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The impact of renewables on spillover effects in electricity markets

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HIGHLIGHTS

- We analyze the effect of renewables on volatility spillovers in electricity markets.
- France and Germany are the main net transmitters in European electricity markets.
- Solar power reduces spillover risks to domestic markets.
- Other renewables, especially wind and hydro power, enhance market connectedness.

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SUMMARY

To address climate change, the EU is rapidly increasing renewable energy in its electricity mix. While supporting decarbonization, this transition raises concerns about market stability, particularly regarding price volatility and price jumps. This study investigates how renewable energy integration impacts volatility spillovers in European electricity markets using the Diebold-Yilmaz spillover index and a dynamic rolling window analysis.

The results reveal a sharp decline in volatility spillovers during the COVID-19 pandemic, followed by a peak during the geopolitical tensions surrounding the Ukraine crisis in early 2022. Regionally, France and Germany emerge as net transmitters of risk, whereas Spain, Italy, and Nordic countries primarily act as net receivers. Regression analyses yield robust evidence that increased total load and shares of other renewables, such as biomass, geothermal, and hydro, heighten market connectedness, while wind and solar power have limited effects on overall spillovers. These findings challenge the conventional belief that renewable energy generally increases market volatility. Instead, our results indicate that solar power can mitigate risk transmission across markets, suggesting that increased solar power integration has the potential to reduce volatility spillovers. The study provides critical insights for policymakers seeking to balance renewable energy expansion with electricity market stability.

1. Introduction

Addressing climate change necessitates the decarbonization of the energy sector, which accounts for a significant portion of the EU's greenhouse gas emissions, see [22]. Consequently, there has been a significant increase in the share of renewable energy sources within the total electricity production mix in recent years, a trend expected to persist in the coming decades.

However, integrating a substantial proportion of renewable energy sources raises concerns about market stability, notably the potential for increased price jumps and greater price volatility, according to [5]. The intermittent nature of renewable energy sources, in contrast to the more consistent output from conventional sources like nuclear or fossil fuels, is a source of uncertainty on the intermittent and volatile production of renewable assets that could cause supply–demand imbalances, instability in the electricity grid, and more volatile pricing behavior, see [8]. This inconsistency, coupled with the challenges of electricity storage, may lead to heightened market uncertainty, thereby escalating price volatility and risk. Moreover, through cross-border electricity trading, changes in the share of renewable energy in one country can induce volatility in its market, potentially spilling over into neighboring markets – even those that rely on more stable generation technologies. Despite these observations, the extent to which the rise in renewable energy sources influences volatility spillovers in integrated electricity markets remains uncertain. This study aims to elucidate the dynamics between renewable energy integration and market volatility

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spillovers, providing insights into the broader implications of Europe's green transition.

While the existing literature predominantly explores the direct impact of weather and renewable energy on electricity prices or on electricity price volatility, few studies address the determinants of spillover effects across countries, which is an increasingly relevant topic given the substantial differences in how nations deploy renewable energy. For instance, France relies heavily on nuclear energy, Norway on hydropower with storage, and Denmark primarily on wind energy, see Fig. 1. Despite these differences, the integration of European electricity markets and the expansion of cross-border electricity trading allow countries to balance local surpluses and deficits in electricity supply. However, this very interconnectedness also implies that volatility driven by the intermittency of renewable energy in one country may spill over into others, potentially amplifying fluctuations across the broader market.

A number of studies have explored related aspects in the literature; however, the majority focus on country-specific dynamics, analyzing the impact of renewable energy or weather conditions on domestic electricity prices or volatility. In particular, [41,42,49] highlight the impact of weather on electricity prices, whereas [5,8,20,37,38,40] detect that renewable energy significantly reduces energy prices. Moreover, [5,6,12,23,24,31,33,45–47] focus on the relationship between renewable energy and price volatility. Regarding the connectedness of electricity markets, [36,48,51] analyze the volatility spillover effects in European markets, whereby only [36] investigate potential determinants of spillover effects, focusing on the impact of economic policy uncertainty on total market connectedness.

However, none of these studies directly addresses how renewable energy sources contribute to the spillover effects across electricity markets. This gap underscores the novelty of the present research, which aims to specifically analyze the impact of increasing renewable energy shares on volatility spillovers across European electricity markets – an aspect that has yet to be thoroughly explored. Hereby, we explicitly differentiate between various types of renewable energy, including solar, wind, and other sources such as hydropower, biomass, and geothermal energy, to capture their potentially distinct effects on spillover dynamics. In particular, this study contributes to the literature by examining volatility spillovers in European electricity prices across nine markets using the Diebold-Yilmaz spillover index, as outlined by [16], following a methodology similar to that applied by [36].

The overall total volatility spillover index is found to be 60.50 %, indicating that more than half of the future volatility in European electricity systems can be attributed to volatility shocks spreading across different markets. The dynamic analysis using a rolling window technique uncovers a decrease in the total spillover during the onset of the COVID-19 pandemic, whereas the total spillover peaked in early 2022, coinciding with the onset of military actions in Ukraine, underscoring the impact of geopolitical events on market volatility. In terms of regional contributions, France and Germany are identified as major contributors to spillover, consistently acting as net transmitters of volatility throughout the period considered, whereas Italy, Spain and the Nordic countries primarily receive risks. Hereby, Denmark became a net transmitter around 2020, indicating an increasing role in spreading risks. In contrast, Estonia, Finland, and Sweden, previously net transmitters, have recently turned into net receivers. This shift highlights the impact of major economic events on electricity demand and market interconnections over time.

To the best of our knowledge, this is the first study to examine the impact of renewable energy sources on spillover effects in electricity markets. Using regression techniques similar to [36], we investigate the factors influencing volatility spillovers across European electricity markets. While considering the potential effects of energy prices and total electricity load, the study primarily focuses on the role of renewable energy proportions in shaping these dynamics. The findings reveal that total spillover tends to increase during periods of higher total load or when the share of other renewable technologies – including biomass, geothermal, and hydro – rises, whereas energy prices have a limited impact on market connectedness.

The panel regression results further clarify the impact of renewables on spillover effects – both transmitted ("to others"), received ("from others"), and net spillovers – while controlling for country-specific effects. Consistent with the findings for the total spillover index, higher system load increases the risk transmitted to other markets, with rising oil prices amplifying these effects. Similarly, volatility spillovers from other countries intensify with higher gas prices, economic growth, and a larger share of other renewable technologies. In contrast, higher emission allowance prices and an increasing share of solar power demonstrate stabilizing effects by reducing risks received from other markets. These findings challenge the common perception that greater renewable energy integration inevitably heightens market volatility. This study contributes to the literature by analyzing the impact of renewable energy sources on volatility spillover effects across European countries,

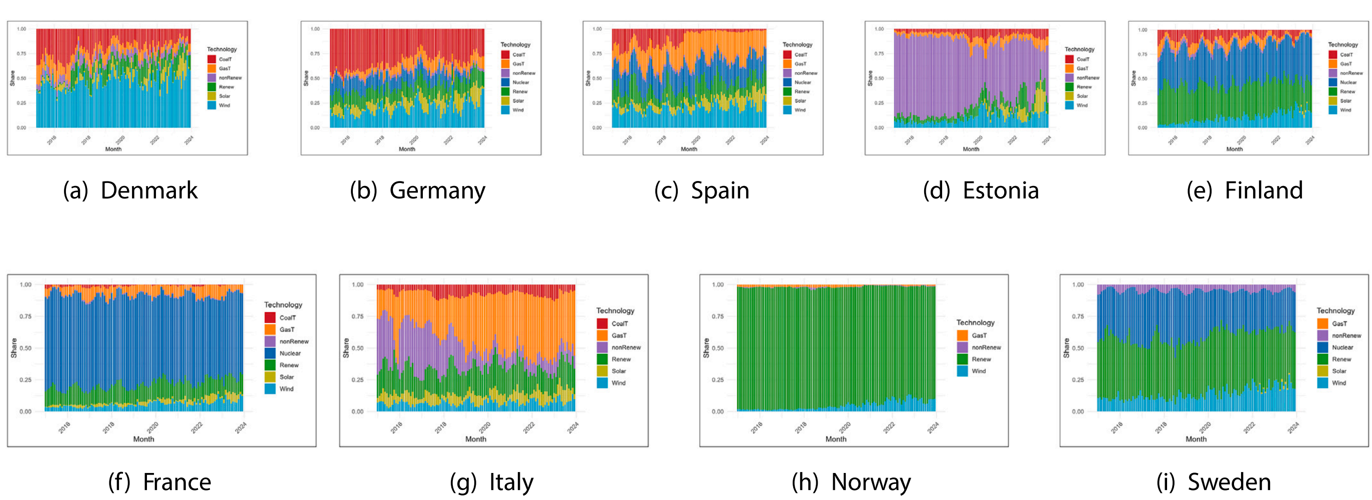


Fig. 1. Overview of technology mix in Switzerland (CH), Germany (DE), Denmark (DK), Spain (ES), Estonia (EE), France (FR), Greece (Gr), Hungary (HU), Italy (IT), Norway (NO), Poland (PL) and Sweden (SE).

shifting the focus from country-specific volatility to cross-border dynamics. Notably, it highlights the risk-mitigating potential of solar power in reducing these spillover effects.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature on determinants of electricity market dynamics, while Section 3 briefly introduces the methodological concepts used. Sections 4 and 5 present the empirical analysis and findings, respectively and finally, Section 6 concludes.

2. Literature review

An important aspect in understanding market dynamics amidst the EU's green transition is the impact of renewable energy on electricity markets. Existing literature predominantly explores the direct impact of weather and renewable energy on electricity prices, however, the majority focus on country-specific aspects, whereas only few studies address the determinants of spillover effects across countries.

Beginning with the literature on the direct impact of renewable energy on electricity prices, analyses such as those by [41,42,49] underscore the influence of weather on electricity market dynamics in the Netherlands, Nord Pool market and Germany, respectively, highlighting renewable energy's role in price setting within country-specific markets, as weather conditions affect not only the demand but also the supply of electricity.

Cevik and Ninomiya [8] extend this to demonstrate how renewable energy influences prices in Europe, using a panel of 24 European countries over the period 2014 to 2021. Hereby, they underline that renewable energy is associated with a significant reduction in wholesale electricity prices across Europe. In addition, [5] focus on the impact of renewable energy on price jumps and volatility in Spain from 2001 to 2013. Hereby, they find a statistically significant negative relationship between the share of renewable generation and the day-ahead market marginal prices. Similarly, [38,40] report that wind power and photovoltaics (PV) exert a negative impact on price levels in Germany during the periods 2015 to 2018 and 2010 to 2017, respectively. Additionally, [37] confirm the negative impact of wind power in the Swedish bidding zone, supporting the Merit-Order Effect for the period 2016 to 2019.

In contrast, [7] detect that the strong expansion of photovoltaics in Germany was not the primary driver of the decline in German wholesale electricity prices during the period from 2011 to 2015. In this line, [27] observe only a mild price dampening effect of renewable energy sources on the formation of day-ahead electricity prices in the German market from 2010 to 2014, while [43] detect modest spill-over effects of the German Energiewende on the Dutch electricity market. Furthermore, using a parsimonious fundamental model, [32] demonstrate in their case study for Germany that emission prices have a larger impact on power prices than renewable energy penetration. However, [20] employ a quantile regression model and demonstrate that forecasted wind production significantly influences both high and low electricity prices in Germany during the period from 2015 to 2018. Hosius et al. [30] analyze the distinct effects of onshore and offshore wind power on wholesale electricity prices in Germany, Western Denmark, and Great Britain from 2015 to 2018. They conclude that offshore wind energy generally has a stronger tendency to reduce both price levels and price volatility compared to onshore wind feed-in.

