Characterizing Electricity Market Integration in the Nord Pool

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Abstract

We empirically study market integration and the propagation of market shocks in the Nord Pool interconnected market. We document an increasing trend of market integration during the last decades in the Nord Pool and clear cycles that account for more integration (larger transmission of shocks) in colder seasons. Larger market integration allows for a higher level of market risk sharing between electricity markets and henceforth it is expected to reduce the probability of occurrence of energy crises and situations of energy shortages in any given market. Further more, in our analysis we differentiate between shock propagation in the two tails of the price variation distribution. Hence, we distinguish downside risk from upside risk spillovers. Market spillovers following price increments in the market are transmitted to a larger extent than those after price reductions. We also document asymmetries related to both, the size of the transaction area and related to weather a given area behaves as a net-exporter or net-importer of electricity. For instance we show that the larger the area of transaction, the smaller the size of the volatility shocks on prices that it receives from the rest of the system.

Keywords: electricity prices; market integration, semivariances; volatility spillovers.

1. Introduction

There is no doubt that the process of transition towards a scheme based on sustainable energy resources that our society currently undergoes multiple challenges that merit considerable research efforts. Among the challenges that require immediate attention, there are technical issues such as the development of the smart grid and the design and development of efficient electricity storage devices. Alongside the technical aspects, there exist also fundamental issues related to the economic and financial sides of energy markets. For instance, issues such as: i) risk pricing, which refers to how the market participants perceive and value the risk of a given energy investment project, ii) market integration, related to the existent physical and economical linkages across different domestic electricity markets which facilitate international market risk sharing, iii) the identification of a correct incentive framework that allows for larger private investment in renewable sources, iv) or the development of new financial tools that can be used to correctly access the financial viability of different renewable energy projects and to hedge against their inherent risks, are of paramount importance for a smooth and effective transition of the world economy towards a sustainable energy paradigm.

Among the former, one important aspect that certainty is in need of further study within energy markets, and their ongoing enhancement as to consider a wider presence of renewable sources, is related to possible changes in the price volatility dynamics of electricity prices, which may be observed as a consequence of a larger integration between different national electricity markets, featured by a variety of renewable and non-renewable generation mixes. This is particularly important since variable renewable generation such as wind and solar power are gaining considerable importance in the generation mix of different markets in the developed world, and they are highly dependent on weather factors. Given that weather intermittency increase electricity spot price volatility in the absence of viable electricity storage

(Benhmad & Percebois, 2016; Ketterer, 2014; Kyritsis et al., 2017; Rintamäki et al., 2017), the possibility of risk sharing that follows from greater electricity market integration becomes crucial, provided that such integration may reduce idiosyncratic exposure to volatility risk in each market, and hence it will likely reduce as well the probability of energy crises and energy shortages in a given national market. Here we study the recent evolution of market integration and the evolution of risk sharing among several national interconnected markets that constitute the Nord Pool[1] We understand risk sharing as a process that allows for a reduction of individual market risk that occurs when idiosyncratic market shocks are smoothed across different markets, via a greater propagation of shocks across different national electricity markets.

We propose to measure the evolution of energy market integration by estimating cross-spillovers between electricity prices in a highly geographical and economically integrated electricity market, namely the Nord Pool, which operates power markets in the Northern European countries including some Baltic countries, Germany and the UK. This is a perfect example of a large risk sharing group of markets. Further more, in our empirical approach we distinguish between spillovers following price increments and reductions. Our results enable us to examine risk propagation and market integration among electricity prices in a dynamic and comprehensive setting, and at the same time to analyze the asymmetric nature of downside and upside risks in electricity markets. The examination that we conduct is of importance for policy makers because the full integration of electricity markets is a long-term goal of the European Union, and also because shocks to electricity prices have direct impact on the well functioning of any production economy. The study of the Nord Pool offers a unique opportunity to identify and address the issues, challenges and benefits of a potentially larger and highly

[1] We include Sweden, Findland, Denmark, Norway, Estonia, Latvia and Lithuania.

integrated electricity market on a European level, as well as the challenges derived from a higher share of electricity generation from renewable sources. Moreover, market-spillovers and international risk sharing need to be considered in any decision regarding optimal plans of consumption and production as long as they influence prices. As a bypass product of our analysis, we also provide insights on the predictability of positive and negative semivariances in these markets, which is instrumental to design optimal hedging mechanisms on the side of both generators and consumers of electricity.

