Vulnerability of European Electricity Markets: A Quantile Connectedness Approach

Helena Chuliá[*][†] Tony Klein[‡] Jorge A. Muñoz Mendoza[§][**] Jorge M. Uribe[††]

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Abstract

The most recent increases in Gas and Electricity prices across Europe dramatically demonstrate how vulnerable we still are to supply shocks. We investigate the transmission of shocks from natural gas prices to local electricity prices in 21 European markets. Using a quantile connectedness model our results reveal that the vulnerability of electricity markets in Europe varies over time and across quantiles. Our findings show that natural gas shocks have a significant and nearly symmetrical impact on extreme quantiles of electricity price returns. However, for intermediate quantiles, there is a notable disconnection between electricity markets and the natural gas market. We also identify the electricity markets that are most and least vulnerable to shocks in natural gas prices. These results have implications for the development of regulations and energy policies aimed at reducing the reliance on natural gas in European economies and promoting the growth of renewable energy sources.

Keywords: energy prices, markets distress, market vulnerability, spillovers.
JEL codes: C22, L94, L95, Q40

[*] Departament d'Econometria, Estadística i Economia Aplicada, Universitat de Barcelona (UB), Spain. Email: hchulia@ub.edu
[†] RISKcenter, Institut de Recerca en Economia Aplicada (IREA), Universitat de Barcelona (UB)
‡ Queen's Management School, Queen's University Belfast, UK. Email: t.klein@qub.ac.uk
[§] Department of Business Management, University of Concepcion, Chile. Email: jormunozm@udec.cl
[**] School of Economics, University of Barcelona, Spain.
[††] Faculty of Economics and Business, Open University of Catalonia, Barcelona, Spain. Email: juribeg@uoc.edu

1. Introduction

Natural gas plays a significant role in electricity generation, particularly in gas-fired power plants, which contribute to a substantial portion of the electricity supply mix. Compared to other power plant types, such as coal or nuclear energy, these gas-fired power plants are very flexible in their electricity production and output can be adjusted to demand relatively easily. The integration of gas-fired power plants into the electricity supply mix inevitably creates interdependencies between gas and electricity markets and it is suggested that these dependencies are actively planned and managed (Chaudry et al., 2014; Sheikhi et al., 2015). Fluctuations in gas prices then directly affect the operational and economic viability of gas-fired power plants and their load management via the merit order scheme, in which the last fuel source for generation is the main determinant for the price of generated electricity. This way, natural gas prices have a significant influence on electricity prices due to interactions between gas and electricity markets (Alexopoulos, 2017). Gas prices affect the cost of electricity generation, which can impact wholesale electricity prices. The bi-directional relationship between natural gas prices and electricity markets need to be taken into consideration in any decision making regarding efforts of carbon emission reduction or neutrality (Johnson & Keith, 2004; Chevallier et al., 2019). Wang et al. (2022) highlight the importance of natural gas as a technological catalyst on the way to scalable cost-effective renewable energy.

This work addresses this interdependence in light of the recent and unprecedented increase in natural gas prices, or more generally, their extreme volatility, all over the Europe. The inevitable link to the energy mix and subsequent change in electricity prices in each country differs significantly, translating to country-specific impacts---and responses. However, this price fragmentation is not new and has been outlined in research already, albeit for price changes of less extreme manifestation. Cassetta et al. (2022) find that electricity prices do not converge despite regulatory harmonization and that the E.U. remains clustered in its price distribution. This is in line with previous findings of dispersion, for example in Telatar & Yasar (2020). One of the reasons for this recent inversion of price convergence is given as differing climate and energy policies on a national level Cassetta et al. (2022), which also plays a significant role in the present research. This work aims to address the vulnerability of the E.U. to natural gas price fluctuations and supply shocks with regard to electricity prices. In our sample, this supply shock is represented by the reduction of imported natural gas from Russia and the subsequent supply change to liquefied natural gas and natural gas from other sources in the vicinity of Europe. Securing this supply is still an ongoing challenge.

Our contributions to existing literature on the link of electricity and natural gas markets is threefold. Firstly, we adapt a novel methodology of Ando et al. (2022) to assess the connectedness of these markets. With this quantile vector autoregression, we provide robust evidence that changes of natural gas prices affect the electricity price distribution differently across quantiles, in particular for periods of substantial in- and decreases. Secondly, we derive a measurement for vulnerability of European electricity markets to changes in natural gas markets and show that clustering is present. For example, the Netherlands, Italy, and the United Kingdom have the most vulnerable electricity markets with regard to natural gas price fluctuations. On the other hand, Spain, Portugal, and Germany show the least vulnerability. Thirdly, we show that there is a significant time-variation of these spillover effects. In recent years, this spillover increased dramatically. All three contributions are highlighting the importance to derive policy and regulatory actions to address this increased dispersion not only on a price level (e.g. Telatar & Yasar, 2020,, Cassetta et al., 2022) but also with regard to time-varying spillover and diverging vulnerability across E.U. member countries.

The remainder of the paper is structured as follows. Section 2 outlines our methodological approach, while Section 3 presents the detailed data. Section 4 exhibits the main results, and finally, Section 5 offers the conclusions and implications of this research.

2. Methodology

In order to assess the interconnectedness between electricity prices in various European markets and natural gas prices, we employ the quantile connectedness method introduced by Ando et al. (2022). This approach builds upon the conventional framework proposed by Diebold and Yilmaz (2012, 2014), but incorporates a quantile vector autoregression model, referred to as QVAR(p), characterized by the following baseline structure:

$$\boldsymbol{y}_t = \boldsymbol{\mu}(\tau) + \sum_{j=1}^{p} \boldsymbol{\Phi}_j (\tau)\boldsymbol{y}_{t-j} + \boldsymbol{u}_t(\tau), \tag{1}$$

where $\boldsymbol{y}_t$ and $\boldsymbol{y}_{t-j}$ are $k \times 1$ dimensional vectors that contain the endogenous variables in t and $t-j$, respectively. In our case, the QVAR(p) model is bivariate since it contains $k = 2$ endogenous variables, that is, the natural gas prices and the electricity prices of a specific market. In addition, the quantile of interest $\tau \in [0,1]$, p is the autoregression order of the QVAR model, $\boldsymbol{\mu}(\tau)$ is a $k \times 1$ dimensional conditional mean vector, $\boldsymbol{\Phi}_j(\tau)$ is a $k \times k$ matrix that contains the coefficients of the QVAR system while $\boldsymbol{u}_t(\tau)$ is a $k \times 1$ dimensional vector with a variance–covariance matrix of dimension $k \times k$, denoted by $\boldsymbol{\Sigma}(\tau)$.

Let $QVMA(\infty)$ be the moving average representation of the $QVAR(p)$ system obtained through Wold's Theorem:

$$\boldsymbol{y}_t = \boldsymbol{\mu}(\tau) + \sum_{i=0}^{\infty} \boldsymbol{\psi}_i (\tau)\boldsymbol{u}_{t-i}, \tag{2}$$

where the $k \times k$ dimensional coefficients matrix, denoted by $\boldsymbol{\psi}_i(\tau)$, follows the recursion $\boldsymbol{\psi}_i(\tau) = \boldsymbol{\Phi}_1\boldsymbol{\psi}_{i-1}(\tau) + \boldsymbol{\Phi}_2\boldsymbol{\psi}_{i-2}(\tau) + \cdots + \boldsymbol{\Phi}_p\boldsymbol{\psi}_{i-p}(\tau)$ with $\boldsymbol{\psi}_0(\tau)$ defined as an identity matrix and $\boldsymbol{\psi}_i(\tau) = 0$ for $i < 0$. The moving average representation is relevant to understand system dynamics and connectedness statistics. To achieve order-invariant variance decompositions of the QVAR system, these connectedness measures employ the methodological framework proposed by Koop et al. (1996) and Pesaran and Shin (1998), hereinafter KPPS. Therefore, for $H = 1,2, \ldots$, we denote the KPPS H-step-ahead forecast error variance decomposition as:

$$\theta_{ij}^{g}(H) = \frac{\Sigma(\tau)_{ii}^{-1} \sum_{h=0}^{H-1}\left(\boldsymbol{e}_i'\boldsymbol{\psi}_h(\tau)\boldsymbol{\Sigma}(\tau)\boldsymbol{e}_j\right)^2}{\sum_{h=0}^{H-1}\left(\boldsymbol{e}_i'\boldsymbol{\psi}_h(\tau)\boldsymbol{\Sigma}(\tau)\boldsymbol{\psi}_h(\tau)'\boldsymbol{e}_i\right)}, \tag{3}$$

where $\Sigma(\tau)_{ii}$ is the standard deviation of the error of the i-th equation in the quantile τ, and $\boldsymbol{e}_i$ is a selection vector with value one at the i-th element and zero otherwise. As the sum of the elements of each row in Equation (3) is not equal to 1 $\left(\sum_{j=1}^{k} \theta_{ij}^{g}(H) \neq 1\right)$, in order to get a unit sum of each row of the variance decomposition matrix, the following normalization must be done for each entry:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{k} \theta_{ij}^{g}(H)}, \tag{4}$$

where by construction $\sum_{j=1}^{k} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{k} \tilde{\theta}_{ij}^{g}(H) = k$. Equation (4) thus constitutes a natural measure of the pairwise directional spillover from variable j to variable i. Next, the total directional spillover received by variable i from all other variables j is:

$$S_{i\leftarrow\circ}^{g}(H) = \sum_{\substack{j=1 \\ j\neq i}}^{k} \tilde{\theta}_{ij}^{g}(H), \tag{5}$$

Similarly, the total directional spillover transmitted by variable i to other variables j is:

$$S_{\circ\leftarrow i}^{g}(H) = \sum_{\substack{j=1 \\ j\neq i}}^{k} \tilde{\theta}_{ji}^{g}(H), \tag{6}$$

The net spillover from variable i to the remaining variables j is:

$$S_{i}^{g}(H) = S_{\circ\leftarrow i}^{g}(H) - S_{i\leftarrow\circ}^{g}(H), \tag{7}$$

Finally, using the KPSS variance decomposition, the adjusted total spillover or system-wide connectedness of Chatziantoniou and Gabauer (2021) and Gabauer (2021) which ranges between $[0,1]$, can be represented by:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{k} \tilde{\theta}_{ij}^{g}(H)}{k-1}, \tag{8}$$

This spillover measure quantifies the contribution of the shocks of the k variables to the forecast error variance (Diebold and Yilmaz, 2009). Usually, this measure is used as a proxy for market risk, therefore, in our case, a higher $S^g(H)$ shows a higher degree of interconnectedness between the variables in the QVAR system.

