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Volatility spillovers and carbon price in the Nordic wholesale electricity markets[☆]

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ABSTRACT

This paper investigates price volatility and spillovers in the Nordic electricity wholesale markets. We use the Time-Varying Parameter Vector Autoregressive (TVP-VAR), Rolling Window-based VAR (RW-VAR), and high dimensional VAR with common factors (VAR-CF) methods and analyze the integration dynamics among these markets and impact of carbon prices on volatility spillovers. We use 107,352 hourly price data from January 2010 to March 2022. The novelty of this research is four-fold. First, we adopt a connectedness approach to explore volatility interactions among the four Nordic markets, contributing to the scarce literature on volatility in this market. Second, we segment the Norwegian market into southern and northern regions, revealing differences in volatility spillover patterns. Third, we investigate the effect of carbon prices on volatility spillovers and market dynamics. Last, we show significant contribution of covariances to interdependence among markets. We find significant connectedness between the Nordic markets, with an average Total Connectedness Index of between 50% (with a system of variance) and 90% (with a system of both variance and covariance). Sweden is the sole net volatility spillover transmitter, while Denmark experiences the largest shocks from the system. We further find that carbon prices exert a 5% significant impact on the volatility spillover index.

1. Introduction

Electricity is a critical service and infrastructure for economic development (Cramton, 2017). Due to the relative non-storable nature of electricity, markets find it is more difficult to match supply and demand than in other commodity markets (Ma et al., 2022; Uribe et al., 2020). With its vulnerability to weather and climate-related conditions, the growing shares of renewables, and increasing price of carbon for electricity generation, the price of electricity has become one of the most volatile financial instruments in liberalized markets (Do et al., 2020).

Electricity market integration can reduce idiosyncratic exposure to volatility risk and limit the probability of energy crises and energy shortages in national or regional markets. The US Energy Policy Act of 1992 promoted electricity wholesale markets by requiring utilities to open the transmission systems, which was followed by formation of a regional network spanning 11 separate spot markets (De Vany and Walls, 1999; Park et al., 2006); since then the price dynamics and integration among 11 US markets have been extensively discussed (see e.g., Mjelde and Bessler, 2009). In the same vein, Australia established the National Electricity Market (NEM) in 1998, made up of five regional markets (Han et al., 2020; Nepal and Foster, 2016). In order to remove cross border barriers between member states, European Union electricity market integration was considered and discussed as early as in 1986 (Do et al., 2020; Jamasb and Pollitt, 2005; Pollitt, 2019), and was put into practice in 1990.[1]

Market integration has been an objective in geographically and economically linked areas, as in the Nordic region. The Nordic electricity market — Nord Pool — is believed to be the best-functioning

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[1] Council Directive 90/377/EEC of 29 June 1990 concerning a community procedure to improve the transparency of gas and electricity prices charged to industrial end-users. Retrieved from: https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:31990L0377.

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market in the world (Amundsen and Bergman, 2006; Haugom et al., 2020; International Energy Agency, 2023; Sousa and Soares, 2020; Uribe et al., 2020). The generation mix in the Nordic region is dominated by renewables. The share of electricity from low carbon sources in Denmark, Norway, Finland, and Sweden, is 72.4, 100, 69.0 and 88.7%, respectively. Even with high levels of clean energy, the Nordic region is expected to experience faster growth in renewables in the future (Bertrand, 2020; Jan, 2019).

Integration of nordic electricity markets is characterized by a variety of renewables (e.g., wind power in Denmark, hydro power in Norway, and nuclear power in Sweden and Finland) and non-renewable (e.g., fossil fuels in Finland) generation mixes. Renewable energy, such as wind power and hydropower, is inherently intermittent due to climatic conditions that, exacerbates price volatility in the absence of feasible storage (Uribe et al., 2020). Actors in Nord Pool are exposed to the risk of price fluctuations in merchant power prices. The volatility of wholesale electricity prices is therefore a key issue. The Nordic market can shed some light on dynamics of price fluctuations in future integrated renewable-dominant electricity markets.

This paper analyses volatility spillovers across the four Nordic countries and examines how carbon prices influence those spillover effects. The study focuses on two research questions: What is the volatility connectedness level among the Nordic electricity markets? Whether and how do changes in carbon prices drive volatility spillovers in the integrated Nordic electricity market?

The Nordic electricity market is formed by Denmark, Finland, Norway, and Sweden and includes 13 bidding areas, with price differences among them. Price movements in these markets enhance the arbitrage opportunities, and spillover effects appear among markets. Price fluctuation (e.g., volatilities) in the same type of market typically has a mutual spillover effect, which implies that the volatility of one market can be passed to another (Guo and Feng, 2021; Lyu and Scholtens, 2024). Cross-spillovers between markets facilitate international risk-sharing. In integrated markets, changes in one local market can affect not only the local consumption and wholesale prices, but also markets of other countries via cross-border trade, as markets aggregate a large amount of interconnected financial transactions. For instance, the wholesale electricity price in Norway is affected by weather conditions, wind generation, and hydro output, as well as climate change policies, and shocks are passed on to the Swedish market. As a result, power companies in Sweden may bear the impact caused by non-local shocks contributed by Norway. Furthermore, the climate policies of, for instance, the European Union emissions trading system (EU ETS), as a well-established carbon market of EU, will increase electricity price levels in general (Aatola et al., 2013). The power enterprises are the most active traders in the EU ETS, and thus the interaction between the Nordic wholesale electricity markets and EU ETS is important.

The novelty of our approach is four-fold. First, we use the connectedness approach based on the time-varying parameter VAR (TVP-VAR, thereafter), rolling window-based VAR (RW-VAR, thereafter), and the high dimensional VAR with common factors (VAR-CF, hereafter) models to analyze integration in the Nordic electricity markets, contributing to the scarce literature in the volatility connectedness in this region. Second, we split the Norwegian market into two price regions to reflect the observed difference in electricity prices between the northern and southern regions. Thirdly, we uncover an important role of the covariances in contributing to the spillovers among the markets, in which the spillovers among covariances weights for nearly half of the whole system's spillover effects. Finally, we examine how carbon price influences those spillover effects since the literature examining the impact of carbon price on electricity market integration is scant. Do et al. (2020) suggests that adoption of carbon price floor improves market integration in physically interconnected markets but sufficient empirical evidence to support this is lacking.

To the best of our knowledge, this is the first study to examine the role of carbon price on volatility spillovers among Nordic electricity markets. Understanding these issues is important for electricity market participants (e.g., electricity producers, retailers, investors, and users) not only in Nordic electricity markets but globally, as they adopt appropriate risk management strategies to hedge against the negative effects of electricity price volatility. This is particularly relevent since the Nordic electricity market is at the heart of Europe's energy transition. It is also important for the sector regulator to devise measures to avoid excessive price volatility.

The remainder of the paper is organized as follows: Section 2 reviews the literature. Section 3 presents the methodology to estimate electricity market volatility spillover effects among the study areas. Section 4 describes the data and sample. Section 5 discusses the empirical results. Section 6 provides additional analysis by estimating a high dimensional VAR with common and including covariances to the interdependence among markets. Section 7 concludes and provides policy implications.

2. Background

Renewable energy (RE) penetration has been increasing globally in the last ten years (BP, 2022). Advanced economies, e.g., the European Union, have generally higher share of renewables, with 39% of gross electricity consumption (International Energy Agency, 2022). However, the source mix of power generation differs across Europe. For instance, Italy, Poland, and Netherlands sectors are dominated by fossil fuels, in France nuclear power is the main source of power generation, and the Nordic region largely relies on renewable energy (Eurostat, 2022). The Nordic countries de-regulated and introduced competition in their power markets in the early 1990s, merging their national markets into a common market – Nord Pool (Flatabo et al., 2003; Hans-Arild, 2016; Torstein Bye and Hope, 2005). Market integration is also progressing in the Baltics and the rest of Europe. Hence, power from different sources and countries that enter the grid can potentially cause volatility.

Nord Pool is transitioning to a system fully based on sustainable energy resources. Specifically, Denmark, as a leading country in wind energy with a long tradition of integrating renewable energy in its electricity sector. The electricity from renewable sources reached 72.4% of the electricity supply by the end of 2020, to which wind energy contributed around 50% and biomass 21.2% (Danish Energy Agency, 2021). In Norway, 100% of the electricity is from low carbon sources, with 98% hydropower, wind, and thermal energy (International Energy Agency, 2022; Ministry of Petroleum and Energy, 2016). Precipitation and inflows to dams and reservoirs are critical due to hydropower's role especially in the Norwegian system. In Finland and Sweden, the share of low carbon sources in power generation is 69.0% and 88.7%, respectively, while the share of renewable energy is 48.8% and 66.3%. In the absence of viable electricity storage, electricity price in Nord Pool is relatively volatile (Ketterer, 2014; Kyritsis et al., 2017; Uribe et al., 2020).

The coupling of electricity markets has been extensively investigated (e.g., Amundsen and Bergman, 2006; Bunn and Gianfreda, 2010; De Vany and Walls, 1999; Do et al., 2020; Gugler et al., 2018; Han et al., 2020; Ma et al., 2022; Nepal and Foster, 2016; and Park et al., 2006). Most studies have focused on the European and Australian electricity markets (Bunn and Gianfreda, 2010; Gugler et al., 2018), using daily spot or forward price data. The volatility spillover effects across different markets is well documented in the literature (e.g., Do et al., 2020; Han et al., 2020; Ma et al., 2022; Uribe et al., 2020). Han et al. (2020) studied the volatility spillovers between prices across five regions in the Australian National Electricity Market (NEM) and found volatility connectedness in this market to be 35.9%.

Connectedness is typically more pronounced between physically interconnected markets. In the same vein, Do et al. (2020) investigated the volatility connectedness between the Irish and Great British markets. They found around 5% volatility connectedness between the two markets over the 2009–2018 period, i.e., lower than the Australian NEM. The low connectedness was believed to be due to inefficient flows across the two interconnectors between Britain and the Irish Single Electricity Market (SEM). Hasan et al. (2021) investigated time-frequency connectedness between Asian electricity sectors and showed that geographically connected markets such as China mainland, India, and Hong Kong are more connected than the geographically distant markets.

Table 1 Panel A summarizes the literature on electricity market integration using connectedness methods. These studies generally find that physically and economically interconnected markets exhibit larger spillovers across the systems, hence larger market risks. In such systems, the risk propagates more easily, allowing for a decrease of idiosyncratic market risks, thus reducing the energy shortages in the domestic markets.

Past studies have focused on the price mechanism in Nord Pool (Haugom et al., 2018; Hellström et al., 2012; Sotiriadis et al., 2016; Souhir et al., 2019), the linkage between Nord Pool electricity price and other energy or emission market prices (Chuliá et al., 2019; Daskalakis and Markellos, 2009; Ma et al., 2022), and electricity spot-forward price relationships in Nord Pool (Botterud et al., 2010; Weron and Zator, 2014). Table 1 Panel B summarizes these. Few studies examine the linkages within the Nord Pool market (Ma et al., 2022; Uribe et al., 2020). The Nord Pool market gives an opportunity to study a highly integrated market with a high share of renewables. We aim to fill this gap by analysing the cross-spillover between prices in the Nord Pool interconnected electricity wholesale market with a variety of renewables.

The methodological frameworks employed in electricity market integration literature ranges from standard cointegration and autoregressive distributed lag analysis (ARDL) (see, e.g., Gugler et al., 2018; Böckers and Heimeshoff, 2014), to time-varying cointegration tests (De Menezes and Houllier, 2016; Nepal and Foster, 2016). However, these techniques (e.g., cointegration) have not considered the dynamics of volatility connectedness in the markets, which is a necessity for assessing the progress toward higher degrees of wholesale power markets integration.

The connectedness strand of literature, developed recently by Diebold and Yilmaz (2009, 2012, 2014), is relevant for our study (hereafter DY method). The DY method constructs the spillover index by forecast error variance decomposition of the VAR model. A notable feature of the DY method is that can describe the direction and dynamics of spillovers. The DY method overcomes not only the problem of fixed parameters assumed in cointegration tests, but also the drawbacks of multivariate GARCH models in capturing time-varying features of spillover effect (Do et al., 2020; Han et al., 2020; Liu and Gong, 2020; Ma et al., 2022). The DY method has advantages, but also drawbacks, namely, i) estimation based on a rolling window VAR (hereafter, RW-VAR) induces loss of observations, ii) arbitrary in selecting window size, and iii) loss of observations in first window. We first analyze connectedness in Nord Pool by DY rolling window VAR, then extend the model to a time-varying parameter VAR (TVP-VAR), following Antonakakis et al. (2020). The TVP-VAR-based approach has advantages such as: (i) insensitivity to outliers due to the underlying Kalman filter, (ii) no need to arbitrarily choose the rolling-window size, (iii) no loss of observations, and (iv) it can be used with low frequency data (Antonakakis et al., 2020; Koop and Korobilis, 2013). We compare the results from both methods.

The methodologies adopted in this study have several advantages. First, by employing a rolling-window technique, the applied methodology may track the degree of spillover effects over time without specifying a set of breakpoints or situations in advance. Second, we extend the DY connectedness to a dynamic approach based on TVP-VAR, which allows the variance-covariance matrix to vary via a Kalman filter estimation with forgetting factor.[2] Third, the spillover measure can be simply aggregated by both RW-VAR and TVP-VAR, allowing for the quantification of diverse spillover effects. Both measures enable differentiating between net shock transmitters and net shock receivers, which in turn helps obtain a better knowledge of the underlying dynamics and improves the formulation of policy implications.

A recent paper related to our study is Uribe et al. (2020). The paper examines the integration and propagation of shocks in the Nord Pool market, covering seven countries. Uribe et al. (2020) 's study examined the period from January 2013 to December 2018. Our study complements and extends the findings of Uribe et al. (2020) by focusing on the integrated Nordic electricity market, and addresses the unique challenges posed by climate change, increasing renewable energy shares, and carbon pricing. To the best of our knowledge, this is the first study to analyze price volatility spillovers and the impact of carbon prices in the Nordic region. Our study covers a longer period, spanning from January 2010 to March 2022, which provides a more comprehensive understanding of market dynamics and allows us to capture a broader range of events that have influenced the electricity market. The extended timeframe in our study enables us to investigate and analyze a more diverse set of market conditions and events, such as the transition of EU ETS from Phase II to Phase III in 2012, the crude oil crisis in 2014 the market coupling of the GB-Irish market in 2018, and the Covid-19 pandemic. Also, due to network congestion between southern and northern Norway, the Norwegian bidding prices should be separated into southern and northern prices (see also Section 4).

Furthermore, we examine whether carbon price can explain connectedness which is ignored by Uribe et al. (2020). Our results indicate that Finland acted as a net transmitter of volatility shocks to Norway between January 2010 and June 2012. However, from June 2012 to June 2018, Finland became a net spillover receiver, primarily from Sweden and Norway. This observation contrasts with Uribe et al.'s conclusion that Finland received volatility shocks from Norway during 2013 and 2015. Since 2018, Finland has returned to being a spillover transmitter to Denmark and Norway, although the effect is less pronounced than during the 2010–2012 period. Notably, Sweden consistently transmits net spillover to Finland throughout the sample, likely due to its role as a net electricity importer from Sweden. These differences in methodology, time period, and findings underscore the unique contributions of our study in providing a deeper understanding of volatility spillovers and market dynamics in the integrated Nordic electricity market.

3. Methodology

The central research question of our study is how volatility connectedness (also known as spillover) in Nordic electricity markets responds to carbon price changes. Following the recent connectedness literature (e.g., Apergis et al., 2017; Do et al., 2020; Han et al., 2020). In the following, we provide a brief overview of the approach. Section 3.1 applies Diebold and Yilmaz (2009, 2012) spillover method to estimate volatility spillover effects in Nord Pool. Section 3.2 constructs the TVP-VAR to estimate the volatility spillover effects. The two methods are based on forecast error variance decomposition from the VAR model.

[2] Kalman filter methods have several desirable properties, e.g., they are fast because state space models encapsulate the Markov property and reduce to a set of recursions. Also, the forgetting factor approaches have been commonly used with state space models; they do not require the use of Markov Chain Monte Carlo, which can be computationally demanding (Antonakakis et al., 2020; Koop and Korobilis, 2013; Dangl and Halling, 2012). The detailed algorithm of the TVP-VAR with Kalman filter and forgetting factors can be found in Koop and Korobilis (2013). Different measures — e.g., the rolling window VAR analysis, are provided in the robustness checks.

Table 1
Relevant literature on electricity market integration and Nord Pool electricity prices.