While the aforementioned studies primarily examine the country-specific effects of renewable energy on electricity prices, a more limited strand of the literature investigates its impact on price volatility, also predominantly within national contexts. Hereby, [5] identify a positive relationship between renewable energy and price volatility in Spain. Similarly, [6,24] confirm the volatility-enhancing effect of wind power in the UK market, while [33,45] report similar associations for the Iberian region and Germany, respectively. Conversely, [46] present a more nuanced view, finding that while wind power increases price volatility in Germany, it reduces volatility in Denmark. Their analysis also highlights that solar power tends to stabilize prices. In contrast, [39] provide evidence that nuclear power acts as a hedging asset against electricity price volatility.

Expanding to a broader perspective, [31] conduct a panel analysis of 19 countries and identify an overall positive impact of wind and solar power on electricity price volatility. This finding is supported by [12,47] for Italy, as well as [23] for the Iberian region. However, these studies primarily concentrate on the effects within individual electricity markets, rather than on cross-border volatility spillovers.

While numerous studies examine spillover effects across electricity markets, they often focus solely on quantifying the spillovers themselves, with little attention given to the underlying drivers. As a result, the determinants of changes in volatility spillovers remain largely unexplored. Research such as [2,28,44] focuses on volatility spillovers within Australian markets, while [29] explores connectedness in Asian utility sectors. Similarly, [18,25] analyze spillovers in Great Britain and between German and French markets, respectively, and [35,50] examine the Nordic electricity wholesale markets. In addition, [11] investigate spillovers from the natural gas market to European electricity markets, and [52] analyze how climate risks propagate into European electricity markets.

Building on these regional and sector-specific analyses, several studies directly investigate the connectedness and spillover effects within the broader European electricity markets. Notably, [19,36,48,51] focus on examining the dynamics of interconnected electricity markets across Europe. Building on a quantile connectedness framework, [19] explore return interlinkages across eleven major European electricity markets, along with natural gas and carbon markets. Their analysis highlights that systemic events affect interconnectedness differently: the COVID-19 pandemic led to a decline in return linkages, whereas the Russia-Ukraine conflict amplified shock transmission across markets. Moreover, [48] focus on 26 European electricity markets. Using a time-varying parameter vector autoregressive model (TVP-VAR), they detect an increase in volatility spillovers over the period from 2007 to 2022, highlighting the strong interconnectedness of European electricity markets. Moreover, the markets of Germany, France, and the Netherlands are the main net transmitters, while the Spanish and Portuguese markets are the main net receivers. In contrast, analyzing ten European electricity markets over the period from 2011 to 2017 via the time-varying Diebold-Yilmaz connectedness measure, [51] conclude the Spanish and German electricity markets are the main transmitters, whereas the French and Italian markets are the main receivers. The study most closely related to ours is that of [36], which confirms the results of [48] in their analysis of spillover effects among 12 European electricity markets over the period from 2009 to 2020. Specifically, Germany and France are identified as the main net transmitters of volatility, while Denmark is found to be the largest net receiver of risk.

While the aforementioned studies primarily focus on describing spillover patterns, [36] take a step further by examining the impact of economic policy uncertainty on volatility spillovers in European markets, finding that policy uncertainty significantly amplifies volatility spillovers. However, their analysis is limited to regressing the total spillover index on the uncertainty index and does not consider the influence of renewable energy shares, nor does it explore country-specific spillovers.

Overall, the existing literature confirms that volatility spillovers occur across multiple electricity markets and that renewable energy plays a significant role in shaping electricity prices and their volatility. However, while the price effects of renewables have been extensively studied, the specific question of how renewable energy sources contribute to spillovers across electricity markets remains unexplored. This important gap in the literature underscores the novelty and relevance of the present study, which aims to systematically analyze how increasing shares of renewable energy influence volatility spillovers across interconnected electricity markets.

3. Methodology

In this study, we investigate how renewable energy integration affects volatility spillovers in European electricity markets. Therefore, we first apply the Diebold-Yilmaz spillover index [16] to measure volatility spillovers across these markets. Subsequently, we employ regression models to examine the impact of renewable energy on the spillover index.

3.1. Volatility spillovers in European electricity markets

The Diebold-Yilmaz (DY) spillover index is employed to analyze volatility spillovers within European electricity markets. Initially introduced in [15] and subsequently refined in [16,17], this index employs variance decomposition techniques from vector autoregression models to quantify the interconnectedness of markets. In particular, the Diebold-Yilmaz index quantitatively assesses the proportion of forecast error variance in a given variable i that can be attributed to shocks in another variable j. This approach not only measures total spillovers across the entire system but also directional spillovers from one variable to another, providing a comprehensive tool for understanding dynamic interrelationships and the transmission of volatility.

As the focus of this study is on volatility spillovers within European electricity markets, we model the vector of volatility series for N European electricity markets, $\mathbf{V}_t = (V_{1,t}, V_{2,t}, \dots, V_{N,t})'$, using an N-variable covariance stationary vector autoregression (VAR) of order P (VAR(P)), which can be formulated as follows:

$$\mathbf{V}_t = \sum_{p=1}^{P} \mathbf{\Phi}_p \mathbf{V}_{t-p} + \boldsymbol{\varepsilon}_t, \tag{1}$$

where $\mathbf{\Phi}_p$ are the coefficient matrices for $\mathbf{V}_{t-p}$ of lag $p = 1, 2, \dots, P$ and $\boldsymbol{\varepsilon}_t$ denotes the vector of innovations. These innovations are assumed to be independently and identically distributed (iid) with a mean of zero and a covariance matrix $\mathbf{\Sigma}$, thus $\boldsymbol{\varepsilon}_t \sim iid(\mathbf{0}, \mathbf{\Sigma})$. Hereby, we follow [36] and estimate the relatively large numbers of parameters by the LASSO approach, see [14]. According to the Wold representation theorem, the moving average representation of the VAR model can be expressed as:

$$\mathbf{V}_t = \sum_{p=0}^{\infty} \mathbf{A}_p \boldsymbol{\varepsilon}_{t-p}, \tag{2}$$

where the $N \times N$ coefficient matrices $\mathbf{A}_p$ are determined recursively by:

$$\mathbf{A}_p = \mathbf{\Phi}_1 \mathbf{A}_{p-1} + \mathbf{\Phi}_2 \mathbf{A}_{p-2} + \cdots + \mathbf{\Phi}_P \mathbf{A}_{p-P} \tag{3}$$

with $\mathbf{A}_0$ being an $N \times N$ identity matrix and $\mathbf{A}_p = \mathbf{0}$ for $p < 0$.

The Diebold-Yilmaz index utilizes these coefficient matrices in its forecast error variance decomposition, which quantifies the proportion of the H-step-ahead error variance in forecasting the variable $\mathbf{V}_i$ attributable to shocks to variable $\mathbf{V}_j$, where $j \neq i$ and $i, j = 1, 2, \dots, N$. To circumvent problems of variable ordering, we follow [16] and use the generalized forecast error variance decompositions of [34]. For a specified forecast horizon H, the contribution of shocks from variable j to the generalized forecast error variance of variable i, denoted as $\theta_{ij}^g(H)$, is calculated using the formula:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (\mathbf{e}_i' \mathbf{A}_h \mathbf{\Sigma} \mathbf{e}_j)^2}{\sum_{h=0}^{H-1} (\mathbf{e}_i' \mathbf{A}_h \mathbf{\Sigma} \mathbf{A}_h' \mathbf{e}_i)}, \tag{4}$$

where $\mathbf{\Sigma}$ represents the covariance matrix of the error vector ε, σ_{jj} denotes the standard deviation of the error term for the jth equation, and $\mathbf{e}_i$ is a selection vector that is one at the ith position and zero elsewhere. The sum of contributions to the generalized forecast error variance does not necessarily equal one within the generalized VAR framework due to the assumption that shocks are not orthogonal. To normalize these contributions and compute the Diebold-Yilmaz spillover index as defined in [16], we adjust the forecast error variances by their respective row sums:

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^{N} \theta_{ij}^g(H)}, \tag{5}$$

ensuring that $\sum_{j=1}^{N} \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H) = N$. So the measure $\tilde{\theta}_{ij}^g(H)$ with $i \neq j$ quantifies the pairwise directional volatility spillovers from electricity market j to market i over a forecast horizon H. This metric effectively captures how shocks in one market influence the forecast error variance in another, highlighting the interconnectedness and impact across different European electricity markets within the specified period.

Following the methodology outlined in [17], we define the total directional volatility spillovers to market i, termed as "from others," using the row sums of off-diagonal entries in the generalized forecast error variance decomposition (GFEVD) matrix. This calculation aggregates the contributions of shocks from all other markets to the forecast error variance of market i. Specifically, it can be computed as:

$$S_{i\leftarrow}(H) = \sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}^g(H) \tag{6}$$

where N represents the total number of markets analyzed, and H is the forecast horizon. This measure effectively captures the cumulative impact of all other markets on market i, highlighting its susceptibility to external influences within the analyzed period. Moreover, the column sums represent the total directional volatility spillovers from market i to the other markets, i.e., "to others," given by:

$$S_{\leftarrow i}(H) = \sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ji}^g(H). \tag{7}$$

In addition, the net directional volatility spillovers identify the electricity markets as net receivers or net transmitters in the volatility spillover system. This metric represents the difference between the total directional volatility spillovers transmitted by and received by individual electricity market i:

$$S_i(H) = S_{\leftarrow i}(H) - S_{i\leftarrow}(H). \tag{8}$$

Finally, the total spillover index quantifies the percentage of forecast error variance in each variable that can be attributed to shocks to all other variables in the system. Specifically, the total spillover index is defined as:

$$S_g(H) = \frac{\sum_{i\neq j} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j} \tilde{\theta}_{ij}^g(H)} \times 100, \tag{9}$$

where $\theta_{ij}(H)$ represents the portion of the H-step ahead forecast error variance of variable i due to shocks in variable j, and H denotes the forecast horizon. Overall, the total spillover index serves as an indicator of the extent of integration among European electricity markets at a system-wide level, see [36].

3.2. The impact of renewable energy share on volatility spillovers

To examine the impact of renewable energy share on volatility spillovers across European electricity markets, this study employs both linear and panel regression analyses. The linear regression model assesses the average effects on the overall market connectedness, while the panel regression allows for controlling both time-invariant and individual-specific heterogeneity, improving efficiency and reducing omitted variable bias.

The key explanatory variable is the share of renewable energy, which is hypothesized to affect not only domestic electricity prices and volatility but also those in neighboring markets through cross-border electricity trade, and therefore the spillovers between the markets. This study also considers several control variables, reflecting the economic growth and energy prices, recognizing their potential influence on electricity market dynamics.

The linear regression model is specified as follows:

$$S_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \cdots + \beta_K x_{K,t} + \varepsilon_t \tag{10}$$

where S_t represents the total volatility spillover index at time $t = 1, 2, \dots, T$, calculated using the Diebold-Yilmaz methodology, see Section 3.1. The K independent variables $x_{1,t}, x_{2,t}, \dots, x_{K,t}$ include the share of renewable energy, macroeconomic factors, and energy prices at time t, see Section 4. The parameters $\beta_1, \beta_2, \dots, \beta_K$ capture the corresponding impact of these variables on the spillover index, while ε_t is the error term, assumed to be independent and identically distributed with zero mean and variance σ^2, thus $\varepsilon_t \sim iid(0, \sigma^2)$.

To control for time-invariant as well as country-specific heterogeneity, we use a panel regression with random effects[1] to examine the impact of renewables on the net spillover indices as well as the spillovers from others and to others. Hereby, the panel regression model is defined as:

$$S_{i,t} = \beta_0 + \beta_1 x_{1,i,t} + \beta_2 x_{2,i,t} + \cdots + \beta_K x_{K,i,t} + u_i + \varepsilon_{i,t}, \tag{11}$$

where $S_{i,t}$ represents either the net spillover index or the spillover index from others or to others for country $i = 1, 2, \dots, N$, the independent variables $x_{1,i,t}, x_{2,i,t}, \dots, x_{K,i,t}$ might be country-specific indicated by the country-specific index, and u_i denotes the random individual specific effect which is uncorrelated with the country-specific regressors.