3. Data

We use data from Bloomberg and ENTOS-E spanning from January 1, 2015, to December 30, 2022, for a comprehensive set of 21 European electricity markets. This dataset encompasses the electricity prices of the following countries: Belgium, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, the Netherlands, Norway, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the UK. Additionally, the dataset incorporates natural gas prices represented by the TTF and UK NBP indices. Our dataset includes a total of 2,084 transaction days for each time series, providing us with a large sample and complete records spanning eight years, which is crucial for accurately estimating spillover statistics from natural gas prices to various quantiles of electricity price distributions in each country. Importantly, our sample includes significant recent events that have impacted the performance of European electricity markets, including the Covid-19 pandemic, the Russian invasion of Ukraine, and the decisions made to address the resulting energy crisis.

Table 1. Descriptive statistics for the daily returns of natural gas and electricity

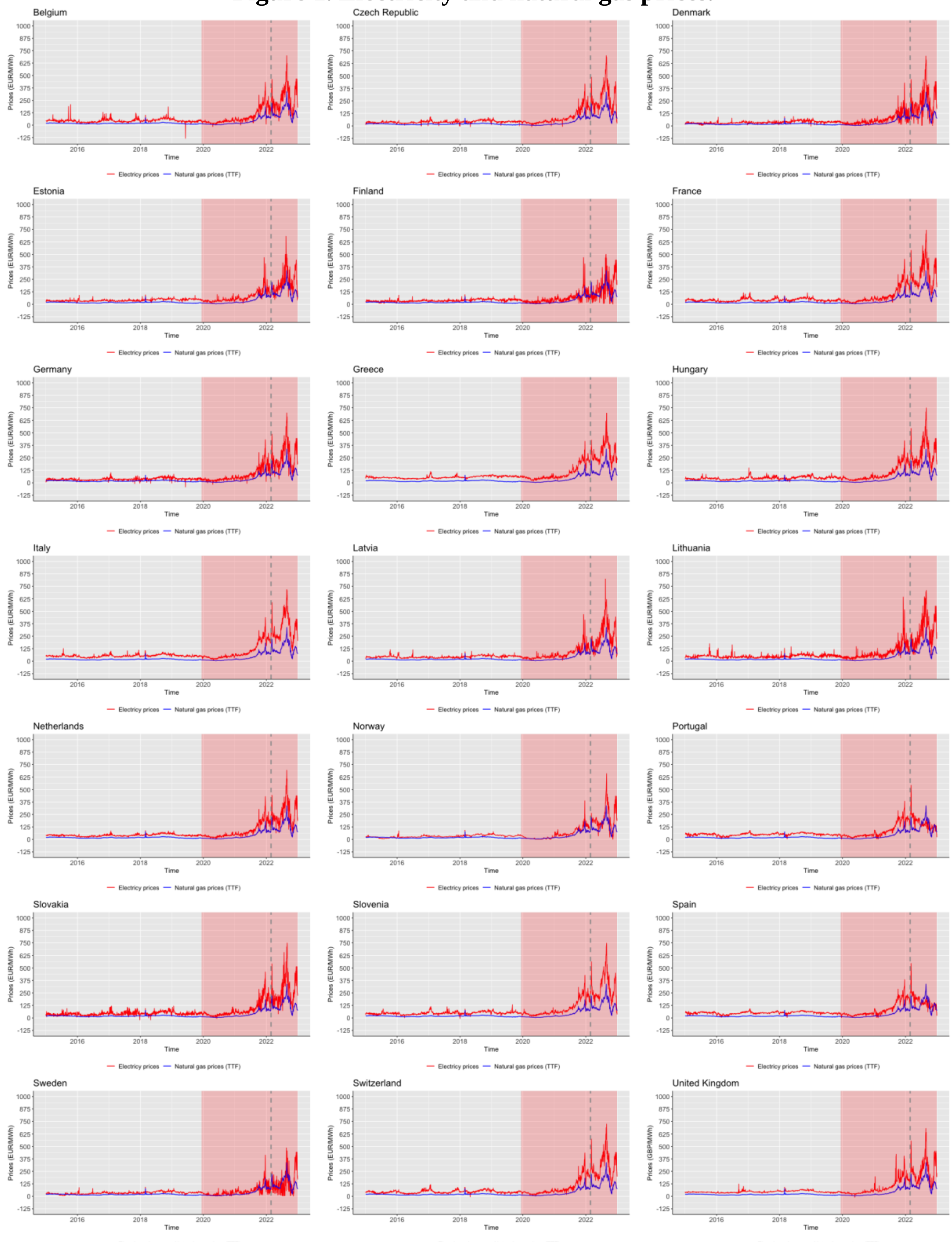
Variable	Obs.	Mean	St. Dev.	Min	Max	Skewness	Kurtosis	Shapiro-Wilk	ADF test
A. Electricity									
Belgium	2,084	10.97	327.71	-548.04	14,760.00	43.82	1969.13	0.03***	-12.58***
Czech Republic	2,084	1.89	117.4	-2,263.62	3,380.45	14.06	568.30	0.11***	-12.25***
Denmark	2,084	14.63	205.88	-792.88	7,882.23	30.71	1098.06	0.11***	-12.47***
Estonia	2,084	2.75	27.2	-80.7	387.39	4.85	57.02	0.71***	-13.25***
Finland	2,084	16.61	197.22	-98.36	7,701.54	29.88	1117.35	0.13***	-11.33***
France	2,084	2.99	33.42	-86.09	995.92	13.91	382.26	0.52***	-13.75***
Germany	2,084	3.51	77.07	-1,696.03	978.89	-5.06	167.66	0.39***	-13.35***
Greece	2,084	0.77	12.05	-50.34	106.34	1.17	10.39	0.91***	-15.22***
Hungary	2,084	1.91	21.94	-74.18	446.77	5.24	88.56	0.77***	-14.35***
Italy	2,084	0.9	13.3	-56.54	85.35	1.04	7.29	0.94***	-14.61***
Latvia	2,084	2.29	23.91	-80.7	387.39	4.25	51.86	0.75***	-13.46***
Lithuania	2,084	4.58	35.41	-73.25	408.27	3.36	26.22	0.76***	-11.89***
Netherlands	2,084	2.06	23.97	-69.76	385.7	6.01	79.91	0.67***	-11.68***
Norway	2,084	2.5	49.61	-92.73	2,065.80	34.95	1438.70	0.16***	-12.85***
Portugal	2,084	3.48	55.7	-91.2	2,050.99	26.68	915.63	0.19***	-11.97***
Slovakia	2,084	183.42	8,083.13	-684.34	369,000.00	45.58	2079.82	0.01***	-12.63***
Slovenia	2,084	1.99	44.56	-587.52	1,743.01	27.65	1133.86	0.23***	-12.83***
Spain	2,084	3.38	51.83	-91.16	1,893.15	25.6	874.81	0.22***	-11.81***
Sweden	2,084	18.37	172.73	-96.38	4,633.52	16.47	356.86	0.18***	-10.21***
Switzerland	2,084	1.22	26.04	-772.71	269.3	-11.35	384.42	0.54***	-13.01***
United Kingdom	2,084	0.79	18.06	-369.4	211.63	-2.2	112.84	0.61***	-12.98***

B. Natural Gas									
TTF	2,084	0.28	6.72	-63.82	96.51	2.69	45.45	0.69***	-13.00***
NBP	2,084	0.77	18.07	-98.55	647.52	23.02	799.79	0.28***	-12.28***

Note: Sampled period extends from January 01, 2015 to December 30, 2022. The TTF natural gas prices are measured in EUR/MWh, and NBP natural gas prices are measured in GBP/ therm. Units of electricity prices are measured in EUR/MWh, except for the UK, which is in GBP/MWh. Shapiro-Wilk refers to the Shapiro and Wilk test for the null of normality. ADF corresponds to the Augmented Dickey-Fuller unit root test (the alternative hypothesis is a stationary process with intercept but without trend). Superscripts ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Figure 1 depicts the dynamics of electricity prices in each country in relation to the TTF natural gas price. Notably, starting from the third quarter of 2021, local electricity prices experienced a significant surge following the rise in natural gas prices. This pattern was further accentuated in the aftermath of the Russian invasion of Ukraine, with the exception of Spain and Portugal, where different dynamics were observed. Table 1 displays the descriptive statistics of the daily returns for electricity and natural gas prices. Panel A illustrates that the daily electricity prices fluctuate between 0.77% (Greece) and 4.58% (Lithuania), with the exception of Belgium (10.97%), Denmark (14.63%), Finland (16.61%), Sweden (18.37%), and Slovakia (183.42%), which have experienced significant moments of high fluctuations and exhibit the highest variability records. The excess kurtosis values and rejection of the Shapiro-Wilk test indicate that the electricity prices in each country do not follow a normal distribution. Furthermore, the ADF test results suggest that the time series of electricity prices in each country exhibit stationarity, which is a crucial characteristic for estimating the QVAR model. Panel B shows that the mean of the returns for both natural gas price indices is approximately 0%. According to the ADF test, the daily returns of both the TTF and NBP indices exhibit stationarity, and similar to the electricity prices, they do not follow a normal distribution.