Panel A: Summary of studies on connectedness in electricity markets				
Reference	Study area	Study period	Model type	Data
Ma et al. (2022)	12 European day-ahead wholesale spot electricity markets	Sep 2009 - Aug 2020	Time-frequency volatility connectedness	Hourly price
Naeem et al. (2022)	Australian National Electricity Market (NEM)	May 2005 - Dec 2020	RW-VAR, time and frequency, and asymmetric connectedness	Daily price
Hasan et al. (2021)	Electricity sector of 10 Asian jurisdictions	Apr 2007 - Aug 2020	RW-VAR connectedness and frequency connectedness (Baruník and Křehlík, 2018)	Daily stock price
Han et al. (2020)	Australian NEM	Jan 2010 - Dec 2017	RW-VAR connectedness	Daily price
Do et al. (2020)	Irish and Great Britain markets	Oct 2009 - Oct 2018	Asymmetric connectedness based on RW-VAR	Half hourly price

Panel B: Summary of studies on Nord Pool electricity markets				
Reference	Topic	Study period	Model type	Data
Souhir et al. (2019)	Electricity market variations on the Nordic stock market returns	Jul 2017 - Dec 2017	VaR, c-DCC-FIGARCH, CVaR and ΔCVaR	Hourly spot electricity price
Sotiriadis et al. (2016)	Price and volatility interrelationships in five European electricity markets	Jan 2009 - Aug 2012	A novel VAR model, CCC-MGARCH model, DCC-MGARCH	Daily spot electricity price
Chuliá et al. (2019)	Links between energy markets in Europe (including Nord Pool)	Nov 2008 - Jun 2016	RW-VAR	17 forward price covering electricity, gas, coal, and carbon
Daskalakis and Markellos (2009)	Links between emission and electricity markets	Sep 2006 - Oct 2007, Mar 2005 - May 2007	Regressions	Daily electricity and carbon price
Hellström et al. (2012)	Possible causes behind electricity price jumps in the Nord Pool	Jan 1996 - Feb 2006	A mixed GARCH–EARJI jump model	Daily spot electricity price
Weron and Zator (2014)	Relationship between spot and futures prices in the Nord Pool	Jan 1998 - Dec 2010	Regression models with GARCH residuals	Weekly price
Botterud et al. (2010)	Spot and futures prices relationships in Nord Pool	1996–2006	Descriptive statistics and simple regression analysis	Weekly price
Haugom et al. (2018)	Forward premium of futures contracts in the Nord Pool	Jan 2004 - Dec 2013	Regressions	Weekly price
Nomikos and Soldatos (2010)	Major risks (e.g., spike risk, short-term risk) in power prices in Nord Pool	Jan 1993 - Feb 2004	Three-factor spike model	Daily system prices

Section 3.3 displays the spillover measures. Section 3.4 investigates the impact of carbon price on this volatility connectedness.

3.1. Rolling window VAR model

Diebold and Yilmaz (2012, 2014) utilized a generalized VAR approach to investigate interdependence across variables. This approach overcomes the Cholesky-type VAR in their earlier study, Diebold and Yilmaz (2009). The connectedness approaches are built from the variance decomposition matrix of an N-variable VAR(p) approximating model; see Eq. (1) below.

$$X_t = \sum_{i=1}^{p} \Phi_i X_{t-i} + \epsilon_t, \epsilon_t \sim N(0, \Sigma_\epsilon) \tag{1}$$

Φ_i is $N \times N$ matrix of polynomial coefficients. ϵ_t is a vector of independently and identically distributed error terms, where Σ_ϵ is the variance-covariance matrix for ϵ_t. In our study, $N = 5$ for five regional markets and t refers to date (i.e., daily time series). The VAR(p) should be covariance stationary. The DY connectedness is based on generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD), developed by Koop et al. (1996) and Pesaran and Shin (1998). The important step to calculate the GIRF and GFEVD is to transform the VAR to its moving average representation – VMA. The moving average coefficients are important to a VAR system's dynamics, since the variance decompositions rely on transformation of these original parameters, hence the key to understanding the dynamics of the system (Diebold and Yilmaz, 2012). We transform the VAR(p) model to its VMA and show in Eq. (2).

$$X_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-i}, \tag{2}$$

where A_i are $N \times N$ coefficient matrices, and subject to the recursion $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \ldots + \phi_p A_{i-p}$, and where $A_o = I_N$ ($N \times N$ identify matrix) and $A_i = 0$ for $i < 0$. These moving average coefficients measure the effects of shocks on variables X_t at different points in time.

The variance decompositions allow us to assess the fraction of the H-step-ahead error variance in forecasting X_n that is due to shocks to X_m, $\forall n \neq m$, for each n. Specifically, for each variable X_n, $(n = 1, 2, \ldots, N)$ we can analyze which fraction of the error variance in forecasting X_n can be attributed to shocks to variable X_m. However, the decomposition of forecast error variance prerequisites isolated shock, yet energy market data often display contemporaneously associated shocks or innovations. Diebold and Yilmaz (2012) adopted the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998). This approach allows for correlated shocks but accounts for them appropriately using the historically observed distribution of the errors, circumventing the variables ordering problem of the identification schemes based on Cholesky factorization. As the shocks to each variable are not orthogonalized, the sum of contributions to the variance of forecast error is not always equal to one. Denoting the H-step-forecast error variance decompositions by $\theta^g_{nm}(H)$, for $H = 1, 2, \ldots, N$ (the contribution of variable m's shocks to n's generalized forecast error variance, θ^g_{nm} (H)), we have Eq. (3).

$$\theta^g_{nm}(H) = \frac{\sigma_{mm}^{-1} \sum_{h=0}^{H-1} \left(e_n' A_h \Sigma_\epsilon e_m\right)^2}{\sum_{h=0}^{H-1} \left(e_n' A_h \Sigma_\epsilon A_h' e_n\right)}, \tag{3}$$

and normalized as

$$\widetilde{\theta}^g_{nm}(H) = \frac{\theta^g_{nm}(H)}{\sum_{m=1}^{N} \theta^g_{nm}(H)} \times 100\%, \tag{4}$$

where g refers to the generalized variance decomposition method. Σ_ϵ is the variance covariance matrix for ϵ_t. The moving average coefficient matrix corresponding to lag h is denoted *as* A_h. σ_{mm} is the *m-th* diagonal element in Σ_ϵ, which denotes the standard deviation of the shocks for the variable m (error term for the *mth* equation). e_n and e_m are both the selection vectors; both the *n-th* entry for e_n and m-th entry for e_m are equal to 1, and 0 otherwise. Then we normalize each entry of the variance decomposition matrix by the row sum as Eq. (4), where the decomposition $\widetilde{\theta}^{g}_{nm}(H)$ measures the spillover from X_m to X_n (X_t is a vector of volatility series for one of the Nordic electricity markets). Note that $\sum_{m=1}^{N}\widetilde{\theta}^{g}_{nm}(H) = 1$ and $\sum_{n,m=1}^{N}\widetilde{\theta}^{g}_{nm}(H) = N$ by construction. The denominator represents the cumulative effect of all the shocks, while the numerator illustrates the cumulative effect of a shock in variable i.

3.2. TVP-VAR model

This section follows the approach of Antonakakis et al. (2020). The objective is to provide a flexible framework for the estimation and interpretation of time variation in the systematic and non-systematic parts of carbon prices and their effect on the rest of the markets. The TVP-VARs are state space models; one advantages is that statistical methods for state space models (based on the Kalman filter) are available. To describe the dynamics of volatility spillovers, the baseline TVP-VAR model is set as follows:

$$X_t = Z_{t-1}B_t + \epsilon_t, \epsilon_t|\Omega_{t-1} \sim N(0, \Sigma_t), \tag{5}$$

and

$$vec(B_t) = vec(B_{t-1}) + \xi_t, \xi_t|\Omega_{t-1} \sim N(0, \Xi_t), \tag{6}$$

where $Z_{t-1} = \begin{pmatrix} X_{t-1} \\ X_{t-2} \\ \vdots \\ X_{t-p} \end{pmatrix}$, and $B_t = \begin{pmatrix} B_{1t} \\ B_{2t} \\ \vdots \\ B_{pt} \end{pmatrix}$.

In the above models, p is the lag order, t is the sample length of the model, and $t = p+1, p+2, \dots, T$. Ω_{t-1} represents all information available until $T = t-1$. X_t is an $N \times 1$ vector containing observations on N time series variables. Z_{t-1} represents $N \times p$ matrix. B_t are $N \times Np$ dimensional coefficient matrices while B_{it} are $N \times N$ matrices. ϵ_t and Σ_t are $N \times 1$ and $N \times N$ matrix, respectively. In eq. (6), $vec(B_t)$ is the vectorisation of B_t, which is an $N \times Np$ dimensional vector. The ξ_t is an $N^2p \times 1$ dimensional vector. Moreover, Ξ_t are $N^2p \times N^2p$ time-varying variance-covariance matrices; ϵ_t and ξ_s are independent of one another for all s and t. Eq. (6), which models the evolution of B_t, can be interpreted as a hierarchical prior for B_t.

For the initialization of Kalman filter, we utilize an uninformative prior for parameters Σ_o and B_o. The mean and the variance of B_0 are chosen to be the OLS point estimates ($\widehat{B}_{OLS}$) and its variance Σ^{B}_{OLS} in a time invariant VAR. Consequently, the Kalman filter technique relies on a forgetting factor that regulates the variation of estimated parameter coefficients with time. As proposed by Koop and Korobilis (2013), the forgetting factor is set at 0.99 given that our parameters do not change considerably across periods. The time-varying coefficients and error covariances are used to estimate the generalized connectedness procedure of DY's spillover index. We transformed Eq. (7) to its VMA,

$$X_t = \sum_{i=0}^{\infty} \Upsilon_{i,t}\epsilon_{t-i}, \tag{7}$$

where $\Upsilon_{i,t} = C_{1,t}\Upsilon_{i-1,t} + C_{2,t}\Upsilon_{i-2,t} + \dots + C_{p,t}\Upsilon_{i-p,t}$. $\Upsilon_t = [\Upsilon_{1,t}, \Upsilon_{2,t}, \Upsilon_{3,t}, \dots, \Upsilon_{p,t}]'$ and $C_t = [C_{1,t}, C_{2,t}, C_{3,t}, \dots, C_{p,t}]'$. Both $C_{i,t}$ and $\Upsilon_{i,t}$ are $N \times N$ dimensional matrices. The H-step-forecast error variance decompositions process can be referred to Eqs. (3) and (4) above.

3.3. Spillover measures

Using the GFEVD (Eqs. (3) and (4)), we construct the following spillover measures:

$$\textit{Total connectedness index } (TCI_t(H)) : \frac{\Sigma_{n,m=1,n\neq m}^{N}\widetilde{\theta}^{g}_{nm,t}(H)}{\Sigma_{n,m=1}^{N}\widetilde{\theta}^{g}_{nm,t}(H)} \times 100, \tag{8}$$

$$\textit{Directional spillovers to } (TO_{n\to m,t}(H)) : \sum\nolimits_{n=1,n\neq m}^{N}\widetilde{\theta}^{g}_{nm}(H), \tag{9}$$

$$\textit{Directional spillovers from } (FROM_{n\leftarrow m,t}(H)) : \sum\nolimits_{m=1,n\neq m}^{N}\widetilde{\theta}^{g}_{nm}(H), \tag{10}$$

$$\text{Net spillovers } (NET_{nm,t}) : TO_{n\to m,t}(H) - FROM_{n\leftarrow m,t}(H), \tag{11}$$

$$\textit{Net pairwise spillovers} : (NPS_{nm}(H)) : \left(\frac{\widetilde{\theta}^{g}_{nm}(\mathrm{H})}{\Sigma_{k=1}^{N}\widetilde{\theta}^{g}_{nk}(H)} - \frac{\widetilde{\theta}^{g}_{mn}(H)}{\Sigma_{k=1}^{N}\widetilde{\theta}^{g}_{jk}(H)}\right) \times 100. \tag{12}$$

3.4. The effect of carbon price on volatility spillovers

Next, we build an Ordinary Least Squares (OLS) regression model to analyze the relationship between carbon price and the volatility spillovers across the Nord Pool market. Other potential effects on volatility spillovers are controlled, namely, natural gas price and oil price. Since gas and crude oil prices are often highly correlated with carbon and electricity prices (Aatola et al., 2013; Chang et al., 2018; Duan et al., 2021), we control the potential effect on volatility spillovers in the Nord Pool market. Eq. (13) provides a straightforward approach to estimate the impacts of these independent variables on the dependent variable, TCI. The linearity and additive nature of the model align well with the OLS estimation framework.

$$y_t = \alpha + \beta_1 Carbon_t + \beta_2 Gas_t + \beta_1 Oil_t + \upsilon_t, \tag{13}$$

y_t denotes the total connectedness index (TCI) as calculated in Eq. (8). The TCI represents the cumulative effect of all the shocks, while the numerator illustrates the cumulative effect of a shock in variable n. $Carbon_t$ denotes the European Union Allowances spot prices, under the European emission trading scheme (EU ETS). υ_t denotes the error term in the regression model.

4. Data

We first examine price volatility and its spillover effects across Nordic markets. The considered markets are in four countries, with 12 bidding areas, which are Denmark (DK1-Western Denmark, DK2-Eastern Denmark), Norway (NO1-Oslo, NO2-Kristiansand, NO3-Trondheim, NO4-Tromsø, NO5-Bergen), Sweden (SE1-Lulea, SE2-Sundsvall, SE3-Stockholm, SE4-Malmo), and Finland. We use a rich sample of 107,352 hourly price data for each region, for the period 1 January 2010 to 31 March 2022, collected from Nord Pool.[3] The carbon, oil, and gas data are obtained from Bloomberg. All prices are quoted in EUR/MWh and are aligned with the time zones.

Uribe et al. (2020) identified an at-least-80% correlation between the prices of each area per country (Denmark, Sweden, and Norway), hence restricted their analysis to a single area and their sample range (2013–2018) is shorter than our sample. Electricity prices in our sample period may have different characteristics, so we first perform correlation tests across bidding areas within individual countries. The correlations between the hourly prices in areas of Denmark, Norway, and Sweden are 83, 66 (average), and 77% (average), respectively.[4] Specifically, DK1 and DK2 are highly correlated, so we calculate the average hourly price as a proxy of price in Denmark. Similarly, we average four prices across

[3] Intraday electricity prices are obtained from Nord Pool Elspot (Day-ahead markets) and Elbas (Intraday markets), https://www.nordpoolgroup.com/services/power-market-data-services/.

[4] Tables for correlation tests can be found in Tables A2-A4 in Appendix A.

Sweden as a proxy for the Swedish electricity price. [5]

For Norway, the price difference between southern and northern/central Norway is rather large, due to (i) low water reservoir in southern Norway, (ii) southern Norway has exported large amounts of energy to the continent, resulting in the supply being unable to meet demand, and (iii) the low transmission capacity from the north to the south. A price bottleneck as well as the differences appeared. Hence, we average the NO1, NO2, and NO5 (which are 98% correlated), and NO3 and NO4 (which are 97% correlated) as two representatives of the Norwegian (southern and northern) prices, respectively. In sum, as an extension to the literature of Nordic market integration (e.g., Uribe et al., 2020), we use five regional wholesale prices in the following model.

Table 2 presents the descriptive statistics of the calculated prices for the five areas – Denmark, Finland, Norway South, Norway North, and Sweden.

Daily realised volatilities (RV) are estimated based on the hourly electricity spot price. Following Frömmel et al. (2014), the realised variance is defined as the summation of the squared price changes over day t (see, e.g., Andersen et al., 2001; Do et al., 2020). Hence, the RV is defined as Eq. (14):

$$RV_t = \sqrt{\sum\nolimits_{j-1}^{M} r_{t,i}^2}, \mathrm{i} = 1, \ldots \mathrm{M}, \mathrm{t} = 1, \ldots, \mathrm{T}, \tag{14}$$

where $r_{t,i}$ denotes the log price change from hour i-1 to i on day t. The sampling frequency is 1-h and M = 24 in our case. Table 3 displays the descriptive statistics of daily volatilities of five areas. Fig. 1 plots the daily volatilities of the five market areas studied. As shown in Table 3 and Fig. 1, price volatility in Norway is generally lower than in the other three countries, while volatility in Denmark is the highest. Around 95% of Norway's electricity generation is from hydropower, and this has given Norway a stable access to inexpensive clean energy. However, for electricity Denmark relies largely on wind power, which is a highly intermittent energy resource and easily affected by weather conditions; hence, higher volatility is expected. All five series are tested stationary, by the Augmented Dickey Fuller test (Dickey and Fuller, 1979).