4. Data

This study first examines volatility spillover effects across European wholesale spot electricity markets. An hourly price dataset covering 9 European day-ahead electricity markets is used to obtain the daily volatility series spanning from January 1, 2015, to December 31, 2023, provided by [21].[2] We focus on the electricity markets of Northern, Western, and Southern Europe,[3] specifically examining Germany, Denmark, Spain, Estonia, Finland, France, Italy, Norway, and Sweden, operated by four power exchanges, EPEX, Nord Pool, OMEL, and GME.[4] These countries are part of a highly interconnected European electricity system, featuring extensive cross-border transmission infrastructure that enables substantial electricity trading between them. Although each country follows a distinct national strategy for its electricity mix, see Fig. 1, the high degree of market integration means that they are not insulated from one another; volatility or imbalances in one market can spill over into others through cross-border flows. This interconnectedness makes the selected countries particularly relevant for analyzing renewable-driven volatility spillovers in an integrated market context. All the electricity spot prices are standardized to be in EUR/MWh and aligned in terms of time zone.

Ma et al. [36] state that electricity cannot be treated as a financial asset due to the non-storability. Therefore, they propose to calculate the variance as the intraday range of prices, which is also used by [48] in the context of electricity prices. Hereby, the volatility measure for each country $i = 1, 2, \dots, N$ and day $t = 1, 2, \dots, T$ is defined as the daily price range, calculated as the difference between the maximum and minimum prices observed on that day:

$$V_{i,t} = \max_{\mathfrak{h}} price_{i,t,\mathfrak{h}} - \min_{\mathfrak{h}} price_{i,t,\mathfrak{h}} \tag{12}$$

where $price_{i,t,\mathfrak{h}}$ with $\mathfrak{h} = 1, 2, \dots, 24$, are hourly electricity spot prices[5] on day t in country $i = 1, 2, \dots, N$.[6] Following [18], we avoid the non-negativity condition in volatility modeling by taking the natural logarithm of volatility. The corresponding descriptive statistics are given in Table 1. Interestingly, we observe a higher volatility in the electricity prices of the Nord Pool market, which are highly interrelated, compared to less connected markets, such as Italy. Overall, the results of the Augmented Dickey–Fuller (ADF) test indicate that all volatility series are stationary.

The objective of this study is to analyze the impact of renewable energy shares on volatility spillovers in European electricity markets. To achieve this, we employ regression methods on the spillover measures.

The primary explanatory variables include the share of electricity generation by technology. Daily generation data for various technologies across countries from January 1, 2015, to December 31, 2023, are sourced from [21]. The technologies are classified into nuclear, solar, wind, other renewables (including biomass, geothermal, hydro, and other renewables), and fossil fuels (comprising gas, oil, coal, waste, and other fossil fuels). The shares are calculated as the proportion of each technology's generation relative to the total electricity generated. For the analysis of the influence of renewables on the total spillover index, we use the aggregated share of electricity generation technologies which is calculated by weighting each country's share of electricity by its total load. To control for electricity demand, the total load per country is also included, using data provided by [21]. Since both the technology shares and total load exhibit non-stationary behavior, we compute logarithmic returns to ensure robust regression results and avoid spurious relationships.

To account for fundamental price drivers and other influencing factors, we incorporate key variables provided by [13]. Specifically, we

[1] The Hausman test prefers in each case the panel regression with random effects over the model with fixed effects, therefore, we only report the results of the random effects model in this study.

[2] We exclude the price data of weekends, following [36], due to relatively low and inactive electricity usage and to allow the inclusion of financial variables in the subsequent regression analysis.

[3] We exclude countries from Eastern Southern Europe from our analysis because they are less integrated into the European Internal Electricity Market due to limited interconnections with Western Europe. Additionally, these countries often operate energy systems that are more regional or national in scope, with varying levels of integration into the broader European grid. Hereby, they rely more heavily on regional exchanges, such as the South-East European Power Exchange (SEEPEX), or on bilateral agreements. Moreover, Iceland, Ireland, and the UK are less integrated into the European Internal Electricity Market. Iceland, in particular, has a unique energy system that relies almost entirely on renewable sources, primarily hydropower and geothermal energy. Overall, the limited integration and divergence in market characteristics make their inclusion in our study infeasible.

[4] It was not feasible to include additional countries from Northern, Western, and Western Southern Europe in our analysis due to the high interconnectivity and shared market structures among certain regions. Specifically, Estonia, Latvia, and Lithuania are part of the Baltic electricity market, while Spain and Portugal operate within the MIBEL (Mercado Ibérico de Electricidade). Similarly, Belgium, Switzerland, Germany, Luxembourg, Austria, and the Netherlands utilize EPEX SPOT as their primary trading platform. These shared market systems result in electricity volatility correlations exceeding 90 %, rendering any statistical analysis involving all these countries impractical. In contrast, the correlation in electricity price volatility among the included countries remains below 75 %, ensuring the feasibility of a statistical analysis.

[5] As we observe negative prices in the electricity markets, we follow [3], and [36] and calculate variances based on the original prices rather than their logarithms.

[6] For a robustness check, we used the realized volatility, similar to [2,9,18,35,50], and obtained similar results. In particular, we observed the same patterns in the Diebold-Yilmaz indices and the regression results mainly remained valid as well.

Table 1
Descriptive statistics for the log volatility per country.

	Min.	Median	Mean	Max.	St.Dev.	Skewness	Kurtosis	ADF
Germany	2.26	3.53	3.77	6.95	0.84	0.96	3.30	−2.69***
Denmark	0.06	3.44	3.57	6.15	0.96	0.23	3.04	−4.21***
Spain	0.77	3.12	3.24	5.62	0.79	0.28	2.80	−3.19***
Estonia	0.91	3.69	3.86	6.75	0.94	0.45	2.77	−3.05***
Finland	0.91	3.57	3.71	6.75	0.93	0.51	3.17	−4.08***
France	1.91	3.53	3.72	6.27	0.76	0.82	3.09	−2.33**
Italy	2.19	3.57	3.72	5.99	0.70	0.76	3.14	−2.16**
Norway	−2.04	2.13	2.27	5.86	1.19	0.14	3.28	−5.89***
Sweden	0.06	3.08	3.26	6.45	1.06	0.44	2.84	−4.63***

This table displays the minimum, median, mean, maximum, standard deviation, skewness and kurtosis of the logarithmized volatility per country. Moreover, the test statistics of the Augmented Dickey–Fuller (ADF) test are reported, whereby *** (**) indicate significance at the 1 % (5 %) level.

control for the prices of essential fuel sources – oil, natural gas, and coal – which influence electricity prices through the Merit Order effect. For European energy prices, we use Brent oil futures, TTF Natural Gas futures and API2 Rotterdam Coal futures as proxies for oil, natural gas and coal prices, respectively. To address the term structure effect when futures contracts roll over, we construct artificial constant maturity futures prices for all fuel sources.

In addition, we include the EU Allowance (EUA) price, which reflects the marginal cost of coal-based electricity production, similar to [26]. Due to the lower liquidity of contracts maturing in other months, we hereby use the 365-day constant maturity price based exclusively on December futures contracts. Furthermore, we account for the broader economic environment, by including the Stoxx Europe 600 index. This index serves as a proxy for overall economic conditions and investor sentiment in Europe while also capturing the performance of companies directly or indirectly involved in energy production, transmission, and consumption.

By incorporating these factors, our dataset establishes a robust foundation for analyzing the impact of renewable technologies and other economic determinants on volatility spillovers in European electricity markets. Given the non-stationarity of all variables, we compute their logarithmic returns. The corresponding descriptive statistics are presented in Table A.5. Overall, most variables display high kurtosis, suggesting the presence of fat tails in their distributions. Notably, the share of solar power in Sweden and Finland exhibits extreme kurtosis, as both countries reported a constant zero share until 2022 and 2023, respectively. Additionally, the high standard deviations of the country-specific technology share variables reflect their inherently volatile behavior over time.

5. Empirical results

This study aims to examine the impact of increasing renewable energy shares on volatility spillovers across European electricity markets. Hereby, we use first-order VARs (p = 1) according to the Bayesian information criterion, which are estimated using LASSO techniques, with a forecast horizon of 10-steps, following [2,18,35,51]. First, the static and dynamic connectedness within the European markets is investigated, followed by an analysis of how renewable energy integration influences volatility spillovers.

5.1. Static analysis

The volatility spillover effects across the nine European wholesale spot electricity markets, approximated by the static Diebold-Yilmaz volatility spillover indices, are displayed in Table 2. Hereby, we report the pairwise directional volatility spillovers from market j to market i, according to Eq. (5), whereby the elements in row i and column j in the table indicate the contributions of volatility shocks in market j to the price volatility of market i. Furthermore, the aggregated measures "from others" and "to others" indicate the contributions of shocks from all other markets to a specific market and the contribution from a specific market to all other markets, respectively. Moreover, we identify the

Table 2
Static volatility spillovers.

	DE	DK	ES	EE	FI	FR	IT	NO	SE	From others
Germany	32.44	10.76	7.26	5.97	3.10	19.34	13.61	3.82	3.70	67.56
Denmark	14.97	32.45	2.55	9.52	6.17	9.24	5.65	4.85	14.61	67.55
Spain	10.99	4.32	52.12	1.96	1.12	12.37	10.68	4.44	2.00	47.88
Estonia	8.95	9.33	2.02	37.56	18.35	6.15	5.01	3.75	8.88	62.44
Finland	5.10	7.45	1.08	22.80	36.81	4.30	3.38	4.58	14.52	63.19
France	19.33	6.45	8.06	3.07	1.93	38.75	16.21	3.98	2.23	61.25
Italy	15.00	5.28	8.16	3.31	2.08	19.69	40.71	3.53	2.24	59.29
Norway	7.13	7.10	4.21	4.03	4.81	8.39	5.67	50.16	8.49	49.84
Sweden	7.60	16.60	1.92	10.02	12.07	6.37	4.13	6.78	34.51	65.49
To others	89.06	67.30	35.24	60.67	49.62	85.84	64.34	35.74	56.68	544.49
Net	21.50	−0.26	−12.64	−1.77	−13.57	24.59	5.05	−14.10	−8.81	**60.50**
	Trans	Rec	Rec	Rec	Rec	Trans	Trans	Rec	Rec	

This table displays the volatility spillovers among the electricity markets of Denmark (DK), Estonia (EE), Finland (FI), France (FR), Germany (DE), Italy (IT), Norway (NO), Spain (ES), and Sweden (SE). The values in the table indicate the pairwise directional spillover from the country listed in the column to the country listed in the row. Values in the row, indicated by "to others," represent the total directional volatility spillovers from a specific market to other markets, whereas the values in the column "from others" indicate total directional volatility spillovers from other markets to a specific market. The net directional volatility spillovers are displayed in the row "net," where the last row indicates whether a market is a net transmitter (Trans) or a net receiver (Rec). The bold value in the row "net" and column "from others" indicates the total volatility spillover.

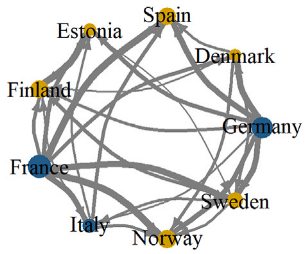


Fig. 2. Volatility spillover network between the European electricity markets. This figure depicts the network graphs of the pairwise directional volatility connectedness across the European electricity markets under consideration computed using the approach of [16] over the full sample period. The blue nodes represent net transmitters, while the yellow nodes indicate net receivers of risk.

net receivers and transmitters in the European electricity markets, using the net directional volatility spillovers.

The total spillover index of 60.50 % indicates that more than half of the future volatility in European electricity systems originates from shocks transmitted across interconnected markets. Hereby, our findings support [36], demonstrating the strong interdependence of European electricity markets and the efficiency of the European electricity network in pricing and dispatch.