The smooth operation of energy markets is fundamental for any production economy (see, for instance Hamilton, 2008, 2013; Mohaddes & Pesaran, 2017, and Kilian & Vigfusson, forthcoming). The study of the linkages between energy markets and the real economy has mainly focused on the role played by fuel-price shocks to the macroeconomy and, consistently, price formation in fuel markets has been extensively investigated alike, including the examination of volatility cross-spillovers between oil, gas and related markets (Bachmeier & Griffin, 2006; Lin & Li, 2015; Panagiotidis & Rutledge, 2007; Geng, Ji, & Fan, 2016; Batten, Ciner, & Lucey, 2017; Chuliá, Furió & Uribe, 2019). This literature has mainly overlooked the price formation mechanism that takes place in power-generation markets, based on renewable sources such as hydropower, wind power or solar generation technologies, with noticeable exceptions in recent times (see for instance Bunn et al. 2016; Hagfors et al. 2016; Mosquera-López, Manotas-Duque, & Uribe, 2017; Mosquera-López, Uribe, & Manotas-Duque, 2017). We fill a gap in the literature by analyzing cross-spillovers between prices on a highly interconnected electricity market that consists of a variety of power sources, remarkably hydro and wind power generation. Also, unlike the previous literature, we analyze separately the volatility transmission, predictability and market integration, following increments and reductions of electricity prices, which is fundamental for assessing the contrasting nature of the

risks faced by electricity consumers and generators (see Mosquera-López, Manotas-Duque, & Uribe, 2017 for a comprehensive discussion of this issue).

To tackle the problem of the asymmetric market risk quantification we follow a branch of the financial economics literature that proposes to quantify "good" and "bad" volatility shocks using realized semivariances (Patton & Sheppard, 2015; Amaya, Christoffersen et al. 2015; Bollerslev et al. 2017; Bollerslev, Zhengzi Li, & Zhao, 2017). These semivariances are constructed only using the negative or positive variations of the intra-day prices as suggested by Barndorff-Nielsen, Kinnebrock, and Shephard (2010). We do not refer to the semivariances as good or bad for an obvious reason: in electricity markets it is not clear whether a reduction of prices is good or bad, it entirely depends on the respective exposure by energy producers or consumers[2]. We also analyze the predictability of positive and negative volatilities using a Heterogeneous Autoregressive model of Realized Volatility (HAR-RV), which links future volatility to historical realized volatility over different time horizons (Corsi, 2009), as has been previously done for other commodities, such as gold (Todorova, 2017).

In our calculations, we consider the following seven countries: Norway, Sweden, Denmark, Finland, Estonia, Lithuania, and Latvia. We use data with an hourly frequency from January 1, 2013, to December 31, 2018. Our main results can be summarized as follows. First, positive and negative shocks to the market are featured by a distinctive persistence, depending on the forecasting horizon. Daily volatilities are more persistent and therefore forecasting power of the HAR model is larger. Regarding market integration we document a clearly increasing trend, both when we use positive or negative semivariances in our calculations. This fact is expected to contribute to a reduction of individual market risk, which occurs when idiosyncratic market shocks are smoothed across different markets. Nevertheless, risk spillovers are larger for

[2] Although this is also true for stocks, market crashes are invariably related to price downturns.

positive semivariances than for the negative ones, so that risk is more shared when the prices increase compared to the case of price reductions. Furthermore, the bigger the area, the smaller the sizes of the volatility shocks that it receives. Consistently, most of the time Norwegian, Swedish and Danish markets are net transmitters of volatility to the rest of the system. The former two are the biggest producers in the Nord Pool.

The rest of this paper is organized as follows. Section two contains the methodology. In section three, we present the data used in our analysis. In section four, we discuss our main results. Finally, in section five, we conclude.

2. Methodology

First, following the Heterogeneous Autoregressive model of the Realized Volatility (HAR-RV) proposed by Corsi (2009), we present a model that links day-ahead realized volatility (RV) in intraday electricity prices with past realized volatility over different time horizons. Unlike Corsi (2009), we differentiate between the effect of positive and negative volatilities on current volatility, on several horizons (see Section 2.1). Second, with the realized volatility measures we estimate positive and negative directional volatility spillovers between the bidding areas of the Nord Pool (see Section 2.2).

2.1. Heterogeneous autoregressive model of the Realized Volatility (HAR-RV)

Following Andersen and Bollerslev (1998), the realized volatility of intraday electricity prices is equal to:

$$RV_t = \sum_{h=1}^{24} r_{t,h}^2, \tag{1}$$

with $t = 1, \dots, T$, where $r_{t,h} = ln\left(\frac{p_{t,h}}{p_{t,h-1}}\right)$ are the intraday returns of electricity prices, t denotes the day of transaction, and h the hour of the day.

Next, as proposed by Barndorff-Nielsen et al. (2010), RV_t is decomposed into positive and negative semivariances. The positive and negative semivariances of day t are equal to:

$$RV_t^+ = \sum_{h=1}^{24} r_{t,h}^2 \cdot I\{r_{t,h} > 0\} \text{ and } RV_t^- = \sum_{h=1}^{24} r_{t,h}^2 \cdot I\{r_{t,h} < 0\}, \quad (2)$$

respectively, with $RV_t = RV_t^+ + RV_t^-$.

