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Assessing the relationship between electricity and natural gas prices in European markets in times of distress

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ABSTRACT

We investigate the transmission of natural gas shocks to electricity prices under different scenarios of electricity generation for 21 European markets, from January 1, 2015 to March 11, 2022, proposing indicators of market vulnerability based on the quantile slopes of the regressions of electricity on natural gas and the distance between the transmission effects at very high and low quantiles of the electricity price distribution. We determine that the level of market integration is the main factor underlying national differentiation. Denmark, Finland, Sweden, and Germany are the most vulnerable markets to natural gas price shocks under distress. Our results highlight a source of vulnerability that only emerges during market distress scenarios for countries with a small, but non-zero, proportion of natural gas in domestic generation mixes under marginal cost-based electricity pricing. Further market integration is proposed to increase resilience in European electricity markets, based on a different set of regressions.

1. Introduction

Recent historical surges in electricity prices around the world, particularly in Europe during 2021 and in the first quarter of 2022, have reminded us of the paramount role of electricity markets for well-functioning modern societies. Understanding the drivers of electricity prices in times of market distress, and particularly how variations of natural gas prices translate into households' and firms' electricity cost, is a critical concern for all nations, from both economic and energy security perspectives. The importance of energy markets for economies, including the relationship of energy markets with banking, the real economy, and other commodities, has recently been studied by Brown et al. (2021), Maitra et al. (2021), van de Ven and Fouquet (2017), and Xiao and Wang (2022), among others.

In this study we investigate the vulnerability of electricity markets to natural gas price variations in 21 European countries, including 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 United Kingdom (UK). Our sample runs from January 1, 2015 to March 11, 2022. The last months of our sample contain the most significant market distress period for electricity and natural gas in Europe in recent decades, which gives us a unique opportunity to analyze linkages between these two markets in times of crisis. We use three indicators to assess different dimensions of this vulnerability, which include the size of the transmission effect from natural gas to electricity markets at extreme quantiles of electricity price distribution, and two measures of the distance between the effect at very high (90th, 95th, and 99th) and low (1st, 5th, 10th) quantiles. We also explore the possible determinants of the variation in the vulnerability indicators across countries, including market size, electricity exports and imports, generation mix, and level of market integration, demonstrating that different levels of market integration explain differences across countries more accurately.

Our study presents a baseline for evaluating market reforms that are likely to occur in Europe in the upcoming years, to highlight the necessity of such reforms and provide insights to inform their execution. Our comparative focus on European markets and methodological approach differentiate us from the previous literature, which restricts the analyses to a few (or single) countries at a time and to average effects (i.e., ignoring market distress scenarios) and generally does not consider

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satisfactory models of energy prices that account for the crucial impact of weather on electricity price fluctuation.

Our contribution fills the gap in the literature regarding the role of natural gas as a primary driver of electricity prices in times of crises, particularly under the current market design in Europe, in which the last generator in the merit order curve—and hence the less efficient—determines the price to be paid to all market participants by their generation. A lack of solid understanding of the relationship between natural gas and electricity prices in times of distress also threatens ambitious plans regarding the European transition to a more sustainable, green, and energy-efficient production scheme that has been committed to with renewed urgency.[1] Europe faces the risk of households on the brink of energy poverty and small businesses, both of which are dramatically affected by electricity prices, negatively perceiving such energy transitions, forcing them to drastically reduce energy consumption, which is already at minimum levels. These historically high increases may be a symptom of the system's inability to comply with energy demand from all agents at all times, and could be an early warning sign of energy crises and foreseeable energy shortages in the not-so-distant future if current geopolitical tensions in Europe further escalate. Finally, electricity prices are a primary component of core inflation, and any large incremental growth in the price of power is also expected to reflect a similar increment in economies' general price indices. Subsequently, dramatic price surges in power markets also menace economies with destabilizing general price dynamics and resurrecting fears of inflation.

Recent record-high electricity prices are mainly related to parallel increments in the price of natural gas. Indeed, the Title Transfer Facility (TTF) and the National Balancing Point (NBP) traded in the Netherlands and the UK, respectively, which are the most important natural gas reference indices in Europe, multiplied by three from August 2021 to March 2022, and by 20 from August 2020 to March 2022. At the same time, their volatility also multiplied by six in the latter period.[2] Bottlenecks in the supply of natural gas observed since summer 2021, and the recent Russian invasion to Ukraine are the main drivers of these dynamics.

The relationship between electricity and natural gas is complex since both goods are substitutes and complements. Natural gas is an input for electricity generation through combined-cycle power plants, whereas electricity and natural gas are substitutes for household heating and commercial facilities. As established by Uribe et al. (2018) for the US market (see also Kyritsis and Andersson (2019) and Scarcioffolo and Etienne (2021)), in times of scarcity, when power generation is costly and both power and gas are closer to maximum price levels, the relationship between the price of gas and the price of power is not only positive, but is also significantly stronger than at other times when both goods are relatively abundant (i.e., when prices are closer to the center of their respective price distributions). In this study, we demonstrate that the same results hold for European markets, although important differences are revealed across countries, particularly due to different levels of integration in the European market network.

Our empirical strategy relies on quantile regressions (Koenker, 2005), which are known to be robust to outliers, which is crucial for modeling electricity prices that are characterized by short-lived, but abrupt and generally unanticipated, spikes (see Weron (2014)). Quantile regressions are also semi-parametric, so they require minimal distributional assumptions in the underlying data generating process. They also offer greater flexibility in the analysis of different scenarios in electricity markets, corresponding to both distinctive weather conditions and different fuel costs in global markets, in particular natural gas. The simplicity of our indicators means that the information revealed can easily be transmitted within different policy circles and to the general public.

The rest of this document is organized as follows: section two presents the literature related to our proposal, section three introduces in detail our methodology, section four contains the data and sources of information used to guarantee the replicability of the study, in the fifth section the results are presented, and section six concludes and presents the policy implications of our study.

2. Related literature

Recent literature has emphasized the rapidly developing nexus between natural gas and electricity markets (see Alexopoulos (2017), Amirnekooei et al. (2017), Brown and Yücel (2008), Chae et al. (2012), Chen et al. (2020), Diagoupis et al. (2016), Ding et al. (2020), He et al. (2020), Liu et al. (2021), Mills et al. (2021), Nakajima and Hamori (2013), Ohler et al. (2020), Scarcioffolo and Etienne (2021), Wang et al. (2018), Woo et al. (2006), Xia et al. (2020), and Yang (2021)). These studies have analyzed the mechanisms by which natural gas prices may impact price formation and market clearing in electricity markets. First, natural-gas-fired power plants are almost invariantly the last to be included in the merit order curve, determining the wholesale electricity rates, thus retail electricity rates, when electricity demand is not satisfied by power generation from the cheaper sources. Second, load-serving entities are frequently the owners of natural-gas-fired power stations; thus, they can implement a direct pass-through of unexpected fuel costs from natural gas to electricity rates onto electricity consumers via automatic mechanisms. Third, as emphasized by Woo et al. (2006), there is a demand-pull effect that derives from a wider spread between electricity price and natural gas fuel cost, when electricity is costly, which raises the demand for natural gas by fostering generators' willingness-to-pay, and inducing less efficient plants to generate. This translates into larger bids for spot gas in bilateral trading and higher observed natural gas prices. These mechanisms may persist in a way that could even endanger the operation of the entire system, and in the worst case scenario, the feedback effects between natural gas and electricity prices establish conditions that are more vulnerable to energy crises and energy shortages.

Another strand in the previous literature quantified the effects of natural gas price variations on electricity prices using an averaging scenario, primarily in the US. For instance, Mills et al. (2021) demonstrated that a decline in natural gas prices in the US from 2008 to 2017 reduced wholesale electricity prices. Ohler et al. (2020) found evidence of Granger-causality from natural gas to electricity prices in the US for both commercial and residential consumers. Alexopoulos (2017) examined the growing importance of natural gas as a predictor for retail electricity prices in the US and its significance for effective policymaking.

Fewer studies have examined the European case, but these studies focus on the average scenario, rather than periods of stress. Four recent studies analyzed European energy markets and the relationship between natural gas and electricity markets, including Chuliá et al. (2019), Hirth (2018), Martínez and Torró (2018), and Mosquera-López and Nursimulu (2019). Although related, the aim of these studies differs from ours, as none emphasized distress scenarios, and the results are based on single markets or a small subset of markets, at most.

Another recent branch of the literature that is directly connected to our study, emphasized the nonlinear nature of price dynamics in electricity markets (see Bunn et al. (2016), Ding et al. (2020), Hagfors et al. (2016), Mosquera-López et al. (2017), Scarcioffolo and Etienne (2021), and Xia et al. (2020)). These nonlinearities are related to electricity

[1] See all recent statements and news on the European Commission's Energy Strategy website, which emphasize the European Union's increasing political commitment to the energy transition to renewable sources (European Commission, 2022). See also the documentation produced during and after the recent Climate Change Conference (COP26) celebrated in Glasgow in November 2021 (United Nations, 2022).

[2] The same pattern can be observed in Asian Liquefied Natural Gas, according to the U.S. Energy Information Administration (EIA, 2022).

markets' dependence on weather, policy, and economic systems, which are plagued by high uncertainties and complexities that make forecasting and understanding price dynamics extremely challenging. Some recent studies examined the relationship between natural gas and electricity prices in abnormally distressed periods. For instance, Scarcioffolo and Etienne (2021) and Uribe et al. (2018) provide evidence of spillovers between natural gas and electricity returns (among other energy commodities) under different market conditions, especially at moderate and high return quantiles of energy prices. Although these two studies are methodologically close to ours, unlike us, they only focused on the US market, conducted bivariate analyses that did not consider the crucial role of weather, and did not provide indicators of vulnerability in times of distress.

3. Methodology

3.1. Modeling the average scenarios of electricity prices with weather factors

Weather factors have been widely used to model the dynamics of electricity prices (Brancucci Martinez-Anido et al., 2016; Kaufmann and Vaid, 2016). Following this reasoning, we begin with a linear specification that explains energy prices as a function of weather variables. More formally, X_{t-1} is the vector containing the observations of explanatory variables on a given market day $t-1$, and Y_t is the price of electricity one day after t. Our objective is to estimate a parameter vector β with the same dimension as the vector of covariates. We present the linear combination as $X_{t-1}{}'\beta$. Finally, ε_t is a random vector that corresponds to the t-th error term. In a linear regression framework:

$$Y_t = X_{t-1}^{'}\beta + \varepsilon_t, \tag{1}$$

where $E(\varepsilon_i) = 0$, then $E(Y_i|X_i) = X_i^{'}\beta$. We regress the electricity price on the one day lagged explanatory variables because today's electricity spot wholesale prices are formed by the bids of market participants the day before. Weather variables in our model are temperature, wind speed, precipitation, and solar irradiance recorded on the Earth's surface. Wind speed is expected to have a negative effect on energy prices, as it constitutes an increasingly relevant input for power generation in Europe. Precipitation is expected to have a negative impact on energy prices, in principle, as it is an indicator of larger water reservoirs for hydraulic generation. Notice, however, that the effect of precipitation is more indirect than that of the other weather factors mainly through its influence on reservoirs, so we can expect a less pronounced overall effect. On its side, irradiance is also expected to reduce energy prices, because greater irradiance is associated with larger power generation capacity by solar cells. Finally, temperature is expected to show an average positive effect on electricity prices for warmer countries, due to cooling requirements, and the expectation reverts for colder countries due to heating needs. Nevertheless, we also expect a nonlinear effect depending on the season (summer versus winter) in both sorts of countries. The size of the effects is expected to vary widely across countries, since all of them have markedly different generation mixes, and also across seasons, due to different heating and cooling requirements, and different generation conditions.

3.2. Modeling tail-risk scenarios by conditional quantile regression

Conditional quantile regression is a methodology for estimating the conditional quantiles of the cumulative distribution of a response variable, in our case electricity prices, given some covariates. In these models, based on Koenker and Bassett (1978), a quantile of the response variable is presented as a linear combination of right-hand-side variables, and estimating the model implies finding the coefficients for that linear combination. Quantile regression allows the comparison of the effect of natural gas price changes on electricity prices when electricity prices are relatively high (high quantiles) or relatively low (low quantiles). Such different quantiles correspond to abnormally high or low electricity prices, and are naturally related with scenarios of scarcity and abundance in electricity generation, respectively. We exemplify this as:

$$Q_\theta(dY_t|\mathrm{X}_{t-1}) = \mathrm{X}_{t-1}\beta(\theta), \tag{2}$$

where $0 < \theta < 1$ and $Q_\theta(.|.)$ denotes the conditional quantile function for the θ-th quantile of the response variable Y_t. $\beta(\theta)$ is a vector that contains the slope coefficients of the quantiles regression associated with the effect of each explanatory variable on the variable Y_t. These slope coefficients can be interpreted as rates of change, as in any ordinary linear model. Thus, the scalar $\beta_k(\theta)$ corresponds to the rate of variation of the θ-th quantile of the dependent variable distribution per unit of change in the value of the k-th regressor such that: $\beta_k = \frac{\partial Q_\theta(dY_t|X_{t-1})}{\partial x_{kt-1}}$. If we extend $X_{t-1}^{'}$ to include natural gas prices with weather factors, we will be particularly interested in the case where k corresponds to natural gas, so we can obtain β_{gas} at different quantiles of electricity prices. The estimations of the quantile slopes are obtained solving a nonlinear problem given by:

$$\beta_{(\theta)} = argmin_\beta E[\rho_\theta(Y - X_i{}'\beta)], \tag{3}$$

with asymmetric loss:

$$\rho_\theta(u) = (1-\theta)I_{\{u<0\}}|\mathrm{u}| + \theta I_{\{u>0\}}|\mathrm{u}|\cdot \tag{4}$$

3.3. Vulnerability indicators

3.3.1. Indicator of the strength of dependency under generation distress

Our first indicator corresponds to the slope quantile coefficient at extremely high quantiles, given by:

$$I_1 \equiv \beta_{gas}(\theta = [0.9, 0.95, 0.99])\cdot \tag{5}$$

The indicator in Equation (5) is interpreted as the effect of natural gas prices on electricity prices when electricity prices are abnormally high to directly examine shock transmission under generation distress. It can be interpreted as a traditional "beta" (regression slope) in a linear regression, but rather than referring to the impact of the explanatory variable on the mean, it references the impact on a given (high) quantile of the explained variable. These high quantiles correspond to high electricity prices observed during generation distress periods.