5. Results

In this section we report the results of empirical analysis by the methods presented in Section 3.3. In the following empirical model, we use fourth-order VARs ($p = 4$) (selected by Schwarz information criterion), with 10-step-ahead forecasts[6] (H = 10). We define the total connectedness index (TCI) by summing all non-diagonal elements of the generalized variance matrix. We define that if this TCI rises, so does network member dependency, therefore higher market risk. On the other hand, if the TCI decreases then the dependence between the members decreases and in turn the market risk decreases.

5.1. Time-varying parameter – vector autoregressive model estimation

5.1.1. Total connectedness index

This section reports the results by the TVP-VAR method. The outcomes corresponding to methodology provided in Sections 3.2 and 3.3 are summarized below. Table 4 presents the averaged spillover effects among the markets, estimated by TVP-VAR model. Figs. 2–7 present dynamic total volatility connectedness, net volatility spillover connectedness, and net pairwise volatility spillovers, estimated by both methods, respectively.

[5] Note that series of SE1- Lulea and SE2- Sundsvall have 98,315 identical hourly prices, hence the correlation between these two is almost equal to 1.

[6] A difference choice of lags, lag = 4, lag = 5, lag = 6, lag = 7, lag = 8 is reported in the Appendix B (see Figure B1). A different choice of forecasting horizon, H = 20, and H = 30, is assessed in Appendix B (see Figure B2). Following most of the literature (e.g., Yilmaz, 2009), we use 10-step-ahead horizon in the main text.

The main diagonal of Table 4 shows own-variance shares of shocks, while the off-diagonal elements reflect the interaction across five markets. The number in the bottom right corner represents the Total Connectedness Index (TCI) of the system. The average volatility TCI is 52.4%, indicating that 52.4% of future volatility in Nord Pool is attributed to volatility shocks spreading across the markets. The internal cross-contribution due to individual shocks is the major driver of future performance across five regions in Nord Pool. Except for Denmark, all the "From Others" directional spillovers (Finland, Norway South, Norway North, and Sweden) are larger than 50%. The largest value, 60.7%, is for Sweden, which means that the electricity price in Sweden bears the largest shocks from other markets, while the Danish electricity market receives on average the smallest shocks, 39.9%, from other markets in the system. As for volatility spillover "To Others," Sweden transmitted 77.5% of shocks to the system while Denmark transmitted 28.8%. The last row of Table 4, "Net Total," shows Sweden was a net transmitter to the system, at 16.8% of volatility spillovers, while the other four prices, as volatility spillover receivers, show negative values. Denmark as a net spillover receiver, bore 11.1% volatility spillovers from the system.

Ma et al. (2022) reported a 44.2% static volatility spillover in the European electricity market, which is lower than our result of volatility spillovers in Nord Pool. Their study included, for instance, United Kingdom, France, Poland, Nord Pool, etc., electricity day-ahead markets. The lower volatility connectedness is explained by insufficient grid interconnections across Europe, while Nord Pool is an integrated market with larger non-local risks transmitted by other markets. Ma et al. (2022) concluded that Denmark received the largest (40.5%) shocks from the system among countries in the Nord Pool. Their result differs from ours, where Denmark (Sweden) received the smallest (largest) shocks from the Nord Pool. In their study, Denmark and Finland are both net shock receivers while Norway and Sweden are net shock transmitters. In our study only Sweden is a shock transmitter.

In most previous studies, the evolution of price and volatility spillovers over time in electricity spot markets is attributed to changes in physical conditions that induce supply and demand shocks. The extent of price integration across European electricity markets is proved to be determined by market-specific factors and shocks in the short term, such as congestion (interconnector capacity) and extreme weather, surges in demand, and changes in electricity market structure in the long run, such as changes in renewable energy shares, total generation capacity, and market reforms, as well as external shocks from the financial market, geopolitical events, etc. (Frömmel et al., 2014; Han et al., 2020; Kyritsis et al., 2017; Chuliá et al., 2019). Hence, we plot the dynamic volatility spillover evolutions to relate to the spillover changes to specific market events and policies (see Fig. 2).

Fig. 2 shows that the dynamic of the TCI fluctuates significantly, between 20.2% and 79.6%, which confirms the necessity of using the TVP-VAR. Significant fluctuations of the TCI correspond to a series of local and global events: the transition of EU ETS from Phase II to Phase III in 2012, the European debt crisis in 2012, the crude oil crisis of mid-2014 to 2015, the surge in the EU emission allowances price in 2018, market coupling of the GB-Irish market in 2018, and the COVID-19 pandemic.

Specifically, we observe that the first plunge of the TCI happened in the second half of 2012 from July to September, falling from 65.2% to 24.8%, and returned to around 55% in November. Intuitively, the fluctuation is contributed by the European debt crisis and the EU ETS transition, which was transiting from Phase II (2008–2012) to Phase III (2013−2020) during the second half of 2012. Due to a large surplus of allowances from phase two, the demand for ETS allowances decreased, which caused a fall in EUA prices, from 30 Euro/emission allowance to 5 Euro/emission allowance. The TCI is found to respond to this event, reflecting a lower market risk when there was a surplus of emission allowances.

We observed a slight trend of increase in 2018, followed by a large spike in September 2018. Upon investigation, in September 2018, the

Table 2
Descriptive statistics – Hourly price of 5 study areas.

	Mean	Minimum	Maximum	Std.Dev	Skewness	Kurtosis	Obs
Denmark	43.06	−200.00	1052.50	36.65	6.24	78.36	107,339
Finland	43.18	−1.73	1400.11	31.46	9.52	228.41	107,339
Norway South	38.40	−0.88	667.92	28.80	3.93	34.48	107,339
Norway North	34.01	−0.01	1400.11	21.12	16.20	810.27	107,339
Sweden	38.11	−1.97	1400.11	24.37	11.68	459.67	107,339

Source: Own elaboration based on data from Nord Pool. Note: Sample includes electricity wholesale prices series from Denmark, Finland, Norway, and Sweden from January 1, 2010 - March 31, 2022.

Table 3
Descriptive statistics – Daily volatilities of five study areas.

	Mean	Minimum	Maximum	Std.Dev	Skewness	Kurtosis	ADF	Obs
Denmark	0.758	0.039	10.726	1.013	4.649	26.917	−24.69***	4473
Finland	0.668	0.029	6.558	0.625	2.533	10.552	−14.65***	4473
Norway South	0.222	0.007	4.150	0.298	4.707	34.438	−22.83***	4473
Norway North	0.261	0.014	5.065	0.316	4.673	36.287	−19.62***	4473
Sweden	0.459	0.018	6.234	0.515	3.530	19.039	−17.80***	4473

Source: Own elaboration based on data from Nord Pool. Note: Daily realised volatility is measured by Eq. (14) above. The electricity daily volatilities from five regions – Denmark, Finland, Norway South, Norway North, and Sweden from January 1, 2010, to March 31, 2022, include 4473 daily observations. The hypothesis of the Augmented Dickey Fuller (ADF) test is H_0: non-stationary against H_1: stationary. The lag length is determined by BIC criterion. * denotes significance at 10% level, ** denotes significance at 5% level, *** denotes significance at 1% level.

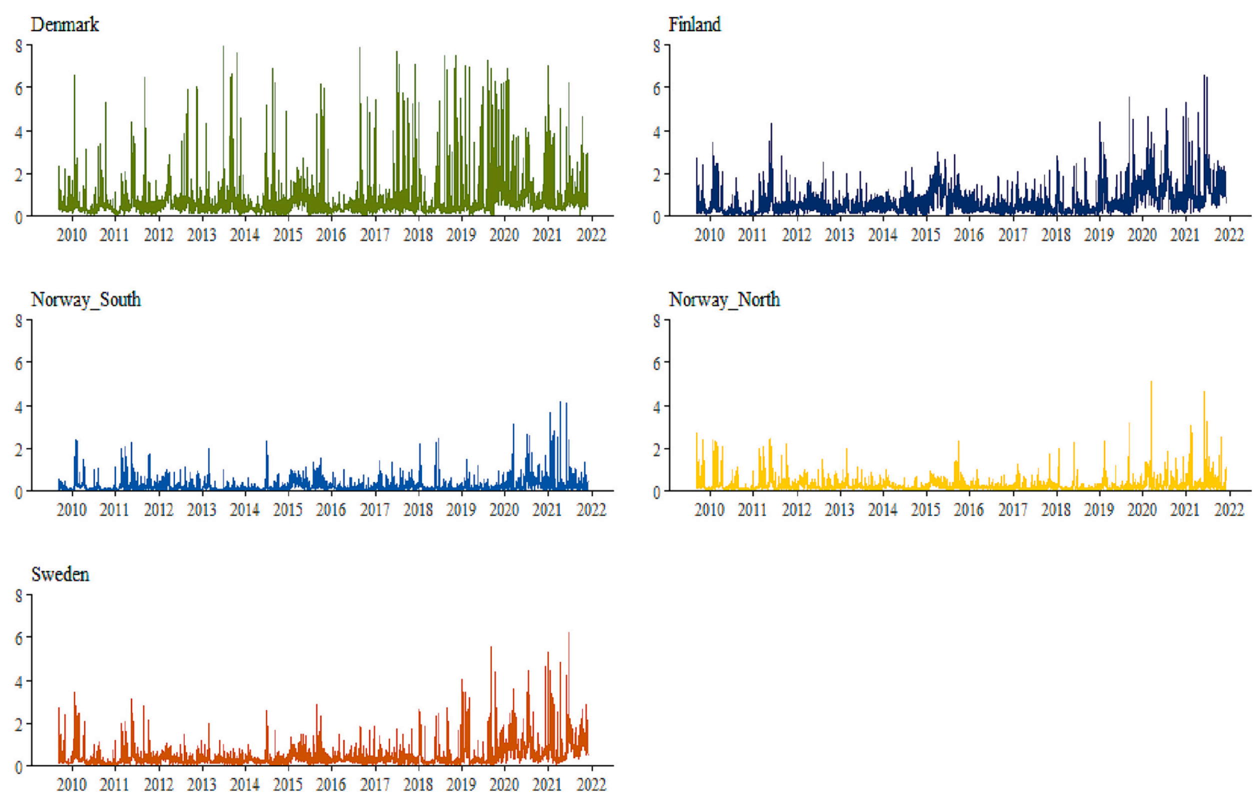

Fig. 1. Plots of daily volatilities of five study areas.
Source: Own elaboration based on data from Nord Pool.
Note: Daily realised volatility is measured by Eq. (10) above. The electricity daily volatilities from five regions – Denmark, Finland, Norway South, Norway North, and Sweden cover the period January 1, 2010 – March 31, 2022, including 4473 daily observations.

Nord Pool launched the GB-Ireland power market coupling, having played a key role in ensuring the islands of Ireland's coupling with the rest of Europe. The joining of a new market typically induced more competition in Nord Pool, as well as in the GB-Ireland market, hence the rising market risk in the Nord Pool.

The outburst of COVID-19 in the spring of 2020 increased the risk level among Nordic electricity markets; TCI surged from 27.2% in April 2020 to 73.5% in October 2021. Moreover, there was an increase in TCI from mid-2020 to the end of 2021. In the post-COVID-19 economic recovery period, prices of natural gas, electricity, and carbon steeply

Table 4
Average connectedness matrix of the system – estimated by TVP-VAR.

	Denmark	Finland	Norway South	Norway North	Sweden	From Others
Denmark	60.13	11.33	7.02	6.48	15.04	39.87
Finland	7.81	45.21	10.82	11.45	24.70	54.79
Norway South	6.21	11.38	47.04	18.02	17.35	52.96
Norway North	5.35	11.15	16.77	46.30	20.41	53.70
Sweden	9.41	20.92	13.35	17.04	39.28	60.72
To Others	28.78	54.78	47.97	53.00	77.52	**TCI =**
Net Total	−11.10	−0.01	−4.99	−0.70	16.80	**52.41**

Source: This spillover table is generated from 10-step-ahead generalized VAR forecast error variance decomposition estimated from TVP-VAR. The nm^{th} entry estimates the fraction of 10-step-ahead error variance in forecasting market n due to exogenous shocks to market m (the spillover from market m to market i: d^{J}_{nm}). According to Eq. 11 ($TO_{n\rightarrow m,t}(H)$ - $FROM_{n\leftarrow m,t}(H)$), we obtain the net total directional connectedness,$NET_{nm,t}$.

increased when energy demand rose. The surge in demand was not matched by increased supplies, and the importing regions competed with one another in the global energy market.

The economic consequences of an electricity supply shortage worsened as the 2021 winter arrived, confirming that COVID-19 and the post-COVID economic recovery increased market risk. However, from the end of 2021, Nordic electricity recovered from the pandemic as wind generation rapidly rose there, and Norway had more rainfall, so that eventually some of its reservoirs reached their highest point since 2015 (Matt, 2022). There was no acute risk of shortages or supply disruptions in the electricity supply in the four countries when 2022 began.

5.1.2. Net directional spillover analysis

To investigate the directional dynamic spillovers for each market in the Nord Pool, Fig. 3 plots the net spillovers with regard to Eq. (11) in Section 3.3 ($NET_{nm,t} = TO_{n\rightarrow m,t}(H)$- $FROM_{n\leftarrow m,t}(H)$) and corresponding to the last row of Table 4, "Net Total." Fig. 4 plots the net pairwise volatility spillover that corresponds to Eq. (12) in Section 3.3. The net pairwise volatility spillover between market n and m is the difference between gross volatility shocks transmitted from market n to m and gross volatility shocks transmitted from m to n (Diebold and Yilmaz, 2012).

We start with Denmark. Fig. 3 indicates Denmark is net volatility spillover receiver over the sample, except for relatively short episodes, for example, briefly being a volatility transmitter at the end of 2016. This is consistent with the averaged results in Table 4, which shows Denmark is the largest receiver of volatility spillover. Fig. 4 further indicates Sweden as a net transmitter of shocks to Denmark (Fig. 3, Denmark-Sweden). From 2010 to early 2014, Denmark is net spillover receiver shocks from Finland, Norway south, Norway north, and Sweden. There are, however, exceptions to when Denmark is a volatility spillover transmitter. For instance, it transmitted shocks to Finland in 2016 and to Southern Norway at the end of 2016. Denmark has the largest share of wind power in generation mix and the effect of intermittent wind power on price volatility is higher. The country imported hydropower from Norway and Sweden, hence the evidence of shock receiver holds reasonably.

The second largest volatility spillover receiver is Southern Norway (Table 4). Southern Norway is an interesting case in Nord Pool as, in the summer of 2022, its water reservoir level became incredibly low and it exported large amounts of electricity to the rest of Europe, resulting in supply and demand unbalance. It is also connected to western Denmark, where the power generation is based on wind while Southern Norway relies on hydropower. Southern Norway benefits from the flexibility of being a hydro producer while being connected to Danish wind power,

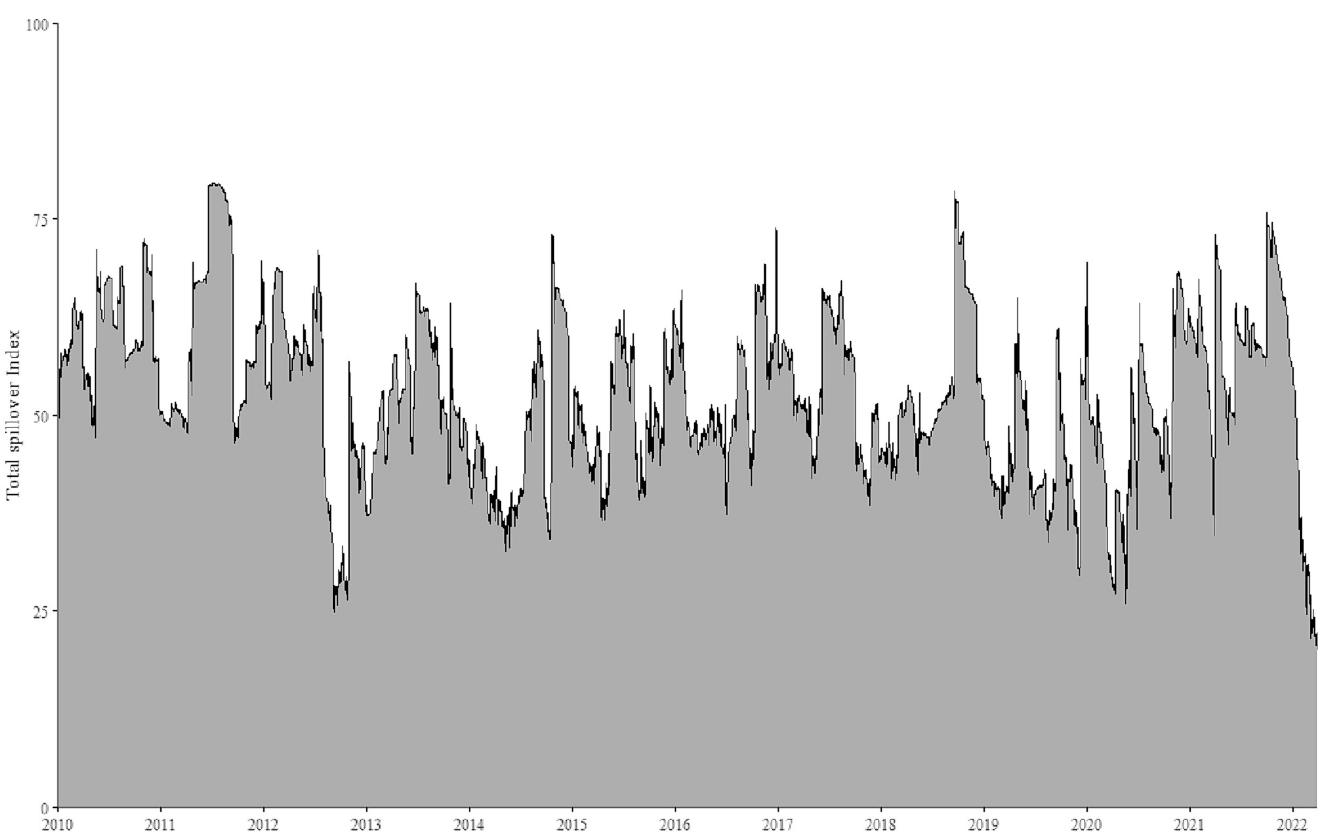

Fig. 2. Dynamic total volatility connectedness – estimated by TVP-VAR.