Once the RV_t is decomposed into positive and negative semivariances, the HAR model is estimated as follows:

$$RV_{d,t+1} = \beta_0 + \beta_1 RV_{d,t}^+ + \beta_2 RV_{w,t}^+ + \beta_3 RV_{m,t}^+ + \beta_4 RV_{d,t}^- + \beta_5 RV_{w,t}^- + \beta_6 RV_{m,t}^- + \varepsilon_t, \quad (3)$$

where RV_d, RV_w, RV_m are equal to daily, weekly, and monthly realized volatility measures, respectively. The weekly and monthly RV measures are equal to: $RV_{w,t} = \frac{1}{7}\sum_{i=0}^{6} RV_{d,t-i}$ and $RV_{m,t} = \frac{1}{30}\sum_{i=0}^{29} RV_{d,t-i}$, respectively.

2.2. Directional volatility spillovers

The spillover indices employed in this study are built on a Vector Autoregressive (VAR) with *N=7* variables, and are drawn from the associated forecast error variance decomposition (FEVD). The errors are estimated from the moving average representation of the VAR as follows:

$$X_t = \Theta(L)\varepsilon_t, \quad (4)$$

$$X_t = \sum_{t=0}^{\infty} A_i \varepsilon_{t-i}, \quad (5)$$

where X_t is a matrix $T \times N$, $\Theta(L) = (I - \phi(L))^{-1}$ and $A_i = \phi A_{i-1} + \phi A_{i-2} + \cdots + \phi A_{i-p}$ is the parameters' matrix, *p* is the number of lags used in the estimation, and *T* is the number of periods. To estimate the FEVD from the h-step ahead forecast, we first identify the structural VAR innovations by imposing restrictions on the MA parameters. In line with

Diebold and Yilmaz's suggestion (2012), we follow the pragmatic path proposed by Koop, Pesaran, and Potter (1996) and Pesaran & Shin (1998), namely the generalized VAR, for the construction of the FEVD.

The errors in the FEVD can be divided into *own variance* shares or *cross variance* shares. The former are the fractions of the system errors that are related to a shock to x_i on itself, while the latter are the portion of the shocks on x_i related to the rest of the variables in the system. Thus, the H-step ahead FEVD can be defined as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i{}' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i{}' A_h \Sigma A_h{}' e_i)}, \tag{6}$$

where Σ is the variance matrix of ε_t, and it should not be confused with the summatuib symbol, σ_{jj} is the standard deviation of the *j*-th equation, and e_j is an extractor vector, with ones in the *i*-th element and zero otherwise. To guarantee that the sum of each row is 1, $\sum_j \theta_{ij}(H) = 1$, each entry of the variance decomposition must be normalized as follows:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{H-1} \theta_{ij}(H)}. \tag{7}$$

With the normalized variance decomposition, a total spillover index can be calculated as:

$$C(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100. \tag{8}$$

This index measures the percentage variance that is explained by the cross-spillovers. It can be extended to a *directional spillover* index, in which the effect of a shock to x_j on the variable x_i is given by the following quantity:

$$C_{i*}(H) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100, \tag{9}$$

conversely, a shock to x_i on x_j is given by:

$$C_{*i}(H) = \frac{\sum_{j=1, i \neq j}^{N} \widetilde{\theta}_{ji}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}(H)} \times 100, \tag{10}$$

with the two directional spillover indices, we construct a *net spillover* index, given by:

$$C_i(H) = C_{*i}(H) - C_{i*}(H). \tag{11}$$

The net spillover index is a measure of the effect related to a shock in the variable x_i on the rest of the system. Therefore, each series within the system will be either a *net receiver* or a *net transmitter* of shocks in each period. It is also possible to construct a *net pairwise spillover* index that accounts for the net spillover effect of the series x_i on x_j, where $i \neq j$. The net pairwise index can be defined as:

$$C_{ij}(H) = \frac{\widetilde{\theta}_{ji}(H) - \widetilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}(H)} \times 100. \tag{12}$$

The estimations above allow us to analyze static spillovers across electricity prices, but they are silent about the dynamics of the system. Dynamics can be introduced in the present context by estimating gross and net spillovers statistics using rolling windows of data, as has been proposed by the exiting literature.

3. Data

The Nord Pool is the leading power market in Europe and one of the biggest integrated markets worldwide. The seven countries that are part of the Nord Pool are Sweden, Finland, Denmark, Norway, Estonia, Latvia, and Lithuania. In the day-ahead electricity market (Elspot), producers and consumers make their bids for the delivery of electricity for each hour of the next day. The markets that are part of the Nord Pool are divided into different bidding areas (currently, there are 15 sub-areas plus the total area). The pricing mechanism functions as

follows: first, the system establishes the prices for each hour of the following day that balance aggregate supply and aggregate demand; second, according to transmission capacity and congestion, different area prices may be established to solve bottlenecks. Table 1 presents the bidding areas with their acronyms, and Figure 1 a map of them.