Germany and France are the largest contributors to volatility spillovers within the transmission system, as indicated by their "to others" Diebold-Yilmaz index values, which exceed 80 %. Additionally, Denmark, Italy, Estonia, and Finland also contribute substantial volatility spillovers. However, over half of the price volatility in these major markets originates from spillovers received from other markets, underscoring their strong integration within the system. In contrast, Spain and Norway exhibit weaker connections with the other markets, as they both receive and transmit less than half of their total volatility.

The net directional volatility connectedness measures the difference between the total directional volatility spillovers transmitted and received by each electricity market, whereby a positive value indicates a "net-transmitter" of volatility spillovers, while a market with a negative value is defined as a "net-receiver". Our results indicate France, Germany, and Italy as net-transmitter, whereby Germany and France have the highest net directional volatility spillovers, indicating these countries dominate the other markets. In line with the findings of [36], we detect that volatility shocks in Germany and France not only contribute to the price volatility in EEX-regulated electricity markets but also spread to the markets beyond them, such as the Nordic markets, see Fig. 2. Notably, our findings, which encompass the turbulent period from 2020 to 2023 – marked by the COVID-19 pandemic and the Ukraine crisis – confirm these patterns, demonstrating that the observed spillover effects persist even amidst these significant disruptions to the global and regional energy markets.

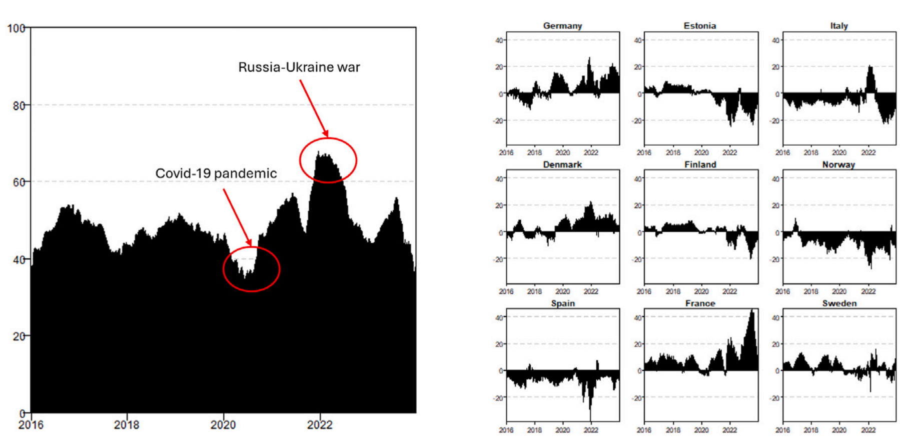
Overall, the Nordic markets predominantly receive volatility spillovers. Directional spillover patterns suggest that Finland and Estonia are highly interconnected, likely because Estonia's only studied connection to the broader system runs through Finland. Similarly, strong interconnections are observed between Finland and Sweden, as well as Sweden and Denmark, which can be attributed to their existing transmission channels.

Interestingly, despite the presence of transmission links between Norway and its neighboring countries – Sweden, Denmark, and Finland – as well as a transmission channel with Germany via the North Sea cable, Norway exhibits minimal integration with the other markets. This disconnection may be attributed to Norway's significant reliance on hydropower and its substantial storage capacity, which reduce its exposure to external volatility. In contrast, the transmission link between Denmark and Germany facilitates considerable directional spillovers between these markets. Similarly, Germany maintains strong connections with France and Italy, likely due to shared transmission networks that span France, Switzerland, Austria, Germany, and Italy. In comparison, Spain transmits little volatility to other markets but absorbs considerable risk, particularly from France and Italy. These findings align with the observations of [48].

5.2. Dynamic analysis

One major limitation of the static total volatility spillover measure is the assumption that the volatility interactions between electricity markets remain constant over time, as stated for example by [36,51]. To address potential changes in volatility connectedness, which can be caused by short-term events or long-term shifts in market fundamentals, we consider dynamic volatility spillovers, using a rolling window technique with a 260-day window, corresponding to one year.

The dynamics of the total volatility spillover index for European electricity markets from January 2016 to December 2023 are illustrated in Fig. 3(a). The total spillover fluctuates between 34 % and 68 %, reflecting temporal variations in the interconnectedness of European electricity markets. A notable decline in the total spillover index occurred at the onset of the COVID-19 pandemic. This reduction suggests that shocks barely propagated across European electricity markets during



(a) Total volatility spillovers (b) Net volatility spillovers

Fig. 3. Dynamic total and net volatility spillovers. These figures show the total volatility spillover index and net spillover indices by country over time, calculated using a 260-day rolling window technique based on the approach of [16].

that period, likely due to widespread economic shutdowns and the resulting decline in industrial electricity demand. In contrast, the total spillover index peaked in early 2022, reaching nearly 70 %, reflecting the heightened volatility triggered by the outbreak of the Russia-Ukraine war and the associated surge in gas prices. These findings are consistent with those of [19], who also report a decrease in market interconnectedness during the pandemic and a sharp increase following the onset of the geopolitical conflict.

Regarding regional contributions, the electricity markets in France, Germany, and Denmark, emerge as the primary contributors to volatility spillovers, consistently acting as net transmitters of risks throughout the analyzed period. Hereby, Germany and France exhibit the highest net directional volatility spillovers, underscoring their status as well-connected hubs within European electricity markets, confirming the results of [10,36]. In contrast, the markets in Norway, Spain, and Italy predominantly act as net receivers of volatility, as illustrated in Fig. 3(b).

The dynamic analysis further reinforces the findings of the static analysis while highlighting temporal shifts in market roles. Notably, Denmark transitions into a net transmitter around 2020, suggesting that the Danish electricity market has increasingly spread risks in recent years. Conversely, Estonia, Finland, and Sweden, which functioned as net transmitters prior to 2020, have become net receivers of volatility more recently. These findings suggest that significant economic events influence electricity demand and reshape the interconnections between European electricity markets over time.

5.3. Impact of renewables

Integrating a significant share of renewable energy sources raises concerns about market stability, particularly the risk of price spikes and increased volatility, as highlighted by [5]. Cross-border electricity trading can amplify these effects, as shifts in renewable energy proportions in one country may trigger volatility that spills over into other markets. This section explores the extent to which the growing share of renewable energy influences volatility spillovers across electricity markets, explicitly distinguishing between solar, wind, and other renewable sources to account for their differing impacts on market dynamics. It is important to emphasize that the focus is not on the absolute level of volatility, but rather on the spillover of volatility across electricity markets and how these spillovers are influenced by the underlying determinants.

In this analysis, regression techniques are employed to examine the factors influencing volatility spillovers, with a particular focus on the share of renewable energy sources. Hereby, electricity generation technologies are classified into nuclear, solar, wind, other renewables (including “Biomass”, “Geothermal”, “Other Renewable”, and “Hydro”), and fossil fuels (such as “Gas”, “Oil”, “Coal”, “Other”, and “Waste”).[7] Additionally, the model accounts for the total load across the considered European countries, alongside key price drivers and fundamental factors that may impact volatility spillovers. These include the prices of essential fuel sources for electricity production – Brent oil, natural gas, and coal – along with the carbon emission price, which supplements the coal price, as highlighted by [26]. In addition, we control for the overall economic activity, investor sentiment, and macroeconomic conditions in Europe by including the Stoxx Europe 660 index, which serves as reference index in Europe.

To begin, we analyze the determinants of market integration across European electricity markets. Therefore, we estimate a linear regression model on the total spillover index,[8] similar to [36], using Ordinary Least Squares (OLS) with Newey-West standard errors to account for potential heteroscedasticity and autocorrelation and report the results in Table 3.

Table 3
Determinants of total spillover in European electricity markets.

Variable	Estimate	Std. Error
(Intercept)	0.0000	(0.0002)
STOXX 600	0.0081	(0.0167)
Oil price	0.0117	(0.0093)
Gas price	0.0043	(0.0057)
Coal price	−0.0022	(0.0072)
EUA	−0.0088	(0.0062)
Total load	0.0156***	(0.0057)
Fossil fuels	−0.0001	(0.0022)
Nuclear	−0.0057	(0.0055)
Renew	0.0231***	(0.0052)
Solar	−0.0001	(0.0010)
Wind	0.0000	(0.0010)

This table reports results from the OLS regressions on the aggregated total spillover index with Newey-West standard errors to correct for heteroscedasticity and autocorrelation. The standard errors are reported in brackets. Statistical significance is indicated by ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

Overall, the results indicate that both total load and the share of other renewables, such as biomass, geothermal, and hydro, significantly influence total spillovers in the market. Specifically, higher total load is associated with increased spillovers, suggesting that rising electricity demand amplifies risk transmission across markets. This finding aligns with the dynamic analysis, which revealed a notable decline in total spillovers during the COVID-19 pandemic and associated economic shutdowns. Furthermore, a larger share of other renewables intensifies spillover effects, highlighting their contribution to market interconnectedness. In contrast, changes in the shares of solar and wind power do not significantly influence the overall connectedness of European electricity markets.

We then examine the impact of renewable energy technologies on transmitted, received, and net spillovers across electricity markets, employing the spillover measures “from others,” “to others,” and “net” to capture these dynamics.[9] To this end, we use a panel regression model with random effects.[10] Heteroscedasticity- and serial correlation-consistent standard errors, as proposed by [4], are applied for within-group estimators. The results are presented in Table 4.

Unlike the linear regression model for the total spillover index, which includes aggregated technology shares, we incorporate country-specific shares of renewable technologies. Additionally, to control for overall electricity demand in Europe, we include the aggregated load as an independent variable rather than country-specific loads. This approach reflects the assumption that higher overall demand can drive increased cross-border electricity transmissions, thereby influencing spillover dynamics between markets.

The results highlight significant differences across the various spillover indices. The “to others” spillover index, which captures the risk transmitted from one country to others, increases notably with higher total load, underscoring the role of overall European electricity demand in enhancing market interconnectedness. Additionally, higher oil prices contribute to increased transmitted risk, likely due to the rise in electricity prices driven by higher energy costs.

[7] For the analysis of the influence of renewables on the total spillover index, we use the aggregated share of electricity generation technologies which is calculated by weighting each country’s share of electricity by its total load.

[8] As the total spillover index is non-stationary according to the Augmented Dickey–Fuller test, we use the log returns to avoid spurious regressions.

[9] To ensure stationary time series, we calculate the log returns of the spillover indices “from others” and “to others”.

[10] The Hausman test favors the random effects model over the fixed effects model, so we report only the results for the random effects specification.

Table 4
Determinants of spillover indices “from others”, “to others” and “net”.

Variable	To others		From others		Net	
	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.
(Intercept)	0.0000	(0.0001)	0.0000	(0.0000)	−0.0001	(0.0024)
STOXX 600	0.0010	(0.0186)	0.0264**	(0.0133)	−1.4627	(1.5567)
Oil price	0.0262***	(0.0088)	0.0134	(0.0097)	0.7517	(0.7514)
Gas price	0.0012	(0.0237)	0.0078*	(0.0044)	−0.5590	(1.3375)
Coal price	0.0016	(0.0184)	0.0080	(0.0098)	−0.4848	(1.5170)
EUA	−0.0081	(0.0118)	−0.0182**	(0.0090)	0.2627	(0.5363)
Total load	0.0223***	(0.0047)	0.0077	(0.0082)	0.7625*	(0.4308)
Fossil fuels	0.0003	(0.0012)	0.0000	(0.0012)	0.0068	(0.0555)
Nuclear	−0.0017	(0.0063)	−0.0014	(0.0030)	0.0266	(0.4902)
Renew	0.0078	(0.0070)	0.0077***	(0.0022)	−0.1117	(0.3527)
Solar	−0.0008	(0.0018)	−0.0011***	(0.0004)	−0.0030	(0.0996)
Wind	0.0015	(0.0019)	0.0009*	(0.0005)	0.0138	(0.0465)

This table reports results from a panel regression on the spillover index “to others”, “from other” and “net” with heteroscedasticity and serial correlation consistent standard errors (Std. E.) by [4]. Statistical significance is indicated by $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

In contrast, the “from others” spillover index is more responsive to changes in economic conditions, input prices, and technology shares. While previous studies, such as [5], detect a significant impact of renewables on volatility, we focus on the effect of renewables on spillover dynamics. Our findings show that a higher share of other renewable sources – such as biomass, geothermal, and hydro – leads to increased volatility spillovers from other countries, suggesting that these technologies absorb more risk. Conversely, a rising share of solar power reduces spillover risks, indicating its stabilizing effect on domestic electricity markets, which aligns with the findings of [46], who observe a stabilizing effect of solar power on volatility. Similarly, higher emission prices dampen spillovers, while rising gas prices amplify risk due to elevated production costs. Interestingly, while the total load significantly influences overall spillovers within the system, the spillover index “from others” remains unaffected by changes in aggregated load. However, increases in the Stoxx Europe 600 index – indicative of economic growth – are associated with higher spillovers, likely driven by increased electricity demand.