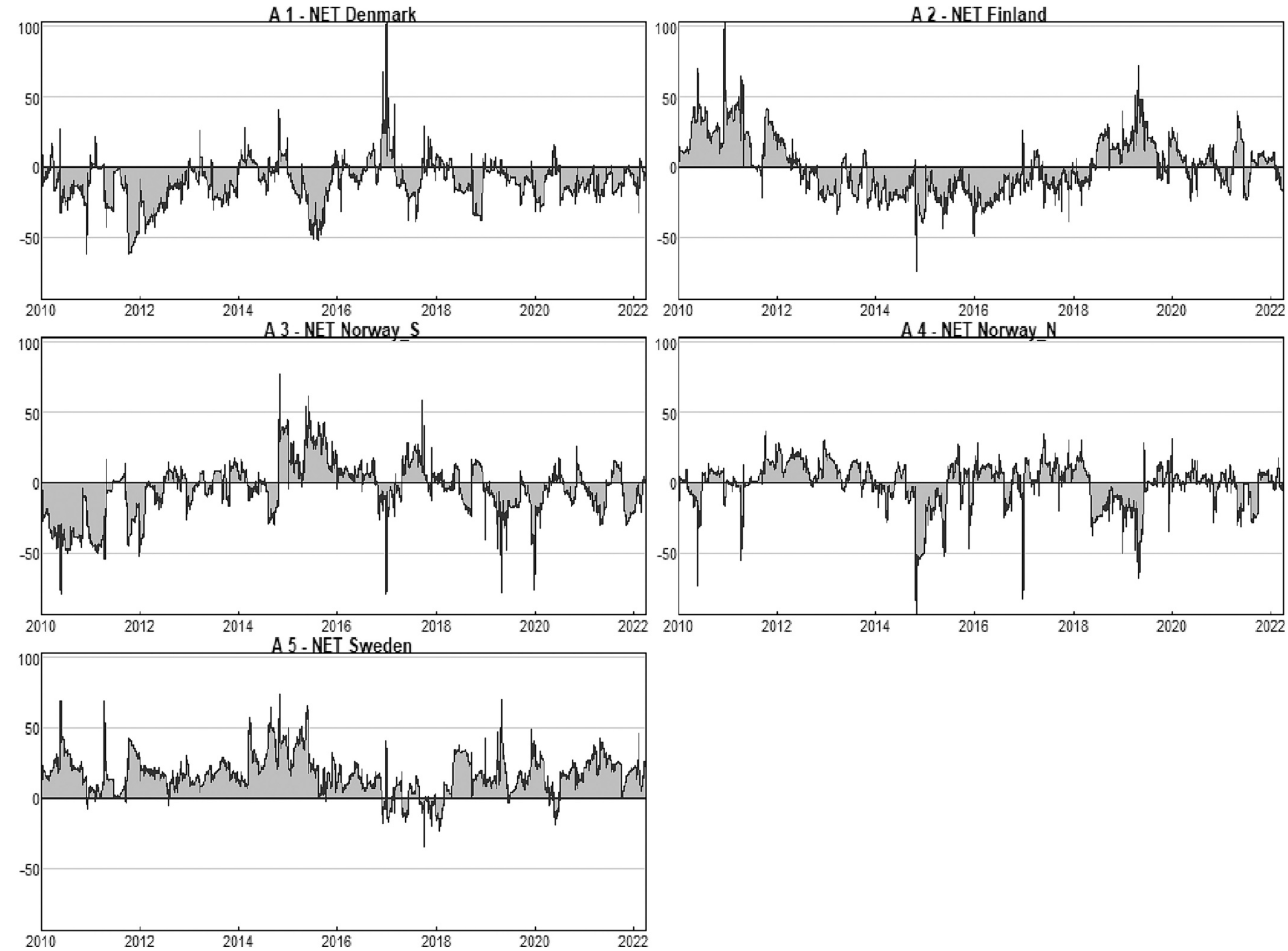

Fig. 3. Net volatility spillovers – estimated by TVP-VAR.

Southern Norway imports wind electricity when the cost of import is lower than the opportunity cost of using own water in the reservoirs. Fig. 3 shows that Southern Norway was a net spillover receiver from 2010 to 2013 and 2016 to 2022.

Northern Norway was a small net receiver of volatility spillover at an aggregated level. As shown in Fig. 3 panel A4, from the second half of 2011 to 2014, Northern Norway was a shock transmitter to the system, as well as during 2015 and 2018. In the rest of the sample period, Northern Norway was a significant shock taker; it received 93.8% volatility from the Nord Pool on 27 Oct 2014, for instance. As for net pairwise spillovers in Fig. 4, Northern Norway was mainly the shock transmitter to Southern Norway from 2010 to 2015 and Finland from 2012 to 2018. In the meantime, net spillovers received by Northern Norway mainly came from Sweden (2010–2015), Southern Norway (2015–2016), and Finland (2019–2020).

Finland is a net volatility spillover transmitter as it received 54.8% spillover effect from the system and transmitted 54.8% to the system (Table 4), showing that Finland is a net break-even, with receiving and transmitting just one hundredth of a percentage point apart. The dynamic plots of net spillovers in Fig. 3 and net pairwise spillovers in Fig. 4 indicate that the net position changed through the sample. Finland was a net transmitter between January 2010 and June 2012, mainly to Norway, then it was a net spillover receiver from June 2012 to June 2018, mainly from Sweden and Norway. The view is slightly different from Uribe et al. (2020), who concluded that Finland received volatility shocks from Norway during 2013 and 2015. Since 2018, Finland went back to being a spillover transmitter to Denmark and Norway; however, the effect was lower than that of 2010 to 2012. It is noteworthy that Sweden persistently transmits net spillover to Finland throughout the sample likely due to being a net importer of electricity from Sweden.

5.2. Rolling window VAR estimation

This section follows the Diebold and Yilmaz (2012)'s rolling window five-variable VAR model to estimate the volatility connectedness in Nord Pool markets. According to the Schwarz information criterion (SIC), the optimal lag length is set as $p = 4$. Horizon is set to 10-step-ahead forecasts and rolling window size 200.[7]

5.2.1. Total connectedness index estimated by RW-VAR

Table 5 shows the variance decomposition matrix. The main diagonal of Table 5 shows own-variance shares of shocks, while the off-diagonal elements reflect the interaction across five markets. Table 5 shows that the total connectedness index (TCI) is 50.9%, slightly lower than the TCI estimated by TVP-VAR. At aggregate level, Sweden transmits the largest, 11%, net volatility spillovers to the system. The Swedish electricity market produces and receives the most volatility spillovers to other markets (72.4%) and from other markets (61.4%) at an aggregated

[7] A difference choice of rolling window size is reported in the robustness check in Appendix B (Figure B3).

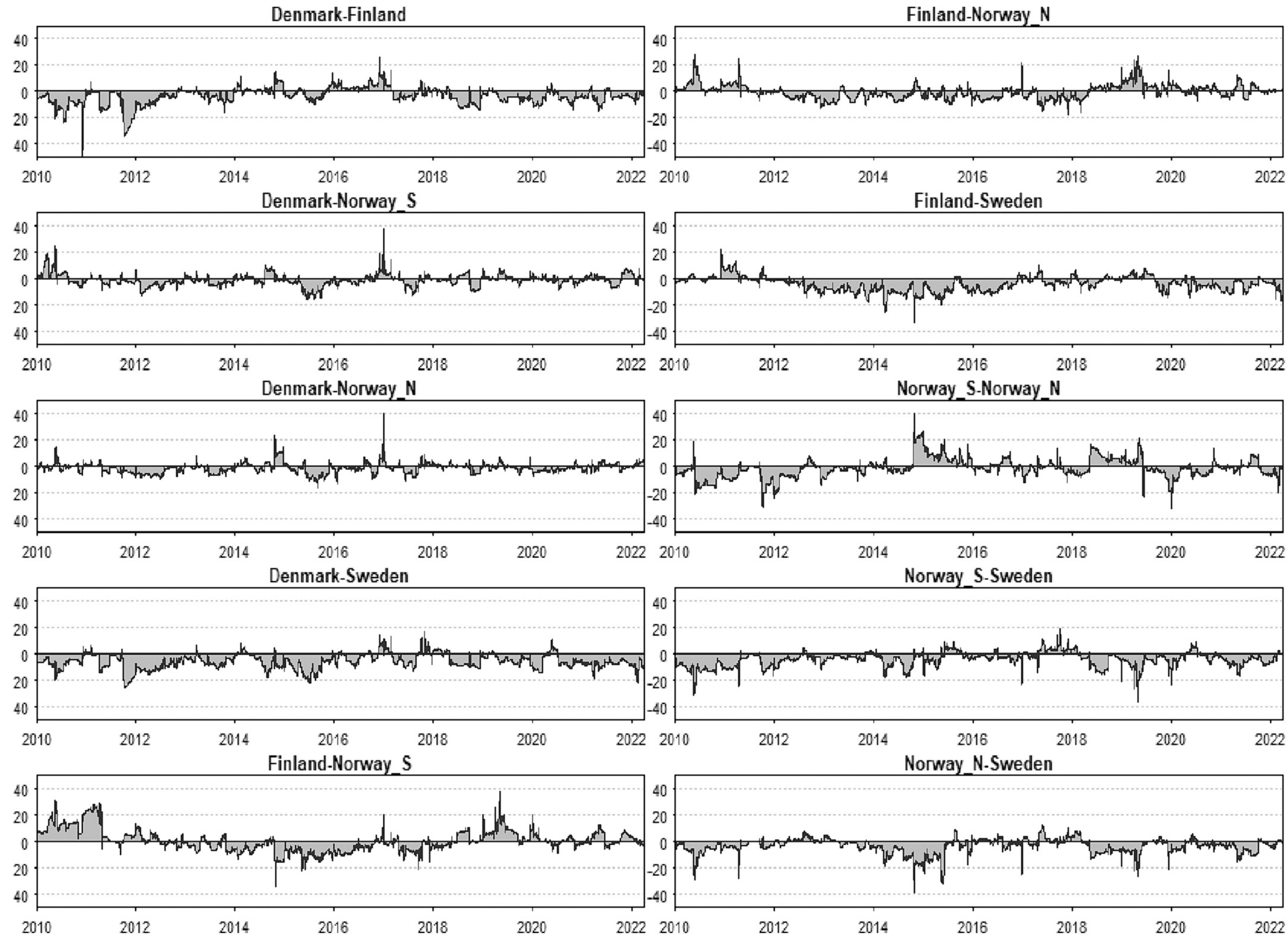

Fig. 4. Net pairwise volatility spillovers - estimated by TVP-VAR.

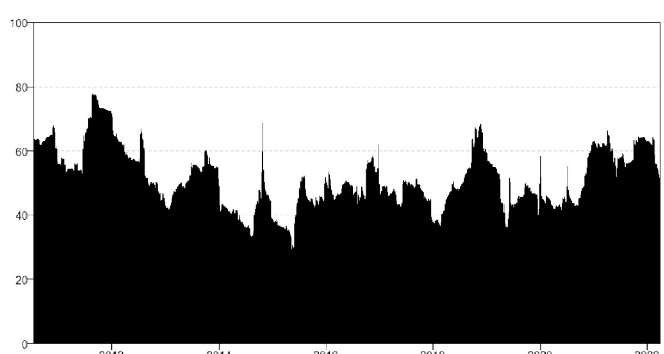

Fig. 5. Dynamic total volatility connectedness – estimated by 200 days rolling window DY2012.

level. Compared to the TVP-VAR estimation, Sweden transmitted 5.1% less net spillover to the system in an RW-VAR. Danish electricity market produces and receives the least volatility spillover from (33.6%) and to (22.3%) the system; the view is consistent with the TVP-VAR measure.

In terms of net volatility spillover, Denmark is a net receiver (−11.3%). The estimated value is almost the same as the TVP-VAR's result for Denmark. Southern Norway receives 51.6% volatility spillover from other markets and produces 51.1% volatility spillovers to the system, making it a net volatility spillover receiver in an averaged measure (−0.43%). However, Northern Norway is classified as a net volatility spillover producer; this result differs from the estimate by TVP-VAR, which shows Northern Norway is a net receiver of spillover. Finland receives the second most significant value of spillover, 54.5% from the other four markets, and has the second largest net volatility spillover in an aggregated level (−3.4%).

Fig. 5 presents the dynamic total connectedness measures of the 200 days rolling-window VAR approach. We observe that the pattern of the TCI is less volatile than that estimated by the TVP-VAR. TCI fluctuates between 77.7% and 27.1%.

Two major patterns are evident from the time variations: First, a trend of decrease in TCI is observed from July 2010 to May 2015. It shows, in general, the volatility spillovers within Nord Pool gradually decreased after the 2008–2010 financial crisis and the 2010–2012 European debt crisis. Three spikes were found during this period. The first (77.7%) was observed on 25 August 2011, following the European debt crisis. The second, reaching 60.3% on 1 October 2013, appeared after a large fall in price of emission allowances under the EU ETS. The fall in emission prices promoted thermal production of fossil fuel resources and affected the value of hydropower negatively. Since thermal power is the opportunity cost of flexible hydropower, the decline in emission prices drove the power prices down. It raised the short-term volatility spillover level in the Nord Pool (NordREG, 2014). The third spike appears on 26 October 2014, reaching 68.9%, corresponding to the plunge in crude oil prices during 2014. Intuitively, we can state that the dependence on the Nord Pool wholesale electricity market increased when the crude oil market price plunged, but TCI decreased to 27% on 14 May 2015 after the crisis had eased.