Table 1. Bidding areas and acronyms

Area	Description	Area	Description
SYS	System Price	NO1	Oslo
SE1	Luleå	NO2	Kristiansand
SE2	Sundsvall	NO3	Molde, Trondheim
SE3	Stockholm	NO4	Tromsø
SE4	Malmö	NO5	Bergen
FI	Finland	EE	Estonia
DK1	Western Denmark	LV	Latvia
DK2	Eastern Denmark	LT	Lithuania

Figure 1. Nord Pool Spot bidding areas map

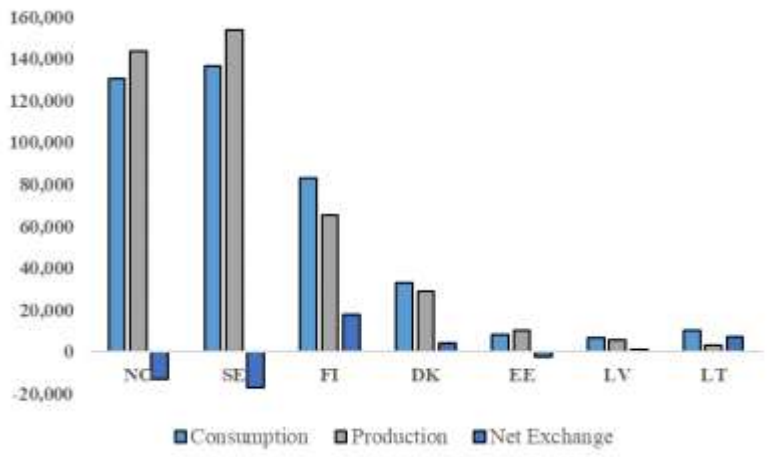
Source: Nord Pool Spot

The day-ahead electricity prices, quoted in EUR/MWh, were obtained from the Nord Pool Spot. The frequency of the prices is hourly, and the sample period starts on January 1, 2013, and ends on December 31, 2018. We restrict the analysis to a single area per country.

Figure 2 presents the average yearly consumption, production and net exchange (consumption minus production) for each country. Sweden, Norway, and Estonia showed a supply surplus,

while Finland, Denmark, Latvia, and Lithuania presented a higher consumption than their generation of electricity. Additionally, Sweden and Norway are responsible for 72% of the Nord Pool total electricity generation, and 65% of the total consumption. Lastly, the net exchange between all the countries of the Nord Pool increased in 52%, from 43,018 GWh interchanged in 2013 to 65,558 GWh in 2018, implying an increment in the market integration during these years.

Figure 2. Average yearly consumption, production, and net exchange, GWh, 2013 –2018



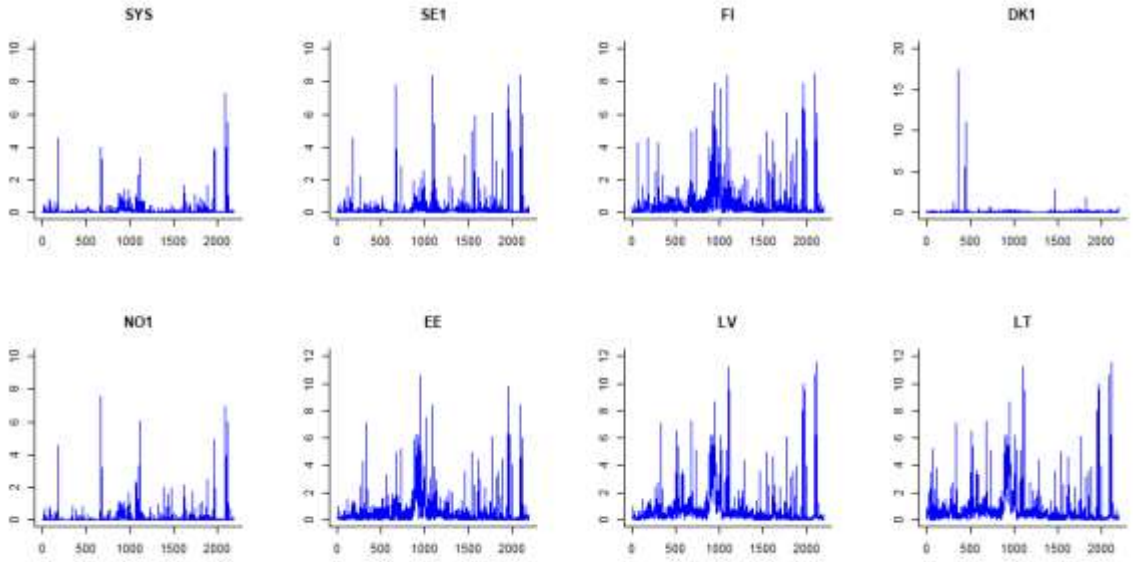
Source: Own elaboration with data from Nord Pool Spot.