3.3.2. Indicators of asymmetry in the response at extreme quantiles

Our second and third indicators measure how much the response of electricity to natural gas prices changes between extremely high and extremely low quantiles of electricity price distribution. The logic of the two indicators is that vulnerability may arise, not only as a consequence of the transmission from natural gas to electricity prices itself, but also because this transmission may intensify precisely during times of market distress when generation is costly and diversification across generation sources is difficult. The first indicator is given by:

$$I_2 \equiv \frac{\beta_{gas}(\theta = \theta_{high})}{\beta_{gas}(\theta = \theta_{low})}, \tag{6}$$

where an I_2 greater than one indicates that a greater proportion of natural gas price is transmitted to the price of electricity when electricity is expensive than when it is cheap. For example, if $I_2 = 2$ for a given country, this indicates that the natural gas price shock is transmitted twice as much when the electricity prices are high than when they are low. Despite the convenient and straightforward interpretation of I_2, one drawback of this indicator is that it is not defined when the transmission at low quantiles is statically equal to zero. For this reason, we propose a third indicator of the distance between the transmission of the natural gas shocks to electricity at high and low quantiles given by:

$$I_3 \equiv \frac{\beta_{gas}(\theta = \theta_{high}) - \beta_{gas}(\theta = \theta_{low})}{2}. \tag{7}$$

The two indicators in Equations (6) and (7) are similar, but convey distinct information. Both measure the distance between the transmission effect recorded when electricity is relatively expensive (i.e.,., $\theta_{high} = [0.9, 0.95, 0.99]$), and when it is relatively cheap (i.e.,., $\theta_{low} = [0.1, 0.05, 0.01]$). The first is relative, in the sense that the scale of the transmission effect from gas to electricity is removed when divided by the low quantile slopes. In contrast, the second indicator does not perform such standardization. The greater any of the two indicators, the greater the distance between the two regimes of the market, and the more vulnerable the market, in the sense that nonlinearities may be unexpected and afflict the market with generation distress, making it more difficult for market participants to determine accurate expectations of future market dynamics.

4. Data

We use data from Bloomberg and ENTOS-E for our set of 21 electricity markets, including 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, from January 1, 2015 to March 11, 2022.[3] We include all markets for which a sample of size of roughly seven years was available. This is important, given our special focus on very high and very low quantiles; that is, we needed to estimate using a relatively large sample size, accounting for sufficient data points in the two tails of electricity price distribution. We also used the sample size for all countries, even when we have earlier information for some of the markets, with the aim of facilitating meaningful comparisons across countries. Notably, our study sample includes clear and historic episodes of market distress in European electricity markets from 2021:Q3 to 2022:Q1.

Our set of variables includes the TTF and the UK NBP, natural gas indices, wholesale electricity prices in each country, and weather-related variables, including wind speed, temperature, precipitation, and irradiance. The latter was retrieved from the solar radiation data, SoDa Service. We use daily data, relying on 1877 transaction days in our sample period for estimations. When there is available information for the prices of more than one zone in a given country (as in the case of Norway, Sweden, and Denmark), we use the information regarding the largest geographical zone.

Table 1 presents the summary statistics of our sample variables. There is wide variability across countries in terms of both weather and electricity prices. Weather variability translates to price variability, not only because it pushes demand in asymmetric ways (i.e., different heating or cooling needs), but also because weather directly impacts generation through variable renewable energy sources, such as solar panels and wind turbines. We also conducted unit root Augmented Dickey Fuller (ADF) tests to ensure the stationarity of our dependent variables before estimation that are available upon request.

Fig. 1 presents the generation mix for each of the countries in our dataset, and Fig. 2 shows the electricity price dynamics compared to natural gas prices. The generation mix reveals heterogeneity in electricity production. The various mixes are also related to different market structures and characterized by divergent levels of market competition in the provision of power. These heterogeneities in generation, and differences in the physical transmission of power between countries, translate into different price dynamics. Nevertheless, Fig. 2 indicates that all prices spiked when natural gas prices increased in the last year of our sample.

[3] Poland has information from August 1, 2015, but there are many missing values, so we opted to exclude it from our research.

5. Results and discussion

Table 2 presents the slope coefficients associated with the effect of natural gas prices and weather variables on electricity prices at two extreme quantiles of the conditional distribution of electricity prices (i.e., $\theta = 0.95$ in Panel A and $\theta = 0.05$ in Panel B), alongside respective standard errors. To facilitate meaningful and direct comparisons of the effects across countries and between different covariates (e.g., gas vs. weather), prior to estimation, all the variables in our data set were standardized to have zero mean and unit variance. Thus, these can be understood as “beta-coefficient” models, in the sense that they are used in traditional linear regression, according to which we analyze the effect of a one-standard deviation shock of the explanatory variable on a given quantile of electricity prices. At the bottom of each panel, we also present the statistic of goodness of fit proposed by He and Zhu (2013), in which the null hypothesis refers to a linear specification of the quantile regression.

Table 2 yields five important insights. i) Natural gas prices (TTF) clearly exert a larger effect on electricity prices than weather variables. ii) The effect of natural gas dramatically rises for the high quantiles (right tail) of the electricity price distribution when electricity is expensive. iii) The effect of weather factors is greater, in terms of statistical significance, for the low quantiles (left tail) of electricity price distribution, which is consistent with marginal cost-based pricing. iv) Heterogeneous effects of weather variables are evident across countries in both tails, according to the generation mix of each country. v) There is an expected negative sign (or zero) effect of wind speed, irradiance, and precipitation for all countries, while the effect of temperature has different signs depending on the country.

First, the dominance of natural gas as a determinant of electricity prices is exemplified by the position of natural gas as the only variable that is consistently significant for all countries at the two tails of the electricity price distribution, with any traditional confidence level, as well as the magnitude of the effect of natural gas being several orders greater than fundamental weather factors. To illustrate this point, let us focus on the case of Denmark, which according to Fig. 1, has the greatest share of wind generation in its generation mix (57.66%), while natural gas only amounted to 4.57% of the generation. When electricity is expensive (Panel A) (i.e., in a scenario of system distress), the effect of natural gas on Danish electricity prices equals 1.31, while the effect of wind is −0.04. Subsequently, the effect of natural gas is approximately 32 times larger than the effect of wind speed. The circumstance differs for low quantiles (Panel B) when electricity is less expensive. In this case, the first two numbers are, respectively, 0.17 and −0.05. Even in this case, the effect of natural gas is approximately three times that of wind speed. This occurs in Denmark and in all the other countries in our sample. There is no single weather factor in any market or generation scenario, which is a match for natural gas prices as a fundamental driver of electricity prices. This is due to current market design in which the costliest generation technology (by general rule, natural gas, in our recent sample period) determines the price of all electricity traded in the market. In this way, the market design manages to revert the importance of natural gas as the least important factor for generation (see Fig. 1) to the most important price driver.

Second, our finding that the effect of natural gas prices on the higher quantiles of electricity prices is always larger than the effect on the lower quantiles for all the countries in our sample (see Fig. 3 as well). This larger effect is particularly notable in Slovakia, Finland, Denmark, Germany, and the Netherlands, and it is considerably smaller for Italy, Spain, and Portugal. This suggests that in times of distress, the volatility of natural gas transmits to electricity prices much more when electricity prices are high than when they are low. For instance, in the case of Germany, the effect of natural gas at the high quantile (Panel A) is 1.26, while it is 0.33 at the low quantile (Panel B). This result holds for all countries in our sample.

Third, the significance of weather variables is clearly higher at lower

Table 1
Descriptive statistics.

Statistic	Electricity Prices	Temperature	Wind Speed	Precipitation	Irradiance	Electricity Prices	Temperature	Wind Speed	Precipitation	Irradiance
	Belgium					*Czech Republic*				
Min	−133.56	−6.16	1.36	0.00	193.65	−10.24	−8.01	1.41	0.00	195.54
Mean	57.22	11.22	7.20	223.25	3072.06	53.76	10.62	4.28	492.50	3192.90
Max	461.95	29.32	23.01	6366.18	8460.75	487.41	27.69	16.06	25,225.00	8476.60
Sds	48.70	6.31	3.38	443.40	2193.96	46.71	7.46	1.86	955.37	2273.85
Skewness	3.63	0.09	1.01	5.03	0.55	4.05	0.12	1.57	10.57	0.49
Kurtosis	17.16	−0.60	1.17	43.03	−0.84	21.05	−0.99	3.52	241.12	−0.97
	Denmark					*Estonia*				
Min	−3.93	−7.34	2.19	0.00	132.49	5.86	−20.56	1.59	0.00	81.17
Mean	44.94	9.84	9.87	265.08	2809.01	50.20	6.93	8.19	266.20	2605.14
Max	464.54	25.18	24.04	4494.28	8338.59	469.03	27.16	20.58	4562.05	8271.84
Sds	38.88	6.34	3.78	431.46	2244.00	35.11	8.18	3.14	434.27	2361.13
Skewness	4.75	0.10	0.65	3.03	0.64	4.63	−0.09	0.64	3.33	0.73
Kurtosis	33.02	−0.94	0.03	13.52	−0.78	33.91	−0.54	0.05	16.65	−0.73
	Finland					*France*				
Min	2.99	−25.87	2.04	0.00	72.37	3.68	−3.38	2.40	0.00	219.34
Mean	43.64	5.37	7.39	295.52	2615.27	57.22	13.21	7.08	337.77	3270.65
Max	469.03	25.15	17.48	3813.50	8234.59	540.66	30.12	17.32	8313.32	8438.24
Sds	29.75	8.81	2.63	429.62	2374.07	52.57	6.37	2.21	551.17	2257.91
Skewness	6.04	−0.22	0.68	2.83	0.69	3.83	0.12	0.82	5.01	0.50
Kurtosis	62.23	−0.32	0.30	11.14	−0.80	18.12	−0.89	0.74	45.13	−0.94
	Germany					*Greece*				
Min	−42.24	−9.40	2.46	0.00	152.04	15.79	−0.99	2.02	0.00	406.96
Mean	49.28	10.37	6.99	214.35	2992.16	68.58	17.65	6.50	159.70	4787.72
Max	487.57	28.14	22.57	2719.73	8358.23	426.90	33.75	18.02	3910.59	8665.93
Sds	44.61	7.06	2.70	268.53	2291.55	47.70	7.17	2.41	367.42	2306.82
Skewness	4.29	0.08	1.33	2.38	0.53	3.39	0.05	0.79	4.45	0.00
Kurtosis	24.33	−0.83	2.35	9.48	−0.93	12.63	−1.08	0.60	27.24	−1.29
	Hungary					*Italy*				
Min	7.44	−10.50	1.49	0.00	226.47	10.66	−0.59	2.76	0.00	312.35
Mean	61.47	11.57	6.24	269.50	3615.35	67.70	15.81	5.55	269.77	4459.97
Max	544.73	29.94	18.91	7577.17	8422.91	587.67	29.59	14.94	13,799.70	8654.48
Sds	50.58	8.69	2.77	575.77	2338.64	53.36	6.80	1.55	558.58	2356.21
Skewness	3.69	−0.03	1.09	5.09	0.30	3.69	0.16	1.25	10.34	0.13
Kurtosis	17.17	−0.98	1.35	40.95	−1.20	16.79	−1.19	2.40	202.00	−1.32
	Latvia					*Lithuania*				
Min	5.86	−19.00	1.24	0.00	108.09	10.21	−18.53	0.29	0.00	136.59
Mean	53.12	7.95	6.98	190.27	2695.33	61.15	7.78	6.84	211.74	2738.91
Max	469.03	27.19	17.63	3870.80	8464.63	643.29	27.70	19.76	5940.40	8427.66
Sds	35.87	8.41	2.88	363.31	2252.68	43.69	8.13	2.81	434.82	2203.40
Skewness	4.56	−0.13	0.65	4.02	0.68	5.11	−0.08	0.84	5.09	0.68
Kurtosis	32.04	−0.51	0.19	23.37	−0.71	43.07	−0.54	0.81	40.08	−0.67
	Netherlands					*Norway*				
Min	5.15	−6.28	2.30	0.00	148.70	0.94	−11.22	2.43	0	82.37
Mean	54.24	11.06	8.47	268.28	2955.96	37.81	6.64	7.37	452.95	2621.9
Max	443.32	29.29	24.47	5167.85	8434.68	387.45	23.81	18.19	3274.94	8414.03
Sds	45.60	6.04	3.72	421.91	2224.24	31.99	6.75	2.43	452.07	2315.72
Skewness	3.90	0.09	1.04	3.16	0.59	3.13	−0.08	1.03	1.84	0.71
Kurtosis	18.86	−0.58	1.22	17.43	−0.82	16.14	−0.77	1.21	4.47	−0.72
	Portugal					*Slovakia*				
Min	2.02	4.74	2.56	0.00	415.17	−21.00	−10.82	1.97	0	212.82
Mean	62.38	16.16	7.57	197.34	4817.50	56.44	10.56	6.52	292.11	3538.12
Max	542.78	30.67	20.30	4267.41	8814.76	541.51	28.06	20.03	5739.29	8595.17
Sds	48.67	4.42	2.43	472.03	2281.02	49.03	8.44	2.54	525.48	2390.47
Skewness	3.63	0.16	0.99	3.63	0.06	3.82	−0.01	1.14	3.63	0.35
Kurtosis	17.12	−0.58	1.55	15.85	−1.28	19.54	−0.99	1.7	19.6	−1.2
	Slovenia					*Spain*				
Min	−7.30	−12.43	0.75	0.00	269.31	2.19	2.06	2.3	0	437.83
Mean	62.67	10.33	3.25	387.30	3622.33	62.36	16.13	5.99	174.58	4784.1
Max	561.96	27.70	12.47	7755.09	8647.34	544.98	29.42	17.14	2791.85	8921.29
Sds	52.35	8.17	1.41	813.53	2392.11	48.66	6.35	1.9	297.06	2390.41
Skewness	3.76	−0.02	1.54	3.39	0.37	3.64	0.18	1.44	3.51	0.09
Kurtosis	17.64	−1.03	4.64	14.79	−1.18	17.23	−1.15	3.01	18.01	−1.29
	Sweden					*Switzerland*				