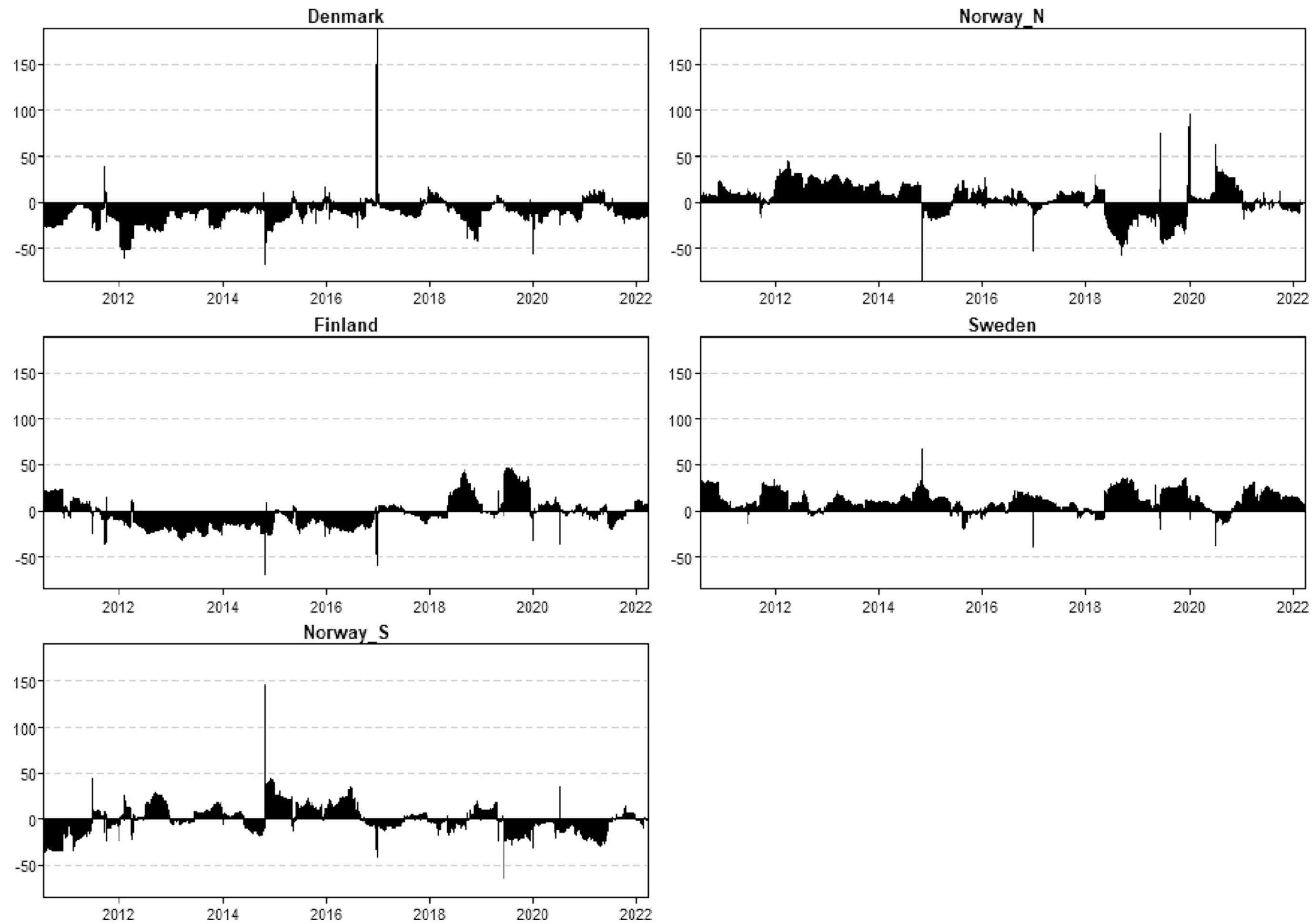

Fig. 6. Net volatility spillovers – estimated by 200 days rolling window.

Second, during the second half of the sample, the TCI mainly fluctuates around 40–60%, with a few exclusions. The launch of the GB-Ireland market coupling in September indeed raised the spillover effect in Nord Pool. We observed a steep increase from September 2018 and a spike of 68.3% on 22 November 2018. Again, the COVID-19 outburst did not affect the volatility spillover effects in Nord Pool immediately but raised the level of spillovers from September 2020, which peaked at 66.1% in April 2021, during the post-pandemic economy recovery.

5.2.2. Net directional spillover analysis

Next, we investigate the net spillover for each market using RW-VAR connectedness. Fig. 6 plots the net volatility spillover in the Nord Pool network with regard to Eq. (11) in Section 3.3 ($NET_{nm,t} = TO_{n\rightarrow m,t}(H)$-$FROM_{n\leftarrow m,t}(H)$), and corresponding to the last row of Table 5, "Net Total." Fig. 7 thus plots the net pairwise volatility spillover. We find:

Denmark receives net volatility spillover from the system throughout the sample period. The volatility spillover mostly comes from Sweden and Southern Norway. As for the net volatility transmitter, Sweden is a net spillover producer to the system, especially to Denmark and Finland. However, the net pairwise volatility spillover between Sweden and Northern Norway changes from time to time. Between 2010 and 2018, Northern Norway was the main contributor of the volatility spillovers that Sweden received; however, from 2018 to 2020 Sweden transmitted relatively large volatility spillovers to Northern Norway.

For Finland, the overall evolution pattern is similar to the TCI pattern measured by TVP-VAR. Finland was a net volatility transmitter from July 2010 to December 2011 and from August 2018 to January 2019. However, the position of a net transmitter was less powerful than that estimated by TVP-VAR from 2010 to 2011. For instance, the net volatility spillover transmitted by Finland to the system reached 66% in May 2010 (by TVP-VAR); however, due to the loss of sample in the rolling window, we cannot observe that value in May using the RW-VAR.

5.3. Effect of carbon price on volatility spillovers

The power industry is the first regulated sector in the EU ETS and is the sector with the highest CO_2 emissions and the most significant carbon trading participant. Higher carbon prices encourage investment in clean power generation and less carbon-intensive technologies, whereas lower carbon prices revive the attractiveness of fossil fuel power generation. Electricity price volatility and spillover effects across the integrated electricity market depend on the EU's carbon price change.

This section analyses the impact of the carbon price on the volatility of connectedness in Nord Pool wholesale electricity markets. Applying Eq. (13) in Section 3.4, Table 6 reports the result of carbon price impact on volatility spillover in Nord Pool electricity markets. Following the literature, electricity prices can easily be affected by other energy prices, such as gas and crude oil prices; hence we control the gas and oil prices in the model. All data are used on a monthly frequency, from January 2010 to March 2022. The rolling-window estimation causes a loss in observation in the first window. We report the results from both 200-days rolling window VAR and 100-days rolling window VAR.

The results show that the carbon price does not have a significant impact on TCI estimated by TVP-VAR and 100-days rolling window VAR. However, the carbon price has 5% significant impact on TCI

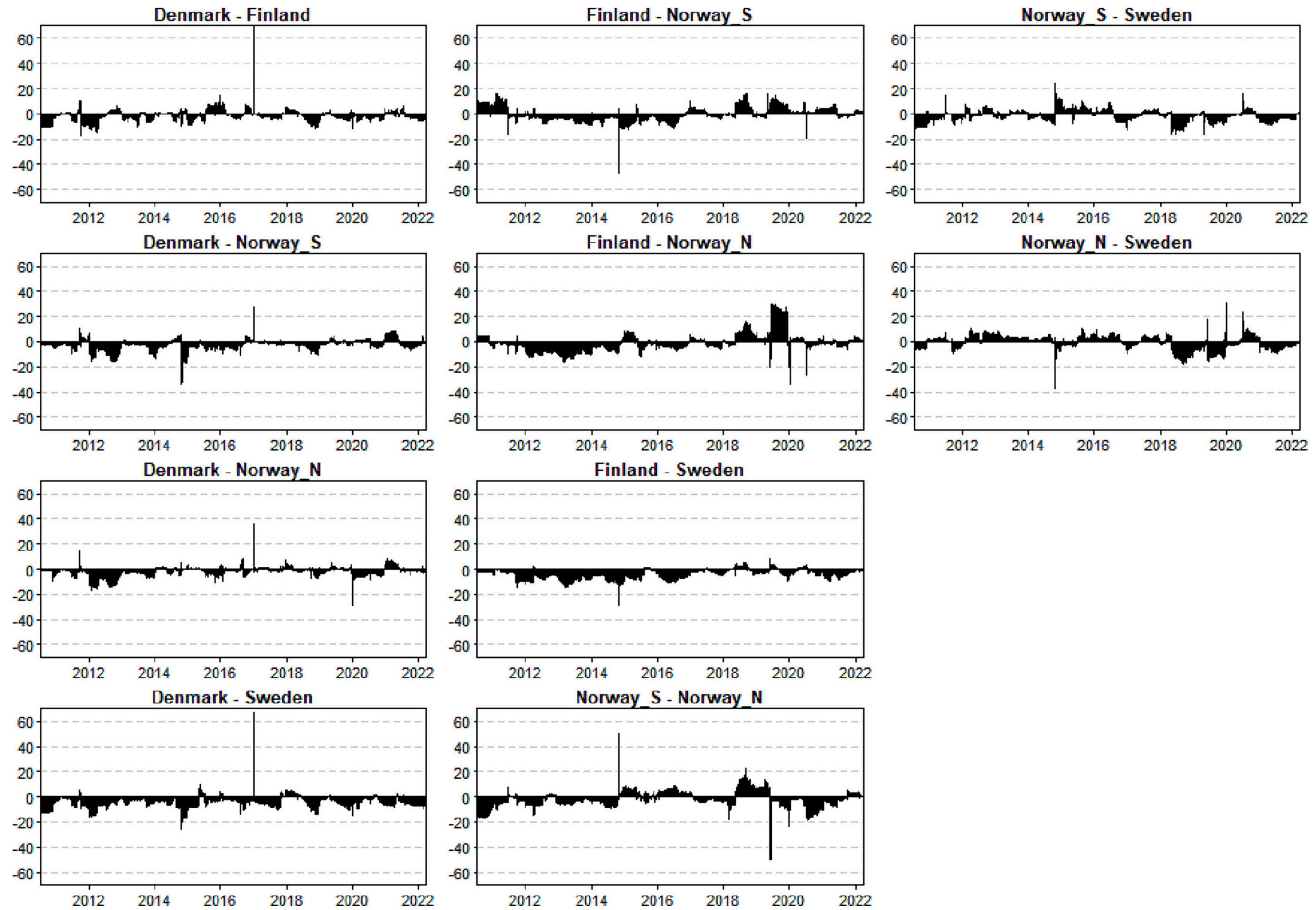

Fig. 7. Net pairwise volatility spillover – estimated by 200 days rolling window.

Table 5
Average connectedness matrix of the system – estimated by 200-days rolling window.

	Denmark	Finland	Norway South	Norway North	Sweden	From Others
Denmark	66.37	8.24	7.5	6.12	11.77	33.63
Finland	6.26	45.53	10.85	13.43	23.93	54.47
Norway South	4.67	10.64	48.45	19.25	16.99	51.55
Norway North	4.06	12.35	17.44	46.46	19.68	53.54
Sweden	7.31	19.85	15.32	18.89	38.62	61.38
To Others	22.31	51.08	51.12	57.69	72.38	**TCI =**
Net Total	−11.32	−3.39	−0.43	4.15	10.99	**50.92**

Source: This spillover table is generated using 10-step-ahead generalized VAR forecast error variance decomposition estimated from 200 days rolling window VAR. The nm^{th} entry estimates the fraction of 10-step-ahead error variance in forecasting market n due to exogenous shocks to market m (the spillover from market m to market i: d^{J}_{nm}). According to Eq. 11 ($TO_{n\rightarrow m,t}(H)$ - $FROM_{n\leftarrow m,t}(H)$), we obtain the net total directional connectedness,$NET_{nm,t}$.

estimated by 200-days rolling window VAR. We find a positive relationship between carbon price and total volatility spillovers estimated by RW-VAR. Meanwhile the crude oil price also has positive effect on TCI estimated by the longer 200-days rolling window VAR, significance in 1% level. The insignificant effect of price of gas on volatility spillover can be explained by the low share of gas power in the Nord Pool market.

Table 6
Impact of carbon price on volatility spillovers in Nord Pool.

	Dependent Variable		
	TCI (TVP)	TCI (RW-200)	TCI (RW-100)
Carbon	0.175	0.164 **	1.309
	(1.033)	(0.058)	(1.025)
Gas	3.603	−0.031	1.626
	(2.192)	(0.150)	(2.173)
Oil	−1.594	0.100 ***	4.963
	(3.197)	(0.029)	(3.168)
Constant	51.045 ***	39.269***	26.515*
	(11.624)	(2.373)	(11.519)
Observations	147	141	144
R^2	0.028	0.206	0.081
Adjusted R^2	0.008	0.189	0.061
Residual Sta.Err	9.659	8.274	9.569
	(df = 143)	(df = 137)	(df = 140)
F statistics	1.381	11.860***	4.090**

Note: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The table presents the estimates of the impacts of carbon prices on total volatility connectedness index across five Nord Pool wholesale electricity prices. The dependent variables are disaggregated monthly total volatility spillovers estimated from both TVP-VAR and RW-VAR. Standard error is reported in the parentheses.

6. Additional analysis

6.1. Model with representative prices

We now select a representative price for each country, considering one bidding zone per country with the exception of Norway, which will have two due to significant price differentials between its northern and southern regions caused by congestion issues. Our focus in selecting representative prices lies in the direction of electricity capacity flows between countries, aligning with our study's theme on spillover effects in the Nord Pool markets.

In Denmark, the DK1 bidding zone interacts with Norway's NO1 and Sweden's SE3, engaging with two countries (whereas DK2 only interacts with Sweden's SE4), leading us to select DK1 as Denmark's representative price due to its broader cross-border exchange. In Sweden, the SE3 zone stands out as the most active and interconnected region, with transmissions to and from other Swedish zones (SE2 and SE4), Finland, Norway's NO1, and Denmark's DK2. Consequently, we selected SE3 as Sweden's representative price. In Norway, we have discussed the price difference between the north and south in section 4. For the northern zones, NO3 was chosen for its connections with SE2 and the southern Norwegian zones. In southern Norway, NO1 was preferred over NO5 and NO2 because it has direct transmissions with NO3 and SE3 (actively connected to Finland and Denmark), and its transmission volume with Sweden surpasses that of NO2. Table 7 shows the descriptive statistics of both the original hourly prices and daily volatilities of 5 representative bidding zones in Nord Pool. Table 8 presents the stationary tests for the volatility series of the five regions.

To further identify the long-memory characteristics of data, which is crucial for building accurate models, we employ the fractional differencing method aimed at estimating the fractional differencing parameter. This parameter critically reflects the memory characteristics of a time series. Theoretically, the fractional differencing model captures the long memory feature of a time series using a parameter d, known as the fractional differencing parameter or the order of integration. When d is: 0, the series is a regular stationary series. When it is between (0, 0.5), the series exhibits long memory but is still stationary. When it is exactly 0.5, the series behaves like a random walk. When it is between (0.5, 1), the series has long memory and is non-stationary, but not a random walk. Lastly, when d is 1 or greater, the series requires differencing to become stationary.[8]

The results show that all five chosen volatility series exhibit long memory, but all are still stationary, demonstrating that these series are stationary over time. This stationarity is further supported by the results of the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Zivot-Andrews tests results shown in Table 8, each of which confirms the stationarity of the series. Such findings ensure the appropriateness of our model selection, underpinning the reliability of our analytical framework. By choosing representative prices as part of our robustness check, we aim to offer a more robust approach to examining the dynamics of price volatility and spillover effects across international electricity markets.

We then observe that the TCI index in Table 9 stands at 50.40%, which is similar to the results in Table 4 – TCI examined to be 52.41%, indicating a high degree of consistency. Specifically, in Table 9, Sweden continues to emerge as the primary transmitter and receiver of volatility shocks, with Denmark exhibiting the lowest magnitude of such shocks. These results further reinforce the robustness of our use of average price in the main text.

In sum, by choosing representative prices as part of our robustness check, we aim to offer a more nuanced approach to examining the dynamics of price volatility and spillover effects across international electricity markets. This method allows us to more accurately capture the characteristics of regional electricity trading, thereby providing deeper insights into the complex interactions within the Nordic electricity market.

6.2. Whole system modelling - realised variances and realised covariances

6.2.1. A time-varying parameter – vector autoregressive model estimation analysis

This subsection aims to integrate covariances into the assessment of variance spillovers. To achieve this objective, we derive our measures of variance using high-frequency intra-day data. This enables us to acquire precise estimations of realised covariance matrices, which we dynamically model on a daily basis. Following Chanatásig-Niza et al. (2022) and Fengler and Gisler (2015), we first compute the returns of the hourly prices as the log return of the hourly prices, then we estimate the realised daily variation and covariation using the covariance matrix definition, so:

$$ReCov = \sum_{i=1}^{m} r_i r_i^{'} = \begin{bmatrix} ReVar_{DK} & ReCov_{DK-FI} & ReCov_{DK-NO\_S} & ReCov_{DK-NO\_N} & ReCov_{DK-SE} \\ \vdots & ReVar_{FI} & ReCov_{FI-NO\_S} & ReCov_{FI-NO\_N} & ReCov_{FI-SE} \\ \vdots & \vdots & ReVar_{NO\_S} & ReCov_{NO\_S-NO\_N} & ReCov_{NO\_S-SE} \\ \vdots & \vdots & \vdots & ReVar_{NO\_N} & ReCov_{NO\_N-SE} \\ ReCov_{SE-DK} & ReCov_{SE-FI} & ReCov_{SE-NO\_S} & \cdots & ReVar_{SE} \end{bmatrix}, \tag{15}$$

Where $r_i = \left(r_{DK,i}, r_{FI,i}, r_{NO_S,i}, r_{NO_N,i}, r_{SE,i}\right)'$ for $i = 1, \ldots, m$, with m being the number of returns in a day. Eq. (15) denotes the covariance matrix, which consists of the realised variance of each market on the diagonal and the realised covariances between the markets on the off-diagonal.