Figure 1. Electricity and natural gas prices.



Note: The sample period spans from January 01, 2015, to December 30, 2022. Returns are measured in percentage points. The units of electricity prices are in EUR/MWh, except for the UK, which is in GBP/MWh. TTF natural gas prices are measured in EUR/MWh, while NBP natural gas prices are denoted in GBP/therm. The gray vertical dashed line indicates the date of the Russian invasion of Ukraine (February 24, 2022). The red shaded area represents the period encompassing the Covid-19 pandemic (since December 2019).

4. Empirical results and discussion

4.1. Natural gas and electricity prices connectedness between extreme quantiles

Figure 2 shows the total connectedness between the natural gas and electricity price returns for each European market across time and for different quantiles of returns distribution[1]. Results are based on a 250-days rolling-window QVAR(1) and a 20-step-ahead forecast. This window length provides a suitable timeframe to capture the spillover dynamics between natural gas and electricity returns over one year.

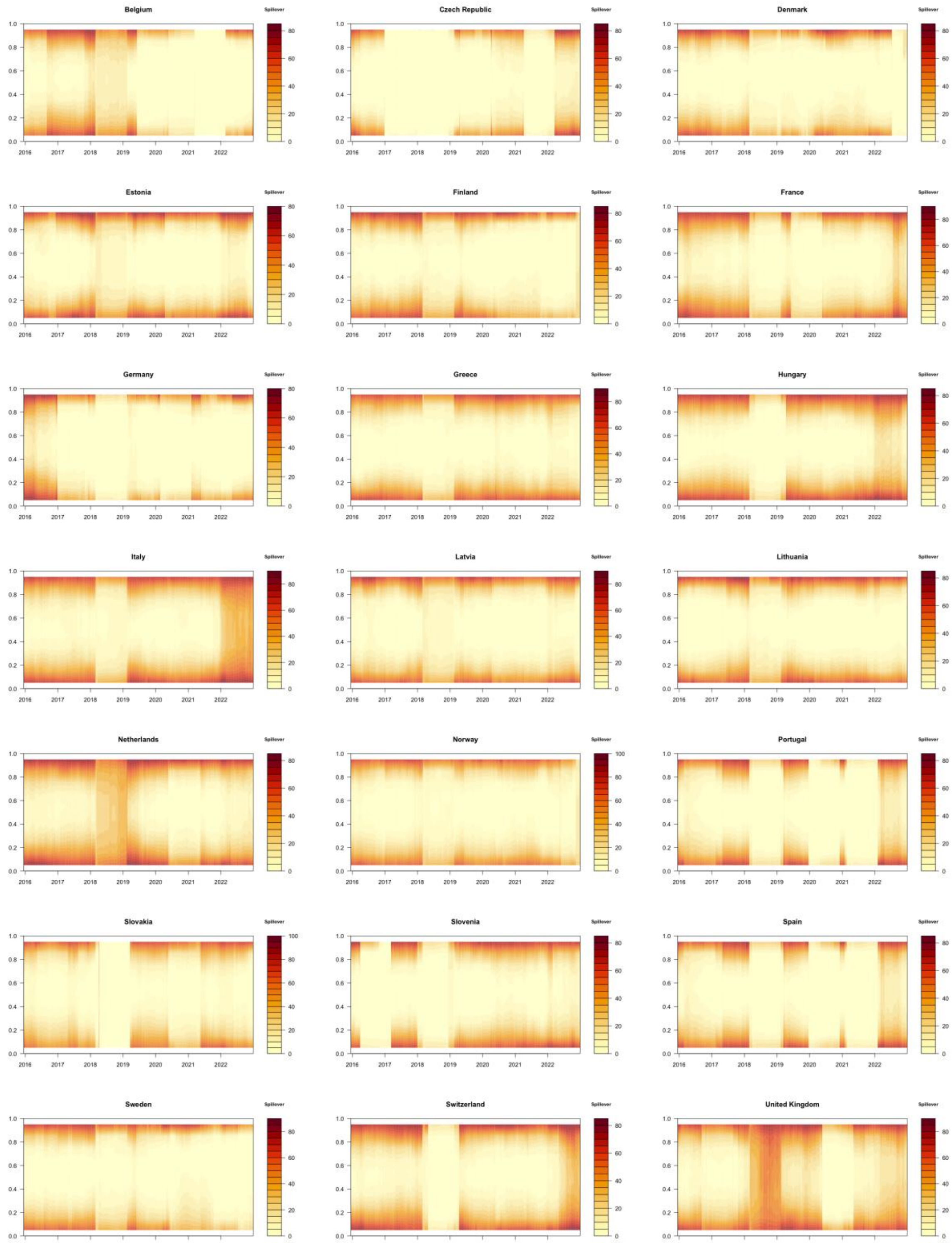
Figure 2 reveals four key insights that are of special interest for analyzing energy policy in European markets. First, total spillovers between natural gas and electricity price returns vary over time as well as across quantiles. This dynamic and asymmetric connectedness between natural gas and electricity prices highlights differences in vulnerability levels of electricity markets and underscores the need for tailored energy policies to address natural gas shocks. Second, natural gas and electricity price returns are practically disconnected in quantiles close to the median. Generally, within the 20% to 80% quantiles, we observe a consistent and rapid weakening of spillovers. Consequently, under normal conditions, European electricity markets are not significantly vulnerable to natural gas shocks. This observation holds true over time. Third, there is a strong connection between natural gas and electricity price returns in extreme quantiles. Spillovers are particularly pronounced for negative returns (quantiles below 20%) and positive returns (quantiles above 80%). Across all countries, we find that the spillover in this bivariate system is at least 40% in these extreme quantiles. These findings support the conclusions of Uribe et al. (2022) highlighting that dependence between electricity and natural gas prices is more substantial during episodes of stress in energy generation and naturally deserve closer monitoring by energy authorities. Thus, it is evident that the vulnerability of European electricity markets increases in extreme scenarios characterized by high and low returns.

Finally, we observe periods where spillovers either disappeared or intensified, regardless of the returns quantile. On one hand, during 2018, we note a weakening of spillovers in most

[1] In all QVAR(1) model estimations, the TTF index serves as the benchmark for natural gas prices. However, it is important to note that we also conducted the same estimations using the NBP index as a reference for natural gas prices, and we obtained similar results.

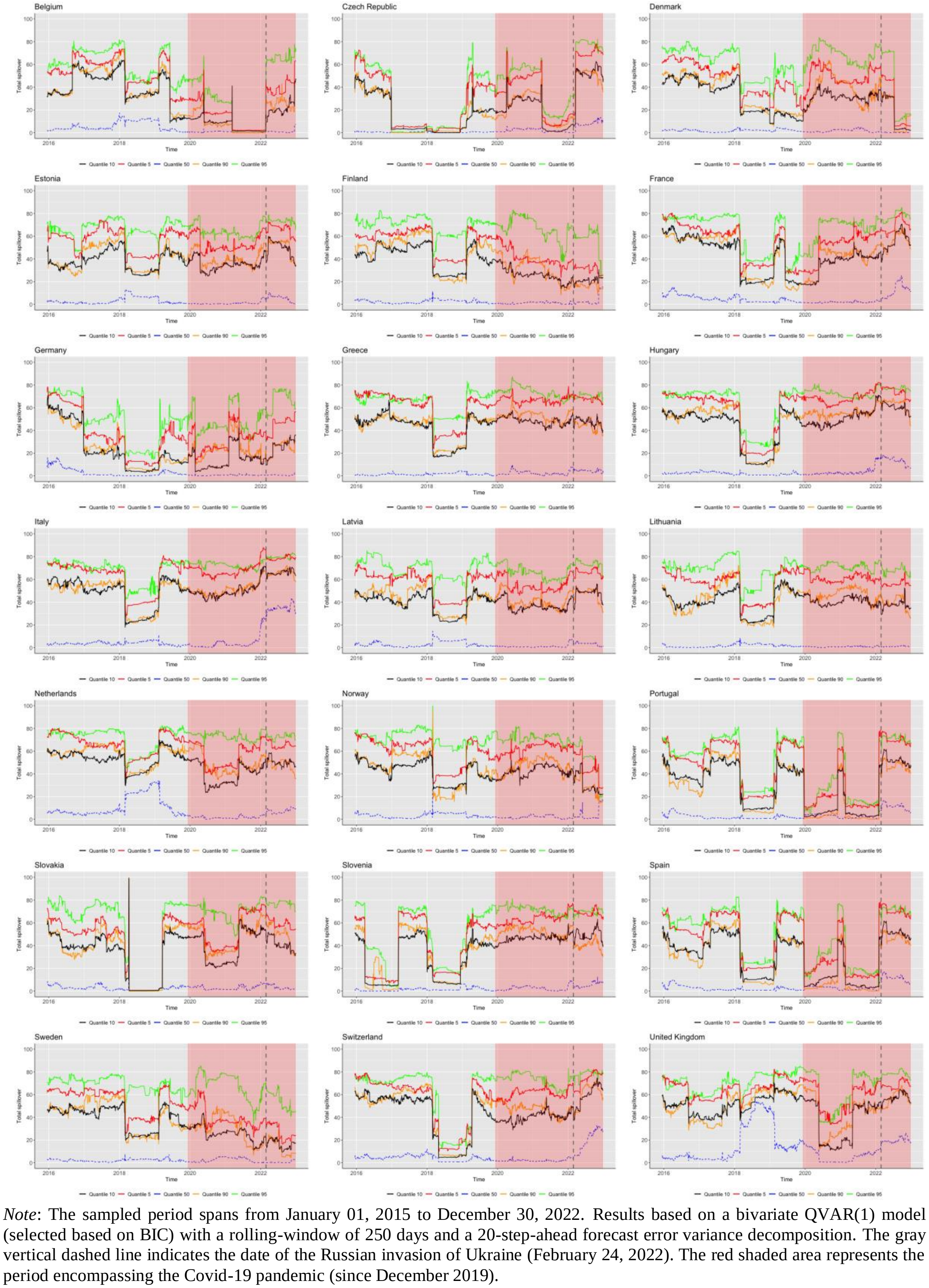
markets (except for Belgium, Netherlands, and the United Kingdom). This could be attributed to systemic factors influencing the dynamics of natural gas and electricity markets. On the other hand, the Russian invasion of Ukraine resulted in intensified spillovers in markets such as France, Hungary, Italy, Portugal, Spain, Switzerland, and the United Kingdom. These intensified spillovers can be attributed to the supply restrictions of Russian natural gas to these markets (European Commission, 2022). These findings are further supported by Figure 3, which depicts the total spillovers for high quantiles (90% and 95%), low quantiles (10% and 5%), as well as for the 50% (median) quantile of natural gas and electricity returns. Specifically, the returns at the 50% quantile exhibit time-varying spillovers, generally lower than 5%. However, for the most extreme return quantiles, we observe more intense spillovers between the natural gas and electricity markets. Figures A1 and A2 in the appendix describe similar results using a 125-days rolling-window, respectively.