(*continued on next page*)

Table 1 (*continued*)

Statistic	Electricity Prices	Temperature	Wind Speed	Precipitation	Irradiance	Electricity Prices	Temperature	Wind Speed	Precipitation	Irradiance
Min	1.64	−14.63	2.40	0.00	77.07	−5.79	−11.02	1.84	0	200.22
Mean	38.38	6.91	8.06	224.29	2684.96	59.08	10.10	6.48	258.42	3535.37
Max	413.48	24.81	19.50	3481.76	8256.65	574.54	28.40	19.52	3790.51	8765.21
Sds	28.48	7.49	2.61	329.04	2336.14	53.60	7.98	2.6	450.86	2365.6
Skewness	4.65	−0.02	0.88	2.93	0.66	3.94	0.03	1.12	3.36	0.47
Kurtosis	37.54	−0.72	0.98	12.37	−0.80	19.58	−0.89	1.4	14.77	−1.03
	United Kingdom					***TTF***	***NBP***			
Min	−10.13	−3.86	2.22	0.00	149.56	3.00	7.25			
Mean	58.74	10.92	7.95	253.51	2918.00	22.62	55.98			
Max	460.96	25.83	21.34	2773.34	8549.24	220.80	512.00			
Sds	47.51	5.17	2.90	335.74	2112.54	21.89	52.11			
Skewness	3.87	0.09	0.91	2.48	0.63	3.87	3.75			
Kurtosis	18.45	−0.68	1.08	8.68	−0.67	18.99	17.88			

Note: Units of electricity prices are EUR/Mwh, except for the UK, which is in GBP/MWh. Units of weather variables include temperature in degrees Celsius, wind speed in m/s, precipitation in an integer in 100th mm, and irradiance in Wh/m^2. Lastly, the TTF natural gas prices are in EUR/MWh, and NBP natural gas prices are in GBP/therm.

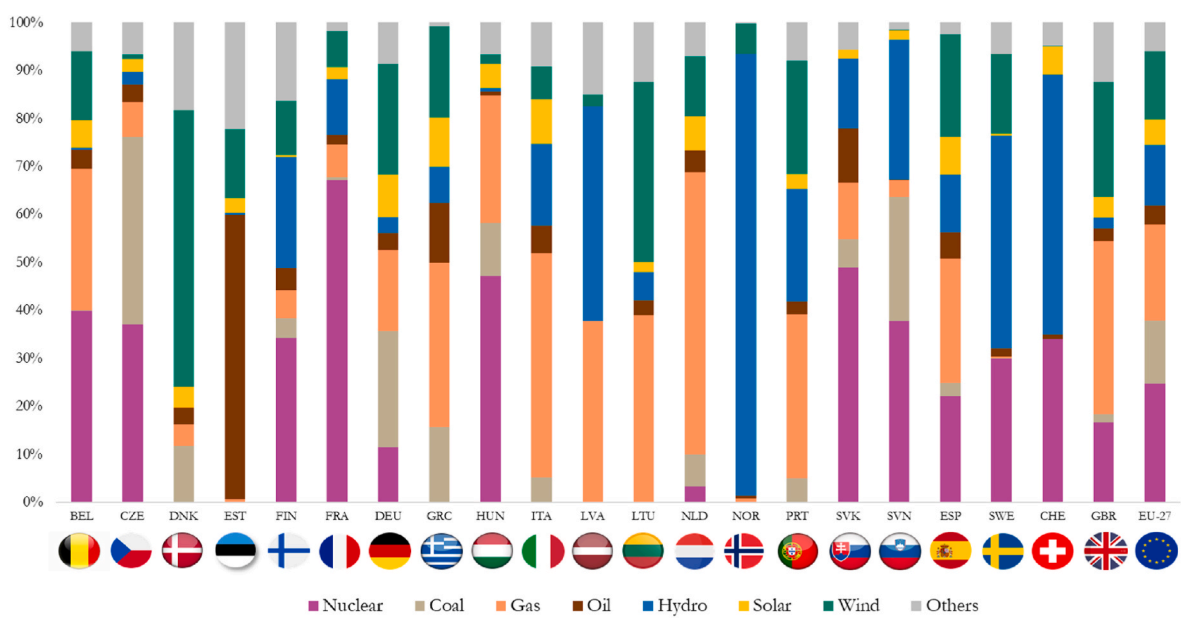

Fig. 1. Generation mix in percentage, year 2020
Note: Authors' own elaboration with data retrieved from ourworldindata.org for the year 2020.

quantiles, corresponding to scenarios of less expensive electricity than at higher quantiles. Indeed, for countries like the Czech Republic, Germany, Italy, Slovenia, Spain, and the UK, wind speed moves from insignificant to significant in statistical terms, when from Panel A to Panel B. The same occurs for irradiance in Estonia, Finland, France, Germany, Hungary, Latvia, Lithuania, the Netherlands, Slovenia, and Spain, and for precipitation in the Czech Republic, Estonia, and France. Overall, weather becomes considerably more relevant when electricity is relatively cheap than when it is more expensive and the system is under pressure.

Our fourth point also relates to the effect of weather on electricity prices; that is, countries' generation mix influences the size of the estimated effect. For instance, focusing on Panel A, in the case of Denmark, the effect of wind speed (as previously noted, wind power amounts to 57.66% of Danish generation) is −0.044, whereas those of irradiance and precipitation are insignificant. This is because the proportion of generation using solar cells in Denmark is only 4.30% and the hydroelectric generation is 0.07%. Notice that the share of generation by solar cells does not significantly differ from the share of natural gas in Denmark, yet renewables are never the costliest generation technologies under distress, so their impact on electricity price formation is null in times of crises, unlike the impact of natural gas. As Denmark represents an extreme case, we next consider Belgium. In Belgium, 5.73% of the generation corresponds to solar cells, and 14.45% to wind turbines, presenting a much more balanced example. This reflects in estimates of the effects of −0.106 for wind speed and −0.096 for irradiance when prices are soaring (Panel A), and virtually the same effect of both sources when electricity is cheap (Panel B), equal to −0.066. Similar analyses can be conducted in other countries, such as Greece and Italy, with considerable generation via both variable renewable technologies.

Our final point relates to the unambiguous effects of weather factors (excluding temperature) on electricity prices; that is, higher wind speed, irradiance, or precipitation indicate that larger amounts of green energy can be generated and electricity will be cheaper (recall that in some cases the effect is insignificant for the reasons noted previously regarding market design). The case of temperature differs because, although it impacts generation, temperature fluctuation primarily impacts prices by affecting the demand for heating or cooling, which considerably varies across countries and seasons (summer versus winter). The effect of temperature on prices is negligible at both tails of the price distribution for only three countries in our sample, Belgium, France, and Slovakia. The effect is positive at low quantiles of electricity

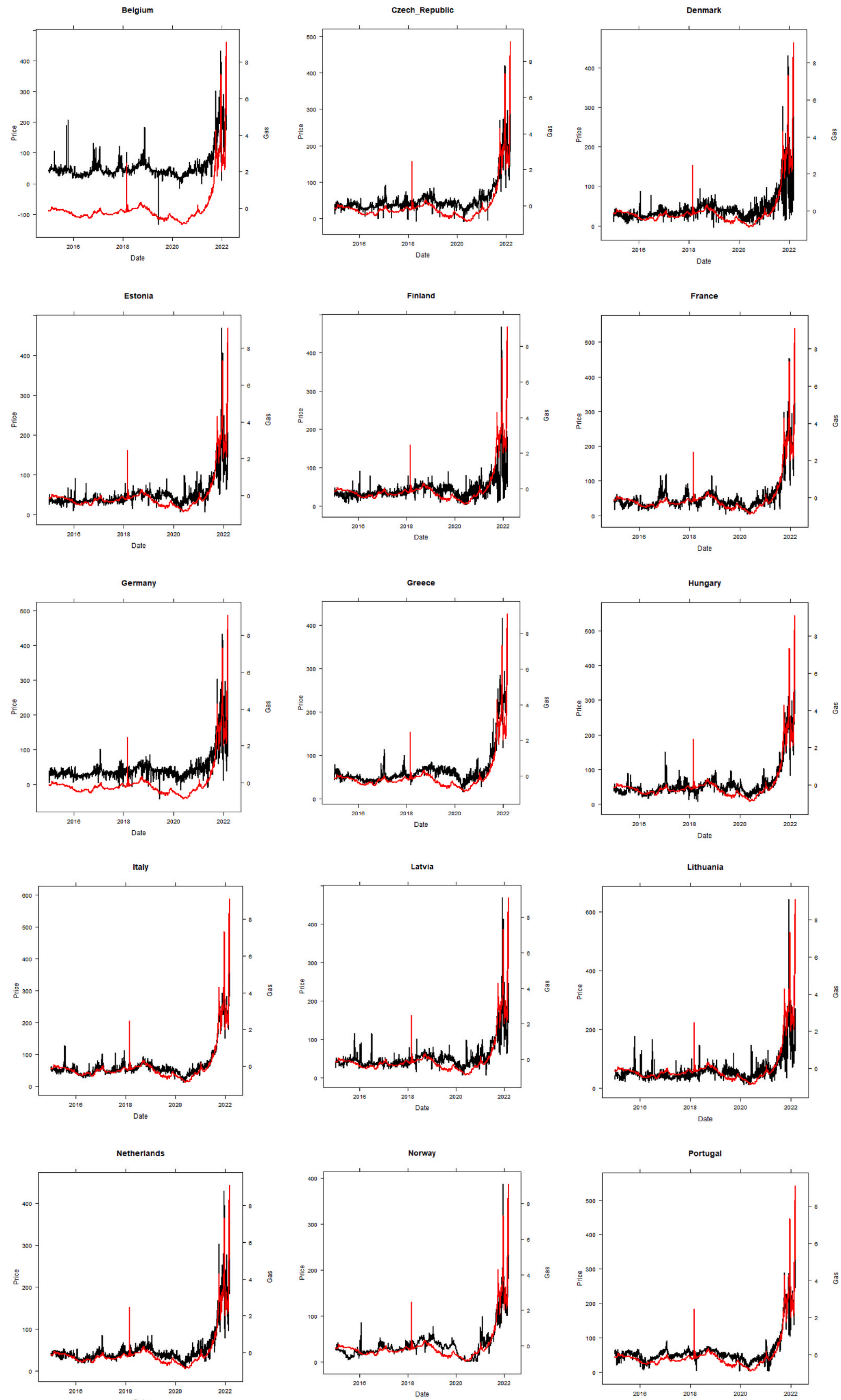

Fig. 2. Electricity (black) and natural gas (red) prices.
Note: The left vertical axis corresponds to electricity prices, and the right vertical axis corresponds to TTF natural gas prices. . (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