Table 10 shows the descriptive statistics of the realised variances and realised covariances of the five bidding zones. Our stationary tests confirm that all the variance and covariances series are stationary over time.[9] Table 11 and Table 12 shows the spillovers in the variance system and covariances system, respectively. While the total variance spillover among markets is around 50% – which is consistent with previous analyses – the total covariance spillover is >80%. These results not only reinforce the strong interdependence among markets but also highlight the contributing role of covariance to their interdependence. We further employ TVP-VAR to estimate the full system by including all variances and covariances in one model.

We present the overall spillover results in Table 13. To understand the contribution of the variances and covariances to the markets' interdependence, we follow Fengler and Gisler (2015) to calculate *own variance spillovers*, *cross variance spillovers*, *own covariances spillovers,* and *cross covariance spillovers* based on outputs of Table 13 and present the results in Table 14.[10] We observed that the dominant factor contributing

[8] The results are shown in Table A6 in Appendix A.

[9] The results of the fractional differencing tests that aimed at estimating the fractional differencing parameter are shown in Table A7 in Appendix A.

[10] Following Femgler and Gisler (2015), *own variance spillovers* is defined as spillovers among variances, while *cross variance spillovers* is the spillovers from variances to covariances. *Own covariances spillovers,* and *cross covariance spillovers* are defined in a similar vein.

Table 7
Descriptive statistics - hourly prices and daily volatilities of 5 bidding zones in Nord Pool.

Panel A: Hourly prices of five representative bidding zones							
	Mean	Minimum	Maximum	St.Dev.	Skewness	Kurtosis	Obs.
DK1	42.00201	−200	2000	37.58594	10.3154	341.4854	107,339
NO1	38.73736	−1.97	667.92	29.28268	3.871317	33.03959	107,339
NO3	34.72078	−0.01	1400.11	21.38077	15.64688	770.2175	107,339
SE3	39.6184	−1.97	1400.11	30.64654	8.989079	219.0297	107,339
FI	43.18087	−1.73	1400.11	31.45592	9.520567	228.4092	107,339
Panel B: Realised volatilities of five representative bidding zones							
	Mean	Minimum	Maximum	St_Dev	Skewness	Kurtosis	Obs
DK1	0.967756	0.027043	14.04637	1.467855	3.548476	10.53657	4473
NO1	0.250115	0.006893	7.440794	0.353742	6.223166	70.34513	4473
NO3	0.296279	0.018108	5.523101	0.346071	4.601583	33.86149	4473
SE3	0.524679	0.029414	7.042009	0.626638	3.117002	11.34313	4473
FI	0.689955	0.029414	8.278457	0.660805	2.720139	9.74936	4473

Table 8
Unit root tests - daily volatilities of five representative bidding zones.

	ADF	Phillips-Perron	Zivot-Andrews	KPSS	Obs
RV_DK1	−27.0974***	−47.7747***	−37.7341***	0.099463*	4473
RV_NO1	−23.7344***	−41.9727***	−32.6448***	0.266849**	4473
RV_NO3	−18.9978***	−38.1075***	−28.1799***	0.377453**	4473
RV_SE3	−17.232***	−33.6582***	−29.2809***	1.058012***	4473
RV_FI	−14.8974***	−35.1174***	−27.1934***	0.555588***	4473

Source: lag length is determined by BIC criterion. The hypothesis of the Augmented Dickey Fuller (ADF) test is H_0: non-stationary against H_1: stationary. The null hypothesis of the Phillips-Perron (PP) test is that there is a unit root, with the alternative that there is no unit root. In the Zivot-Andrews tests, the null hypothesis is that the series has a unit root with structural break(s) against the alternative hypothesis that they are stationary with break(s). Kwiatkowski– Phillips–Schmidt–Shin (KPSS) tests are used for testing a null hypothesis that an observable time series is stationary around a deterministic trend (i.e. trend-stationary) against the alternative of a unit root. * Denotes significance at 10% level, ** denotes significance at 5% level, *** denotes significance at 1% level.

Table 9
Connectedness matrix of the volatility system – estimated by TVP-VAR model.

	Denmark	Finland	Norway South	Norway North	Sweden	From Others
Denmark	67.58	9.45	7.03	5.15	10.80	32.42
Finland	5.99	45.76	10.41	11.40	26.44	54.24
Norway South	5.62	11.77	47.02	18.23	17.35	52.98
Norway North	3.98	12.38	17.13	45.95	20.57	54.05
Sweden	6.18	22.82	13.19	16.13	41.69	58.31
To Others	21.77	56.41	47.76	50.90	75.16	**TCI = 50.40**
Net Total	−10.65	2.17	−5.21	−3.15	16.85	

Source: This spillover table is generated from 10-step-ahead generalized VAR forecast error variance decomposition estimated from TVP-VAR. Lag = 4 selected by SIC. The nm^{th} entry estimates the fraction of 10-step-ahead error variance in forecasting market n due to exogenous shocks to market m (the spillover from market m to market i: d^{J}_{nm}). According to Eq. 11 ($TO_{n\rightarrow m,t}(H)$ - $FROM_{n\leftarrow m,t}(H)$), we obtain the net total directional connectedness,$NET_{nm,t}$.

to the whole system TCI is the spillover effect from own covariances, accounting for a significant share of 47.9%. By contrast, only 13.62% is explained by own variance spillovers. Chanatásig-Niza et al. (2022) conducted a study that examined the volatility spillover connectedness in Australian electricity markets by considering both variances and covariances as a full system.

Our findings are aligned with Chanatásig-Niza et al. (2022)'s study, as they also observed that the spillover effect from own covariances contributes the most, while own variance spillovers have the smallest share. The findings indicate that there is a mutual reliance between the markets, which is more accurately characterized when considering covariances. This underscores the importance of including covariances in the model and reveals features of strong interdependence in the Nord Pool.

6.2.2. *High dimensional VAR with common factor*

Considering the full system of variances and covariances as in previous analysis, we have a 15-dimensional VAR, which can reasonably be argued as a high-dimensional system. This type of system often requires a model specification that allows for strong cross-sectional dependence. In addition, as Nordic region is tightly geographical and economical linked, its member markets can share common factors that are unobservable. To address this concern in the methodological approach, we conduct a full system (with both variances and covariances) analysis by employing a high-dimensional VAR with common factors (VAR-CF, hereafter) proposed by Miao et al. (2023) to accommodate interconnectedness and temporal co-variability among considered Nordic markets. In a similar spirit of Uddin et al. (2023), we then adapt the connectedness approach proposed by Diebold and Yilmaz (2012) to estimate the overall connectedness matrix, followed by spillover contributions of variances and covariances suggested by Fengler and Gisler

Table 10
Descriptive statistics - realised variance and realised covariances of five representative bidding zones in Nord Pool.

	Mean	Min	Max	St_Dev	Skew	Kurt	ADF	Phillips-Perron	Zivot-Andrews	KPSS	Obs
Panel A: Realised Variance											
RV_DK1	3.091	0.001	197.300	11.121	5.891	47.896	−36.543***	−51.494***	−40.617***	0.072	4473
RV_NO1	0.188	0.000	55.365	1.219	28.845	1120.049	−41.115***	−57.598***	−43.065***	0.3652***	4473
RV_NO3	0.208	0.000	30.505	0.909	19.203	560.072	−34.431***	−51.287***	−37.029***	0.4454***	4473
RV_SE3	0.668	0.001	49.590	2.136	9.640	144.525	−30.221***	−45.579***	−36.695***	1.008***	4473
RV_FI	0.913	0.001	68.533	2.411	10.446	193.188	−28.303***	−46.319***	−34.768***	0.6065***	4473
Panel B: Realised Covariance											
DK1_NO1	0.190	−0.944	42.627	1.038	22.154	722.519	−39.135***	−52.008***	−41.549***	0.3743***	4473
DK1_NO3	0.190	−1.075	22.679	0.793	15.460	328.199	−36.431***	−47.460***	−39.565***	0.3292***	4473
DK1_SE3	0.424	−1.325	42.533	1.679	13.692	259.661	−36.641***	−53.498***	−41.519***	0.7398***	4473
DK1_FI	0.403	−2.403	38.724	1.564	14.767	295.330	−38.002***	−58.610***	−43.216***	0.5551***	4473
NO1_NO3	0.106	−0.454	17.964	0.508	16.620	430.088	−35.666***	−44.648***	−37.877***	0.1979**	4473
NO1_SE3	0.175	−0.236	33.476	0.920	19.489	533.982	−37.901***	−49.252***	−40.224***	0.3752***	4473
NO1_FI	0.166	−5.894	29.956	0.844	18.921	509.599	−38.327***	−58.746***	−41.071***	0.316***	4473
NO3_SE3	0.205	−0.144	23.858	0.813	14.178	302.747	−32.511***	−41.442***	−35.719***	0.3986***	4473
NO3_FI	0.196	−0.487	19.114	0.692	12.397	236.370	−30.918***	−46.777***	−34.357***	0.3627***	4473
SE3_FI	0.540	−0.859	42.039	1.828	10.813	170.874	−31.528***	−48.658***	−37.324***	0.8188***	4473

Source: lag length is determined by BIC criterion. The hypothesis of the Augmented Dickey Fuller (ADF) test is H_0: non-stationary against H_1: stationary. The null hypothesis of the Phillips-Perron (PP) test is that there is a unit root, with the alternative that there is no unit root. In the Zivot-Andrews tests, the null hypothesis is that the series has a unit root with structural break(s) against the alternative hypothesis that they are stationary with break(s). Kwiatkowski– Phillips–Schmidt–Shin (KPSS) tests are used for testing a null hypothesis that an observable time series is stationary around a deterministic trend (i.e. trend-stationary) against the alternative of a unit root. * Denotes significance at 10% level, ** denotes significance at 5% level, *** denotes significance at 1% level.

Table 11
Connectedness matrix of the realised variance system – estimated by TVP-VAR.

	RV_DK1	RV_FI	RV_NO1	RV_NO3	RV_SE3	From Others
RV_DK1	67.52	10.58	5.22	4.09	12.59	32.48
RV_FI	6.03	44.44	10.41	10.15	28.97	55.56
RV_NO1	4.67	15.48	42.77	16.66	20.41	57.23
RV_NO3	3.55	14.85	17.97	39.56	24.07	60.44
RV_SE3	6.22	25.37	12.13	13.75	42.52	57.48
To Others	20.48	66.28	45.73	44.65	86.04	263.19
Net Total	−12.00	10.72	−11.50	−15.79	28.56	**TCI = 52.64**

Table 12
Connectedness matrix of the realised covariances system – estimated by TVP-VAR.

	DK1_NO1	DK1_NO3	DK1_SE3	DK1_FI	NO1_NO3	NO1_SE3	NO1_FI	NO3_SE3	NO3_FI	SE3_FI	From Others
DK1_NO1	16.64	8.61	9.14	7.97	9.46	13.7	12.37	7.22	6.77	8.08	83.36
DK1_NO3	9.27	16.12	9.99	8.32	9.05	8.51	7.66	12.21	10.5	8.4	83.88
DK1_SE3	8.97	9.09	18.24	13.92	5.57	8.65	7.82	7.68	7.03	13.04	81.76
DK1_FI	8.7	8.68	15.32	19.02	5.27	7.91	8.11	6.89	7.32	12.77	80.98
NO1_NO3	10.26	9.37	6.29	5.3	16.2	13	11.49	11	9.83	7.26	83.76
NO1_SE3	12.09	7.16	7.77	6.57	10.7	16.3	14.28	8.36	7.76	9.05	83.74
NO1_FI	11.67	7	7.43	6.99	10.3	15.2	15.85	7.87	8.35	9.35	84.15
NO3_SE3	6.95	10.67	7.55	5.97	9.5	8.82	7.8	17.32	14.7	10.76	82.68
NO3_FI	6.89	9.66	7.16	6.47	9	8.55	8.62	15.44	16.8	11.43	83.24
SE3_FI	6.83	6.63	11.54	10.45	5.4	8.63	8.5	9.43	9.82	22.77	77.23
To Others	81.64	76.88	82.2	71.95	74.2	93	86.65	86.09	82	90.15	824.78
NET	−1.72	−7	0.44	−9.02	−9.53	9.23	2.5	3.41	−1.23	12.92	**TCI = 82.48**

(2015).

The VAR-CF with a p-lag order can be specified as follows:

$$X_t = \sum_{i=1}^{p} \Phi_i X_{t-i} + \Lambda f_t + \epsilon_t, t = 1, 2, \ldots, T \tag{16}$$

where $\Lambda = (\lambda_1, \lambda_2, \ldots, \lambda_N)'$ is the $N \times R$ a matrix of the factor loadings corresponding to the R-dimensional vector of common factors, f_t. We follow the three-step approach of Miao et al. (2023) to estimate the coefficient matrices and the variance-covariance matrix of error terms (i.e., Φ_i, Λ, and Σ_ϵ).[11] These estimated outputs are then used to calculate the connectedness indices as presented earlier in section 3.

We present the overall connectedness results estimated using the VAR-CF framework and the spillover contributions of variances and covariances in Table 15 and Table 16, respectively.

Overall, we find a consistent results with section 6.2.1 in an essence

[11] We follow Uddin et al. (2023) to choose the lag order p of VAR-CF as 1 to ensure enough degree of freedom. We do not present the whole estimation procedure to conserve space and refer to section 3 of Miao et al. (2023) for a detail description. We thank the referee for a suggestion of the VAR-CF model.

Table 13
Connectedness matrix of the full system – estimated by TVP-VAR model.

	RV_DK1	RV_NO1	RV_NO3	RV_SE3	RV_FI	DK1_NO1	DK1_NO3	DK1_SE3	DK1_FI	NO1_NO3	NO1_SE3	NO1_FI	NO3_SE3	NO3_FI	SE3_FI	FROM others
RV_DK1	40.49	3.08	2.66	6.91	5.49	4.72	5.1	6.79	7.32	1.93	2.86	2.65	2.61	2.35	5.03	59.51
RV_NO1	1.72	13.32	5.7	6.82	5.14	8.23	4.75	4.87	4.2	7.9	11.04	9.55	5.82	5.36	5.58	86.68
RV_NO3	1.4	5.55	12.7	7.81	5.1	4.93	7.04	5.04	4.07	6.65	6.37	5.47	11.46	9.68	6.73	87.30
RV_SE3	2.44	4.47	5.34	16.32	10.03	4.31	4.45	7.8	6.31	3.46	5.64	4.85	6.06	5.78	12.74	83.68
RV_FI	2.45	4.1	4.48	12.45	18.27	4.25	3.97	6.62	7.16	3.43	5.33	5.31	5.12	5.95	11.1	81.73
DK1_NO1	2.2	7.75	4.66	6.29	4.91	12.41	6.41	6.57	5.7	7.78	10.42	9.07	5.34	5.04	5.45	87.59
DK1_NO3	2.25	4.79	7.22	6.52	4.63	6.86	12.52	7.73	6.34	6.76	6.52	5.62	8.76	7.57	5.89	87.48
DK1_SE3	3.24	4.38	4.57	10.37	6.83	6.06	6.84	13.14	10.15	4.01	5.9	5.11	5.5	5.07	8.83	86.86
DK1_FI	3.61	4.03	4.16	9	7.36	5.98	6.59	11.33	14	3.9	5.5	5.42	5.04	5.39	8.7	86.00
NO1_NO3	1.18	7.61	6.65	5.27	4.11	8.01	6.78	4.61	3.95	12.76	10.27	8.82	7.96	7.18	4.83	87.24
NO1_SE3	1.36	8.88	5.26	6.87	5.09	8.84	5.22	5.43	4.66	8.43	11.99	10.34	6	5.63	5.98	88.01
NO1_FI	1.38	8.48	5.03	6.58	5.42	8.57	5.08	5.24	5.01	8.15	11.33	11.6	5.69	6.14	6.29	88.40
NO3_SE3	1.35	5.1	9.9	8.08	5.3	5.04	7.41	5.4	4.41	6.88	6.48	5.52	11.9	10.08	7.15	88.10
NO3_FI	1.25	4.86	8.94	7.79	5.77	5.03	6.82	5.22	4.82	6.64	6.34	6.21	10.7	11.76	7.84	88.24
SE3_FI	2.1	4.2	5.18	14.17	9.74	4.37	4.52	7.49	6.85	3.63	5.59	5.3	6.19	6.61	14.06	85.94
TO others	27.95	77.28	79.74	114.93	84.91	85.19	80.98	90.14	80.96	79.56	99.59	89.25	92.26	87.83	102.16	1272.7
NET	−31.56	−9.40	−7.56	31.26	3.18	−2.40	−6.49	3.28	−5.04	−7.68	11.58	0.85	4.17	−0.41	16.22	**TCI= 84.85**

Table 14
Spillover contributions under TVP-VAR model.