The daily realized volatilities (total, positive and negative) were estimated from the hourly electricity spot prices returns after eliminating outliers. Non-positive prices were replaced by adding a constant to all prices in such a way that they become positive[3]. Figure 3 plots the total volatility for the system price and for each country in our sample. After the second half of 2014, all areas experienced an increase in their respective realized volatilities, which is especially true for the smallest markets within the system.

[3] As an exercise of robustness, the non-positive prices were also eliminated by replacing them with the price of the previous hour. The results obtained are very similar.

Regarding the descriptive statistics (Table 2), Estonia, Latvia and Lithuania present the higher average realized volatility. However, bigger markets like Sweden, Norway and Denmark exhibit higher order risk with the higher skewness and kurtosis.

Figure 3. Daily realized volatility (RV) measures, January 2013 - December 2018



Note: the realized volatility measures were estimated after eliminating the outliers from the intraday spot prices. Negative prices (including the zero) were considered as outliers, and were replaced by adding a constant to all prices in such a way that they become positive.

Table 2. Realized volatility descriptive statistics

	SE1	DK1	FI	NO1	EE	LT	LV
Mean	0.207	0.065	0.507	0.124	0.567	0.714	0.686
Median	0.056	0.025	0.198	0.016	0.233	0.376	0.348
Maximum	8.384	17.433	8.410	7.557	10.571	11.537	11.537
Minimum	0.001	0.000	0.001	0.000	0.001	0.001	0.001
Std. Dev.	0.656	0.462	0.938	0.472	1.007	1.151	1.142
Skewness	7.753	30.885	4.223	9.159	4.199	4.131	4.258
Kurtosis	73.160	1056.327	24.918	105.409	25.395	25.312	26.448
Observations	2191	2191	2191	2191	2191	2191	2191

4. Results and discussion

In order to characterize volatility in each market, we employ a HAR model to estimate the effect of positive and negative daily (RV_d), weekly (RV_w) and monthly (RV_m) volatilities on the day-ahead total volatility (see Table 3). Daily volatilities have the largest explanatory power on day-ahead realized volatility, with a 63% of the slope estimates being statistically significant (10 significant coefficients out of 16 estimations), followed by monthly volatilities, with a 44%, and lastly by weekly volatilities with 31%. Moreover, only three out of the 29 statistically significant slope estimates have a negative sign, which indicates volatility clustering. Additionally, the model with volatility decomposition between positive and negative presents a better performance than the one that does not distinguish between them (see Appendix A), indicating that decomposing volatility indeed enhances the forecast power of the model.

Regarding the effect of positive versus negative volatilities, positive volatilities are more frequently statistically significant than negative volatilities, independently on the time horizon, which indicates that price increments affect day-ahead realized volatility more significantly than price decreases. This result shows that consumers face a persistently higher risk in the integrated market than producers.

Table 3. Heterogeneous Autoregressive model of Realized Volatility (HAR-RV) estimation results

	SYS	SE1	FI	DK1	NO1	EE	LV	LT
Intercept	0.043***	0.089***	0.092***	0.026	0.048***	0.116***	0.120***	0.129***
	(0.010)	(0.017)	(0.022)	(0.017)	(0.011)	(0.025)	(0.029)	(0.031)
RV_D^+	0.129*	0.459***	0.449***	-0.265	0.476***	0.467***	0.602***	0.490***
	(0.075)	(0.080)	(0.069)	(0.268)	(0.072)	(0.070)	(0.072)	(0.067)
RV_D^-	0.535***	0.219***	0.001	0.171	0.075	0.012	0.113	0.223***
	(0.086)	(0.096)	(0.088)	(0.187)	(0.093)	(0.079)	(0.084)	(0.079)
RV_W^+	0.287	0.384	0.387*	0.283	0.251	0.640***	0.715***	0.700***
	(0.209)	(0.248)	(0.207)	(0.823)	(0.210)	(0.202)	(0.188)	(0.187)
RV_W^-	0.206	-0.066	0.462*	0.084	0.268	0.126	-0.295	-0.258
	(0.258)	(0.304)	(0.259)	(0.582)	(0.278)	(0.240)	(0.229)	(0.229)
RV_M^+	-0.118	-0.458	1.190***	2.785*	-0.909**	1.081***	0.190	0.283
	(0.355)	(0.461)	(0.340)	(1.439)	(0.390)	(0.335)	(0.258)	(0.260)
RV_M^-	0.369	0.670	-1.175	-1.976*	1.333**	-1.070**	0.167	0.046
	(0.471)	(0.613)	(0.440)	(1.048)	(0.528)	(0.441)	(0.348)	(0.352)
$Adj\ R^2$	0.187	0.180	0.386	0.005	0.179	0.425	0.436	0.413

Note: *, **, and *** indicate significance at a 90%, 95%, and 99% confidence level, respectively. RV_d, RV_w, RV_m account for daily, weekly, and monthly realized volatility, respectively.