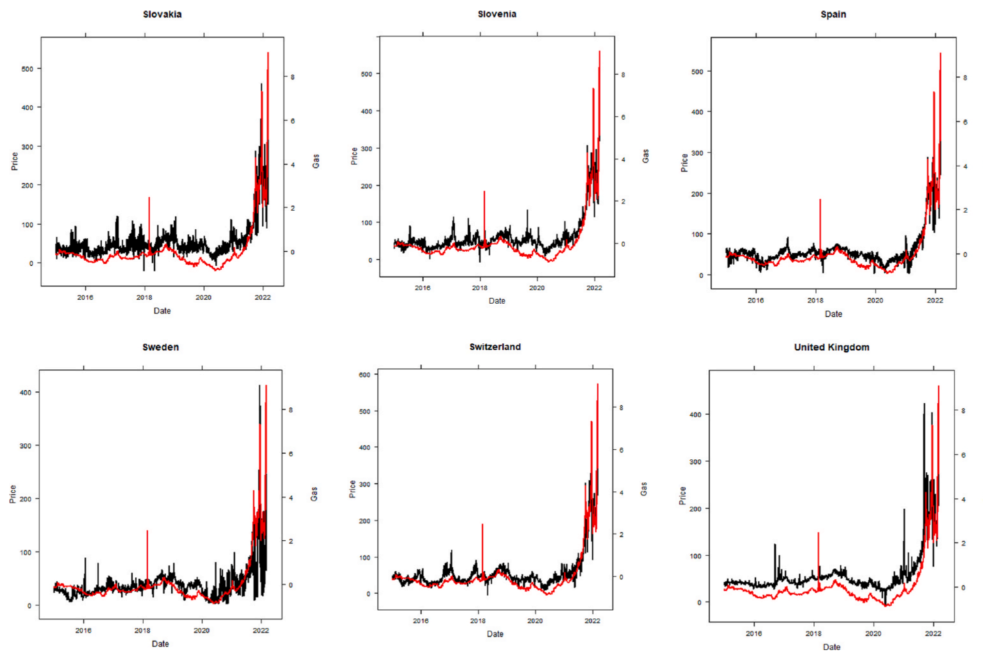

Fig. 2. (*continued*).

prices (i.e., summer season, non-distress periods) for most countries, indicating that the need for greater cooling that emerges when temperature increases significantly pushes up electricity prices. In contrast, the effect disappears for most of the countries when we move to Panel A, which references the expensive electricity periods that are predominantly observed during the winter. Interestingly, the effect continues to be positive and significant at the high quantiles for only the Czech Republic, Germany, Greece, Italy, and the UK. Notably, only Norway records a negative effect of temperature at both tails of the price distribution. This can be explained with two facts. During the winter season, hydroelectric power generation may be halted due to frozen water reservoirs when temperatures drop below zero degrees Celsius, resulting in less efficient technologies producing electricity. This is indeed a very relevant concern for Norway, which generates more than 92% of its electricity using hydropower, as shown by Mosquera-López et al. (2018). Conversely, during the summer season (associated with the low quantiles), freezing is no longer a concern, but greater temperatures might still trigger electricity prices due to increased cooling requirements. Indeed, the effect of temperature on electricity prices is also negative for other countries, such as Finland, Sweden, and Switzerland, in the same low quantiles (Panel B).

Regarding the goodness of fit of our models, the last two rows of Panels A and B of Table 2, show He and Zhu's (2013) statistic, which considers the null hypothesis of linearity in the quantile regression on a given quantile. As can be observed when $\theta = 0.95$ and $\theta = 0.05$, the null hypothesis is not rejected for 17 of the 21 countries examined; hence, the linear quantile regression seems appropriate as a benchmark for our analysis. We present two additional statistics in Table 3, including a Wald test of the hypothesis of equal slopes across the quantiles and Pseudo R^2 (see Koenker and Machado (1999)), which measures the degree of fit of the quantile regression models. The Wald test indicates that the null hypothesis is rejected for natural gas at any traditional confidence level for all countries in our sample. The results for the weather variables are mixed, as it seems that some effects could still be modeled in linear terms without significant loss for some countries. Finally, the Pseudo R^2 indicates the model adjustment across the whole density, modeling the quantiles of electricity independently. This number falls between a minimum value of 0.36 for Finland and a maximum of 0.76 for Italy. The most typical values are between 0.6 and 0.7, including countries like Belgium, the Czech Republic, France, Greece, Hungary, Portugal, the Netherlands, Norway, Slovenia, Spain, Sweden, Switzerland, and the UK. Overall, we can conclude that the model fit is adequate. Finally, given that the variables in our models are observed prices and meteorological variables, and both are measured with a high level of precision, measurement error is not a concern. In case it was, an alternative sieve quantile estimation provided by Hausman et al. (2021) would be in order.

Now we turn to our first indicator of vulnerability, I_1, which corresponds to the slope, *beta*, of electricity on natural gas, at very high quantiles. In Fig. 3, we present the indicator when $\theta = 0.95$, and $\theta = 0.05$. The variability of the quantile slope is greater at the left tail of the electricity price distribution than at the right tail, indicating that generation distress is a generalized fact in the markets, rather than being entirely related to market idiosyncrasies. Cases wherein the quantile slope is greater than one mean that the natural gas shock induces a more than proportional response in electricity price quantile, and the opposite holds for slopes lower than one.

Regarding the other indicators of vulnerability, we compute the ratio of transmission described in Equation (6), and the distance indicator presented in Equation (7), corresponding to I_2 and I_3, respectively, for each country in our sample, setting $\theta = 0.95$ for the high quantiles and $\theta = 0.05$ for the low quantiles, then conduct extensive robustness exercises, some of which can be found in the Appendix. In our robustness checks, we change the quantiles at which the statistics are constructed (i.e., $\theta_{high} = 0.99,\ 0.90$ and $\theta_{low} = 0.01, 0.10$). We also change the natural gas prices reference index to NBP in the UK. In all the cases, virtually identical results are obtained, and the ranking of vulnerability constructed based on our indicator remains unaltered.

The two indicators are plotted in Fig. 4; I_2 on the left and I_3 on the right. A number greater than one in I_2 indicates that the price of natural gas is transmitted to the price of electricity at a greater proportion when electricity is expensive than when it is cheap. For example, the indicator I_2 for Denmark is equal to 7.86, which is the result of dividing the effect of natural gas on electricity when the price of electricity is high by the effect when electricity has a low price (see Table 2). The I_3 indicator for Denmark is 0.57. Both cases clearly indicate that price is transmitted more upwards (when prices tend to be high) than downwards (when prices tend to be low).

The effects are less pronounced for the third indicator than for the second, but the rankings remain similar. For instance, the top and bot-

Table 2
Effect of natural gas prices and weather variables on quantile 0.95 and 0.05 of electricity prices.

Panel A. 0.95 electricity prices quantile

Country	Belgium	Czech Republic	Denmark	Estonia	Finland	France	Germany
Intercept	0.494***	0.553***	0.750***	0.714***	0.909***	0.519***	0.597***
	(0.029)	(0.026)	(0.037)	(0.031)	(0.048)	(0.019)	(0.023)
TTF	1.094***	1.218***	1.313***	1.112***	1.167***	1.166***	1.261***
	(0.050)	(0.058)	(0.087)	(0.072)	(0.109)	(0.028)	(0.052)
Temperature	−0.038	0.049***	0.050*	0.011	−0.028	−0.038	0.041*
	(0.033)	(0.018)	(0.030)	(0.031)	(0.052)	(0.024)	(0.023)
Wind Speed	−0.106***	−0.009	−0.044*	−0.086***	−0.137***	−0.033*	−0.021
	(0.028)	(0.019)	(0.024)	(0.021)	(0.040)	(0.019)	(0.019)
Precipitation	−0.034*	−0.002	0.038***	−0.008	0.008	0.020	−0.048**
	(0.018)	(0.021)	(0.011)	(0.009)	(0.043)	(0.019)	(0.021)
Irradiance	−0.096***	−0.033*	0.003	0.010	0.020	0.010	−0.021
	(0.033)	(0.018)	(0.030)	(0.030)	(0.053)	(0.024)	(0.023)
GOF-t	0.006	**0.004**	**0.003**	**0.002**	**0.005**	**0.003**	**0.004**
P-value	0.000	0.070	0.080	0.240	0.010	0.030	0.080

Country	**Greece**	**Hungary**	**Italy**	**Latvia**	**Lithuania**	**Netherlands**	**Norway**
Intercept	0.590***	0.577***	0.386***	0.663***	0.739***	0.426***	0.613***
	(0.012)	(0.022)	(0.015)	(0.056)	(0.062)	(0.015)	(0.021)
TTF	1.204***	1.151***	1.137***	1.176***	1.176***	1.190***	1.130***
	(0.025)	(0.027)	(0.019)	(0.119)	(0.127)	(0.026)	(0.042)
Temperature	0.096***	0.033	0.094***	0.035	0.012	0.028	−0.060***
	(0.015)	(0.031)	(0.018)	(0.036)	(0.031)	(0.019)	(0.020)
Wind Speed	−0.019**	−0.048**	0.010	−0.110***	−0.113***	−0.018	−0.047***
	(0.009)	(0.023)	(0.016)	(0.028)	(0.018)	(0.016)	(0.015)
Precipitation	−0.023	−0.044***	0.007	−0.035*	−0.036***	−0.005	−0.030***
	(0.021)	(0.008)	(0.019)	(0.020)	(0.012)	(0.014)	(0.010)
Irradiance	−0.052***	−0.043	−0.066***	−0.034	0.036	−0.009	−0.011
	(0.016)	(0.031)	(0.018)	(0.030)	(0.028)	(0.019)	(0.019)
GOF-t	0.011	**0.003**	**0.004**	**0.002**	**0.003**	0.006	0.009
P-value	0.000	0.200	0.030	0.250	0.150	0.000	0.000

Country	**Portugal**	**Slovakia**	**Slovenia**	**Spain**	**Sweden**	**Switzerland**	**United Kingdom**
Intercept	0.343***	0.714***	0.515***	0.341***	0.806***	0.435***	0.380***
	(0.009)	(0.038)	(0.015)	(0.010)	(0.039)	(0.018)	(0.032)
TTF	1.088***	1.257***	1.105***	1.099***	1.226***	1.145***	1.201***
	(0.017)	(0.080)	(0.019)	(0.021)	(0.082)	(0.037)	(0.066)
Temperature	−0.011	0.022	0.037	0.016	−0.051	−0.007	0.027**
	(0.008)	(0.040)	(0.023)	(0.011)	(0.042)	(0.019)	(0.013)
Wind Speed	−0.012	−0.040	−0.028*	−0.001	−0.121***	−0.029*	−0.047***
	(0.008)	(0.025)	(0.016)	(0.011)	(0.020)	(0.017)	(0.012)
Precipitation	−0.018**	−0.029	0.004	0.012*	0.016	0.003	0.007
	(0.007)	(0.026)	(0.016)	(0.007)	(0.022)	(0.007)	(0.015)
Irradiance	0.019*	−0.071*	−0.037	0.007	−0.025	−0.034*	−0.029*
	(0.010)	(0.039)	(0.023)	(0.012)	(0.036)	(0.020)	(0.017)
GOF-t	**0.006**	**0.002**	**0.003**	**0.004**	**0.003**	**0.002**	**0.002**
P-value	0.010	0.240	0.050	0.240	0.080	0.320	0.210

Panel B. 0.05 electricity prices quantile

Country	**Belgium**	**Czech Republic**	**Denmark**	**Estonia**	**Finland**	**France**	**Germany**
Intercept	−0.445***	−0.466***	−0.702***	−0.554***	−0.776***	−0.467***	−0.535***
	(0.026)	(0.021)	(0.024)	(0.014)	(0.029)	(0.033)	(0.023)
TTF	0.494***	0.480***	0.167***	0.372***	0.187***	0.453***	0.327***
	(0.056)	(0.039)	(0.048)	(0.028)	(0.069)	(0.066)	(0.050)
Temperature	0.003	0.066***	−0.026	0.033***	−0.063**	−0.011	0.035**
	(0.014)	(0.013)	(0.026)	(0.012)	(0.027)	(0.012)	(0.017)
Wind Speed	−0.066***	−0.065***	−0.052***	−0.032***	−0.047**	−0.022**	−0.079***
	(0.017)	(0.007)	(0.020)	(0.011)	(0.020)	(0.010)	(0.015)
Precipitation	−0.013	0.021*	−0.037	0.022***	0.000	−0.037**	−0.009
	(0.032)	(0.011)	(0.029)	(0.008)	(0.016)	(0.017)	(0.009)
Irradiance	−0.066***	−0.043***	−0.012	−0.036***	−0.050*	−0.056***	−0.037**
	(0.017)	(0.009)	(0.029)	(0.013)	(0.028)	(0.009)	(0.016)
GOF-t	**0.004**	**0.005**	**0.006**	**0.002**	0.008	**0.003**	**0.004**
P-value	0.040	0.010	0.010	0.310	0.000	0.020	0.080