Energy prices, electricity demand, and generation technologies influence spillovers both to and from other countries, but the net spillover remains largely unexplained. This may be due to the net spillover balancing out transmitted and received risks, thereby masking individual contributions.

To summarize our results challenge the prevailing view that a greater share of renewable energy sources invariably leads to heightened market volatility, as solar power has the potential to stabilize the domestic electricity market.

5.4. Robustness and sensitivity analyses

We conduct several additional analyses to evaluate the robustness of our results, see Appendix B with Tables B.6–B.13 and Figs. B.4–B.8. First, we conduct a series of robustness checks by applying alternative specifications of the Diebold-Yilmaz spillover index to assess the sensitivity of our results to different methodological assumptions. Specifically, we increase the lag order to two and the forecasting horizon to 20, and additionally estimate both a standard VAR model and the Time-Varying Parameter VAR (TVP-VAR) model proposed by [1], following the approach of [48].

Overall, the main findings remain robust, although some variations emerge across specifications. Increasing the lag order tends to slightly reduce the estimated spillovers across European electricity markets and results in fewer statistically significant effects; in particular, the previously observed significance of STOXX Europe 600 index and solar power vanishes under this specification. In contrast, increasing the forecasting horizon or employing the standard VAR or TVP-VAR models results in higher overall connectedness and more significant spillover effects, particularly in the time-varying setting. However, we observe that the net spillover indices derived from the TVP-VAR model exhibit greater volatility and frequent spikes, see Fig. B.5(c), suggesting that this specification may be less stable and more sensitive to short-term fluctuations than the rolling window approach used in the main analysis.

Second, following the approach of [2,9,18,35,50], we employ realized volatility instead of the daily price range to estimate volatility in European electricity markets. The static total spillover is calculated as 54.86, which is slightly lower than the spillover derived from daily price ranges. Notably, Germany and France are identified as net transmitters of spillovers, while the Nordic countries, Italy, and Spain are net receivers, further supporting our main findings.

The dynamic analysis underlines our main findings as it reveals a clear decline in total spillovers at the onset of the COVID-19 pandemic, reflecting reduced market integration during this period, followed by increased integration in early 2022. The regression analyses underscore the significant influence of total load and renewable energy generation on the total spillover index. However, the key determinants vary across spillover indices, specifically those transmitted to others, received from others, and net spillover changes.

Third, while our primary analysis includes the overall STOXX Europe 600 index as proxy for economic activity, we assess whether a narrower focus on the performance of the industrial sector within the broader European market influences the results by including the STOXX Europe 600 Industrial Goods & Services (SXNP) index. The results remain unchanged, highlighting the robustness of our conclusions.

Fourth, we explore whether a more disaggregated approach to generation technologies yields different results. In the main analysis, we aggregate the shares of biomass, geothermal, hydro, and other renewables into a single variable. However, since countries like Spain, Italy, Norway and Sweden rely on hydro power in their electricity markets, we test whether isolating hydro power as a standalone variable influences the results. Our findings reveal that hydro power has a positive impact on both the total spillover and the spillover originating from other renewables. This suggests that the strong influence of renewables on spillovers is primarily driven by the share of hydro power, which is highly flexible and can be effectively controlled. Furthermore, the disaggregated share of renewables now affects the net spillover, while all other results remain consistent with our main analysis.

Similarly, we refine the treatment of fossil fuels. While the primary analysis combines all fossil fuels into a single category, we disaggregate them into gas power, coal power, and other fossil fuels (including oil, waste, and related sources). Overall, the results remain largely unchanged. This indicates that the share of fossil fuels has a negligible effect on spillover dynamics across European electricity markets.

Finally, we replace the overall load with country-specific load values in our panel regressions to investigate whether country-specific information offers greater explanatory power for spillovers. The results show that country-specific load values significantly influence risks transmitted to other countries, similar to the impact observed for the overall total load on outward spillovers. However, neither net spillovers nor spillovers received from other markets exhibit any sensitivity to changes in country-specific load values, further underlining our main findings.

To conclude, our robustness analyses confirm the reliability of the main findings. By testing alternative specifications, including a narrower focus on the industrial sector, disaggregating generation technologies, and refining the treatment of fossil fuels, we find that the results remain largely consistent. Notably, the significant influence of renewables on spillovers is primarily driven by hydro power, while fossil fuels exhibit minimal impact. Additionally, replacing the overall load with country-specific load values demonstrates that load-driven spillovers are robust, particularly for risks transmitted to other markets. Overall, these tests underscore the robustness and stability of our results, reinforcing the validity of our conclusions.

6. Conclusion

This study critically examines the influence of renewable energy integration on volatility spillovers across European electricity markets, a vital aspect in understanding market dynamics amidst the EU's green transition. Hereby, we apply the Diebold-Yilmaz methodology to investigate the spillovers between nine European electricity markets, namely, Germany, Denmark, Estonia, Spain, Finland, France, Italy, Norway, and Sweden, using hourly price data from 2015 to 2023.

The results reveal that more than half of the future volatility in European electricity systems can be attributed to volatility shocks spreading across different markets. Hereby, the dynamic analysis using a rolling window technique uncovers a decline in total spillovers during the onset of the COVID-19 pandemic and a sharp peak in early 2022, underscoring the influence of geopolitical events on market volatility. These results align with the findings of [19], who similarly observe reduced interconnectedness during the pandemic and heightened spillovers following the Russia-Ukraine conflict. France and Germany are identified as net transmitters of risk, in line with [10,36], whereas the other countries primarily receive risks.

In addition, our analysis of the factors driving volatility spillovers in European electricity markets yields relevant and policy-relevant insights. While [36] only investigate the impact of economic policy uncertainty on total volatility spillovers in European electricity markets, our focus is particularly on the influence of different renewable energy technologies. Hereby, we extend the approach of [36] and also analyze the effect on directional and net spillover indices. Our findings reveal that overall market connectedness tends to increase during periods of higher total system load or when the share of other renewable technologies, such as biomass, geothermal, and hydro, rises. In contrast, total volatility spillovers exhibit a relatively limited effect on overall spillover dynamics.

The risk transmitted to other countries also rises with increasing system load, while higher oil prices further amplify the spillovers to other markets. Similarly, volatility spillovers from other countries intensify with increasing gas prices, economic growth, and a greater share of other renewable technologies. Notably, higher emission allowance prices and an increasing share of solar power exhibit stabilizing effects on domestic markets by reducing the risks received from other countries.

Ultimately, these findings suggest that the strategic expansion of renewable energy not only aligns with climate policy objectives but also might enhance stability in electricity markets by mitigating cross-border volatility spillovers. This study contributes to the broader discourse on energy policy, emphasizing the need for continued investment in renewable technologies to ensure a resilient and sustainable energy future for Europe.

CRediT authorship contribution statement

Amelie Schischke: Writing – original draft, Software, Investigation, Data curation, Writing – review & editing, Validation, Methodology, Formal analysis, Conceptualization. **Andreas Rathgeber:** Supervision, Conceptualization, Writing – review & editing, Resources.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve the readability and language of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Data description

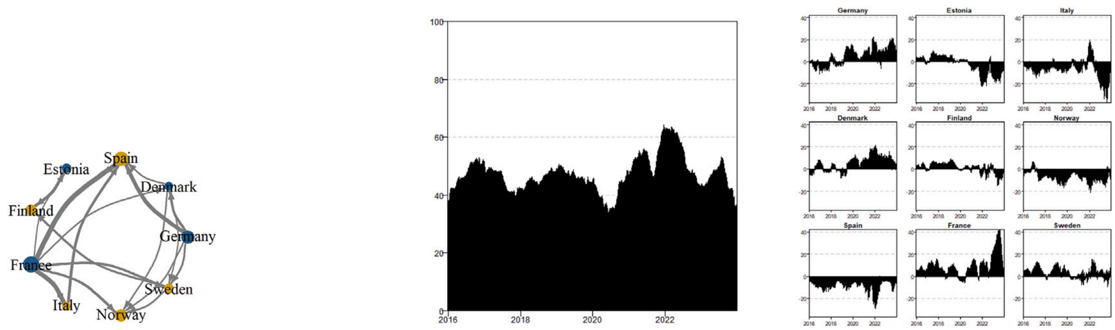
Table A.5
Descriptive statistics for the exogenous variables.