After estimating the effect of past volatility measures on day-ahead volatility, and differentiating the effect of positive volatilities (which accounts for price increments) and negative volatilities (which accounts for price reductions) for each country within the Nord Pool, we assess how much of each market's volatility is transmitted (received) to (from) other areas, i.e., the directional volatilities spillovers between domestic markets.

Using a moving window of 730 days (two years), we estimated dynamic cross volatility spillovers among market areas. From our results, first, the total volatility spillover index is plotted in Figure 4. During the full period of analysis, positive volatility cross-spillovers are always higher than the negative ones, indicating that shocks to the system that generate a price increase (consumer's risk) are more transmitted than shocks from decreases in it (producer's risk). Therefore, when prices are high, the volatility transmission is higher, which corresponds to periods of relative electricity scarcity. Moreover, the total index shows seasonal volatility transmission between the markets: during the colder months, the transmission of shocks is

higher than in other months. This patter gives rise to a clear cyclicality in the dynamics of market integration.

Of upmost importance our results show that during the period analyzed the integration between the Nord Pool markets has increased both following price reductions and price increments. A higher integration indicates a larger transmission of shocks across the markets and therefore a higher level of international market risk sharing, which allows smother patterns of electricity consumption and production (which are desirable under de assumption of risk-averse market participants and regulators). This result implies that if a country receives a volatility shock, such shock will be transmitted to the whole system, diversifying the risk across all countries and reducing domestic exposure to price variations. This in turn contributes to the reduction of the probability of domestic energy shortages, which could potentially derived in a scenario of energy crisis.

Figure 4. Total volatility spillovers: RV, RV+, and RV-, January 2013 - December 2018

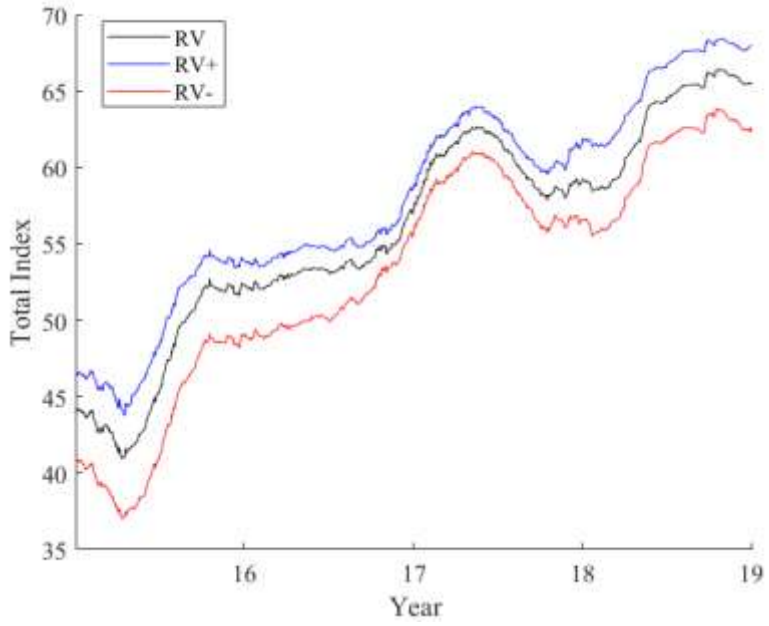


Figure 5 presents the net pairwise directional spillovers for the total realized volatility, i.e., the difference between volatility shocks transmitted and received between pair of countries. The countries in columns are transmitters of shocks, while those in rows are receivers. The biggest markets, Sweden, Norway, and Finland are most of the time transmitting shocks to the other countries, while the smallest actors of the market, Denmark, Estonia, Latvia, and Lithuania, by general rule receive shocks from the others. Estonia only shocks Latvia and Lithuania, which is explained by the fact that Estonia acts as a link enabling the other two to connect to the whole Scandinavian market. Additionally, despite their similar price dynamics, the interaction between Latvia and Lithuania is minimum. Hence, the transmission of shocks is determined mainly by the size of the market and the location of the country.

Figures 6 and 7 show the net pairwise directional spillovers differentiating between positive and negative realized volatility. We find that transmission of shocks is symmetrical in this case, but is higher in the case of positive volatility, showing once more that consumer's risk is more transmitted than producer's risk, or in other words that consumer's price risk is relatively more shared across the different markets than producer's price risk.