Country	**Greece**	**Hungary**	**Italy**	**Latvia**	**Lithuania**	**Netherlands**	**Norway**
Intercept	−0.387***	−0.479***	−0.32***	−0.519***	−0.562***	−0.341***	−0.603***
	(0.011)	(0.013)	(0.012)	(0.014)	(0.015)	(0.023)	(0.011)
TTF	0.628***	0.510***	0.720***	0.451***	0.435***	0.575***	0.684***
	(0.023)	(0.031)	(0.023)	(0.030)	(0.025)	(0.046)	(0.015)
Temperature	0.048***	0.030***	0.053***	0.112***	0.121***	0.031***	−0.181***

(*continued on next page*)

Table 2 (*continued*)

Panel A. 0.95 electricity prices quantile

Country	Belgium	Czech Republic	Denmark	Estonia	Finland	France	Germany
	(0.011)	(0.011)	(0.007)	(0.011)	(0.015)	(0.006)	(0.015)
Wind Speed	−0.018***	−0.020***	−0.019**	−0.022***	−0.014	−0.043***	−0.023**
	(0.006)	(0.005)	(0.008)	(0.007)	(0.009)	(0.008)	(0.012)
Precipitation	−0.007	−0.004	−0.007	−0.008	−0.017	0.004	0.005
	(0.006)	(0.014)	(0.009)	(0.008)	(0.029)	(0.007)	(0.009)
Irradiance	−0.022**	−0.026**	−0.048***	−0.039***	−0.051***	−0.066***	0.022
	(0.010)	(0.010)	(0.008)	(0.011)	(0.017)	(0.008)	(0.017)
GOF-t	**0.003**	**0.004**	**0.004**	**0.002**	**0.002**	**0.005**	0.009
P-value	0.200	0.160	0.020	0.350	0.220	0.010	0.000
Country	**Portugal**	**Slovakia**	**Slovenia**	**Spain**	**Sweden**	**Switzerland**	**United Kingdom**
Intercept	−0.411***	−0.597***	−0.443***	−0.418***	−0.848***	−0.396***	−0.331***
	(0.028)	(0.021)	(0.019)	(0.029)	(0.022)	(0.013)	(0.011)
TTF	0.711***	0.364***	0.600***	0.708***	0.235***	0.564***	0.594***
	(0.061)	(0.043)	(0.042)	(0.046)	(0.044)	(0.027)	(0.023)
Temperature	0.122***	0.024	0.034**	0.172***	−0.111***	−0.075***	0.014***
	(0.020)	(0.016)	(0.015)	(0.012)	(0.018)	(0.009)	(0.002)
Wind Speed	−0.023	−0.003	−0.060***	−0.069***	−0.022	0.004	−0.023***
	(0.018)	(0.012)	(0.010)	(0.014)	(0.016)	(0.009)	(0.002)
Precipitation	−0.070**	0.009	−0.003	−0.004	−0.017	−0.008**	0.001
	(0.031)	(0.008)	(0.006)	(0.009)	(0.015)	(0.004)	(0.002)
Irradiance	−0.030	−0.048***	−0.030**	−0.034**	−0.010	−0.049***	−0.005**
	(0.026)	(0.016)	(0.012)	(0.016)	(0.016)	(0.008)	(0.002)
GOF-t	**0.002**	**0.001**	**0.003**	**0.008**	0.007	**0.003**	0.006
P-value	0.510	0.490	0.040	0.020	0.000	0.040	0.000

Note: This table presents the slopes and associated bootstrapping standard errors of transmission from gas prices and weather to electricity prices at high ($\theta = 0.95$) and low quantiles ($\theta = 0.05$). It also presents He and Zhu's (2013) statistic and p-value. Bold numbers indicate that the null hypothesis of linearity on a given quantile cannot be rejected at conventional confidence level.

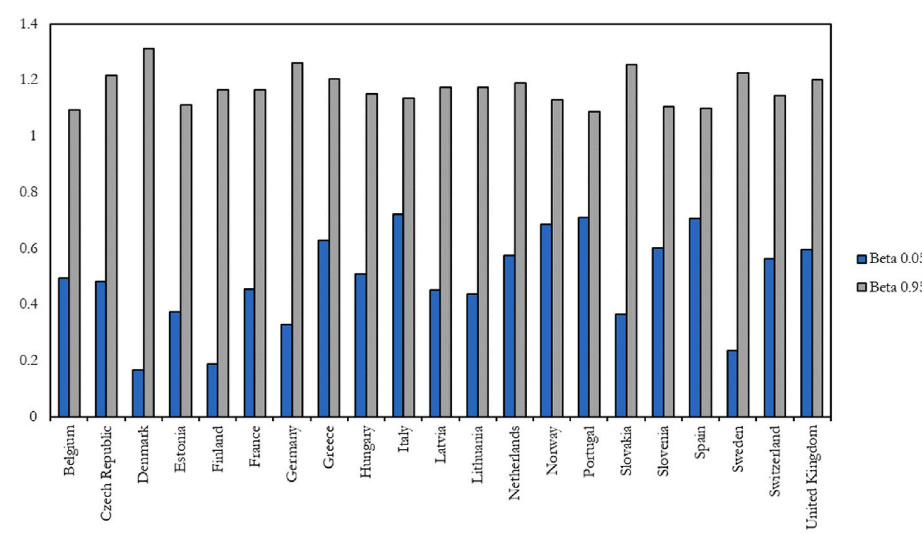

Fig. 3. I_1 **indicator**
Note: This figure presents the beta estimates of regression slopes for 0.95 (I_1 indicator) and 0.05 quantile.

tom five countries, which correspond to the most and least vulnerable, respectively, are the same according to both indicators; namely, Denmark, Finland, Sweden, Germany, and Slovakia are the most vulnerable, whereas Portugal, Spain, Italy, Norway, and Slovenia are the least vulnerable. There are some notable differences in the middle of the cross-sectional distribution of the countries' indicators, whether considering the second or the third. For instance, on the left of Fig. 4, the Czech Republic and the UK move two positions downward, while Switzerland and Belgium move upward. Movement is not greater than two positions in any case. Such variations can be explained by the fact that I_2 factors out the magnitude of the effect of the transmission because it is a ratio, whereas I_3 does not.

Overall, our two indicators emphasize the nonlinear transmission of natural gas prices to electricity prices, which affects national European markets in diverse ways. Denmark and Finland present higher ratios, and are therefore the most vulnerable to natural gas price shocks such as those observed in 2021 and the beginning of 2022. Asymmetric resilience in terms of I_2 in the electricity markets of our sample account for heterogeneities in power generation sources and level of market integration. Note that Denmark and Finland are not countries with a large dependence on natural gas, which implies that the generation mix is not determining countries' resilience to natural gas shocks (see Fig. 1).

Fig. 5 presents the effect of natural gas prices on the total distribution of electricity prices, and the effect of the weather variables for the two

Table 3
Wald test and Pseudo R^2 of the quantile regressions.

Country	Belgium	Czech Republic	Denmark	Estonia	Finland	France	Germany
TTF	42.949***	108.196***	117.184***	100.819***	61.276***	35.466***	68.433***
Temperature	1.519	3.768***	7.899***	0.833	1.350	4.052***	2.259**
Wind Speed	0.924	1.686	0.943	3.809***	1.601	0.996	1.857*
Precipitation	0.997	0.395	4.003***	2.071*	1.008	1.523	2.199*
Irradiance	0.769	0.287	0.397	1.338	0.560	2.329**	1.699
Pseudo-R2	0.662	0.655	0.499	0.504	0.360	0.680	0.616
Country	**Greece**	**Hungary**	**Italy**	**Latvia**	**Lithuania**	**Netherlands**	**Norway**
TTF	81.159***	73.377***	135.262***	50.967***	20.859***	49.505***	31.596***
Temperature	5.866***	0.877	2.697**	1.862*	3.772***	0.566	7.605***
Wind Speed	3.664***	3.024***	1.622	4.656***	13.276***	1.585	4.088***
Precipitation	2.766**	22.579***	1.080	0.723	2.081*	0.553	1.889*
Irradiance	5.627***	1.464	5.016***	1.285	1.976*	2.992**	1.312
Pseudo-R2	0.696	0.647	0.762	0.536	0.478	0.728	0.607
Country	**Portugal**	**Slovakia**	**Slovenia**	**Spain**	**Sweden**	**Switzerland**	**United Kingdom**
TTF	268.976***	107.331***	84.085***	25.324***	142.34***	75.45***	31.958***
Temperature	26.504***	0.461	1.890*	23.913***	3.065***	4.836***	2.121*
Wind Speed	0.612	1.512	3.079***	6.312***	3.800***	3.433***	1.838
Precipitation	1.440	3.54***	1.384	1.314	2.252**	10.904***	0.376
Irradiance	3.247***	0.266	2.123*	4.106***	1.561	4.774***	2.725**
Pseudo-R2	0.748	0.572	0.672	0.741	0.422	0.718	0.684

Note: This table presents the Wald statistic for all the regressions estimated at different quantiles of electricity prices distribution to test the hypothesis of equal slopes across the quantiles. The table also shows the Pseudo R^2 of the degree of fit of the models.

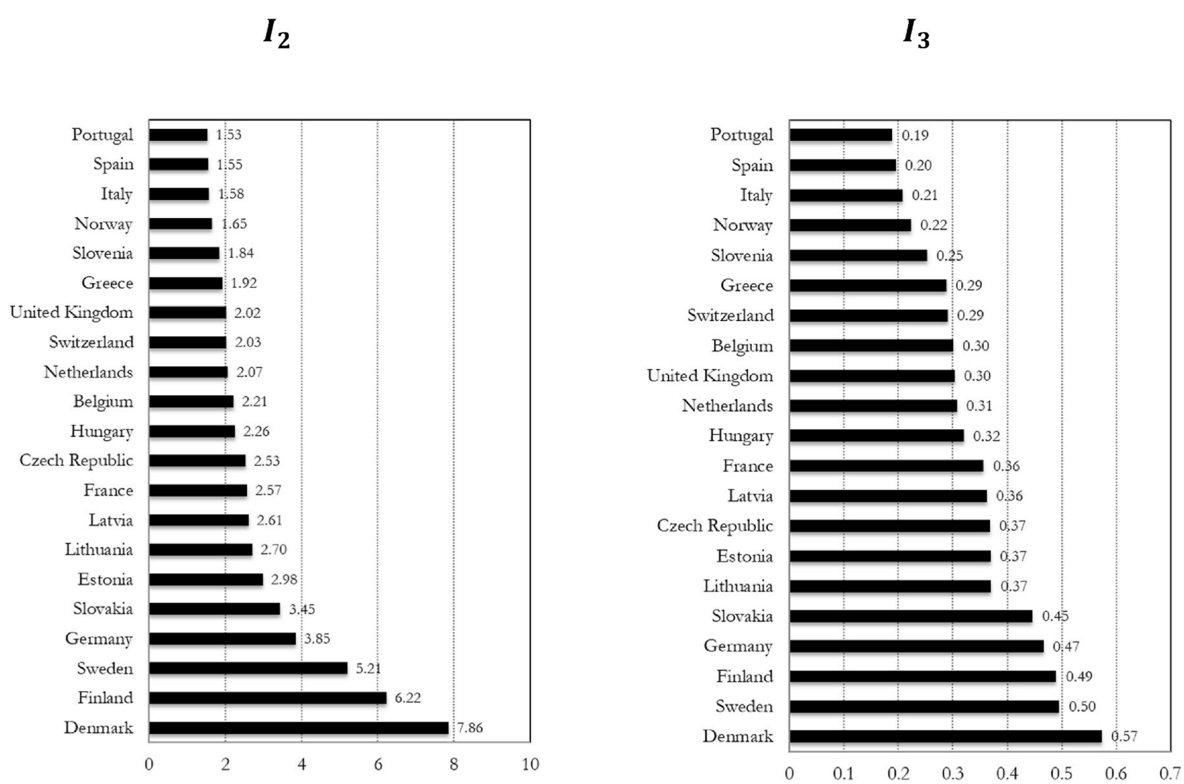

Fig. 4. I_2 **and** I_3 **indicators.**
Note: This figure shows the indicators I_2 (left side) and I_3 (right side) of the transmission from gas to electricity prices at high quantiles ($\theta = 0.9\ 5$) over low quantiles ($\theta = 0.05$), respectively.

countries that exhibit the lowest transmission of natural gas price shocks (Spain and Portugal), and the two countries with the highest ratios of transmission (Denmark and Finland). In all the cases, we find clearly increasing effects from lower to higher quantiles, although at very different paces in the four countries. For instance, in Finland, the effect increases at a stable and low step for most of the distribution and then jumps at extremely high quantiles.