	Min.	Median	Mean	Max.	St.Dev.	Skewness	Kurtosis	ADF
EUA	−0.19	0.00	0.00	0.17	0.03	−0.42	7.31	−49.54***
Oil price	−0.26	0.00	0.00	0.13	0.02	−0.90	14.56	−50.59***
Gas price	−0.35	−0.00	0.00	0.38	0.04	0.28	17.71	−44.86***
Coal price	−0.24	0.00	0.00	0.40	0.03	1.01	28.95	−41.90***
STOXX 600	−0.13	0.00	0.00	0.08	0.01	−0.96	14.94	−46.91***
Total load DE	−0.28	0.00	−0.00	0.29	0.05	−0.10	15.69	−61.31***
Total load DK	−0.23	0.00	0.00	0.21	0.04	0.26	7.24	−57.61***
Total load ES	−0.25	−0.00	−0.00	0.25	0.04	0.07	11.50	−56.32***
Total load EE	−0.37	0.00	−0.00	0.37	0.04	0.01	14.30	−58.61***
Total load FI	−0.25	0.00	−0.00	0.27	0.03	−0.10	9.84	−50.43***
Total load FR	−0.32	0.00	−0.00	0.35	0.05	0.05	9.11	−52.50***
Total load IT	−0.49	−0.00	−0.00	0.43	0.07	−0.12	17.42	−61.06***
Total load NO	−0.15	0.00	0.00	0.21	0.03	0.22	6.73	−48.16***
Total load SE	−0.21	−0.00	−0.00	0.24	0.04	0.39	6.73	−54.84***
Total load	−0.24	0.00	0.00	0.34	0.04	0.50	16.89	−55.93***
DE Fossil fuels	−1.05	0.00	−0.00	0.97	0.23	−0.32	5.30	−56.15***
DE Wind	−2.65	−0.02	0.00	2.65	0.65	0.02	3.54	−56.23***
DE Nuclear	−0.62	0.00	−0.00	0.56	0.09	−0.13	7.89	−57.40***
DE Renew	−0.37	−0.00	0.00	0.39	0.08	0.01	4.14	−65.34***
DE Solar	−2.14	0.01	0.00	1.63	0.42	−0.19	4.50	−65.72***
DK Wind	−2.49	−0.00	0.00	2.47	0.61	0.10	4.58	−61.86***
DK Fossil fuels	−1.58	0.00	−0.00	1.78	0.45	−0.06	3.37	−62.24***
DK Renew	−3.87	0.01	0.00	4.10	0.58	−0.09	10.80	−57.96***
DK Solar	−2.87	0.03	0.00	2.90	0.75	−0.09	3.81	−68.81***
ES Fossil fuels	−0.91	0.01	−0.00	1.15	0.21	−0.00	5.24	−53.61***
ES Nuclear	−0.39	0.00	0.00	0.36	0.07	−0.27	6.51	−51.97***
ES Renew	−0.49	−0.00	0.00	0.52	0.14	0.03	3.68	−63.04***
ES Wind	−2.07	−0.00	0.00	2.08	0.50	−0.03	3.96	−56.57***
ES Solar	−1.94	0.00	0.00	1.89	0.38	−0.10	5.98	−59.04***
EE Fossil fuels	−0.84	0.00	−0.00	0.92	0.12	−0.12	14.04	−61.01***
EE Wind	−2.69	−0.01	0.00	3.88	0.81	0.17	3.77	−61.87***
EE Renew	−0.84	0.00	0.00	0.85	0.16	0.16	6.26	−54.90***
EE Solar	−3.52	0.00	0.00	3.74	0.52	−0.04	11.08	−69.29***
FI Nuclear	−0.37	0.00	0.00	0.40	0.08	−0.04	6.42	−55.35***
FI Fossil fuels	−1.16	0.00	−0.00	1.19	0.18	0.01	9.56	−55.05***
FI Renew	−0.60	−0.00	−0.00	0.62	0.11	0.04	6.72	−59.47***
FI Wind	−2.64	−0.00	0.00	3.32	0.71	0.14	3.80	−60.02***
FI Solar	−1.15	0.00	−0.00	1.10	0.12	−0.95	32.95	−67.98***
FR Nuclear	−0.18	−0.00	−0.00	0.19	0.03	0.03	6.40	−58.69***
FR Renew	−0.43	−0.00	0.00	0.52	0.09	0.19	5.21	−56.99***
FR Fossil fuels	−1.88	0.00	−0.00	1.43	0.26	−0.38	8.87	−56.39***
FR Wind	−1.87	−0.01	0.00	2.03	0.56	0.15	3.25	−58.49***
FR Solar	−1.09	0.00	0.00	1.12	0.28	−0.20	3.92	−68.31***
IT Fossil fuels	−0.50	0.00	0.00	0.32	0.08	−0.45	5.69	−57.66***
IT Renew	−0.52	−0.00	−0.00	0.54	0.08	0.20	6.98	−60.16***
IT Wind	−2.43	−0.01	−0.00	2.87	0.71	0.11	3.42	−57.18***
IT Solar	−1.96	−0.00	−0.00	1.53	0.32	−0.18	6.25	−65.29***
NO Renew	−0.18	0.00	−0.00	0.26	0.03	0.18	10.15	−57.37***
NO Wind	−2.51	−0.00	0.00	2.14	0.56	−0.05	3.98	−58.89***
NO Fossil fuels	−0.81	0.00	0.00	0.65	0.13	−0.07	6.51	−56.69***
SE Renew	−0.80	0.00	−0.00	1.03	0.15	0.03	6.91	−58.41***
SE Nuclear	−0.37	0.00	0.00	0.28	0.06	−0.45	6.50	−51.90***
SE Fossil fuels	−0.55	0.00	−0.00	0.68	0.11	0.16	6.20	−51.99***
SE Wind	−2.50	−0.00	0.00	1.92	0.52	−0.00	3.99	−56.67***
SE Solar	−2.33	0.00	0.00	1.83	0.27	0.07	19.86	−73.28***
Nuclear	−0.21	−0.00	−0.00	0.23	0.04	0.08	7.54	−55.03***
Fossil fuels	−0.63	0.00	−0.00	0.70	0.13	−0.23	5.39	−54.10***
Renew	−0.25	0.00	0.00	0.18	0.05	−0.05	4.37	−56.05***
Solar	−1.10	0.00	0.00	0.88	0.21	−0.26	4.65	−60.26***
Wind	−1.24	−0.00	0.00	1.34	0.36	0.12	3.33	−53.41***

This table displays the minimum (Min.), median, mean, maximum (Max.), standard deviation (St. Dev.), skewness (Skew.) and kurtosis (Kurt.) of the logarithmic returns for the exogenous variables. Additionally, the test statistics of the Augmented Dickey–Fuller (ADF) test are reported, with *** indicating significance at the 0.1 % level. The reported variables include the shares of nuclear, solar, wind, other renewables (biomass, geothermal, hydro, and other), and fossil fuels (gas, oil, coal, waste, and other fossil fuels) for the countries Germany (DE), Denmark (DK), Spain (ES), Estonia (EE), Finland (FI), France (FR), Italy (IT), Norway (NO), and Sweden (SE), as well as the aggregated shares weighted by each country's electricity load. The table also includes the total load per country and aggregated across countries. Furthermore, the control variables such as the prices of essential fuel sources (Brent oil futures (Oil price), TTF Natural Gas futures (Gas price), and API2 Rotterdam Coal futures (Coal price)), the EU Allowance (EUA) price, and the Stoxx Europe 600 index (STOXX) are also reported.

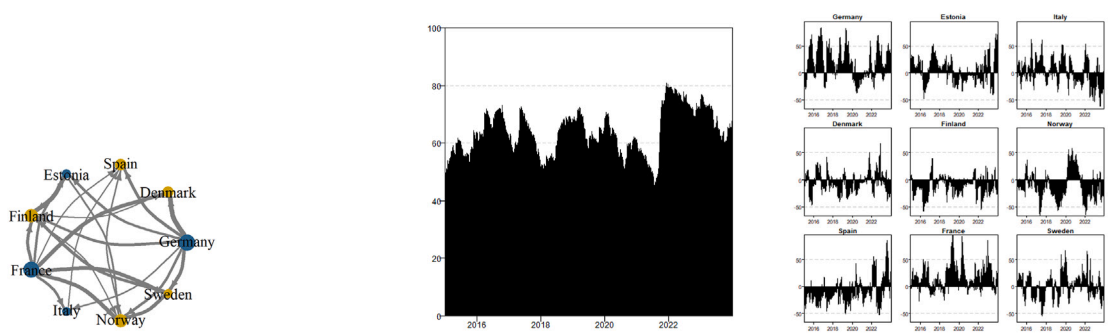
Appendix B. Robustness and sensitivity analyses

B.1. Robustness with focus on the Diebold-Yilmaz spillover methodology



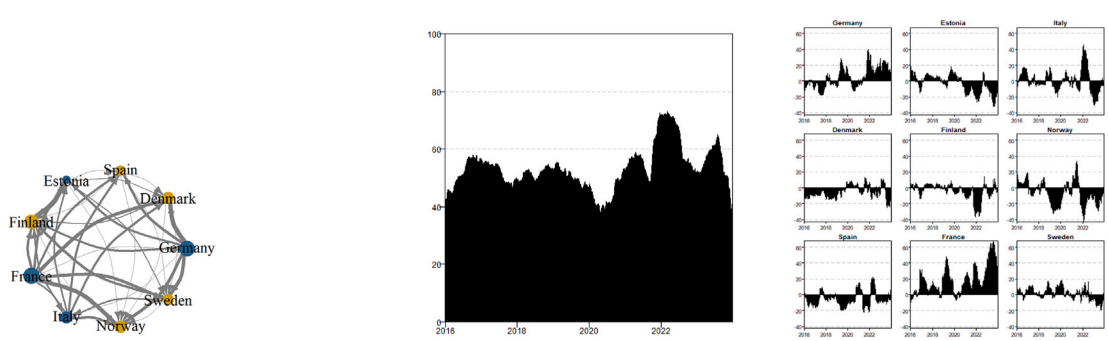
(a) Volatility spillovers network (b) Total volatility spillovers (c) Net volatility spillovers

Fig. B.4. Dynamic total and net volatility spillovers. These figures show the network graph for the entire sample period as well as the dynamic total volatility spillover index and net spillover indices by country, when the number of lags in the VAR model is increased to two.



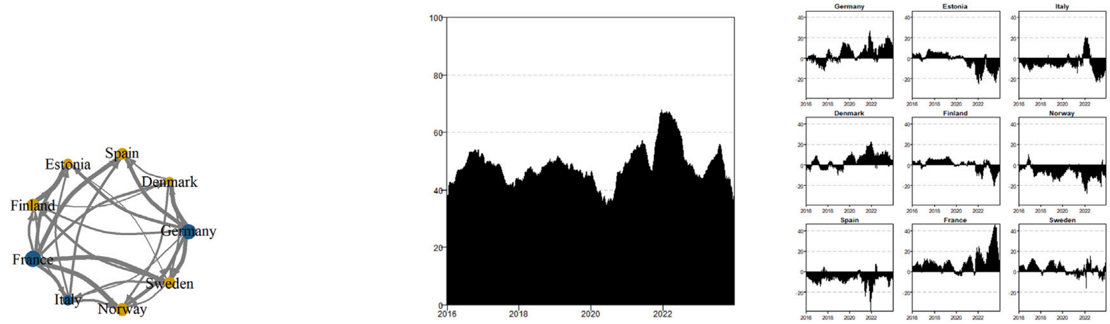
(a) Volatility spillovers network (b) Total volatility spillovers (c) Net volatility spillovers

Fig. B.5. Dynamic total and net volatility spillovers. These figures show the network graph for the entire sample period as well as the dynamic total volatility spillover index and net spillover indices by country, when the the time-varying parameter VAR of [1] is used.



(a) Volatility spillovers network (b) Total volatility spillovers (c) Net volatility spillovers

Fig. B.6. Dynamic total and net volatility spillovers. These figures show the network graph for the entire sample period as well as the dynamic total volatility spillover index and net spillover indices by country, when the standard VAR model is used.



(a) Volatility spillovers network (b) Total volatility spillovers (c) Net volatility spillovers

Fig. B.7. Dynamic total and net volatility spillovers. These figures show the network graph for the entire sample period as well as the dynamic total volatility spillover index and net spillover indices by country, the forecast horizon is set to 20.

Table B.6
Robustness analysis of total spillover index.

Variable	Original		Lags		TVP-VAR		VAR		Horizon	
	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.
(Intercept)	0.0000	(0.0002)	0.0000	(0.0002)	0.0001	(0.0003)	−0.0001	(0.0002)	0.0000	(0.0002)
STOXX 600	0.0081	(0.0167)	0.0008	(0.0158)	−0.0178	(0.0252)	−0.0032	(0.0138)	0.0086	(0.0168)
Oil price	0.0117	(0.0093)	0.0102	(0.0084)	0.0152	(0.0132)	0.0153**	(0.0072)	0.0115	(0.0093)
Gas price	0.0043	(0.0057)	0.0011	(0.0057)	0.0006	(0.0101)	0.0060	(0.0049)	0.0047	(0.0058)
Coal price	−0.0022	(0.0072)	−0.0012	(0.0067)	−0.0043	(0.0101)	−0.0026	(0.0066)	−0.0024	(0.0072)
EUA	−0.0088	(0.0062)	−0.0061	(0.0064)	−0.0130	(0.0106)	−0.0030	(0.0047)	−0.0090	(0.0062)
Total load	0.0156***	(0.0057)	0.0114*	(0.0061)	−0.0068	(0.0196)	0.0147***	(0.0046)	0.0156***	(0.0057)
Fossil fuels	−0.0001	(0.0022)	−0.0007	(0.0027)	0.0060	(0.0045)	−0.0005	(0.0018)	−0.0001	(0.0022)
Nuclear	−0.0057	(0.0055)	−0.0089	(0.0062)	0.0132	(0.0088)	−0.0001	(0.0049)	−0.0057	(0.0055)
Renew	0.0231***	(0.0052)	0.0174***	(0.0052)	0.0091	(0.0112)	0.0179***	(0.0042)	0.0233***	(0.0052)
Solar	−0.0001	(0.0010)	0.0013	(0.0010)	0.0016	(0.0017)	0.0007	(0.0007)	−0.0001	(0.0010)
Wind	0.0000	(0.0010)	−0.0012	(0.0013)	0.0022	(0.0019)	0.0001	(0.0009)	0.0000	(0.0010)

The table reports robustness results from the regression on the total spillover index with Newey-West standard errors (Std. E.). The first set of results corresponds to the original findings presented in the main analysis. The subsequent columns, labeled “Lags”, show the results when the number of lags in the VAR model is increased to two. Next, the columns titled “TVP-VAR” and “VAR” display the outcomes when the time-varying parameter VAR of [1] or the standard VAR model are used instead of the VAR model with LASSO regularization. Finally, we present the results if the forecast horizon is doubled. Statistical significance is indicated by $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table B.7
Robustness analysis of spillover index “to others”.