Figure 2. Total connectedness between electricity and natural gas price returns across time and quantiles.



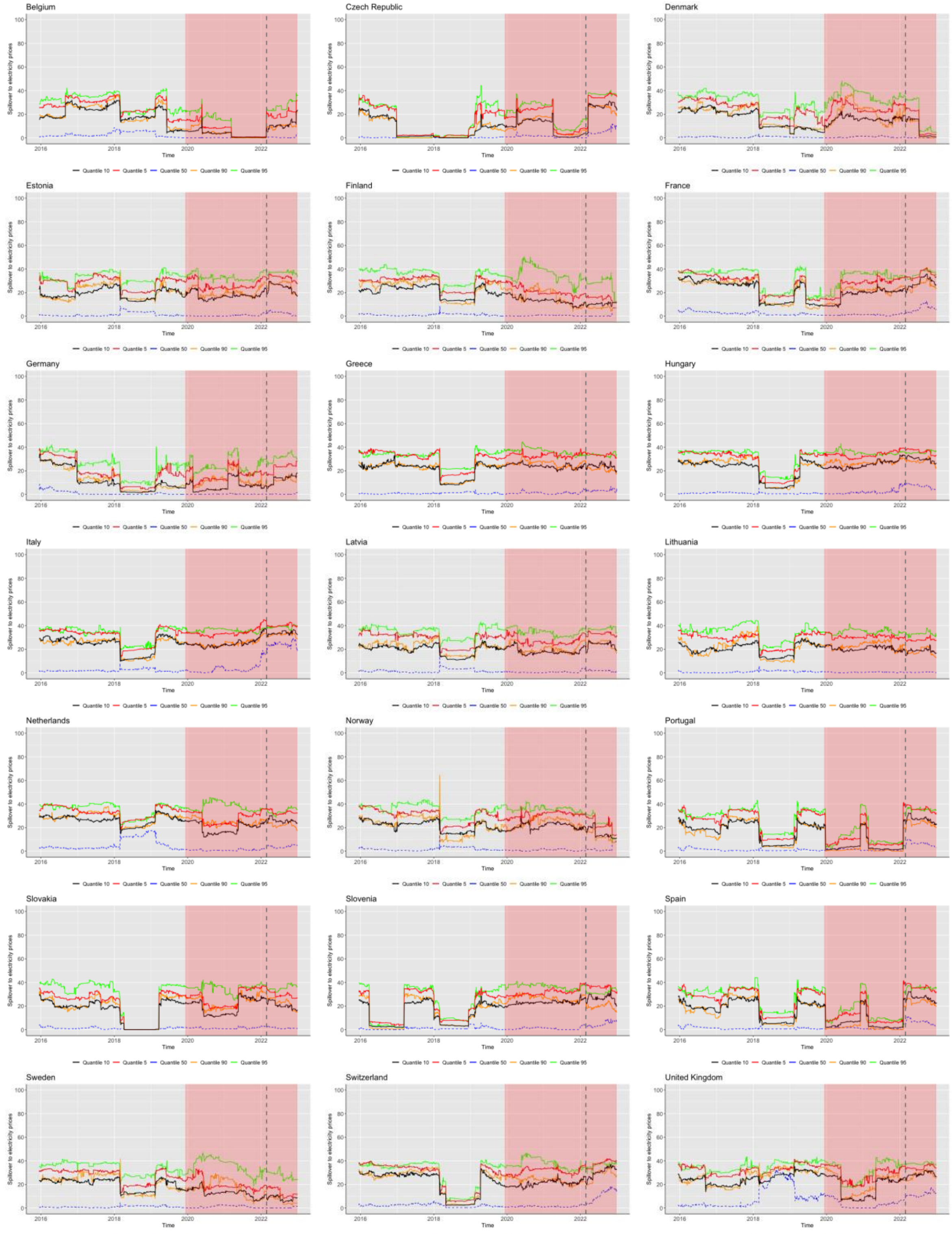
Note: The sampled period spans from January 01, 2015 to December 30, 2022. Results based on a bivariate QVAR(1) model (selected based on BIC) with a rolling-window of 250 days and a 20-step-ahead forecast error variance decomposition.

Figure 3. Total connectedness index between electricity and natural gas price returns (quantiles 5, 10, 50, 90 and 95).



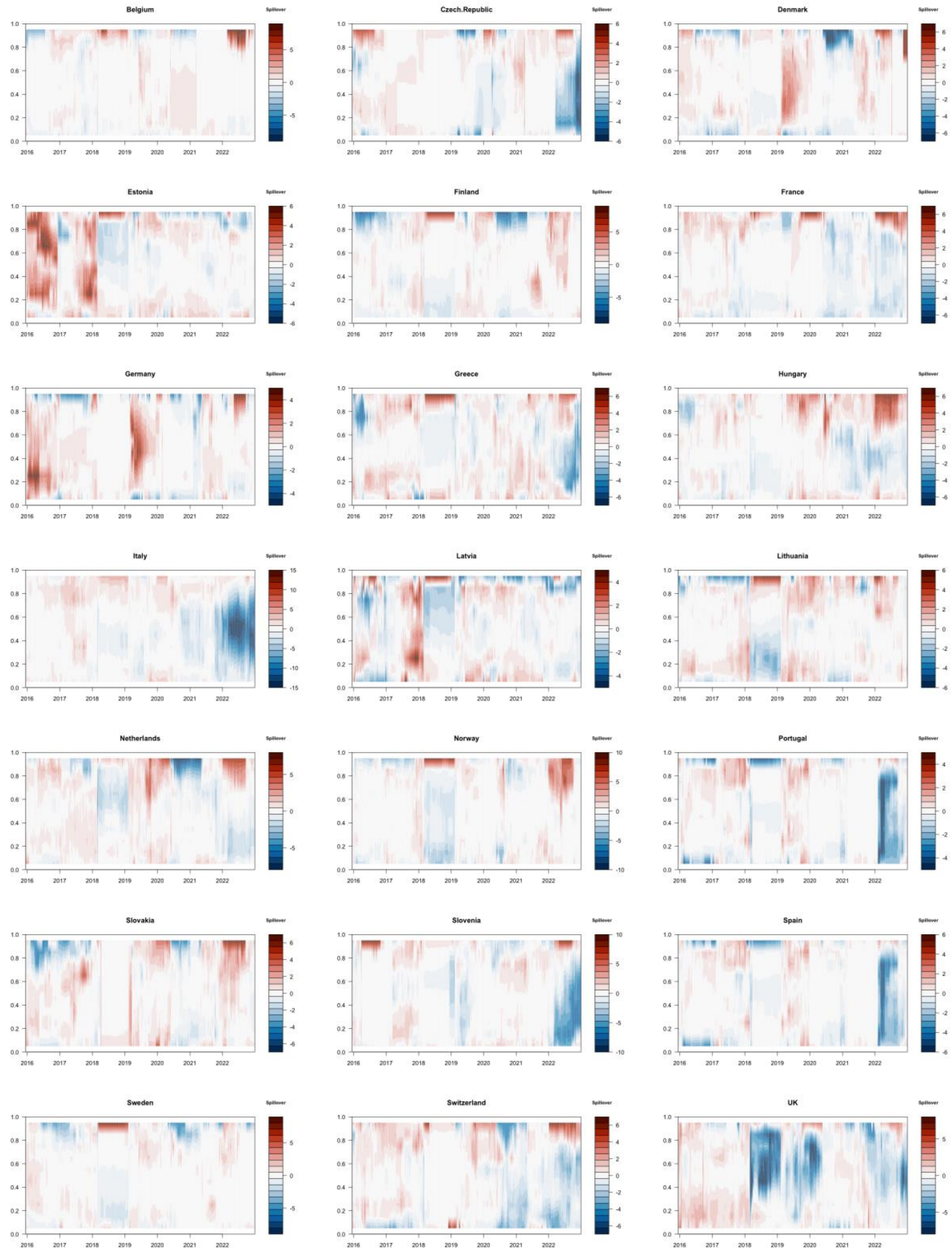
Note: The sampled period spans from January 01, 2015 to December 30, 2022. Results based on a bivariate QVAR(1) model (selected based on BIC) with a rolling-window of 250 days and a 20-step-ahead forecast error variance decomposition. The gray vertical dashed line indicates the date of the Russian invasion of Ukraine (February 24, 2022). The red shaded area represents the period encompassing the Covid-19 pandemic (since December 2019).