Figure 5. Net pairwise directional spillovers, RV, January 2013 - December 2018

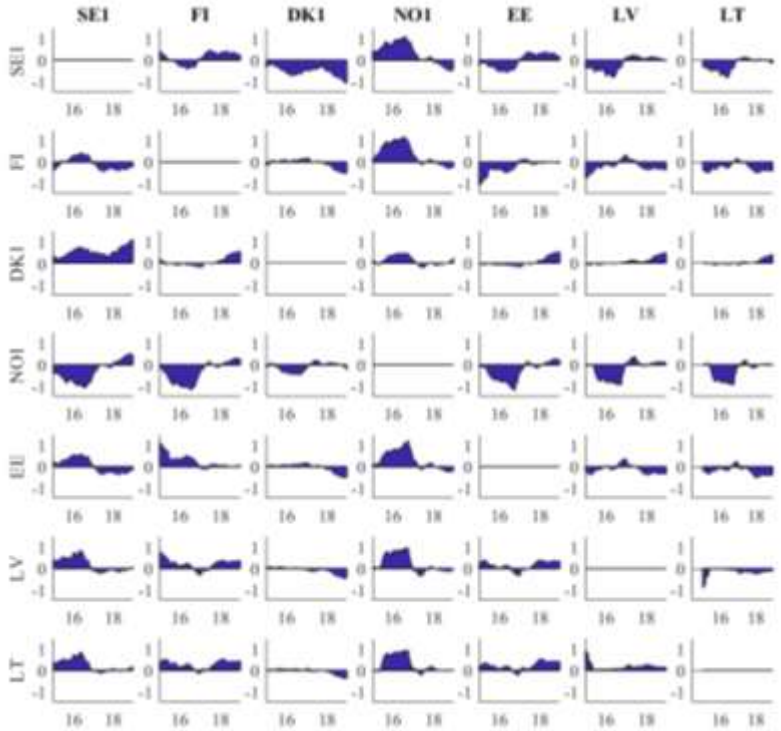


Figure 6. Net pairwise directional spillovers, RV+, January 2013 - December 2018

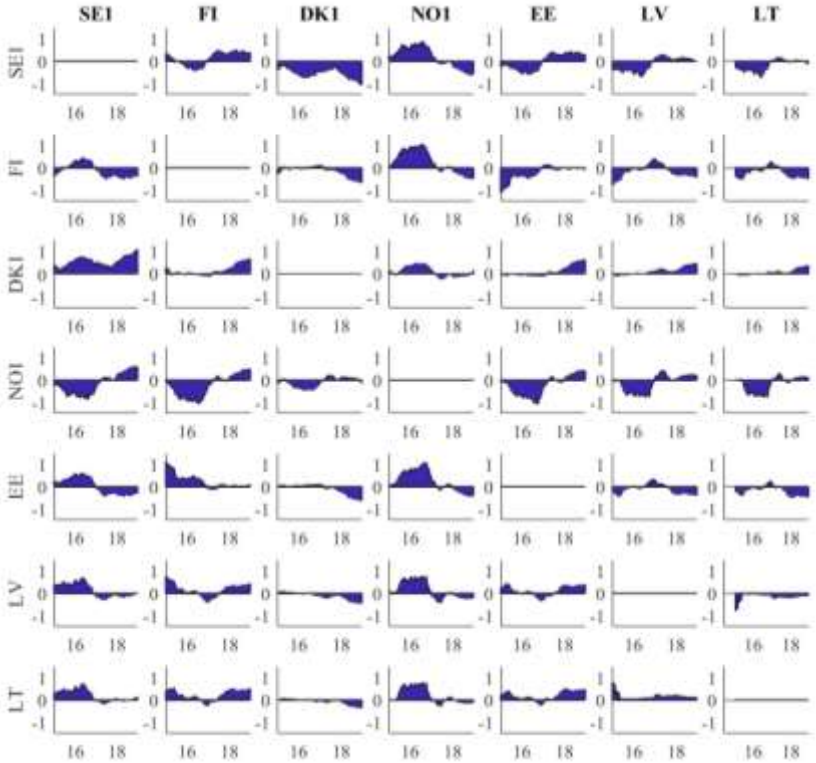
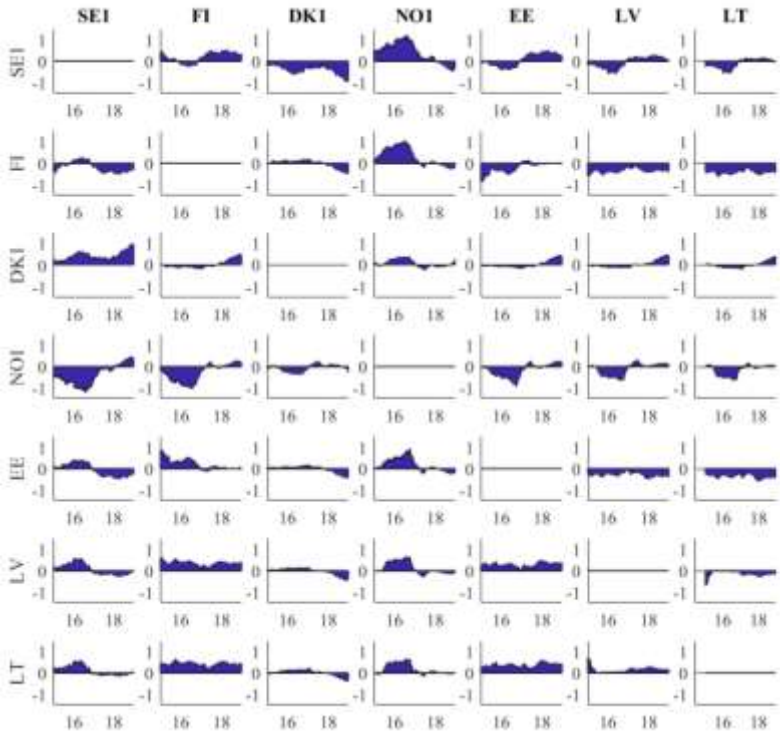