We now investigate the factors underlying the cross-sectional heterogeneities regarding our proposed vulnerability indicators. Table 4 presents the results of the regressions using I_2 (Panel A) or I_3 (Panel B) as the dependent variables and several explanatory variables. This set of regressors include an indicator of market (des)integration, the

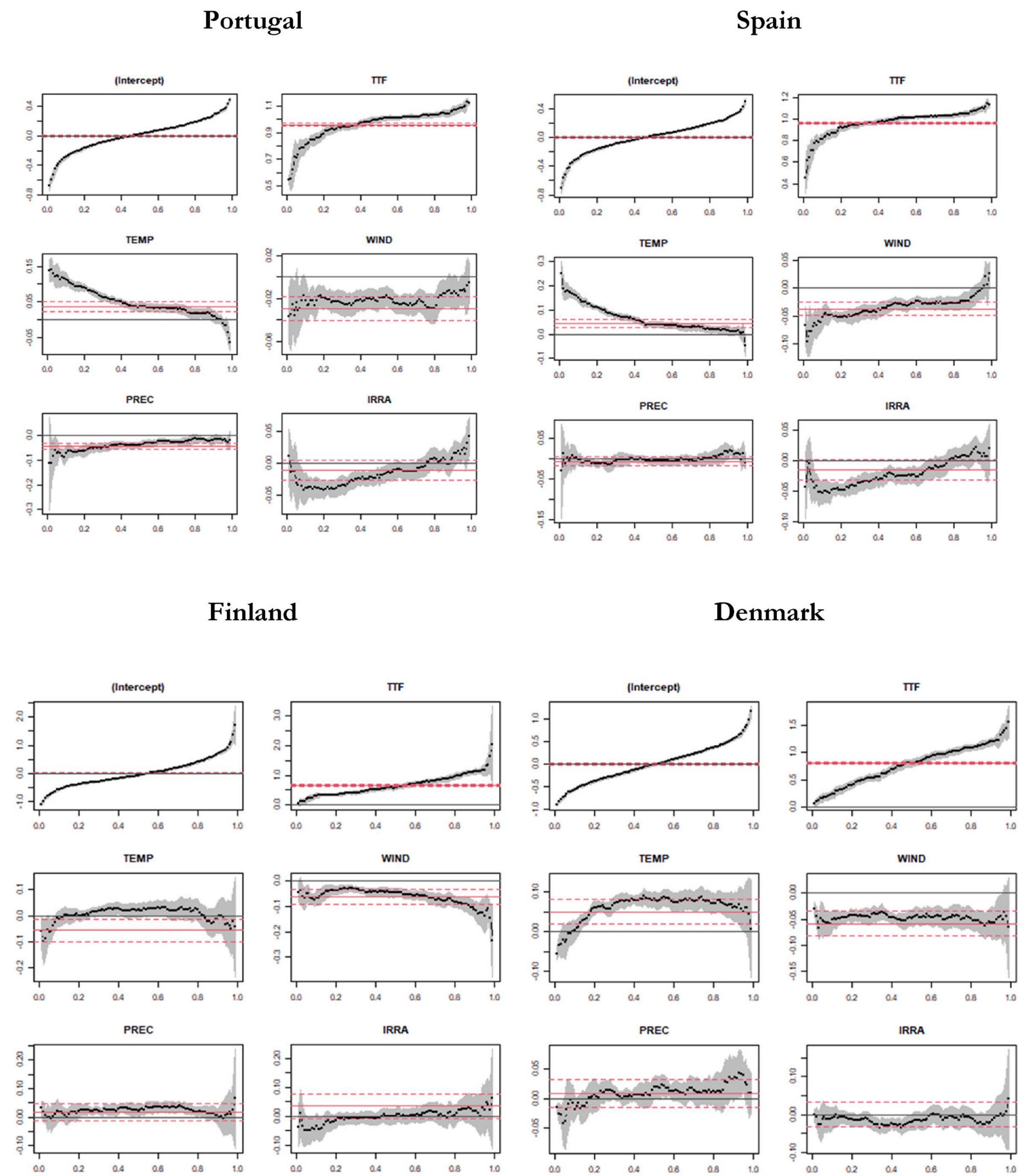

Fig. 5. The effect of natural gas prices and weather covariates on electricity prices at different quantiles of price distribution for Portugal, Spain, Finland, and Denmark.

Note: The horizontal axis presents the quantiles of electricity prices (5th and 95th), while the vertical axis is the effect of the explanatory variable. The dotted black lines are the varying influences across quantiles, alongside 95% confidence intervals. The red solid line is the effect at the mean of the price distribution, with associated confidence intervals. The explanatory variables are GAS through the TTF, TEMP is the average temperature, WIND is the average wind speed, PREC is the average precipitation, and IRRA is the irradiance of the capital of the respective country. . (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

proportion of generation attributable to natural gas, hydro, wind, and solar generation, and the total exports and imports for each country. A note of caution must be shared at this point. We use only 21 observations (one per country) to conduct these regressions, severely limiting the number of explanatory regressors that can be simultaneously included in our exercise.

We construct our own indicator of market integration referencing previous research in international economics (see, for instance, Rangvid et al. (2016) or Uribe and Chuliá (2021)); that is, we estimate a general factor of electricity prices, as the first principal component of our series of 21 electricity prices, then regress each price series on this general factor to obtain the residuals. Our estimate of market integration is the average of the absolute value of the residual series for each country. The higher the indicator, the less integrated a market. Recent examples in the literature that also employ statistics of market integration based on energy prices include Böckers and Heimeshoff (2014), Nitsche et al.

Table 4
Determinants of market vulnerability.

Panel A. I_2 indicator						
Specification	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	2.887***	2.887***	2.887***	2.887***	2.887***	2.887***
	(0.281)	(0.334)	(0.283)	(0.227)	(0.228)	(0.205)
(Des)integration	1.075***		0.948***	0.991**	1.294***	1.343***
	(0.288)		(0.324)	(0.373)	(0.289)	(0.254)
Natural Gas		−0.707*	−0.283	−0.584*	−0.319	−0.453*
		(0.343)	(0.324)	(0.277)	(0.301)	(0.242)
Hydro				−0.586*	−0.843***	−0.716***
				(0.294)	(0.261)	(0.237)
Wind				0.436		
				(0.298)		
Solar				0.107		
				(0.346)		
Exports					0.344	
					(0.267)	
Imports						0.560**
						(0.229)
Adjusted-R2	0.392	0.140	0.384	0.601	0.598	0.677
Panel B. I_3 indicator						
Specification	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Intercept	0.342***	0.342***	0.342***	0.342***	0.342***	0.342***
	(0.019)	(0.021)	(0.019)	(0.015)	(0.012)	(0.013)
(Des)Integration	0.061***		0.053**	0.068**	0.085***	0.080***
	(0.019)		(0.022)	(0.026)	(0.016)	(0.016)
Natural Gas		−0.042*	−0.018	−0.035*	−0.013	−0.032*
		(0.022)	(0.022)	(0.019)	(0.016)	(0.015)
Hydro				−0.060**	−0.065***	−0.055***
				(0.020)	(0.014)	(0.015)
Wind				0.002		
				(0.020)		
Solar				0.001		
				(0.024)		
Exports					0.041**	
					(0.014)	
Imports						0.034**
						(0.015)
Adjusted-R2	0.300	0.115	0.289	0.521	0.699	0.662

Note: This table presents regressions of market vulnerability on possible determinants and standard errors. ***, **, and * indicate statistical significance at 99%, 95%, and 90% confidence levels, respectively.

(2010), and Robinson (2007). A recent alternative approach, explored by Batalla-bejerano et al. (2019), is estimating a gravity model as in international trade. Although attractive, it is unclear how to apply the model to obtain individual estimates of disintegration, as required by this inquiry.

Our general electricity factor accounts for 87.9% of the total variability of idiosyncratic country prices, which is a considerably large fraction. According to Table 4, the indicator of market (des)integration is the only variable that remains significant across all explanatory regressions in the table, and also has a larger magnitude in comparison to the other covariates. Once again, this set of regressions was conducted after standardizing the right-hand-side variables to have zero mean and unit variance; thus, it is a beta-coefficient model and the magnitudes are comparable between the various explanatory variables. Notice that the effect of market (des)integration is consistently very close to or above unity in Panel A, and is greater than all other effects in the two panels. It is also notable that model adjustment, as measured by the R^2 of the regressions, significantly increases when we include market (des)integration within the set of explanatory variables. Our models explain up to 60% of the variability in Panel A, and close to 70% in Panel B.

Our results regarding market integration are congruent with classical trade theory, according to which larger markets allocate resources in a more efficient manner, satisfying the demands of the various integrated markets more efficiently. Greater integration also allows greater international consumption risk-sharing, which minimizes single country's consumption risks. In the absence of international market integration, shocks cannot be diversified-away through trade. It seems that in addition to these classical arguments, we can also add that more integrated markets lead to a greater stability concerning the transmission effects of natural gas prices on domestic electricity prices.

We next analyze the effect of the proportion of natural gas in the generation mix. When this effect is significant, it has a negative sign, indicating that the greater the electricity generation via natural gas, the smaller the vulnerability indicators. This is revealed because our statistics focus on the relative strength of the transmission from gas to electricity under different scenarios of distress, emphasizing systems' exacerbated vulnerability during costly generation periods. The nonlinearities that we identify put the system at risk precisely because they are unexpected by market participants and regulators. Markets that are more accustomed to regularly managing a high transmission from natural gas to electricity prices can potentially navigate unexpected shocks to international fuel markets more effectively than those that are relatively isolated from these market dynamics during periods of unconstrained and regular operation.

6. Conclusions and policy implications

Our results contribute to a more comprehensive understanding of price formation mechanisms in electricity markets during abnormally high-stress periods. Although the price setting mechanisms are similar across the various European markets overall, considerable variations are revealed in terms of system transmission from natural gas to electricity prices. Denmark, Finland, Sweden, and Germany present the highest indicators of transmission from natural gas to electricity prices, which are significantly and consistently larger than the other markets in our sample, particularly Southern European markets. Spain, Italy, Portugal, and Norway present the lowest vulnerability indicators; however, even in these cases, the price increments of natural gas that occur when electricity price is high are not expected to be offset by future natural gas price reductions when electricity generation is less expensive.

Our results inform the recent efforts of the European Commission (EC) to mitigate the soaring price of electricity in the EU (European Commission, 2021). The EC acknowledges the theoretical convenience of the current price setting mechanism, while also calling for an urgent debate regarding novel pricing and regulatory mechanisms to make the system more resilient to the kind of shocks observed in 2021 and 2022. In particular, the EC highlights the need to isolate the European system from the great uncertainty implied by the variability of fossil fuel markets, particularly natural gas, and more importantly, from an energy security perspective, to gain independence from geopolitical aspirations external to the EU (European Commission, 2021). We provide quantitative information to support these claims.

From a medium-run perspective, our results emphasize the convenience of greater market integration across European countries, which is based on both geographic and economic interconnections. Market integration is fundamental to the future of the European electricity market. In fact, ENTSO-E's System Needs Study (TYNDP, 2020) finds that 128 GW of additional cross-border transmission capacity must be reinforced to achieve European energy transition goals by 2040. Consequently, we highlight the importance of further studies on the level of Europe's power market integration dynamics, shedding some light on the different potential roadmaps and requirements for each country to invest in networks, storage, transmission, and distribution grids. Lastly, other market determinants such as tightness or competitiveness levels may be explored by future literature.

CRediT authorship contribution statement

Jorge M. Uribe: Conceptualization, Methodology, Writing – original draft. **Stephania Mosquera-López:** Data curation, Software, Writing – review & editing. **Oscar J. Arenas:** Data curation, Software.

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.

Appendix A. Effect of natural gas prices and weather variables on quantile 0.99 and 0.01 of electricity prices

Panel A. 0.99 electricity prices quantile

Country	Belgium	Czech Republic	Denmark	Estonia	Finland	France	Germany
Intercept	0.973***	0.751***	1.164***	1.392***	1.711***	0.794***	0.933***
	(0.078)	(0.028)	(0.080)	(0.274)	(0.425)	(0.038)	(0.043)
TTF	1.191***	1.265***	1.551***	1.777***	2.033**	1.233***	1.438***
	(0.032)	(0.012)	(0.183)	(0.597)	(0.792)	(0.047)	(0.052)
Temperature	−0.137**	−0.002	0.006	−0.066	−0.044	−0.126***	−0.046
	(0.057)	(0.027)	(0.075)	(0.208)	(0.116)	(0.038)	(0.038)
Wind Speed	−0.127	−0.041**	−0.066	−0.129	−0.236***	−0.016	−0.033*
	(0.078)	(0.020)	(0.058)	(0.106)	(0.087)	(0.032)	(0.019)
Precipitation	−0.074	−0.009	0.008	−0.020	0.064	−0.015	−0.021
	(0.053)	(0.024)	(0.019)	(0.094)	(0.106)	(0.025)	(0.035)
Irradiance	−0.168***	−0.039	0.040	0.053	0.060	0.033	0.034
	(0.063)	(0.024)	(0.080)	(0.172)	(0.105)	(0.035)	(0.036)
GOF-t	**0.001**	**0.000**	**0.001**	**0.000**	**0.001**	**0.001**	**0.001**
P-value	0.170	0.370	0.270	0.420	0.140	0.200	0.120
Country	**Greece**	**Hungary**	**Italy**	**Latvia**	**Lithuania**	**Netherlands**	**Norway**
Intercept	0.783***	0.891***	0.611***	1.394***	1.670***	0.756***	0.924***
	(0.028)	(0.044)	(0.047)	(0.254)	(0.348)	(0.050)	(0.148)
TTF	1.228***	1.174***	1.226***	1.853***	1.780**	1.413***	1.194***
	(0.026)	(0.015)	(0.104)	(0.575)	(0.707)	(0.114)	(0.328)
Temperature	0.114***	0.017	0.177***	−0.070	−0.309	0.019	−0.118*
	(0.023)	(0.061)	(0.044)	(0.213)	(0.248)	(0.043)	(0.062)
Wind Speed	0.041*	−0.020	0.048*	−0.208*	−0.205	−0.066**	−0.123***
	(0.023)	(0.025)	(0.028)	(0.120)	(0.135)	(0.029)	(0.023)
Precipitation	−0.076*	−0.081***	−0.004	−0.062	−0.071	0.025	−0.067
	(0.046)	(0.026)	(0.044)	(0.074)	(0.517)	(0.043)	(0.043)
Irradiance	−0.137***	−0.094	−0.131***	0.104	0.416*	−0.042	−0.084**
	(0.027)	(0.059)	(0.042)	(0.203)	(0.228)	(0.042)	(0.038)
GOF-t	**0.001**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**
P-value	0.350	0.300	0.380	0.750	0.440	0.400	0.140
Country	**Portugal**	**Slovakia**	**Slovenia**	**Spain**	**Sweden**	**Switzerland**	**United Kingdom**
Intercept	0.489***	1.137***	0.834***	0.502***	1.504***	0.658***	1.294***
	(0.015)	(0.067)	(0.068)	(0.024)	(0.154)	(0.039)	(0.277)
TTF	1.12***	1.379***	1.032***	1.127***	1.748***	1.171***	2.200***
	(0.007)	(0.041)	(0.048)	(0.012)	(0.322)	(0.021)	(0.605)
Temperature	−0.065***	−0.008	0.158*	−0.049*	−0.013	−0.101***	0.133
	(0.013)	(0.098)	(0.084)	(0.025)	(0.147)	(0.032)	(0.168)
Wind Speed	−0.005	−0.008	−0.061**	0.026**	−0.239***	−0.013	−0.056
	(0.010)	(0.074)	(0.029)	(0.012)	(0.059)	(0.017)	(0.116)
Precipitation	−0.017	−0.053	−0.022	−0.008	−0.021	0.004	0.012