Figure 4. Total directional connectedness from natural gas price returns to electricity prices (quantiles 5, 10, 50, 90 and 95).



Note: The sampled period spans from January 01, 2015 to December 30, 2022. Results based on a bivariate QVAR(1) model (selected based on BIC) with a rolling-window of 250 days and a 20-step-ahead forecast error variance decomposition. The gray vertical dashed line indicates the date of the Russian invasion of Ukraine (February 24, 2022). The red shaded area represents the period encompassing the Covid-19 pandemic (since December 2019).

Figure 5. Net total directional connectedness in electricity markets across time and quantiles.



Note: The sample period spans from January 01, 2015 to December 30, 2022. Results based on a bivariate QVAR(1) model (selected based on BIC) with a rolling-window of 250 days and a 20-step-ahead forecast error variance decomposition.

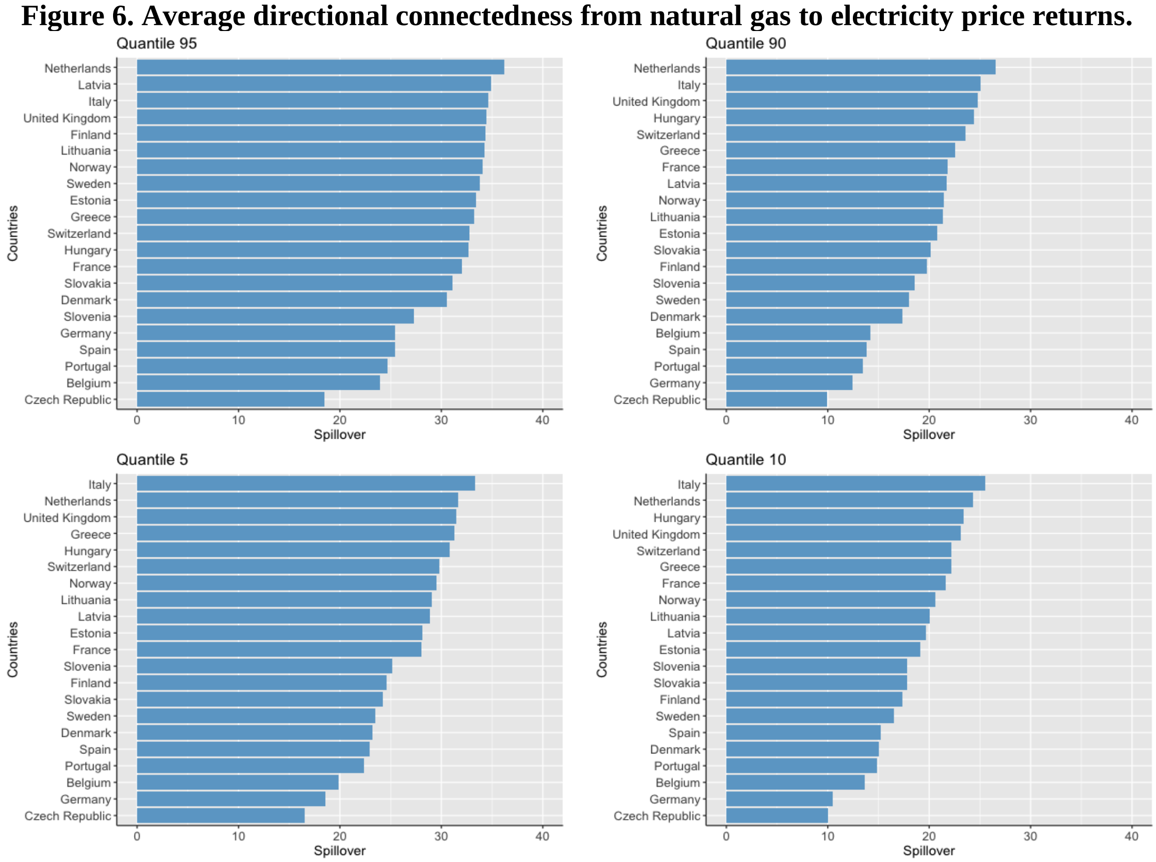
Figure 4 shows the directional spillover from the natural gas market to the electricity market in each country. This spillover serves as an indicator of the vulnerability of European electricity markets to natural gas price shocks. This connectedness measure is also time-varying, and in nearly all cases, it remains below 40%, with an average spillover of 30%. In other words, around 30% of the 20-days-ahead forecast error variance decomposition of electricity price returns can be attributed to shocks originating from the natural gas market. Furthermore, the results demonstrate that directional spillovers at quantile 50% are close to 0%, while they are higher for extreme return quantiles. Notably, there is a certain symmetry in the response of electricity prices to natural gas price shocks between the extreme quantiles. For instance, the directional spillovers for the 5% and 95% return quantiles exhibit striking similarity, as do the 10% and 90% quantiles. This finding indicates that the vulnerability of European electricity markets exhibits an almost symmetrical response in extreme quantiles, while remaining nearly zero in medium quantiles. Figure A3 in the appendix shows similar results, albeit with slightly greater volatility using a 125-days rolling-window. Lastly, Figure 5 illustrates the net spillover for electricity price returns, revealing mixed and varying results across time and quantiles. Notably, we observe the net receiver nature of certain electricity markets following the Russian invasion of Ukraine, including the Czech Republic, Greece, Italy, Portugal, Slovenia, Spain, Switzerland, and the United Kingdom. This finding holds across various quantiles. Figure A4 in the appendix displays similar results, using a 125-day rolling window.

4.2. Vulnerability of the electricity markets

The previous section established that the directional spillovers from the natural gas market to various electricity markets in Europe exhibit temporal variations and differ across quantiles. This measure of connectedness serves as a dynamic vulnerability indicator for each electricity market concerning shocks originating from the natural gas market. To provide an average measure of vulnerability for the entire period, Figure 6 displays the average directional spillover. Three important results emerge. First, there is a similarity in the magnitude of vulnerability between extreme quantiles. The average spillover for high positive returns (95% quantile) is 30%, while the vulnerability to negative return scenarios (5% quantile) stands at 26%. Between the 90% and 10% quantiles, the average directional spillovers are 20% and 19% respectively. Contrary to the findings of Uribe et al. (2022), this indicates a certain degree of symmetry in the response of electricity markets to shocks transmitted by the natural gas market.

Second, specific electricity markets vulnerable to fluctuations in the natural gas market are clearly identified. The Netherlands, Italy, the United Kingdom, and Switzerland emerge as the most vulnerable markets to natural gas price shocks across both high returns (95% and 90% quantiles) and negative returns (5% and 10% quantiles). These countries should establish regulatory mechanisms to mitigate the transmission of shocks from the natural gas market and promote the transition to renewable energy sources to reduce dependency. Third, the least vulnerable electricity markets are accurately identified as well. The Czech Republic, Germany, Belgium, Portugal, and Spain demonstrate lower vulnerability across different extreme quantiles. While there may be slight differences in the ranking, the magnitude of the average spillover is not significantly affected. Similar results, using a 125-day rolling window, are presented in Figure A5 of the appendix.

Figure 6. Average directional connectedness from natural gas to electricity price returns.



Note: Average directional connectedness from natural gas to electricity price returns. The sample period spans from January 01, 2015 to December 30, 2022. Results based on a bivariate QVAR(1) model (selected based on BIC) with a rolling-window of 125 days and a 20-step-ahead forecast error variance decomposition.

5. Conclusions and policy implications

This study contributes to the existing literature on the policy of electricity markets by employing a novel approach based on quantile vector autoregressions to analyze the vulnerability of these markets to natural gas price shocks. The findings of this study have relevant implications for policymakers and risk analysts across the European Union.

First, the study demonstrates that natural gas price shocks impact different segments of the electricity price distribution. Specifically, extreme quantiles of the distribution, corresponding to periods of substantial electricity price increases or decreases, are particularly sensitive to natural gas price fluctuations. This emphasizes the need for increased market monitoring during these episodes, as they are associated with heightened market turmoil and volatility. Governments and regulatory authorities should pay special attention to these extreme quantiles to ensure market stability and protect vulnerable consumers from sudden price spikes.

