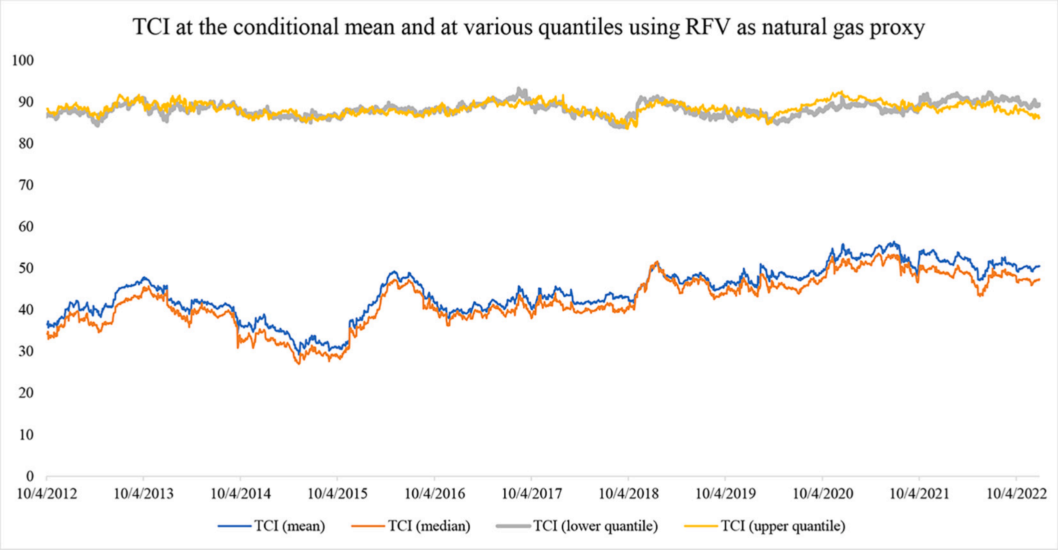
Panel B. Impact of war

	DNK	FIN	NOR	SWD	FRA	GER	ITA	NTH	SPN	UK	PLN
δ_1 (middle)	0.33*** (2.87)	−0.47*** (−4.52)	0.86*** (8.63)	0.94*** (8.92)	0.97*** (11.19)	0.39*** (3.80)	1.17*** (8.98)	1.58*** (9.33)	0.96*** (7.33)	−0.38*** (−2.92)	0.85*** (8.70)
δ_1 (lower)	0.06*** (2.71)	0.15*** (8.57)	0.10** (2.61)	0.26*** (11.56)	0.33*** (12.04)	0.03 (1.44)	0.28*** (12.51)	0.15*** (7.58)	0.51*** (15.97)	−0.09*** (−5.16)	0.32*** (12.61)
δ_1 (upper)	−0.14*** (−4.68)	−0.10*** (−4.22)	−0.50*** (−10.58)	−0.16*** (−9.22)	−0.12*** (−5.35)	−0.35*** (−12.85)	−0.07*** (−4.15)	−0.11*** (−4.50)	0.23*** (7.23)	−0.27*** (−9.46)	0.31*** (13.13)

Note: This table presents the estimates of coefficients, α_1 and δ_1, in Eq. (14) at the country-level regression using $PCI_{EUA\text{-}Electricity}$ as the dependent variable. ***, **, and * indicate statistical significance at 10%, 5%, and 1% level, respectively.

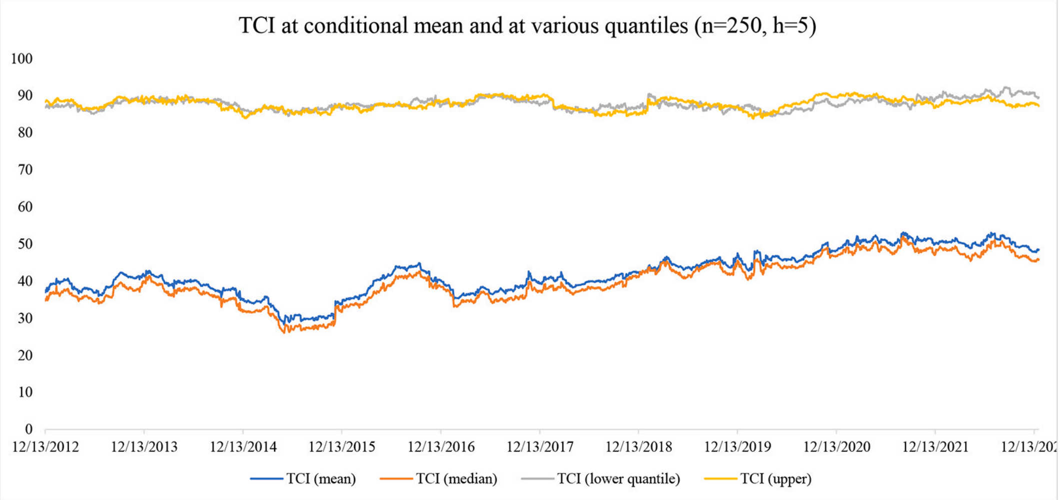
A.6. Robustness check using RFV as natural gas proxy

Note: This figure shows the time-varying Total Connectedness Index (TCI) of the system at the conditional mean and at various quantiles, during the research period, using RFV as natural gas proxy.