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Panel A. 0.99 electricity prices quantile							
Country	Belgium	Czech Republic	Denmark	Estonia	Finland	France	Germany
	(0.020)	(0.068)	(0.041)	(0.009)	(0.034)	(0.018)	(0.114)
Irradiance	0.041**	−0.080	−0.238***	0.019	−0.029	0.003	−0.092
	(0.018)	(0.101)	(0.082)	(0.024)	(0.167)	(0.020)	(0.168)
GOF-t	**0.002**	**0.000**	**0.000**	**0.001**	**0.000**	**0.001**	**0.001**
P-value	0.030	0.720	0.360	0.180	0.490	0.260	0.250
Panel B. 0.01 electricity prices quantile							
Country	**Belgium**	**Czech Republic**	**Denmark**	**Estonia**	**Finland**	**France**	**Germany**
Intercept	−0.704***	−0.818***	−0.903***	−0.750***	−1.120***	−0.641***	−0.770***
	(0.059)	(0.054)	(0.017)	(0.038)	(0.032)	(0.039)	(0.091)
TTF	0.263**	0.463***	0.056**	0.326***	0.035	0.389***	0.265**
	(0.114)	(0.055)	(0.024)	(0.015)	(0.043)	(0.076)	(0.127)
Temperature	−0.033	0.265***	−0.058***	0.062*	−0.061*	0.038	0.058
	(0.035)	(0.067)	(0.008)	(0.037)	(0.033)	(0.023)	(0.094)
Wind Speed	−0.059**	−0.051	−0.029***	−0.080**	−0.043*	−0.051***	−0.034
	(0.025)	(0.063)	(0.008)	(0.034)	(0.025)	(0.019)	(0.052)
Precipitation	−0.003	0.033	−0.015***	0.037*	0.032**	−0.036	0.002
	(0.022)	(0.072)	(0.003)	(0.019)	(0.014)	(0.064)	(0.046)
Irradiance	−0.062	−0.088	−0.002	−0.092*	−0.036	−0.095***	0.022
	0.044	0.065	0.01	0.048	0.042	0.026	0.091
GOF-t	**0.001**	0.002	**0.001**	**0.000**	**0.000**	**0.000**	**0.001**
P-value	0.060	0.000	0.120	0.470	0.280	0.410	0.420
Country	**Greece**	**Hungary**	**Italy**	**Latvia**	**Lithuania**	**Netherlands**	**Norway**
Intercept	−0.512***	−0.653***	−0.445***	−0.697***	−0.792***	−0.509***	−0.7751***
	(0.056)	(0.043)	(0.021)	(0.041)	(0.029)	(0.026)	(0.068)
TTF	0.583***	0.302***	0.609***	0.323***	0.223***	0.392***	0.676***
	(0.103)	(0.087)	(0.008)	(0.042)	(0.060)	(0.049)	(0.150)
Temperature	0.114***	0.049***	0.036**	0.149***	0.074***	0.050**	−0.146***
	(0.025)	(0.009)	(0.016)	(0.036)	(0.014)	(0.022)	(0.054)
Wind Speed	−0.021	−0.034***	−0.033***	−0.027**	0.028***	−0.033***	−0.052***
	(0.015)	(0.012)	(0.011)	(0.013)	(0.009)	(0.007)	(0.020)
Precipitation	−0.034	−0.017	0.005	−0.014	0.007	−0.012	0.001
	(0.027)	(0.038)	(0.025)	(0.009)	(0.008)	(0.014)	(0.025)
Irradiance	−0.047	−0.013	−0.021	−0.084*	−0.044***	−0.072***	0.024
	(0.030)	(0.009)	(0.015)	(0.047)	(0.012)	(0.020)	(0.028)
GOF-t	**0.001**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	0.003
P-value	0.130	0.770	0.260	0.590	0.080	0.520	0.000
	Portugal	**Slovakia**	**Slovenia**	**Spain**	**Sweden**	**Switzerland**	**United Kingdom**
Intercept	−0.672***	−0.799***	−0.618***	−0.709***	−1.098***	−0.573***	−0.429***
	(0.047)	(0.042)	(0.033)	(0.045)	(0.012)	(0.033)	(0.033)
TTF	0.545***	0.321***	0.463***	0.452***	0.070***	0.388***	0.445***
	(0.014)	(0.027)	(0.026)	(0.087)	(0.018)	(0.067)	(0.066)
Temperature	0.138***	0.054	0.110***	0.249***	−0.074***	−0.034***	0.014
	(0.019)	(0.049)	(0.035)	(0.031)	(0.017)	(0.013)	(0.010)
Wind Speed	−0.036**	0.045*	−0.012	−0.067***	−0.052***	−0.011	−0.044***
	(0.015)	(0.024)	(0.020)	(0.020)	(0.010)	(0.013)	(0.011)
Precipitation	−0.114	0.006	0.006	−0.031	−0.001	−0.016	0.005
	(0.116)	(0.041)	(0.018)	(0.070)	(0.004)	(0.010)	(0.007)
Irradiance	0.011	−0.073	−0.065***	−0.042	−0.013	−0.087***	−0.033
	(0.025)	(0.047)	(0.024)	(0.032)	(0.015)	(0.013)	(0.023)
GOF-t	**0.000**	**0.000**	**0.000**	**0.001**	0.002	**0.000**	**0.000**
P-value	0.590	0.370	0.640	0.480	0.000	0.480	0.700

Note: This table presents the slopes and associated bootstrapping standard errors of transmission from gas prices and weather to electricity prices at high ($\theta = 0.99$) and low quantiles ($\theta = 0.01$). It also presents He and Zhu's (2013) statistic and p-value. Bold numbers indicate that the null hypothesis of linearity on a given quantile cannot be rejected at conventional confidence level.

Appendix B. Effect of natural gas prices and weather variables on quantile 0.90 and 0.10 of electricity prices

Panel A. 0.90 electricity prices quantile							
Country	Belgium	Czech Republic	Denmark	Estonia	Finland	France	Germany
Intercept	0.342***	0.414***	0.558***	0.556***	0.674***	0.370***	0.448***
	(0.015)	(0.019)	(0.019)	(0.019)	(0.026)	(0.020)	(0.020)
TTF	1.102***	1.097***	1.195***	1.112***	1.111***	1.086***	1.166***
	(0.021)	(0.044)	(0.042)	(0.036)	(0.047)	(0.045)	(0.046)
Temperature	−0.013	0.039**	0.061***	0.050**	−0.012	−0.044**	0.050**
	(0.018)	(0.016)	(0.020)	(0.025)	(0.033)	(0.021)	(0.023)

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Panel A. 0.90 electricity prices quantile

Country	Belgium	Czech Republic	Denmark	Estonia	Finland	France	Germany
Wind Speed	−0.078***	−0.031**	−0.055***	−0.096***	−0.114***	−0.047***	−0.018
	(0.011)	(0.012)	(0.017)	(0.017)	(0.019)	(0.017)	(0.017)
Precipitation	−0.023**	0.000	0.031	0.012*	0.004	0.030	−0.043***
	(0.011)	(0.017)	(0.023)	(0.007)	(0.015)	(0.023)	(0.007)
Irradiance	−0.081***	−0.028*	−0.020	0.006	0.018	−0.011	−0.033
	(0.017)	(0.015)	(0.022)	(0.024)	(0.031)	(0.021)	(0.023)
GOF-t	**0.006**	0.012	**0.007**	0.009	0.010	**0.004**	**0.011**
P-value	0.020	0.000	0.020	0.000	0.000	0.100	0.020

Country	**Greece**	**Hungary**	**Italy**	**Latvia**	**Lithuania**	**Netherlands**	**Norway**
Intercept	0.472***	0.433***	0.286***	0.484***	0.510***	0.303***	0.512***
	(0.017)	(0.017)	(0.012)	(0.019)	(0.029)	(0.018)	(0.014)
TTF	1.155***	1.099***	1.126***	1.088***	1.032***	1.117***	1.075***
	(0.038)	(0.035)	(0.024)	(0.036)	(0.061)	(0.042)	(0.030)
Temperature	0.118***	0.055**	0.057***	0.045**	0.021	0.036**	−0.054***
	(0.021)	(0.023)	(0.014)	(0.021)	(0.032)	(0.015)	(0.015)
Wind Speed	0.007	−0.042***	−0.003	−0.102***	−0.091***	−0.028**	−0.045***
	(0.012)	(0.013)	(0.011)	(0.015)	(0.014)	(0.013)	(0.011)
Precipitation	−0.042***	−0.036***	0.012	−0.054**	−0.025	0.001	−0.028**
	(0.012)	(0.003)	(0.015)	(0.025)	(0.026)	(0.016)	(0.012)
Irradiance	−0.098***	−0.062***	−0.029*	−0.003	0.037	−0.019	−0.007
	(0.021)	(0.023)	(0.014)	(0.019)	(0.031)	(0.016)	(0.013)
GOF-t	0.022	0.015	0.011	**0.009**	**0.009**	**0.009**	0.014
P-value	0.000	0.000	0.000	0.030	0.030	0.010	0.000

Country	**Portugal**	**Slovakia**	**Slovenia**	**Spain**	**Sweden**	**Switzerland**	**United Kingdom**
Intercept	0.272***	0.524***	0.366***	0.275***	0.640***	0.330***	0.235***
	(0.010)	(0.024)	(0.017)	(0.009)	(0.020)	(0.011)	(0.014)
TTF	1.064***	1.175***	1.070***	1.065***	1.174***	1.105***	1.084***
	(0.021)	(0.049)	(0.033)	(0.018)	(0.039)	(0.018)	(0.031)
Temperature	0.009	0.042	0.046*	0.015	−0.018	−0.028*	0.007
	(0.009)	(0.032)	(0.024)	(0.012)	(0.024)	(0.015)	(0.013)
Wind Speed	−0.015*	−0.033*	−0.036**	−0.016	−0.094***	−0.042***	−0.030***
	(0.008)	(0.019)	(0.015)	(0.010)	(0.014)	(0.010)	(0.009)
Precipitation	−0.018*	−0.037***	0.000	0.015	0.029	0.008	0.008
	(0.010)	(0.009)	(0.019)	(0.011)	(0.020)	(0.009)	(0.010)
Irradiance	0.007	−0.074**	−0.019	0.013	−0.038*	−0.036**	0.007
	(0.010)	(0.031)	(0.024)	(0.012)	(0.022)	(0.016)	(0.012)
GOF-t	**0.009**	**0.004**	0.011	**0.006**	0.012	**0.007**	**0.006**
P-value	0.070	0.150	0.000	0.310	0.000	0.070	0.130