Furthermore, the study highlights the risks associated with the strong interdependence between natural gas and electricity markets, particularly during periods of market turmoil. When electricity demand exceeds supply from renewable or nuclear sources, natural gas prices become crucial for meeting the demand, leading to a transmission of fuel market volatility to electricity markets. This indicates the necessity to decouple electricity markets from natural gas prices, as fuel markets are known for their volatility and susceptibility to financialization. Maintaining a strong connection between the two markets during market turmoil can indirectly impact the stability of electricity markets.

Importantly, the research findings underscore the time-varying nature of spillover effects from natural gas to electricity. Recent times have witnessed relatively high spillover effects, suggesting the need for continuous monitoring and proactive risk management strategies. Moreover, the analysis reveals that certain European markets, such as Spain, Portugal, Italy, and Slovenia, act as net givers of shocks to the system, in recent years, while others like Hungary, the Netherlands, Belgium, and Switzerland continue to be net receivers, particularly during scenarios of high positive electricity returns, indicating their greater vulnerability.

Our study also provides a rank of vulnerability in countries during the sample period. Italy and Netherlands emerge as the most vulnerable market according to our summary statistics of vulnerability, while the Czech Republic and Germany are shown to be the least vulnerable (followed closely by Spain, Portugal and Belgium). Future research could explore policy and economic factors influencing the vulnerability of electricity markets and investigate potential strategies for further reducing the dependence on natural gas and enhancing the integration of renewable energy sources.

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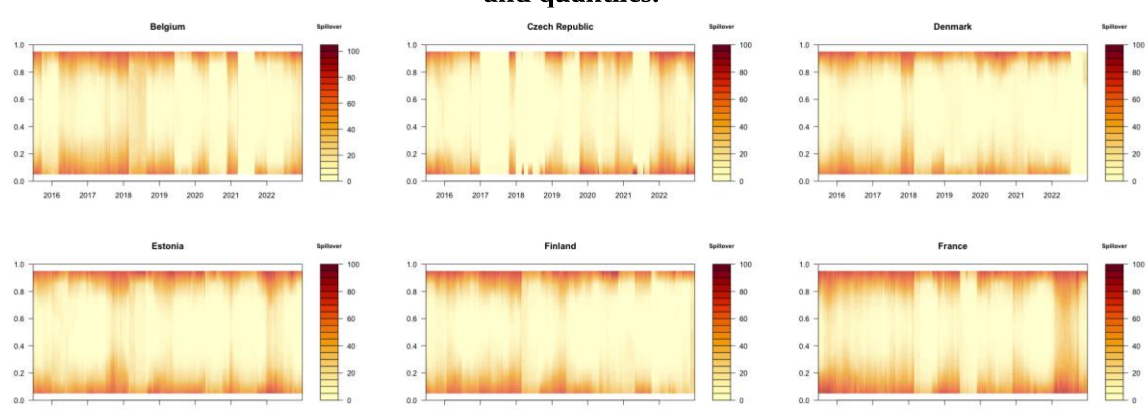
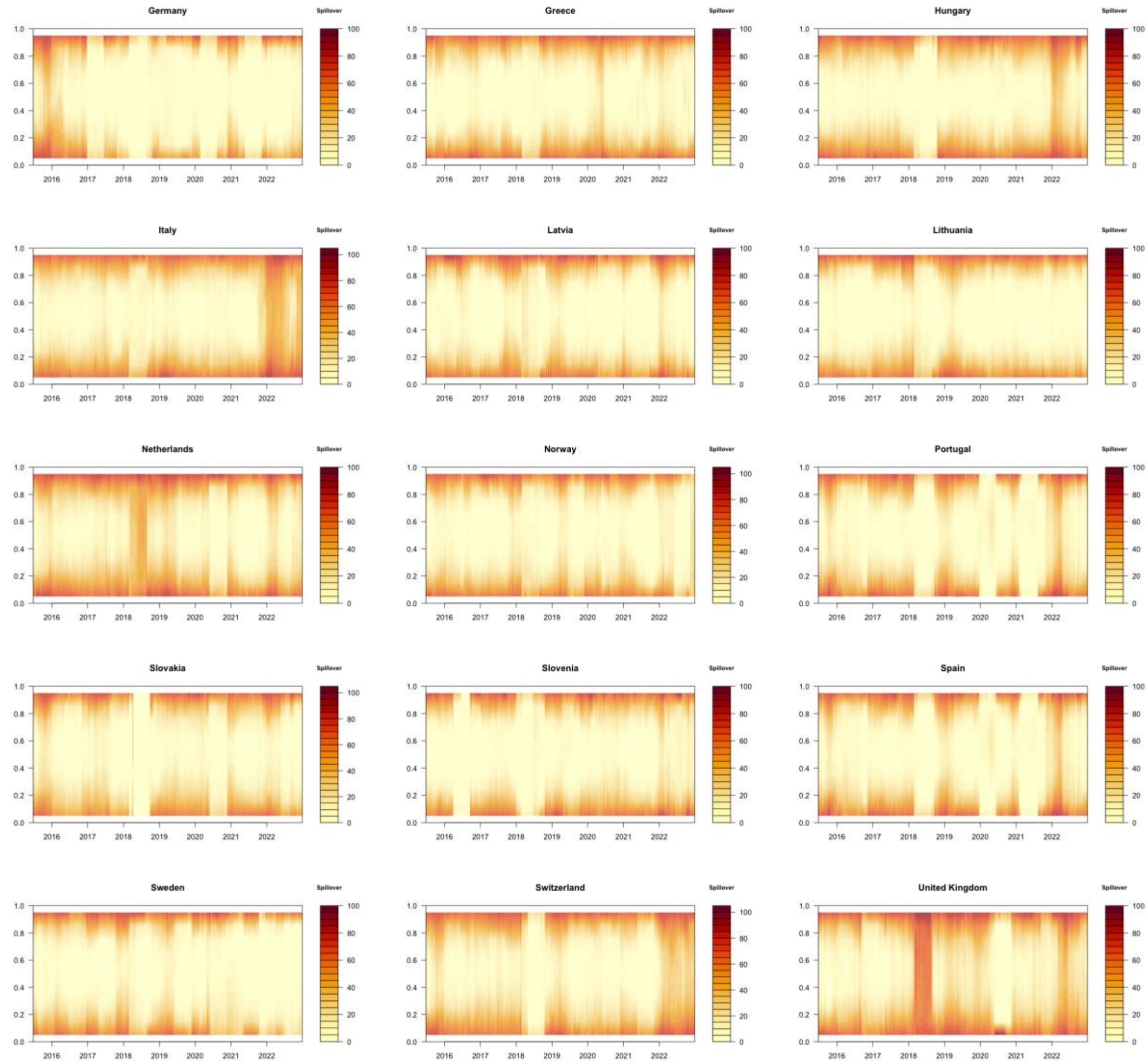
Appendix

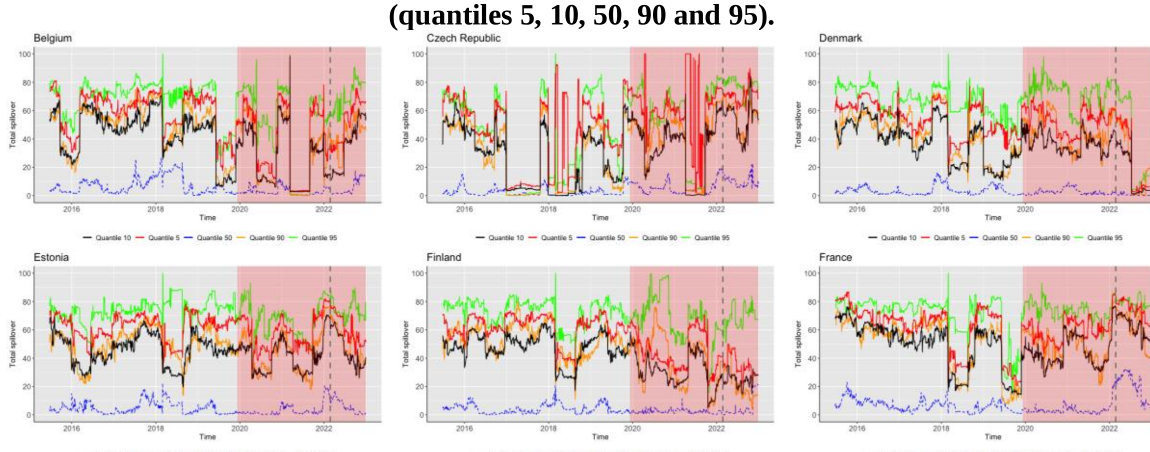
Figure A1. Total connectedness between electricity and natural gas price returns across time and quantiles.