Cross volatility spillovers	18.78%
Cross covariance spillovers	19.72%
Own volatility spillovers	13.62%
Own covariance	47.89%

that the Nordic electricity markets are strongly interdependence with a Total Connectedness of nearly 90% considering the spillovers contributed by both variances and covariances. Besides, covariances have contributed significantly to the spillovers of the system with its own covariances spillovers being at nearly half (47%) of the whole system's spillover. These results, again, confirm the robustness of the strong interdependence among considered Nordic electricity markets and the significant role of variances, and particularly, covariances in contributing to their interrelationship.

7. Conclusion

This paper examines price volatility and its spillover effects across Nordic electricity wholesale markets. The four Nord Pool countries studied comprise 12 regional markets. Denmark (DK1-Western Denmark, DK2-Eastern Denmark), Norway (NO1-Oslo, NO2-Kristiansand, NO3-Trondheim, NO4-Tromsø, NO5-Bergen), Sweden (SE1-Lulea, SE2-Sundsvall, SE3-Stockholm, SE4-Malmo), and Finland. We use a rich sample of 107,352 hourly prices for each of the region, ranging from 1 January 2010 to 31 March 2022, collected from Nord Pool. The novelty of our approach is threefold. First, we use the connectedness approach based on both the TVP-VAR, RW-VAR, and VAR-CF models to analyze integration in Nordic electricity markets, contributing to the scarce literature in the electricity volatility connectedness across four countries (Sweden, Finland, Denmark, Norway). Second, we divide the Norwegian market due to observed differences between northern and southern electricity prices. Third, we examine how changes in carbon price influence those spillover effects.

Our results show that the average volatility TCI estimated by TVP-VAR (RW-VAR) is 52.4% (50.9%), indicating that 52.4% (50.9%) of the future volatility in Nord Pool is attributed to volatility shocks spreading across the markets. As for TVP-VAR measure, our results show that Sweden is the only net volatility spillover transmitter while Denmark bears the most significant shocks from the system. The dynamic evolution of total connectedness index responded to the EU ETS's transition from Phase II to Phase III, indicating that the decrease of market risk in Nord Pool corresponds to a surplus of emission allowances in EU ETS. In addition, the launch of GB-Irish power market coupling into Nord Pool increased the market risk in Nord Pool.

The RW-VAR connectedness shows that both Sweden and Northern Norway are net volatility spillover transmitters at an aggregated level. The Danish market produces and receives the least volatility spillover from (33.6%) and to (22.3%) the system; the view is consistent with the TVP-VAR measure. A spike in total connectedness index appeared after a large price fall of emission allowances under EU ETS in 2013. The fall in emission prices promoted the thermal production of fossil fuel resources and affected the value of water negatively. Since thermal power is the opportunity cost of flexible hydropower with a reservoir, the decline in emission prices drove the power prices down. It raised the short-term volatility spillover level in the Nord Pool. The result further shows that carbon price does not have a significant impact on TCI estimated by TVP-VAR and 100-days rolling window VAR. However, the carbon price has 5% level significant impact on TCI estimated by 200-days rolling window VAR. The positive relationship between carbon price and total volatility spillovers estimated by RW-VAR is observed.

The findings of our study are beneficial for electricity market participants. Our results show that volatilities in integrated Nordic wholesale electricity markets are affected by carbon prices, market coupling,

Table 15
Connectedness matrix of the full system – estimated by VAR-CF model.

	RV_DK1	RV_NO1	RV_NO3	RV_SE3	RV_FI	DK1_NO1	DK1_NO3	DK1_SE3	DK1_FI	NO1_NO3	NO1_SE3	NO1_FI	NO3_SE3	NO3_FI	SE3_FI	FROM others
RV_DK1	18.62	3.18	2.08	11.27	9.74	4.10	4.11	10.06	8.81	2.78	5.59	4.11	5.48	4.90	12.95	89.18
RV_NO1	11.40	14.63	3.05	10.45	13.70	4.68	2.00	4.36	3.85	3.02	8.66	5.60	3.84	2.99	8.23	85.83
RV_NO3	9.32	3.83	10.48	6.28	5.76	4.13	5.36	5.95	5.24	4.64	6.08	4.80	9.28	7.57	7.74	85.99
RV_SE3	17.32	3.21	2.23	20.99	16.06	1.72	2.34	8.28	6.89	1.23	3.41	2.46	4.30	3.98	16.79	90.21
RV_FI	16.17	3.24	2.21	15.92	21.34	1.91	2.42	7.12	7.37	1.50	3.48	2.86	4.40	4.80	15.62	89.04
DK1_NO1	14.08	3.70	2.48	11.68	11.84	4.19	4.03	8.64	7.81	3.15	5.99	4.68	5.66	5.44	12.77	101.95
DK1_NO3	12.02	1.72	2.63	6.40	5.65	5.31	10.32	9.29	7.49	6.16	5.73	4.07	9.14	7.18	8.53	91.32
DK1_SE3	12.65	1.70	1.27	6.79	4.65	6.12	5.92	16.25	13.12	3.62	6.82	5.70	5.16	4.78	11.10	89.39
DK1_FI	12.12	1.40	0.96	6.10	5.34	6.01	4.77	14.22	16.44	3.23	6.83	6.83	4.31	5.38	12.36	89.86
NO1_NO3	5.55	2.61	2.38	1.57	1.49	8.01	8.80	5.79	4.76	13.76	10.07	7.59	9.64	8.63	4.39	81.29
NO1_SE3	8.78	8.18	1.74	5.14	5.61	8.93	3.87	6.51	5.91	5.75	13.04	10.10	4.49	4.18	6.73	85.90
NO1_FI	6.95	3.85	0.84	2.71	2.45	10.74	3.96	7.72	8.67	6.26	14.47	14.55	3.82	5.25	7.02	84.70
NO3_SE3	13.95	3.38	3.47	12.22	12.24	3.06	4.32	7.57	6.82	3.27	4.89	3.69	7.15	6.72	12.89	98.50
NO3_FI	7.91	1.20	3.67	4.05	4.35	4.24	7.27	6.16	6.36	6.94	5.64	5.08	12.75	15.16	8.39	84.01
SE3_FI	15.45	2.24	1.69	14.22	12.80	2.90	2.90	9.31	9.23	2.13	4.65	4.09	4.79	5.41	18.08	91.81
TO others	163.7	43.45	30.71	114.81	111.68	71.83	62.07	110.99	102.34	53.68	92.31	71.66	87.04	77.20	145.50	89.18
NET	74.49	−42.38	−55.28	24.60	22.64	−30.11	−29.25	21.61	12.48	−27.60	6.42	−13.04	−11.46	−6.81	53.69	TCI= **89.26**

Table 16
Spillover contributions under VAR-CF model.

Cross volatility spillovers	19.17%
Cross covariance spillovers	17.62%
Own volatility spillovers	16.25%
Own covariance spillovers	46.96%

public health events, and the production of neighboring regions.

Another important finding emerged from the whole system (with both variances and covariances) analyses using TVP-VAR and VAR-CF is a significant role of the covariances in network spillovers. We observe that by including covariances in the system, the total connectedness increases to between 80 and 90% compared to a total connectedness of around 50% observed in a system of variances alone. A further analysis highlights a significant contribution of the *own covariance spillovers,* which accounts for nearly half of the total connectedness.

Rolling window-based VAR connectedness estimation is defined in the literature as being sensitive to the choice of rolling-window size. Further research can be controlling more variables when testing the impact of carbon price on volatility spillovers in Nordic markets — for instance including economics policy uncertainty and extreme weather conditions in the control variables. Another possibility is to test at different frequencies of the model to obtain a more conclusive result. In addition, results emerged from our whole system analysis suggests that it is equally important to consider covariances in analysing the network of volatility connectedness.

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CRediT authorship contribution statement

Chenyan Lyu: Data curation, Formal analysis, Investigation, Writing – original draft, Software, Writing – review & editing. **Hung Xuan Do:** Investigation, Methodology, Software, Validation, Formal analysis. **Rabindra Nepal:** Conceptualization, Methodology, Supervision, Writing – review & editing, Investigation. **Tooraj Jamasb:** Conceptualization, Methodology, Supervision, Writing – review & editing, Investigation.

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.

Data availability

Datasets related to this electricity intraday prices can be found at Nord Pool Elspot (Day-ahead markets) and Elbas (Intraday markets), https://www.nordpoolgroup.com/services/power-market-data-services/. This research dataset obtained from Nord Pool is confidential and cannot be redistributed or posted on a website. Access requests to Nord Pool data portal shall be made to Nord Pool. Datasets related to energy market prices and carbon market prices can be found at Thomson Reuters Eikon, and Bloomberg and are available upon reasonable request with the corresponding author.

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Appendix A

Table A1
Descriptive statistics - Hourly price of 12 bidding areas in four countries.

	Mean	Minimum	Maximum	St.Dev.	Skewness	Kurtosis	Obs.
DK1	42.00201	−200	2000	37.58594	10.3154	341.4854	107,339
DK2	44.12143	−200	2000	38.96399	8.750168	218.682	107,339
NO1	38.73736	−1.97	667.92	29.28268	3.871317	33.03959	107,339
NO2	38.26797	−1.97	667.92	28.6716	4.021594	35.54512	107,339
NO3	34.72078	−0.01	1400.11	21.38077	15.64688	770.2175	107,339
NO4	33.30415	−0.01	1400.11	21.14664	16.1768	807.6549	107,339
NO5	38.20615	−0.09	667.92	28.73403	3.929935	34.55545	107,339
SE1	35.34896	−1.97	1400.11	21.54276	15.34869	745.5188	107,339
SE2	35.35997	−1.97	1400.11	21.55098	15.33141	744.3542	107,339
SE3	39.6184	−1.97	1400.11	30.64654	8.989079	219.0297	107,339
SE4	42.12483	−1.97	1400.11	33.46208	7.729993	159.2808	107,339
FI	43.18087	−1.73	1400.11	31.45592	9.520567	228.4092	107,339

Note: Some data is missing in the original data file from Nord Pool. On 28 March 2010, wholesale prices at 03:00 am were missing for all areas, resulting in a total of 13 NA entries in our sample. Since we have a large dataset, we kept 13 NAs in our hourly data.

Table A2
Correlation test across bidding areas in Denmark.

	DK1	DK2
DK1	1	
DK2	0.834	1

Table A3
Correlation test, bidding areas in Norway.

	NO1	NO2	NO3	NO4	NO5
NO1	1				
NO2	0.988	1			
NO3	0.441	0.390	1		
NO4	0.427	0.374	0.972	1	
NO5	0.989	0.994	0.403	0.388	1

Table A4
Correlation test, bidding areas in Norway.

	SE1	SE2	SE3	SE4
SE1	1			
SE2	1	1		
SE3	0.697	0.697	1	
SE4	0.624	0.625	0.949	1

Table A5
Average connectedness matrix of the system – estimated by 100 days rolling window.

	Denmark	Finland	Norway South	Norway North	Sweden	From Others
Denmark	56.33	10.33	10.09	9.20	14.05	43.67
Finland	8.79	43.84	10.95	13.52	22.90	56.16
Norway South	7.08	11.14	46.61	18.88	16.28	53.39
Norway North	7.00	12.19	17.21	44.42	19.18	55.58
Sweden	10.27	19.19	14.84	18.48	37.22	62.78
To Others	33.14	52.84	53.09	60.08	72.41	**TCI = 54.31**
Net Total	−10.53	−3.32	−0.30	4.50	9.64	

Source: This spillover table is generated based on 10-step-ahead generalized VAR forecast error variance decomposition estimated from 200 days rolling window VAR. The ij^{th} entry estimates the fraction of 10-step-ahead error variance in forecasting market i due to exogenous shocks to market j (the spillover from market j to market i: d_{ij}^{J}). From Eq. 16 ($C_{ij,t} = C_{i\to j,t}(J) - C_{i\leftarrow j,t}(J)$), we obtain the net total directional connectedness, $C_{ij,t}$.

Table A6
Long memory characteristics of five representative realised volatilities in Nord Pool.

Realised Volatility	d_value
DK1	0.2569
NO1	0.3656
NO3	0.4301
SE3	0.4242
FI	0.4049

Table A7
Long memory characteristics of 5 representative realised variances and 10 covariances in Nord Pool.

Realised Variance	d_value
DK1	0.1911
NO1	0.1221
NO3	0.2368
SE3	0.3073
FI	0.3076
Realised Covariance	d_value
DK1_NO1	0.1874
DK1_NO3	0.2595
DK1_SE3	0.1933
DK1_FI	0.1449
NO1_NO3	0.3039
NO1_SE3	0.2280
NO1_FI	0.1388
NO3_SE3	0.3655
NO3_FI	0.3056
SE3_FI	0.2767

Appendix B

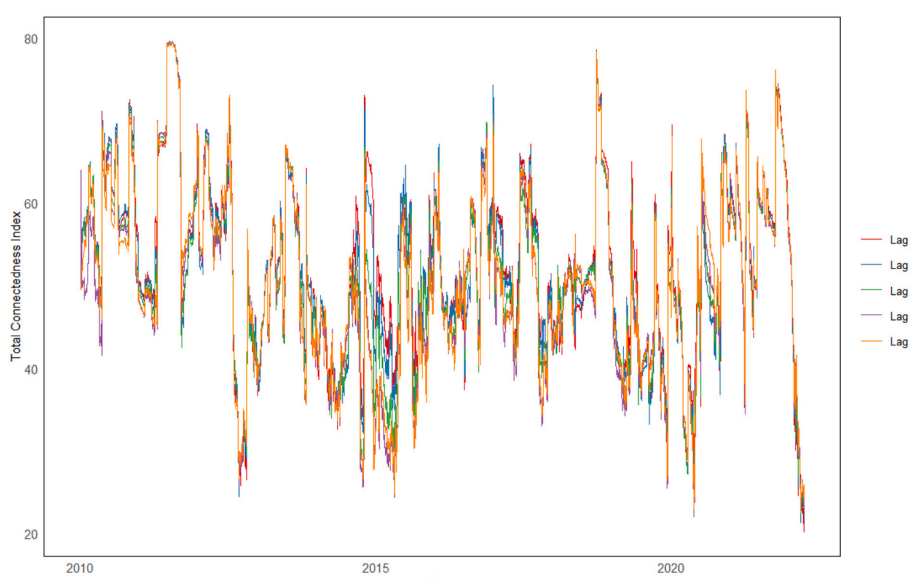

Fig. B1. Sensitivity of the Total Connectedness Index to TVP-VAR lag structure (lag4–8).
Note: In the main text we used lag 4 as selected by Schwarz information criterion. Here in the robustness check we tried lag 4, lag5, lag6, lag7, and lag8 in the model (lag 8 was chosen by Akaike information criterion, lag7 was chosen by Hannan-Quinn Criterion). The averaged total connectedness index for lag 4, lag5, lag6, lag7, and lag8 are reported as 52.41%, 51.92%, 51.01%, 50.92%, and 50.62%.

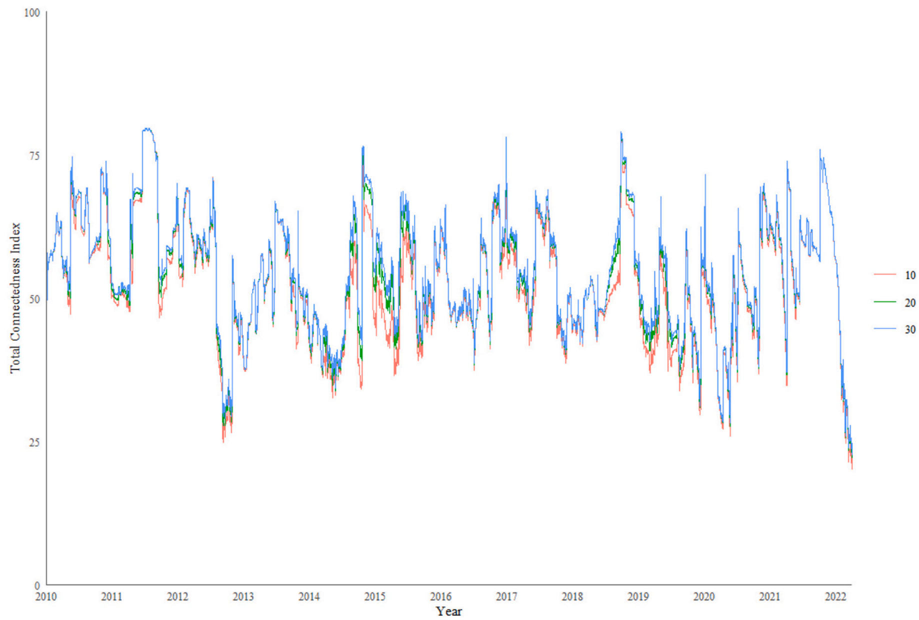

Fig. B2. Sensitivity of the Total Connectedness Index to TVP-VAR H-step-ahead forecasts.
Note: In the main text we used H = 10 step-ahead-forecasts. Here in the robustness check we H = 20 and H = 30 in the model. The averaged total connectedness index for lag 4, lag5, lag6, lag7, and lag8 are reported as 52.41%, 51.92%, 51.01%, 50.22%, and 50.62%.