Variable	Original		Lags		TVP-VAR		VAR		Horizon	
	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.
(Intercept)	0.0000	(0.0001)	0.0000	(0.0001)	0.0000	(0.0002)	0.0000	(0.0001)	0.0000	(0.0001)
STOXX 600	0.0010	(0.0186)	0.0080	(0.0259)	0.0539	(0.0549)	−0.0018	(0.0182)	0.0018	(0.0187)
Oil price	0.0262***	(0.0088)	0.0214***	(0.0057)	−0.0199	(0.0300)	0.0143**	(0.0071)	0.0262**	(0.0088)
Gas price	0.0012	(0.0237)	−0.0191	(0.0244)	−0.0164	(0.0339)	−0.0032	(0.0074)	0.0017	(0.0240)
Coal price	0.0016	(0.0184)	−0.0024	(0.0096)	0.0590	(0.0390)	0.0287	(0.0226)	0.0013	(0.0185)
EUA	−0.0081	(0.0118)	0.0087	(0.0059)	0.0110	(0.0219)	−0.0071	(0.0062)	−0.0083	(0.0119)
Total load	0.0223***	(0.0047)	0.0177	(0.0197)	−0.0028	(0.0280)	0.0096**	(0.0039)	0.0223***	(0.0047)
Fossil fuels	0.0003	(0.0012)	0.0068**	(0.0029)	0.0046	(0.0043)	−0.0026	(0.0021)	0.0003	(0.0012)
Nuclear	−0.0017	(0.0063)	−0.0118*	(0.0064)	−0.0341**	(0.0172)	−0.0072	(0.0086)	−0.0017	(0.0063)
Renew	0.0078	(0.0070)	0.0108**	(0.0036)	−0.0028	(0.0070)	0.0003	(0.0018)	0.0079	(0.0070)
Solar	−0.0008	(0.0018)	0.0018	(0.0026)	−0.0052***	(0.0014)	−0.0010	(0.0006)	−0.0008	(0.0018)
Wind	0.0015	(0.0019)	0.0010	(0.0013)	−0.0027**	(0.0010)	−0.0012*	(0.0006)	0.0015	(0.0019)

The table reports robustness results from the regression on the spillover index “to others” with heteroscedasticity and serial correlation consistent standard errors (Std. E.) by [4]. The first set of results corresponds to the original findings presented in the main analysis. The subsequent columns, labeled “Lags”, show the results when the number of lags in the VAR model is increased to two. Next, the columns titled “TVP-VAR” and “VAR” display the outcomes when the time-varying parameter VAR of [1] or the standard VAR model are used instead of the VAR model with LASSO regularization. Finally, we present the results if the forecast horizon is doubled. Statistical significance is indicated by $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table B.8
Robustness analysis of spillover index “from others”.

Variable	Original		Lags		TVP-VAR		VAR		Horizon	
	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.
(Intercept)	0.0000	(0.0000)	0.0000	(0.0000)	0.0001*	(0.0000)	−0.0001**	(0.0000)	0.0000	(0.0000)
STOXX 600	0.0264**	(0.0133)	0.0122	(0.0195)	−0.0320	(0.0309)	0.0065*	(0.0036)	0.0270**	(0.0134)
Oil price	0.0134	(0.0097)	0.0211**	(0.0105)	0.0281*	(0.0171)	0.0154	(0.0094)	0.0133	(0.0097)
Gas price	0.0078*	(0.0044)	−0.0080*	(0.0043)	−0.0056*	(0.0033)	0.0077**	(0.0028)	0.0083*	(0.0043)
Coal price	0.0080	(0.0098)	0.0150	(0.0115)	−0.0009	(0.0029)	0.0003	(0.0038)	0.0076	(0.0097)
EUA	−0.0182**	(0.0090)	0.0008	(0.0074)	−0.0014	(0.0096)	−0.0019	(0.0018)	−0.0184**	(0.0091)
Total load	0.0077	(0.0082)	−0.0013	(0.0093)	−0.0020	(0.0097)	0.0074*	(0.0041)	0.0076	(0.0082)
Fossil fuels	0.0000	(0.0012)	−0.0010	(0.0011)	0.0015	(0.0017)	0.0005	(0.0007)	0.0000	(0.0012)
Nuclear	−0.0014	(0.0030)	−0.0065	(0.0047)	0.0187**	(0.0057)	0.0029	(0.0041)	−0.0014	(0.0030)
Renew	0.0077***	(0.0022)	0.0075	(0.0060)	0.0062*	(0.0037)	0.0080**	(0.0033)	0.0077***	(0.0023)
Solar	−0.0011***	(0.0004)	−0.0002	(0.0006)	0.0012*	(0.0006)	−0.0006*	(0.0004)	−0.0011**	(0.0004)
Wind	0.0009*	(0.0005)	−0.0001	(0.0007)	0.0012	(0.0008)	0.0010	(0.0010)	0.0009*	(0.0005)

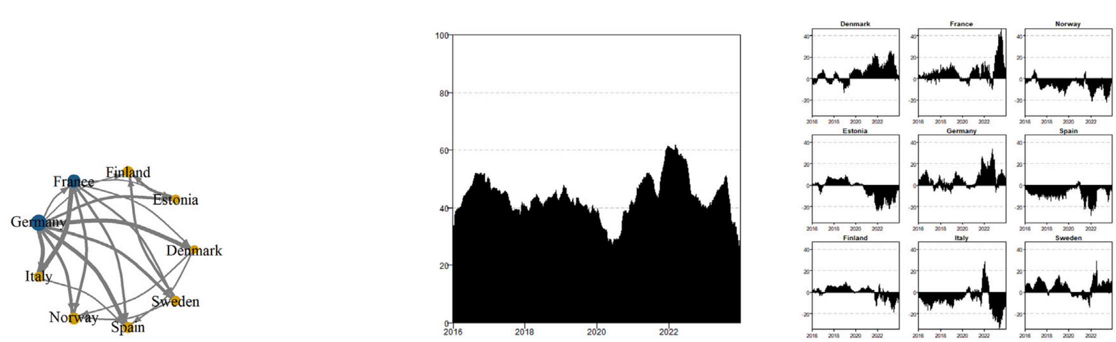
The table reports robustness results from the regression on the spillover index “from others” with heteroscedasticity and serial correlation consistent standard errors (Std. E.) by [4]. The first set of results corresponds to the original findings presented in the main analysis. The subsequent columns, labeled “Lags”, show the results when the number of lags in the VAR model is increased to two. Next, the columns titled “TVP-VAR” and “VAR” display the outcomes when the time-varying parameter VAR of [1] or the standard VAR model are used instead of the VAR model with LASSO regularization. Finally, we present the results if the forecast horizon is doubled. Statistical significance is indicated by $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table B.9
Robustness analysis of net spillover index.

Variable	Original		Lags		TVP-VAR		VAR		Horizon	
	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.
(Intercept)	−0.0001	(0.0024)	0.0012	(0.0010)	0.0023	(0.0118)	0.0030	(0.0023)	−0.0001	(0.0024)
STOXX 600	−1.4627	(−1.5567)	0.3916	(1.1535)	2.3061	(3.8937)	−0.6740	(1.2535)	−1.4513	(1.5509)
Oil price	0.7517	(0.7514)	−0.0311	(0.5054)	−0.8979	(2.1616)	0.1436	(0.4238)	0.7509	(0.7512)
Gas price	−0.5590	(−1.3375)	0.1407	(0.8249)	−0.1184	(2.3045)	−0.3116	(0.5037)	−0.5585	(1.3477)
Coal price	−0.4848	(−1.5170)	−0.9850	(0.6087)	1.6984	(1.4593)	0.4086	(0.4538)	−0.4839	(1.5291)
EUA	0.2627	(0.5363)	0.1378	(0.2014)	−0.3495	(1.6027)	−0.2529	(0.4139)	0.2603	(0.5409)
Total load	0.7625*	(0.4308)	0.0417	(0.6082)	−0.7736	(2.5623)	0.1230	(0.2089)	0.7671*	(0.4314)
Fossil fuels	0.0068	(0.0555)	0.2429**	(0.1053)	0.2391	(0.3921)	−0.0475	(0.0343)	0.0077	(0.0556)
Nuclear	0.0266	(0.4902)	−0.4143	(0.4399)	−3.1543**	(1.2744)	−0.0558	(0.3527)	0.0268	(0.4903)
Renew	−0.1117	(0.3527)	0.1773	(0.1977)	−0.864	(0.7034)	−0.3977***	(0.0910)	−0.1074	(0.3511)
Solar	−0.0030	(0.0996)	0.0077	(0.0344)	−0.3594***	(0.0708)	−0.0454	(0.0392)	−0.0031	(0.0999)
Wind	0.0138	(0.0465)	0.0135	(0.0335)	−0.2311**	(0.1029)	−0.0655*	(0.0367)	0.0143	(0.0466)

The table reports robustness results from the regression on the net spillover index with heteroscedasticity and serial correlation consistent standard errors (Std. E.) by [4]. The first set of results corresponds to the original findings presented in the main analysis. The subsequent columns, labeled “Lags”, show the results when the number of lags in the VAR model is increased to two. Next, the columns titled “TVP-VAR” and “VAR” display the outcomes when the time-varying parameter VAR of [1] or the standard VAR model are used instead of the VAR model with LASSO regularization. Finally, we present the results if the forecast horizon is doubled. Statistical significance is indicated by $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

B.2. Robustness with focus on the regression results



(a) Volatility spillovers network (b) Total volatility spillovers (c) Net volatility spillovers

Fig. B.8. Dynamic total and net volatility spillovers. These figures show the network graph for the entire sample period as well as the dynamic total volatility spillover index and net spillover indices by country, when realized volatility is used instead of daily price ranges.

Table B.10
Robustness analysis of total spillover index.

Variable	Original		Realized vola		STOXX industrials		Fossil fuels		Hydro	
	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.
(Intercept)	0.0000	(0.0002)	−0.0001	(0.0002)	0.0000	(0.0002)	0.0000	(0.0002)	0.0000	(0.0002)
STOXX 600	0.0081	(0.0167)	−0.0036	(0.0189)			0.0084	(0.0170)	0.0081	(0.0166)
STOXX Ind.					0.0013	(0.0142)				
Oil price	0.0117	(0.0093)	0.0078	(0.0095)	0.0124	(0.0092)	0.0115	(0.0095)	0.0118	(0.0091)
Gas price	0.0043	(0.0057)	−0.0056	(0.0065)	0.0042	(0.0057)	0.0041	(0.0055)	0.0042	(0.0058)
Coal price	−0.0022	(0.0072)	−0.0022	(0.0094)	−0.0024	(0.0072)	−0.0019	(0.0068)	−0.0022	(0.0073)
EUA	−0.0088	(0.0062)	−0.0116	(0.0080)	−0.0081	(0.0062)	−0.0088	(0.0062)	−0.0089	(0.0063)
Total load	0.0156***	(0.0057)	0.0167**	(0.0077)	0.0157***	(0.0057)	0.0152***	(0.0058)	0.0176***	(0.0068)
Fossil fuels	−0.0001	(0.0022)	−0.0010	(0.0033)	−0.0001	(0.0022)	−0.0032	(0.0029)	−0.0007	(0.0024)
Gas							0.0006	(0.0019)		
Coal							−0.0005	(0.0013)		
Nuclear	−0.0057	(0.0055)	0.0061	(0.0079)	−0.0057	(0.0055)	−0.0067	(0.0056)	−0.0055	(0.0055)
Renew	0.0231***	(0.0052)	0.0162**	(0.0065)	0.0232***	(0.0052)	0.0241***	(0.0052)	0.0070	(0.0047)
Hydro									0.0173***	(0.0045)
Solar	−0.0001	(0.0010)	0.0003	(0.0012)	−0.0001	(0.0010)	−0.0002	(0.0010)	−0.0001	(0.0010)
Wind	0.0000	(0.0010)	−0.0007	(0.0014)	0.0000	(0.0010)	−0.0002	(0.0010)	0.0000	(0.0010)

The table reports robustness results from the regression on the total spillover index with Newey-West standard errors (Std. E.). The first set of results corresponds to the original findings presented in the main analysis. The subsequent columns, labeled “Realized Vola”, show the results when realized volatility is used instead of daily price ranges. Next, the columns titled “STOXX Industrials” display the outcomes when the STOXX Europe 600 Industrial Goods & Services index replaces the overall STOXX Europe 600 index. Finally, we present the results for the disaggregation of generation technologies, with “Fossil Fuels” referring to the breakdown of fossil fuel sources into the share of gas, coal and others and “Hydro” representing hydro power as a standalone variable. Statistical significance is indicated by ***$p < 0.01$, **$p < 0.05$, and *$p < 0.10$.