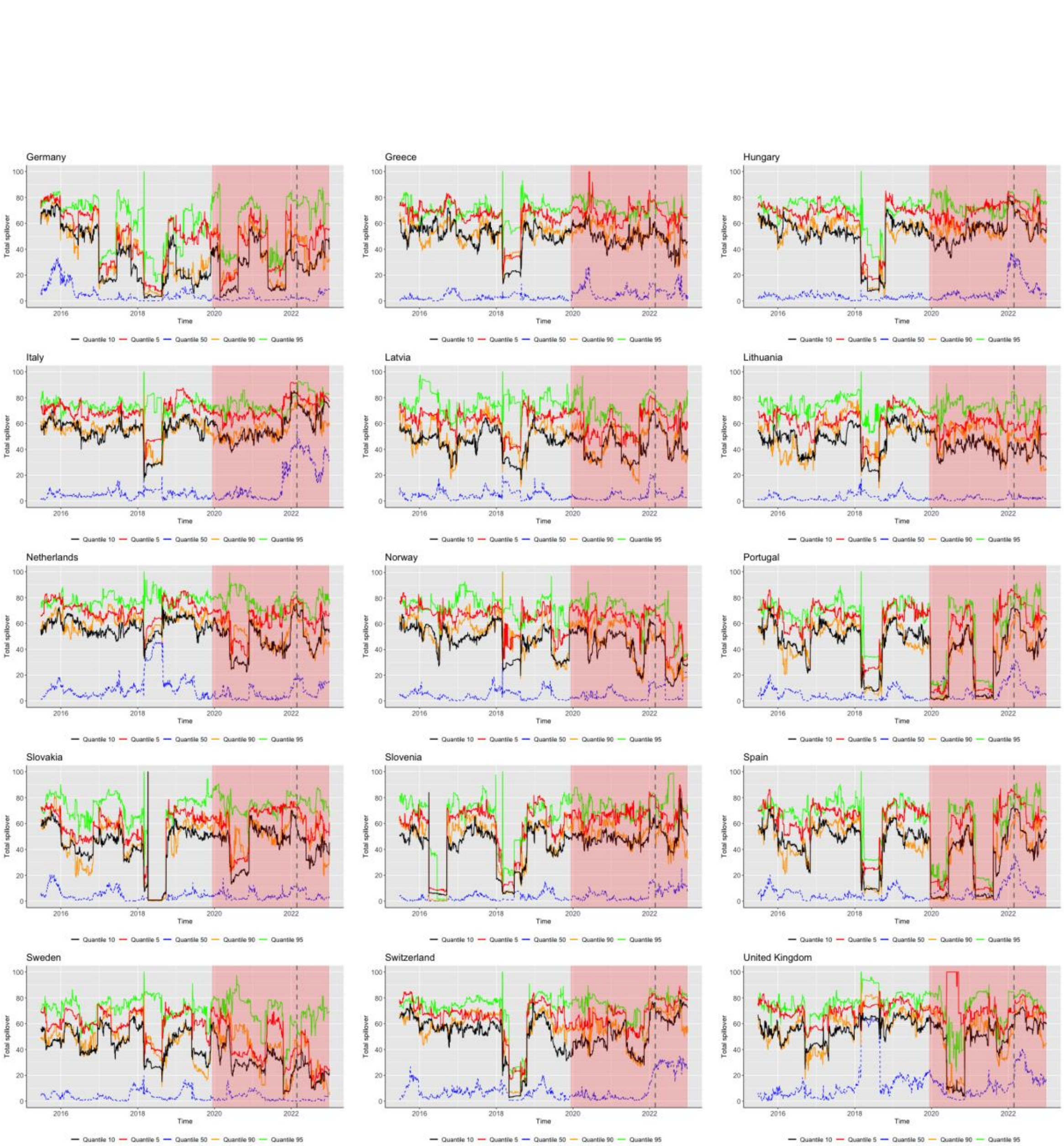




Note: The sampled period spans from January 01, 2015 to December 30, 2022. Results based on a bivariate QVAR(1) model (selected based on BIC) with a rolling-window of 125 days and a 20-step-ahead forecast error variance decomposition.

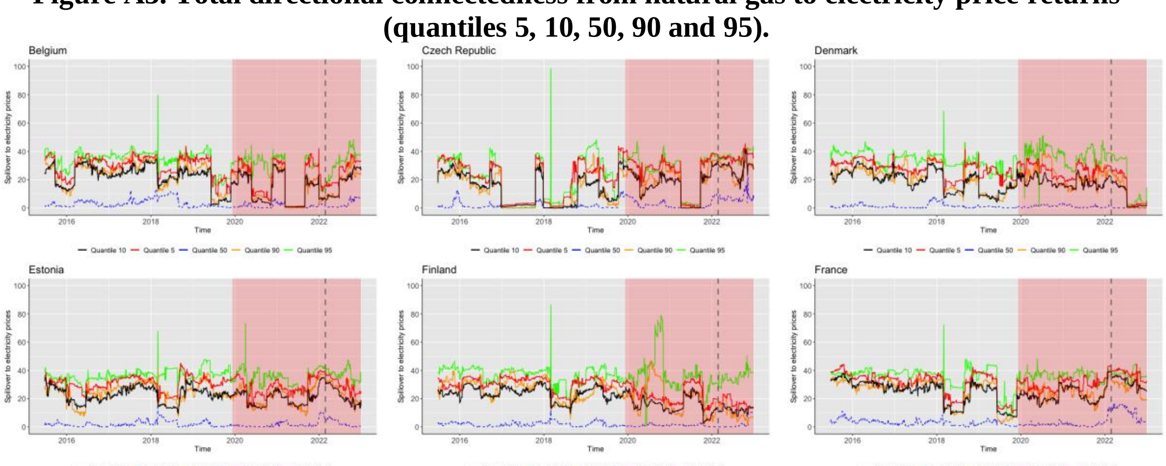
Figure A2. Total connectedness index between electricity and natural gas price returns (quantiles 5, 10, 50, 90 and 95).

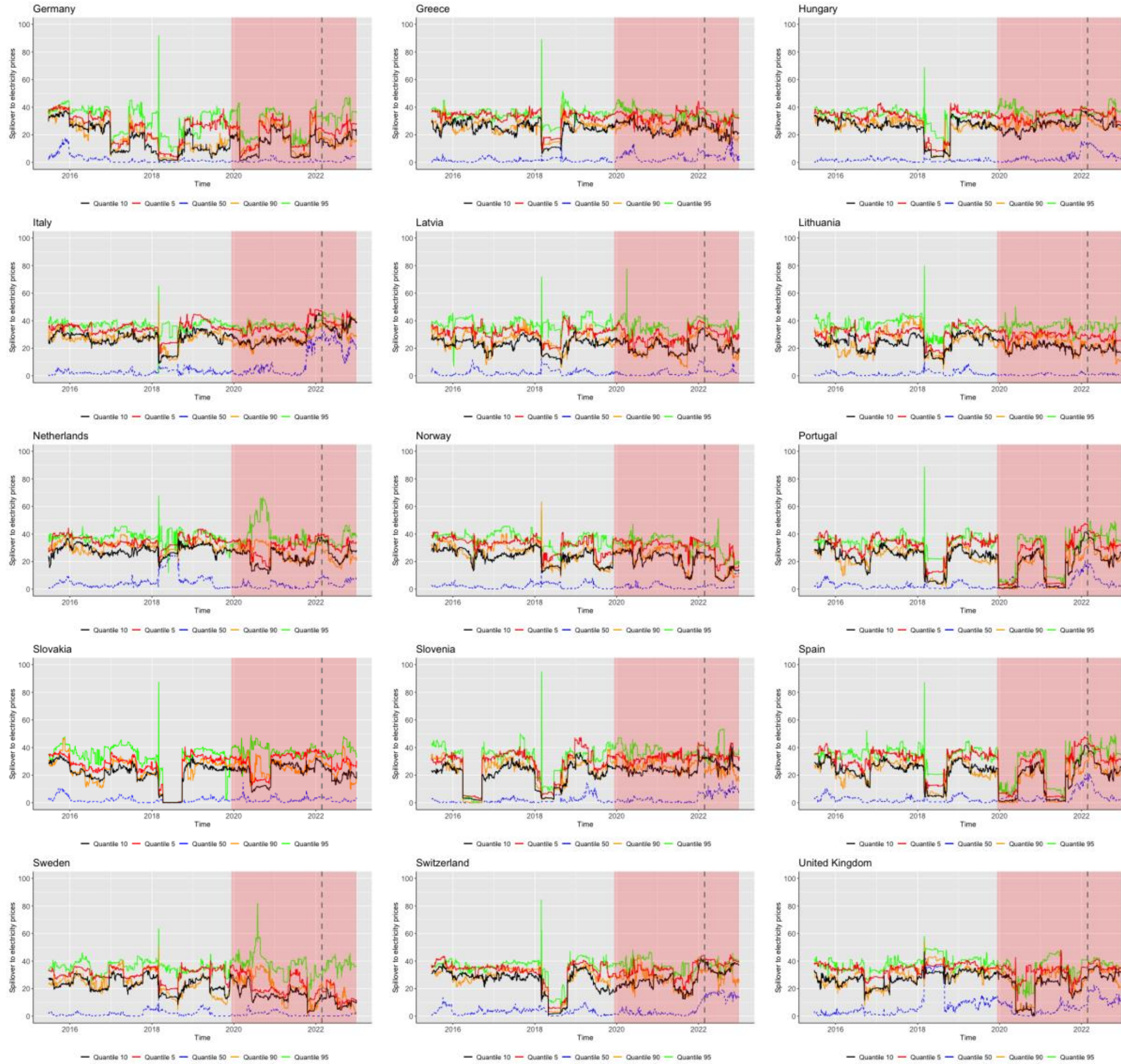




Note: The sampled period spans from January 01, 2015 to December 30, 2022. Results based on a bivariate QVAR(1) model (selected based on BIC) with a rolling-window of 125 days and a 20-step-ahead forecast error variance decomposition. The gray vertical dashed line indicates the date of the Russian invasion of Ukraine (February 24, 2022). The red shaded area represents the period encompassing the Covid-19 pandemic (since December 2019).