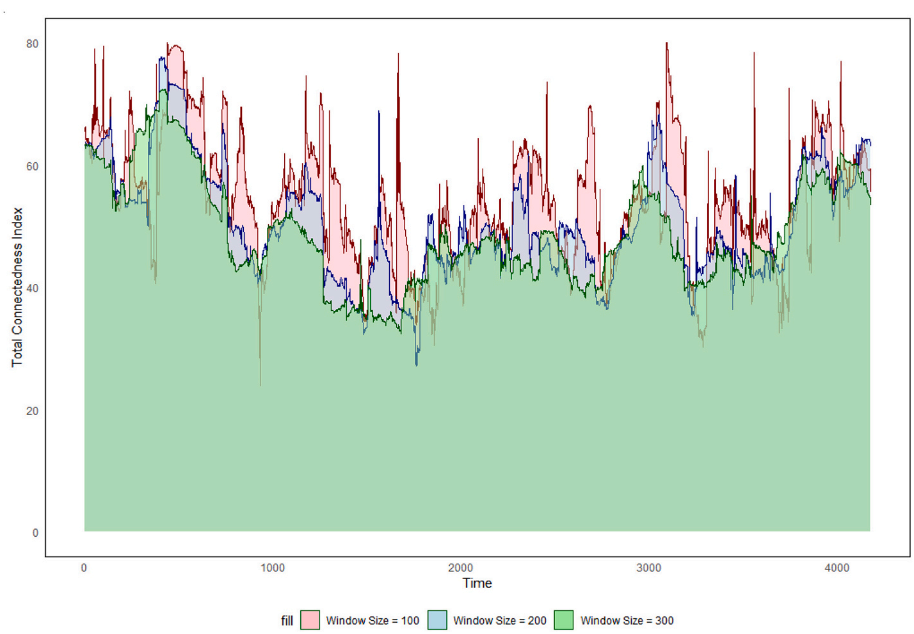

Fig. B3. Sensitivity of the Total Connectedness Index to RW-VAR rolling window size (100, 200, and 300).
Note: The averaged total connectedness index for window size 100, 200 and 300 are reported as 54.31%, 50.22%, and 48.96%.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107559.

References

Aatola, P., Ollikainen, M., Toppinen, A., 2013. Impact of the carbon price on the integrating European electricity market. Energy Policy 61, 1236–1251. https://doi.org/10.1016/j.enpol.2013.06.036.

Amundsen, E.S., Bergman, L., 2006. Why has the Nordic electricity market worked so well? Util. Policy 14, 148–157. https://doi.org/10.1016/j.jup.2006.01.001.

Andersen, T.G., Bollerslev, T., Diebold, F.X., Labys, P., 2001. The distribution of realized exchange rate volatility. J. Am. Stat. Assoc. 96, 42–55. https://doi.org/10.1198/016214501750332965.

Antonakakis, N., Chatziantoniou, I., Gabauer, D., 2020. Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. J. Risk Financ. Manag. 13 https://doi.org/10.3390/jrfm13040084.

Apergis, N., Baruník, J., Lau, M.C.K., 2017. Good volatility, bad volatility: what drives the asymmetric connectedness of Australian electricity markets? Energy Econ. 66, 108–115. https://doi.org/10.1016/j.eneco.2017.06.010.

Baruník, J., Křehlík, T., 2018. Measuring the frequency dynamics of financial connectedness and systemic risk. J. Financ. Econ. 16, 271–296. https://doi.org/10.1093/jjfinec/nby001.

Bertrand, J., 2020. Is the Nordic region the new hotspot for renewables? [WWW Document]. URL. https://green-giraffe.eu/publication/blog-post/nordic-region-new-hotspot-renewables/.

Böckers, V., Heimeshoff, U., 2014. The extent of European power markets. Energy Econ. 46, 102–111. https://doi.org/10.1016/j.eneco.2014.09.004.

Botterud, A., Kristiansen, T., Ilic, M.D., 2010. The relationship between spot and futures prices in the Nord Pool electricity market. Energy Econ. 32, 967–978. https://doi.org/10.1016/j.eneco.2009.11.009.

BP, 2022. BP Energy Outlook 2022 edition [WWW Document]. URL. https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/energy-outlook/bp-energy-outlook-2022.pdf (accessed 6.10.22).

Bunn, D.W., Gianfreda, A., 2010. Integration and shock transmissions across European electricity forward markets. Energy Econ. 32, 278–291. https://doi.org/10.1016/j.eneco.2009.09.005.

Bye, Torstein, Hope, E., 2005. Deregulation of electricity markets: the Norwegian experience. Econ. Polit. Wkly. 40, 5269–5278.

Chanatásig-Niza, E., Ciarreta, A., Zarraga, A., 2022. A volatility spillover analysis with realized semi(co)variances in Australian electricity markets. Energy Econ. 111, 106076 https://doi.org/10.1016/j.eneco.2022.106076.

Chang, K., Ge, F., Zhang, C., Wang, W., 2018. The dynamic linkage effect between energy and emissions allowances price for regional emissions trading scheme pilots in China. Renew. Sust. Energ. Rev. 98, 415–425. https://doi.org/10.1016/j.rser.2018.09.023.

Chuliá, H., Furió, D., Uribe, J.M., 2019. Volatility spillovers in energy markets. Energy J. 40 https://doi.org/10.5547/01956574.40.3.hchu.

Cramton, P., 2017. Electricity market design. Oxf. Rev. Econ. Policy 33, 589–612. https://doi.org/10.1093/oxrep/grx041.

Dangl, T., Halling, M., 2012. Predictive regressions with time-varying coefficients. J. Financ. Econ. 106, 157–181. https://doi.org/10.1016/j.jfineco.2012.04.003.

Danish Energy Agency, 2021. Denmark's climate status and outlook [WWW Document]. URL. https://ens.dk/en/our-services/projections-and-models/denmarks-energy-and-climate-outlook.

Daskalakis, G., Markellos, R.N., 2009. Are electricity risk premia affected by emission allowance prices? Evidence from the EEX, Nord Pool and Powernext. Energy Policy 37, 2594–2604. https://doi.org/10.1016/j.enpol.2009.02.010.

De Menezes, L.M., Houllier, M.A., 2016. Reassessing the integration of European electricity markets: a fractional cointegration analysis. Energy Econ. 53, 132–150. https://doi.org/10.1016/j.eneco.2014.10.021.

De Vany, A.S., Walls, W.D., 1999. Cointegration analysis of spot electricity prices: insights on transmission efficiency in the western US. Energy Econ. 21, 435–448. https://doi.org/10.1016/S0140-9883(99)00019-5.

Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. J. Am. Stat. Assoc. 74, 427–431. https://doi.org/10.2307/2286348.

Diebold, F.X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ. J. 119, 158–171. http://www.jstor.org/stable/20485298.

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28, 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006.

Do, H.X., Nepal, R., Jamasb, T., 2020. Electricity market integration, decarbonisation and security of supply: dynamic volatility connectedness in the Irish and Great Britain markets. Energy Econ. 92, 104947 https://doi.org/10.1016/j.eneco.2020.104947.

Duan, K., Ren, X., Shi, Y., Mishra, T., Yan, C., 2021. The marginal impacts of energy prices on carbon price variations: evidence from a quantile-on-quantile approach. Energy Econ. 95, 105131 https://doi.org/10.1016/j.eneco.2021.105131.

Eurostat, 2022. Renewable energy statistics [WWW Document]. URL. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Renewable_energy_statistics#:~:text=In%202020%2C%20renewable%20energy%20sources,and%2033%20%25%2C%20respectively (accessed 6.10.22).

Fengler, M.R., Gisler, K.I.M., 2015. A variance spillover analysis without covariances: what do we miss? J. Int. Money Financ. 51, 174–195. https://doi.org/10.1016/j.jimonfin.2014.11.006.

Flatabo, N., Doorman, G., Grande, O.S., Randen, H., Wangensteen, I., 2003. Experience with the Nord Pool design and implementation. IEEE Trans. Power Syst. 18, 541–547. https://doi.org/10.1109/TPWRS.2003.810694.

Frömmel, M., Han, X., Kratochvil, S., 2014. Modeling the daily electricity price volatility with realized measures. Energy Econ. 44, 492–502. https://doi.org/10.1016/j.eneco.2014.03.001.

Gugler, K., Haxhimusa, A., Liebensteiner, M., 2018. Integration of European electricity markets: evidence from spot prices. Energy J. 39 https://doi.org/10.5547/01956574.39.SI2.kgug.

Guo, L.-Y., Feng, C., 2021. Are there spillovers among China's pilots for carbon emission allowances trading? Energy Econ 103, 105574. https://doi.org/10.1016/j.eneco.2021.105574.

Han, L., Kordzakhia, N., Trück, S., 2020. Volatility spillovers in Australian electricity markets. Energy Econ. 90, 104782 https://doi.org/10.1016/j.eneco.2020.104782.

Hans-Arild, B., 2016. The Nord Pool market model. In: ASEAN energy market integration (AEMI). http://www.asean-aemi.org/wp-content/uploads/2016/03/AEMI-Forum-November-2015-Bredesen-Feb2016.pdf.

Hasan, M., Arif, M., Naeem, M.A., Ngo, Q.-T., Taghizadeh-Hesary, F., 2021. Time-frequency connectedness between Asian electricity sectors. Econ. Anal. Policy 69, 208–224. https://doi.org/10.1016/j.eap.2020.12.008.

Haugom, E., Hoff, G.A., Molnár, P., Mortensen, M., Westgaard, S., 2018. The forward premium in the Nord Pool power market. Emerg. Mark. Financ. Trade 54, 1793–1807. https://doi.org/10.1080/1540496X.2018.1441021.

Haugom, E., Molnár, P., Tysdahl, M., 2020. Determinants of the forward premium in the Nord Pool electricity market. Energies 13, 1111. https://doi.org/10.3390/en13051111.

Hellström, J., Lundgren, J., Yu, H., 2012. Why do electricity prices jump? Empirical evidence from the Nordic electricity market. Energy Econ. 34, 1774–1781. https://doi.org/10.1016/j.eneco.2012.07.006.

International Energy Agency, 2022. World energy statistics and balances [WWW Document]. URL. https://www.iea.org/countries/china (accessed 6.10.22).

International Energy Agency, 2023. Electricity Market Report 2023. Paris.

Jamasb, T., Pollitt, M., 2005. Electricity market reform in the European Union: review of progress toward liberalization & integration. Energy J. 26, 11–41.

Jan, R., 2019. Future thinking – Empowering the market [WWW Document]. URL. https://www.nordpoolgroup.com/4a45a1/globalassets/download-center/whitepaper/whitepaper_future_thinking.pdf (accessed 8.10.22).

Ketterer, J.C., 2014. The impact of wind power generation on the electricity price in Germany. Energy Econ. 44, 270–280. https://doi.org/10.1016/j.eneco.2014.04.003.

Koop, G., Korobilis, D., 2013. Large time-varying parameter VARs. J. Econ. 177, 185–198. https://doi.org/10.1016/j.jeconom.2013.04.007.

Koop, G., Pesaran, M.H., Potter, S.M., 1996. Impulse response analysis in nonlinear multivariate models. J. Econ. 74, 119–147. https://doi.org/10.1016/0304-4076(95)01753-4.

Kyritsis, E., Andersson, J., Serletis, A., 2017. Electricity prices, large-scale renewable integration, and policy implications. Energy Policy 101, 550–560. https://doi.org/10.1016/j.enpol.2016.11.014.

Liu, T., Gong, X., 2020. Analyzing time-varying volatility spillovers between the crude oil markets using a new method. Energy Econ. 87, 104711 https://doi.org/10.1016/j.eneco.2020.104711.

Lyu, C., Scholtens, B., 2024. Integration of the international carbon market: A time-varying analysis. Renew. Sustain. Energy Rev. 191, 114102. https://doi.org/10.1016/j.rser.2023.114102.

Ma, R., Liu, Z., Zhai, P., 2022. Does economic policy uncertainty drive volatility spillovers in electricity markets: time and frequency evidence. Energy Econ. 107, 105848 https://doi.org/10.1016/j.eneco.2022.105848.

Matt, F., 2022. How Norway became Europe's biggest power exporter [WWW Document]. URL. https://www.power-technology.com/analysis/how-norway-became-europes-biggest-power-exporter/.

Miao, K., Phillips, P.C.B., Su, L., 2023. High-dimensional VARs with common factors. J. Econ. 233, 155–183. https://doi.org/10.1016/j.jeconom.2022.02.002.

Ministry of Petroleum and Energy, 2016. Renewable energy production in Norway [WWW Document]. URL. https://www.regjeringen.no/en/topics/energy/renewable-energy/renewable-energy-production-in-norway/id2343462/#:~:text=In%20Norway%2C%2098%20percent%20of,of%20most%20of%20the%20production (accessed 6.10.22).

Mjelde, J.W., Bessler, D.A., 2009. Market integration among electricity markets and their major fuel source markets. Energy Econ. 31, 482–491. https://doi.org/10.1016/j.eneco.2009.02.002.

Naeem, M.A., Karim, S., Rabbani, M.R., Nepal, R., Uddin, G.S., 2022. Market integration in the Australian National Electricity Market: fresh evidence from asymmetric time-frequency connectedness. Energy Econ. 112, 106144 https://doi.org/10.1016/j.eneco.2022.106144.

Nepal, R., Foster, J., 2016. Testing for market integration in the Australian national electricity market. Energy J. 37 https://doi.org/10.5547/01956574.37.4.rnep.

Nomikos, N.K., Soldatos, O.A., 2010. Modelling short and long-term risks in power markets: empirical evidence from Nord Pool. Energy Policy 38, 5671–5683. https://doi.org/10.1016/j.enpol.2010.05.015.

NordREG, 2014. Nordic Market Report 2014 - Development in the Nordic electricity market [WWW Document]. http://www.nordicenergyregulators.org/wp-content/uploads/2014/06/Nordic-Market-Report-2014.pdf (accessed 8.26.22).

Park, H., Mjelde, J.W., Bessler, D.A., 2006. Price dynamics among U.S. electricity spot markets. Energy Econ. 28, 81–101. https://doi.org/10.1016/j.eneco.2005.09.009.

Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Econ. Lett. 58, 17–29. https://doi.org/10.1016/S0165-1765(97)00214-0.

Pollitt, M.G., 2019. The European single market in electricity: an economic assessment. Rev. Ind. Organ. 55, 63–87. https://doi.org/10.1007/s11151-019-09682-w.

Sotiriadis, M.S., Tsotsos, R., Kosmidou, K., 2016. Price and volatility interrelationships in the wholesale spot electricity markets of the Central-Western European and Nordic region: a multivariate GARCH approach. Energy Syst. 7, 5–32. https://doi.org/10.1007/s12667-014-0137-1.

Souhir, B.A., Heni, B., Lotfi, B., 2019. Price risk and hedging strategies in Nord Pool electricity market evidence with sector indexes. Energy Econ. 80, 635–655. https://doi.org/10.1016/j.eneco.2019.02.001.

Sousa, J., Soares, I., 2020. Demand response, market design and risk: A literature review. Util. Policy 66, 101083. https://doi.org/10.1016/j.jup.2020.101083.

Uddin, G.S., Luo, T., Yahya, M., Jayasekera, R., Rahman, M.L., Okhrin, Y., 2023. Risk network of global energy markets. Energy Econ. 125, 106882 https://doi.org/10.1016/j.eneco.2023.106882.

Uribe, J.M., Mosquera-López, S., Guillen, M., 2020. Characterizing electricity market integration in Nord Pool. Energy 208, 118368. https://doi.org/10.1016/j.energy.2020.118368.

Weron, R., Zator, M., 2014. Revisiting the relationship between spot and futures prices in the Nord Pool electricity market. Energy Econ. 44, 178–190. https://doi.org/10.1016/j.eneco.2014.03.007.