Table B.11
Robustness analysis of spillover index “to others”.

Variable	Original		Realized vola		STOXX industrials		Country-specific load		Fossil fuels		Hydro	
	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.
(Intercept)	0.0000	(0.0001)	−0.0001	(0.0001)	0.0000	(0.0001)	0.0000	(0.0001)	0.0000	(0.0001)	0.0000	(0.0001)
STOXX 600	0.0010	(0.0186)	−0.0646	(0.0642)			0.0023	(0.0191)	0.0022	(0.0234)	0.0014	(0.0233)
STOXX Ind.					0.0009	(0.0168)						
Oil price	0.0262***	(0.0088)	0.0438***	(0.0130)	0.0262***	(0.0096)	0.0260***	(0.0089)	0.0282***	(0.0109)	0.0281**	(0.0110)
Gas price	0.0012	(0.0237)	−0.0216**	(0.0096)	0.0012	(0.0237)	0.0024	(0.0239)	0.0176	(0.0232)	0.0174	(0.0232)
Coal price	0.0016	(0.0184)	−0.0052	(0.0288)	0.0016	(0.0183)	0.0004	(0.0186)	−0.0150	(0.0135)	−0.0148	(0.0136)
EUA	−0.0081	(0.0118)	0.0099	(0.0074)	−0.0081	(0.0115)	−0.0084	(0.0118)	−0.0170	(0.0106)	−0.0170	(0.0108)
Total load	0.0223***	(0.0047)	0.0156	(0.0179)	0.0223***	(0.0047)			0.0254***	(0.0043)	0.0289***	(0.0033)
Country-load							0.01480***	(0.0038)				
Fossil fuels	0.0003	(0.0012)	−0.0020	(0.0021)	0.0003	(0.0012)	0.0004	(0.0013)	0.0014	(0.0017)	−0.0002	(0.0015)
Gas									0.0008	(0.0006)		
Coal									0.0001	(0.0003)		
Nuclear	−0.0017	(0.0063)	−0.0102	(0.0093)	−0.0017	(0.0063)	−0.0013	(0.0067)	−0.0034	(0.0064)	−0.0059	(0.0068)
Renew	0.0078	(0.0070)	0.0200*	(0.0114)	0.0078	(0.0070)	0.0075	(0.0071)	0.0049	(0.0100)	0.0078***	(0.0018)
Hydro											0.0014	(0.0082)
Solar	−0.0008	(0.0018)	0.0005	(0.0027)	−0.0008	(0.0018)	−0.0008	(0.0017)	−0.0007	(0.0022)	−0.0009	(0.0022)
Wind	0.0015	(0.0019)	−0.0005	(0.0005)	0.0015	(0.0019)	0.0015	(0.0019)	0.0017	(0.0023)	0.0013	(0.0022)

The table reports robustness results from the regression on the spillover index “to others” with heteroscedasticity and serial correlation consistent standard errors (Std. E.) by [4]. The first set of results corresponds to the original findings presented in the main analysis. The subsequent columns, labeled “Realized Vola”, show the results when realized volatility is used instead of daily price ranges. Next, the columns titled “STOXX Industrials” display the outcomes when the STOXX Europe 600 Industrial Goods & Services index replaces the overall STOXX Europe 600 index. Additionally, we include results where country-specific load values (Country-load) are used in place of the total load. Finally, we present the results for the disaggregation of generation technologies, with “Fossil Fuels” referring to the breakdown of fossil fuel sources into the share of gas, coal and others and “Hydro” representing hydro power as a standalone variable. Statistical significance is indicated by ***$p < 0.01$, **$p < 0.05$, and *$p < 0.10$.

Table B.12
Robustness analysis of spillover index “from others”.

Variable	Original		Realized vola		STOXX industrials		Country-specific load		Fossil fuels		Hydro	
	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.
(Intercept)	0.0000	(0.0000)	0.0000	(0.0001)	0.0000	(0.0000)	0.0000	(0.0000)	0.0000	(0.0001)	0.0000	(0.0001)
STOXX 600	0.0264**	(0.0133)	0.0063	(0.0280)			0.0270*	(0.0138)	0.0292*	(0.0161)	0.0293*	(0.0165)
STOXX Ind.					0.0110	(0.0081)						
Oil price	0.0134	(0.0097)	0.0119	(0.0121)	0.0150	(0.0105)	0.0134	(0.0097)	0.0145	(0.0124)	0.0146	(0.0122)
Gas price	0.0078*	(0.0044)	−0.0004	(0.0048)	0.0075*	(0.0044)	0.0085**	(0.0041)	0.0067	(0.0052)	0.0069	(0.0053)
Coal price	0.0080	(0.0098)	0.0216*	(0.0113)	0.0076	(0.0096)	0.0073	(0.0092)	0.0140	(0.0101)	0.0139	(0.0100)
EUA	−0.0182**	(0.0090)	−0.0341*	(0.0196)	−0.0167**	(0.0083)	−0.0184**	(0.0091)	−0.0218**	(0.0104)	−0.0219**	(0.0105)
Total load	0.0077	(0.0082)	0.0089	(0.0057)	0.0078	(0.0082)			0.0113	(0.0091)	0.0087	(0.0094)
Country-load							0.0001	(0.0018)				
Fossil fuels	0.0000	(0.0012)	0.0032	(0.0024)	0.0000	(0.0012)	0.0003	(0.0009)	0.0011	(0.0007)	0.0002	(0.0011)
Gas									0.0000	(0.0004)		
Coal									−0.0001	(0.0001)		
Nuclear	−0.0014	(0.0030)	0.0125	(0.0087)	−0.0013	(0.0030)	−0.0024	(0.0035)	−0.0033	(0.0032)	−0.0009	(0.0037)
Renew	0.0077***	(0.0022)	0.0005	(0.0026)	0.0077***	(0.0022)	0.0075***	(0.0021)	0.0093***	(0.0020)	−0.0028*	(0.0016)
Hydro											0.0078***	(0.0021)
Solar	−0.0011***	(0.0004)	−0.0002	(0.0007)	−0.0011***	(0.0004)	−0.0012***	(0.0004)	−0.0011***	(0.0004)	−0.0011***	(0.0004)
Wind	0.0009*	(0.0005)	0.0025	(0.0023)	0.0009*	(0.0005)	0.0009*	(0.0005)	0.0011	(0.0007)	0.0009	(0.0006)

The table reports robustness results from the regression on the spillover index “from others” with heteroscedasticity and serial correlation consistent standard errors (Std. E.) by [4]. The first set of results corresponds to the original findings presented in the main analysis. The subsequent columns, labeled “Realized Vola”, show the results when realized volatility is used instead of daily price ranges. Next, the columns titled “STOXX Industrials” display the outcomes when the STOXX Europe 600 Industrial Goods & Services index replaces the overall STOXX Europe 600 index. Additionally, we include results where country-specific load values (Country-load) are used in place of the total load. Finally, we present the results for the disaggregation of generation technologies, with “Fossil Fuels” referring to the breakdown of fossil fuel sources into the share of gas, coal and others and “Hydro” representing hydro power as a standalone variable. Statistical significance is indicated by $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Table B.13
Robustness analysis of net spillover index.

Variable	Original		Realized vola		STOXX industrials		Country-specific load		Fossil fuels		Hydro	
	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.	Estimate	Std. E.
(Intercept)	−0.0001	(0.0024)	−0.0043**	(0.0017)	0.0000	(0.0025)	0.0001	(0.0024)	0.0011	(0.0028)	0.0010	(0.0028)
STOXX 600	−1.4627	(−1.5567)	−1.7433	(2.5541)			−1.4201	(1.5941)	−1.5713	(1.9872)	−1.6264	(1.9891)
STOXX Ind.					−0.5704	(1.4331)						
Oil price	0.7517	(0.7514)	1.4867	(1.0807)	0.6610	(0.7696)	0.7446	(0.7647)	0.8408	(0.9506)	0.8293	(0.9600)
Gas price	−0.5590	(−1.3375)	−0.7821	(0.5790)	−0.5447	(1.3403)	−0.5248	(1.3152)	0.5029	(1.1683)	0.4753	(1.1684)
Coal price	−0.4848	(−1.5170)	−1.9787**	(0.9723)	−0.4601	(1.5127)	−0.5202	(1.5025)	−1.9312*	(0.9870)	−1.9090*	(0.9895)
EUA	0.2627	(0.5363)	1.4244***	(0.5136)	0.1733	(0.5277)	0.2515	(0.5304)	−0.1817	(0.4348)	−0.1732	(0.4405)
Total load	0.7625*	(0.4308)	0.9425	(0.9655)	0.7573*	(0.4295)			0.6460	(0.6062)	0.9637*	(0.5553)
Country-load							0.6136	(0.4242)				
Fossil fuels	0.0068	(0.0555)	−0.1876***	(0.0656)	0.0067	(0.0554)	0.0034	(0.0625)	0.0652	(0.0708)	−0.0365	(0.0767)
Gas									0.0186	(0.0502)		
Coal									0.0023	(0.0144)		
Nuclear	0.0266	(0.4902)	−0.2290	(0.3065)	0.0251	(0.4904)	0.0667	(0.5369)	0.0422	(0.5646)	−0.2352	(0.6035)
Renew	−0.1117	(0.3527)	0.4335**	(0.2027)	−0.1128	(0.3530)	−0.1185	(0.3526)	−0.4172	(0.4911)	0.5618***	(0.1427)
Hydro											−0.4828	(0.3728)
Solar	−0.0030	(0.0996)	−0.0815	(0.0853)	−0.0034	(0.0993)	−0.0005	(0.1014)	0.0069	(0.1189)	−0.0015	(0.1191)
Wind	0.0138	(0.0465)	−0.0537*	(0.0309)	0.0139	(0.0465)	0.0159	(0.0483)	0.0087	(0.0560)	−0.0043	(0.0570)

The table reports robustness results from the regression on the net spillover index with heteroscedasticity and serial correlation consistent standard errors (Std. E.) by [4]. The first set of results corresponds to the original findings presented in the main analysis. The subsequent columns, labeled “Realized Vola”, show the results when realized volatility is used instead of daily price ranges. Next, the columns titled “STOXX Industrials” display the outcomes when the STOXX Europe 600 Industrial Goods & Services index replaces the overall STOXX Europe 600 index. Additionally, we include results where country-specific load values (Country-load) are used in place of the total load. Finally, we present the results for the disaggregation of generation technologies, with “Fossil Fuels” referring to the breakdown of fossil fuel sources into the share of gas, coal and others and “Hydro” representing hydro power as a standalone variable. Statistical significance is indicated by $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.10$.

Data availability

Data will be made available upon request.

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