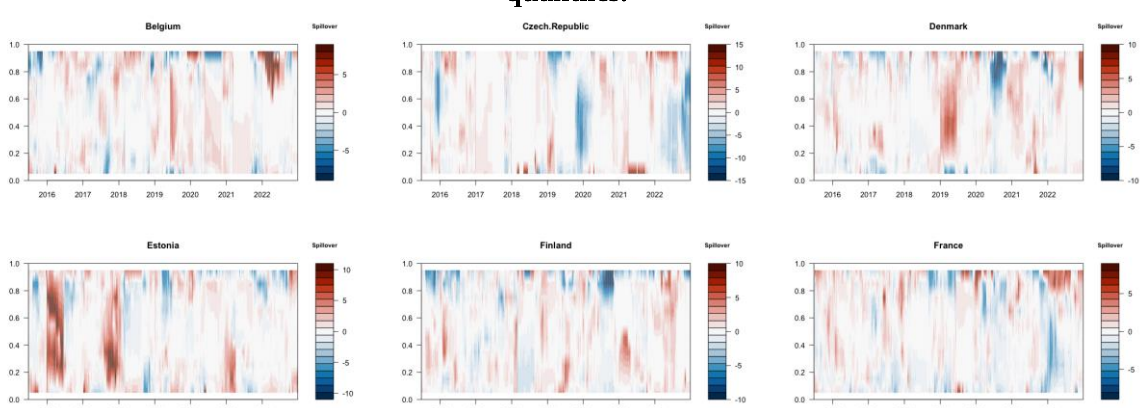
Figure A3. Total directional connectedness from natural gas to electricity price returns (quantiles 5, 10, 50, 90 and 95).

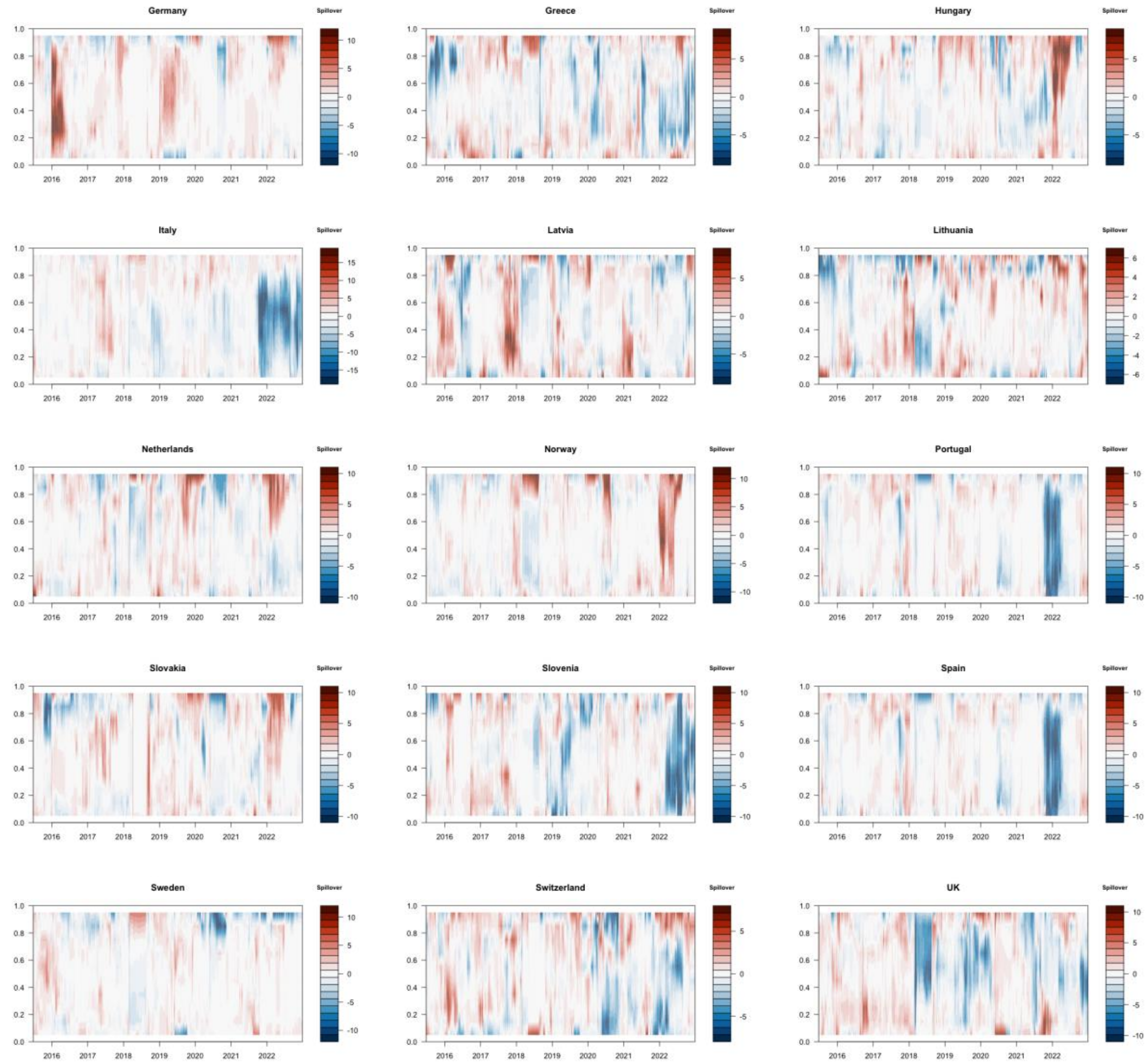




Note: The sampled period spans from January 01, 2015 to December 30, 2022. Results based on a bivariate QVAR(1) model (selected based on BIC) with a rolling-window of 125 days and a 20-step-ahead forecast error variance decomposition. The gray vertical dashed line indicates the date of the Russian invasion of Ukraine (February 24, 2022). The red shaded area represents the period encompassing the Covid-19 pandemic (since December 2019).

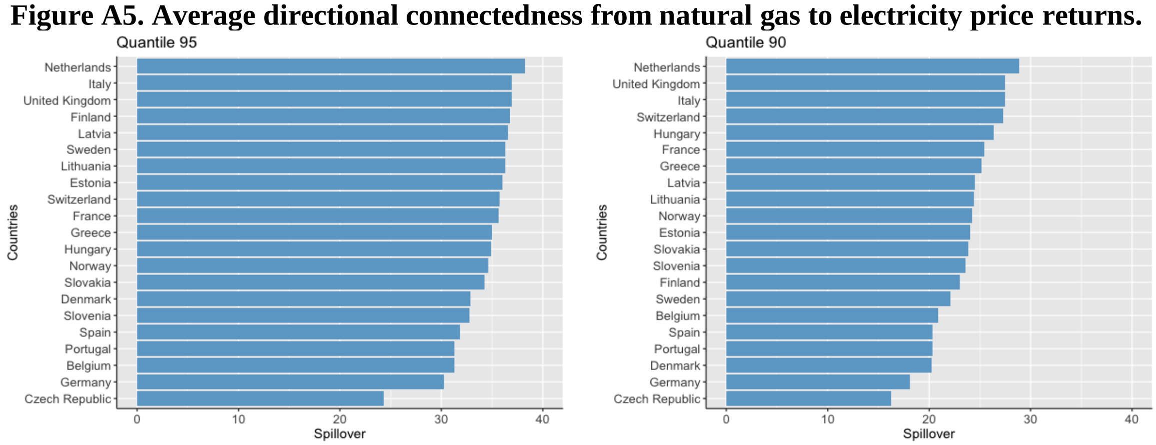
Figure A4. Net total directional connectedness in electricity markets across time and quantiles.

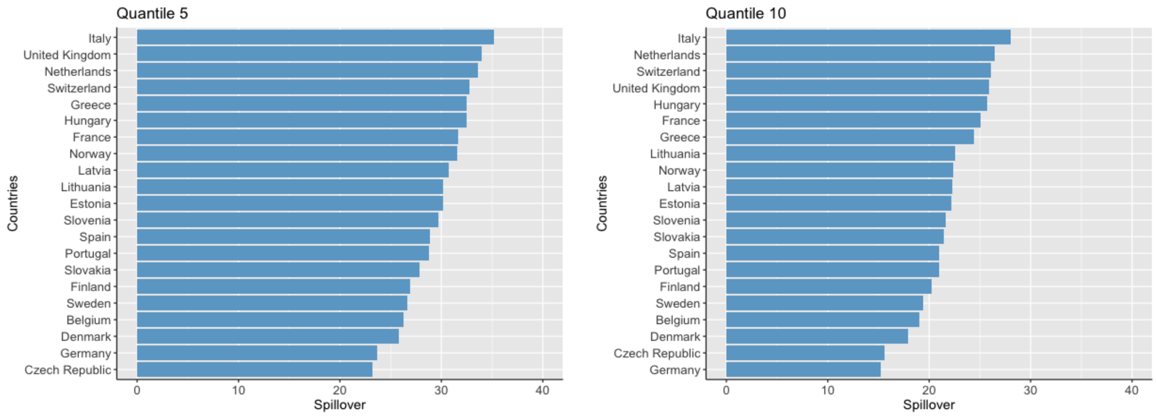




Note: The sample period spans from January 01, 2015 to December 30, 2022. Results based on a bivariate QVAR(1) model (selected based on BIC) with a rolling-window of 125 days (selected based on BIC) and a 20-step-ahead forecast error variance decomposition.

Figure A5. Average directional connectedness from natural gas to electricity price returns.





Note: Average directional connectedness from natural gas to electricity price returns. The sample period spans from January 01, 2015 to December 30, 2022. Results based on a bivariate QVAR(1) model (selected based on BIC) with a rolling-window of 125 days and a 20-step-ahead forecast error variance decomposition.