Figure 7. Net pairwise directional spillovers, RV-, January 2013 - December 2018



5. Conclusions

Using hourly electricity prices for the seven countries of the Nord Pool we calculated daily, weekly, and monthly realized volatilities, and we decomposed them into positive and negative. We find that among the three horizons for which the semivariances were constructed, daily volatilities house the higher explanatory power over day-ahead volatilities. We document that risk exposure of consumers and producers of electricity is asymmetric, and that it depends on the dynamics of the tails of the electricity price distribution. This is a relevant feature of electricity markets that market players should take into account for their buying/selling strategies, and for market operators that must plan the optimal dispatch of electricity.

We also estimated spillover indices among the Nord Pool areas and by this mean we accessed the dynamics of market integration and international risk sharing in electricity markets in a time-varying fashion. We document that total spillovers in the Nord Pool have considerably increased since 2015, signaling larger electricity market integration, and hence increasing

benefits of economical and physical market integration, which allow for a higher level of risk sharing across the markets that conform the Nord Pool. This is important because it shows that in more physical and economical interconnected markets, the risk propagates more fluently, allowing for a reduction of idiosyncratic market risks, and therefore reducing the probability of energy shortages in domestic markets (which is confirmed by the fact that price increments propagate more than price reductions). We also show that net-exporters of electricity and larger markets, like Norway and Sweden, receive fewer spillovers than the other countries and are by general rule net transmitters of volatility.

Our results are of importance for regulators that seek to evaluate the benefits of a greater physical and economical integration of national electricity markets. We show that indeed such process has been accompanied by an increment in the level of risk sharing across the markets, meaning that a larger proportion of the price expected variation in a given market is due to shocks arising from other markets (in opposition to idiosyncratic shocks), and therefore signaling a higher level of international risk sharing across the markets. Larger market integration allows for a higher level of market risk sharing between electricity markets and henceforth it is expected to reduce the probability of occurrence of energy crises and energy shortages in any given market.

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Appendix

A. Heterogeneous Autoregressive model of Realized Volatility (HAR-RV) estimation results with volatility decomposition

	SYS	SE1	FI	DK1	NO1	EE	LV	LT
Intercept	0.042***	0.088***	0.067***	0.053***	0.047***	0.064***	0.082***	0.088***
	(0.010)	(0.017)	(0.022)	(0.012)	(0.011)	(0.022)	(0.026)	(0.027)
RV_D	0.320***	0.350***	0.260***	-0.007	0.303***	0.265***	0.387***	0.376***
	(0.023)	(0.023)	(0.024)	(0.023)	(0.022)	(0.024)	(0.023)	(0.023)
RV_W	0.237***	0.191***	0.448***	0.166***	0.287***	0.432***	0.270***	0.276***
	(0.045)	(0.044)	(0.045)	(0.061)	(0.046)	(0.045)	(0.043)	(0.044)
RV_M	0.093	0.036	0.160***	0.035	0.031	0.191***	0.225***	0.223***
	(0.063)	(0.065)	(0.046)	(0.112)	(0.065)	(0.045)	(0.044)	(0.045)
$Adj\ R^2$	0.185	0.179	0.378	0.004	0.176	0.414	0.427	0.407

Note: *, **, and *** indicate significance at a 90%, 95%, and 99% confidence level, respectively. RV_d, RV_w, RV_m account for daily, weekly, and monthly realized volatility, respectively.