A.7. Robustness check using different specifications to compute the TCI

Note: This figure shows the time-varying Total Connectedness Index (TCI) of the system at the conditional mean and at various quantiles, during the research period, using alternative VAR model specifications.



A.8. Granger causality test results

Panel A. Total connectedness index (TCI)

	TCI (median)	TCI (lower tail)	TCI (upper tail)
COVID	6.38**	1.61	2.96*
WAR	3.71*	2.66*	0.97

Panel B. Cross-Spillover Index between Gas and Electricity

	$\text{CSI}_{\text{Gas-Electricity}}$ (median)	$\text{CSI}_{\text{Gas-Electricity}}$ (lower tail)	$\text{CSI}_{\text{Gas-Electricity}}$ (upper tail)
COVID	3.38*	2.55	6.42**
WAR	2.92*	2.63*	3.67*

Panel C. Cross-Spillover Index between EUA and Electricity

	$\text{CSI}_{\text{EUA-Electricity}}$ (median)	$\text{CSI}_{\text{EUA-Electricity}}$ (lower tail)	$\text{CSI}_{\text{EUA-Electricity}}$ (upper tail)
COVID	3.91*	16.94***	0.12
WAR	3.73*	3.55*	0.07

Note: This table shows the results of Granger causality test on a vector autoregressive model (VAR) ($p = 1$) with the Null hypothesis being that the column variable is affected by itself but not by the row variable. The endogenous variables included in the VAR model are the variables presented in Eq. (13). The numbers in each column are the Chi-square statistics of a Granger causality test. ***, **, * indicate significant at the 1%, 5%, and 10% levels, respectively.

A.9. Volatility connectedness table

	GAS	EUA	DNK	FIN	NOR	SWD	FRA	GER	ITA	NTH	SPN	UK	PLN	*From*
GAS	86.6	2.4	0.6	0.6	1.2	1.0	0.5	0.5	2.3	1.1	1.3	0.6	1.2	*13.4*
EUA	1.4	89.8	0.7	0.6	0.6	0.8	0.7	0.5	1.0	0.8	1.1	1.3	0.9	*10.2*
DNK	0.4	0.4	52.8	8.3	6.6	5.5	3.6	14.4	0.9	3.0	0.4	0.6	3.1	*47.2*
FIN	0.4	0.6	8.7	60.0	8.9	10.6	2.2	2.3	0.9	1.3	0.6	0.7	3.0	*40.0*
NOR	1.0	0.5	6.8	9.0	63.2	7.9	1.0	2.2	0.6	3.3	0.7	2.4	1.4	*36.8*
SWD	1.0	1.8	3.1	4.8	4.2	78.1	1.1	0.8	0.9	1.2	0.5	1.2	1.3	*21.9*
FRA	0.5	0.5	3.4	1.9	1.0	2.3	56.1	14.2	5.1	7.7	2.9	1.5	2.8	*43.9*
GER	0.6	0.4	13.9	1.8	2.0	1.1	13.8	51.2	2.7	5.9	1.1	1.5	4.0	*48.8*
ITA	3.1	1.4	0.5	0.8	0.9	1.3	7.0	2.9	73.4	1.5	3.3	0.9	3.1	*26.6*
NTH	0.8	0.4	3.4	1.4	3.6	1.3	9.1	7.7	1.9	64.9	1.4	1.8	2.4	*35.1*
SPN	1.2	0.7	0.4	0.7	0.7	0.6	4.0	1.4	3.7	1.1	82.6	0.6	2.4	*17.4*
UK	1.2	0.5	0.8	0.8	3.0	2.1	2.6	2.3	1.3	2.2	0.5	81.6	1.1	*18.4*
PLN	1.2	0.8	3.8	2.5	1.5	1.1	3.2	4.8	2.1	2.1	4.7	1.4	70.7	*29.4*
To	*12.8*	*10.3*	*46.0*	*33.2*	*34.3*	*35.5*	*48.8*	*54.0*	*23.3*	*31.1*	*18.6*	*14.5*	*26.6*	

(continued on next page)

(*continued*)

	GAS	EUA	DNK	FIN	NOR	SWD	FRA	GER	ITA	NTH	SPN	UK	PLN	*From*
NSI	−0.7	0.1	−1.2	−6.8	−2.5	13.6	4.9	5.2	−3.3	−4.0	1.2	−3.9	−2.7	
TCI	**29.91**													
CSI$_{\text{Gas-Electricity}}$	**1.0**													
CSI$_{\text{EUA-Electricity}}$	**0.8**													

Note: This appendix reports the average connectedness indexes using volatility series across the sample assets, estimated based on mean-based connectedness framework of Diebold and Yilmaz (2012). Volatility is measured by the squared absolute logarithm return. NSI denotes Net Spillover Index. TCI indicates Total Connectedness Index. CSI represents Cross-market Spillover Index.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107633.

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