Panel B. 0.10 electricity prices quantile

Country	**Belgium**	**Czech Republic**	**Denmark**	**Estonia**	**Finland**	**France**	**Germany**
Intercept	−0.325***	−0.379***	−0.557***	−0.463***	−0.580***	−0.332***	−0.409***
	(0.017)	(0.016)	(0.020)	(0.014)	(0.024)	(0.016)	(0.015)
TTF	0.599***	0.536***	0.241***	0.437***	0.315***	0.640***	0.428***
	(0.034)	(0.031)	(0.047)	(0.032)	(0.050)	(0.037)	(0.033)
Temperature	0.005	0.037***	0.002	0.029***	−0.013	−0.036***	0.063***
	(0.007)	(0.004)	(0.014)	(0.006)	(0.018)	(0.009)	(0.016)
Wind Speed	−0.058***	−0.063***	−0.051***	−0.024***	−0.065***	−0.033***	−0.068***
	(0.006)	(0.006)	(0.011)	(0.004)	(0.017)	(0.006)	(0.014)
Precipitation	0.000	0.020***	−0.017*	0.018***	0.018	−0.030**	−0.020*
	(0.004)	(0.006)	(0.009)	(0.005)	(0.018)	(0.013)	(0.011)
Irradiance	−0.059***	−0.038***	−0.009	−0.015*	−0.035	−0.047***	−0.058***
	(0.007)	(0.005)	(0.016)	(0.008)	(0.026)	(0.008)	(0.015)
GOF-t	**0.008**	0.010	**0.008**	**0.003**	**0.008**	0.006	**0.004**
P-value	0.010	0.000	0.010	0.300	0.040	0.000	0.450

Country	**Greece**	**Hungary**	**Italy**	**Latvia**	**Lithuania**	**Netherlands**	**Norway**
Intercept	−0.326***	−0.379***	−0.268***	−0.430***	−0.468***	−0.259***	−0.515***
	(0.009)	(0.018)	(0.011)	(0.015)	(0.011)	(0.015)	(0.013)
TTF	0.680***	0.637***	0.742***	0.525***	0.445***	0.689***	0.713***
	(0.017)	(0.035)	(0.026)	(0.033)	(0.021)	(0.034)	(0.025)
Temperature	0.035***	0.042***	0.057***	0.108***	0.117***	0.025***	−0.170***
	(0.006)	(0.008)	(0.004)	(0.008)	(0.012)	(0.003)	(0.016)
Wind Speed	−0.011**	−0.036***	−0.013***	−0.030***	−0.026***	−0.029***	−0.016*
	(0.005)	(0.003)	(0.003)	(0.004)	(0.007)	(0.002)	(0.009)
Precipitation	−0.015***	0.006***	−0.019***	−0.015***	−0.005	0.000	−0.009
	(0.003)	(0.002)	(0.004)	(0.005)	(0.007)	(0.002)	(0.011)
Irradiance	−0.021***	−0.033***	−0.064***	−0.033***	−0.035***	−0.043***	0.011
	(0.007)	(0.008)	(0.005)	(0.008)	(0.011)	(0.005)	(0.017)

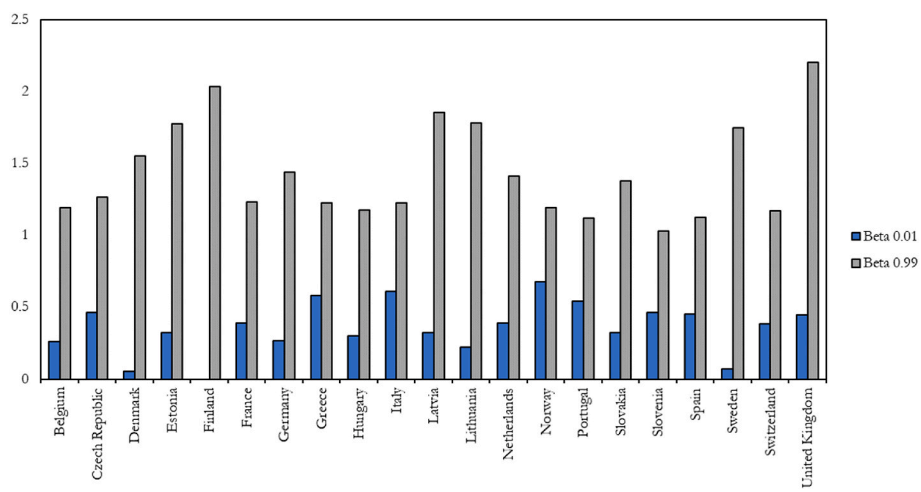
(*continued on next page*)

(*continued*)

Panel A. 0.90 electricity prices quantile							
Country	Belgium	Czech Republic	Denmark	Estonia	Finland	France	Germany
GOF-t	**0.010**	**0.013**	**0.009**	**0.004**	**0.005**	**0.006**	0.020
P-value	0.090	0.010	0.010	0.390	0.180	0.040	0.000
Country	**Portugal**	**Slovakia**	**Slovenia**	**Spain**	**Sweden**	**Switzerland**	**United Kingdom**
Intercept	−0.284***	−0.478***	−0.354***	−0.290***	−0.692***	−0.300***	−0.277***
	(0.014)	(0.019)	(0.016)	(0.016)	(0.025)	(0.019)	(0.009)
TTF	0.811***	0.443***	0.661***	0.813***	0.273***	0.689***	0.655***
	(0.029)	(0.038)	(0.033)	(0.027)	(0.054)	(0.038)	(0.016)
Temperature	0.112***	0.011	0.045***	0.148***	−0.062**	−0.063***	0.004
	(0.011)	(0.011)	(0.009)	(0.011)	(0.029)	(0.010)	(0.002)
Wind Speed	−0.022**	−0.004	−0.035***	−0.052***	−0.044**	0.003	−0.022***
	(0.011)	(0.006)	(0.005)	(0.011)	(0.019)	(0.006)	(0.003)
Precipitation	−0.071***	−0.003	−0.015***	−0.003	−0.051***	−0.031***	−0.001
	(0.019)	(0.006)	(0.005)	(0.007)	(0.018)	(0.004)	(0.005)
Irradiance	−0.038***	−0.056***	−0.035***	−0.052***	−0.067**	−0.056***	−0.012***
	(0.014)	(0.009)	(0.010)	(0.011)	(0.028)	(0.008)	(0.004)
GOF-t	**0.008**	**0.002**	0.007	0.025	0.021	0.010	0.020
P-value	0.070	0.760	0.000	0.000	0.000	0.000	0.000

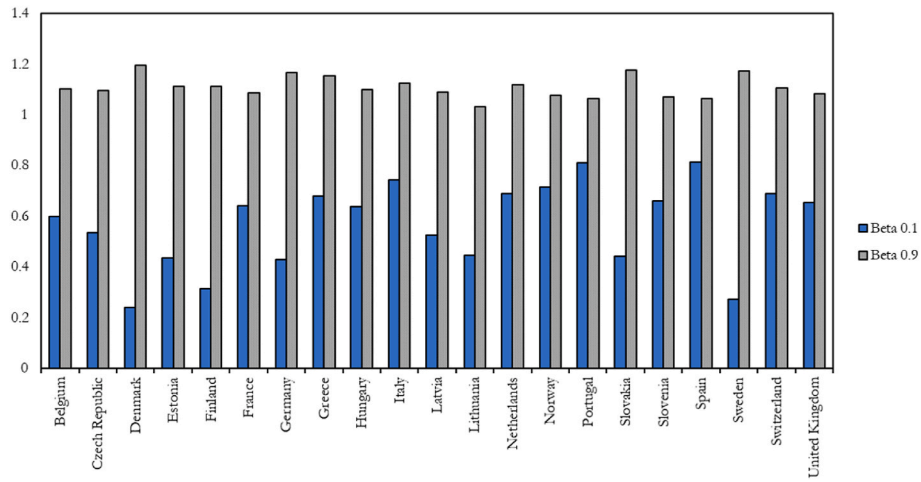
Note: This table presents the slopes and associated bootstrapping standard errors of transmission from gas prices and weather to electricity prices at high ($\theta = 0.90$) and low quantiles ($\theta = 0.10$). It also presents He and Zhu's (2013) statistic and p-value. Bold numbers indicate that the null hypothesis of linearity on a given quantile cannot be rejected at conventional confidence level.

Appendix C. I_1 indicator for 0.99 quantile



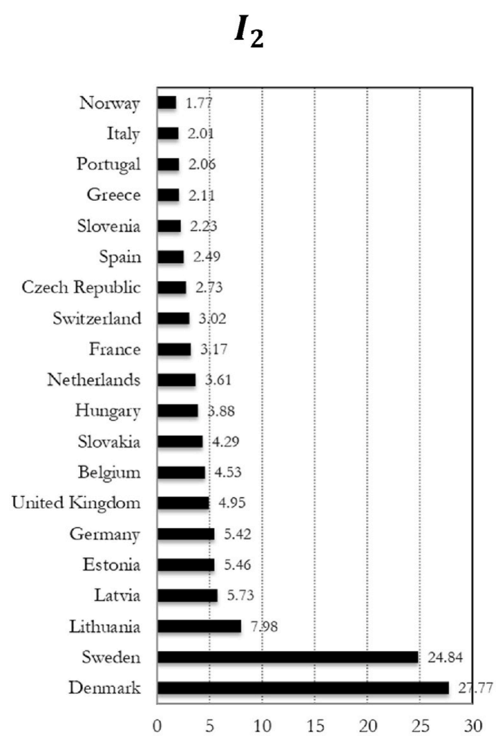
Note: This figure presents the beta estimates of regression slopes for 0.99 (I_1 indicator) and 0.01 quantile.

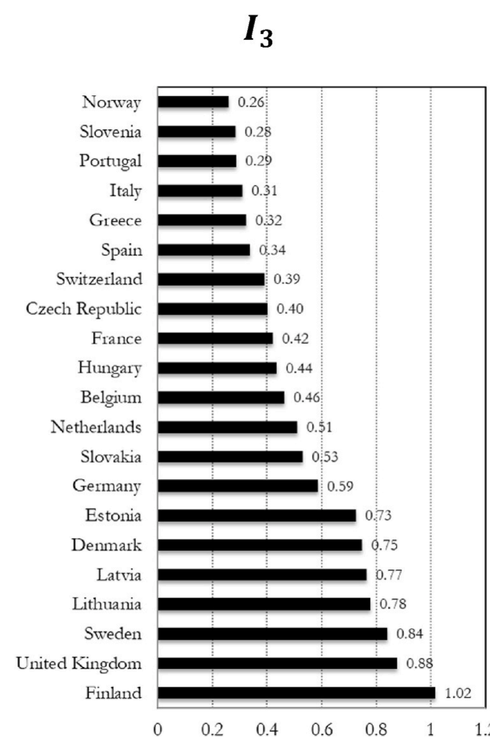
Appendix D. I_1 indicator for 0.90 quantile



Note: This figure presents the beta estimates of regression slopes for 0.90 (I_1 indicator) and 0.10 quantile.

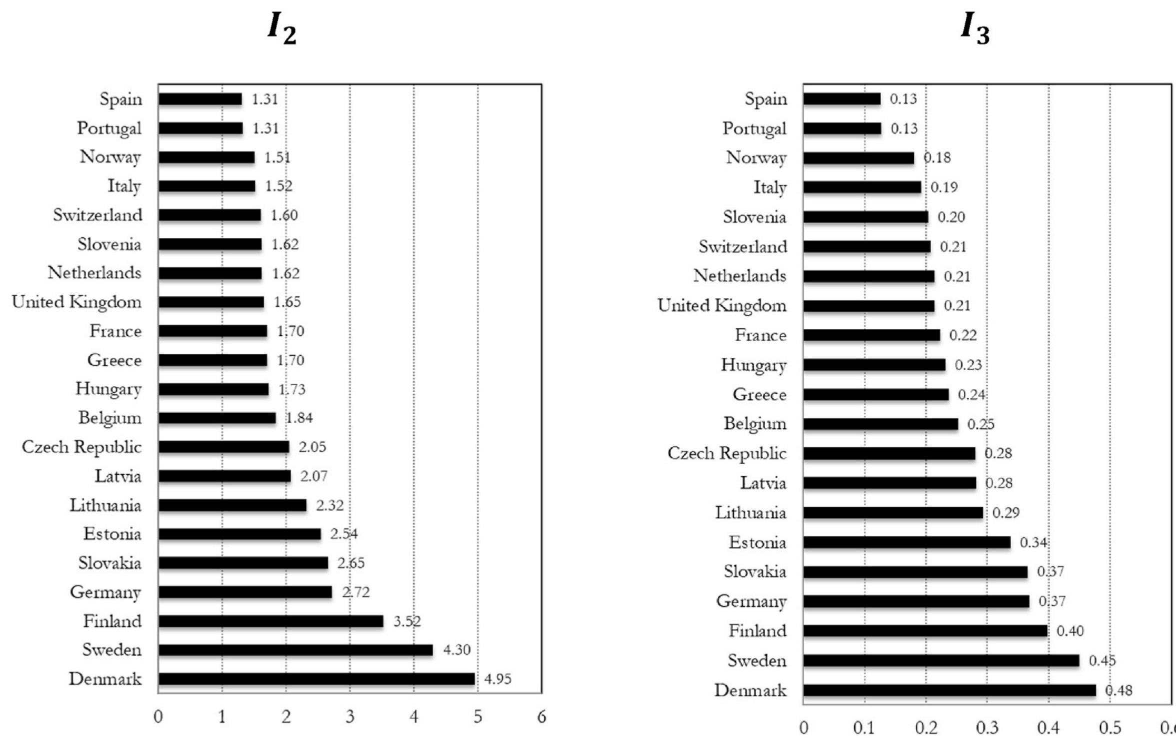
Appendix E. I_2 and I_3 for 0.99 and 0.01 quantiles





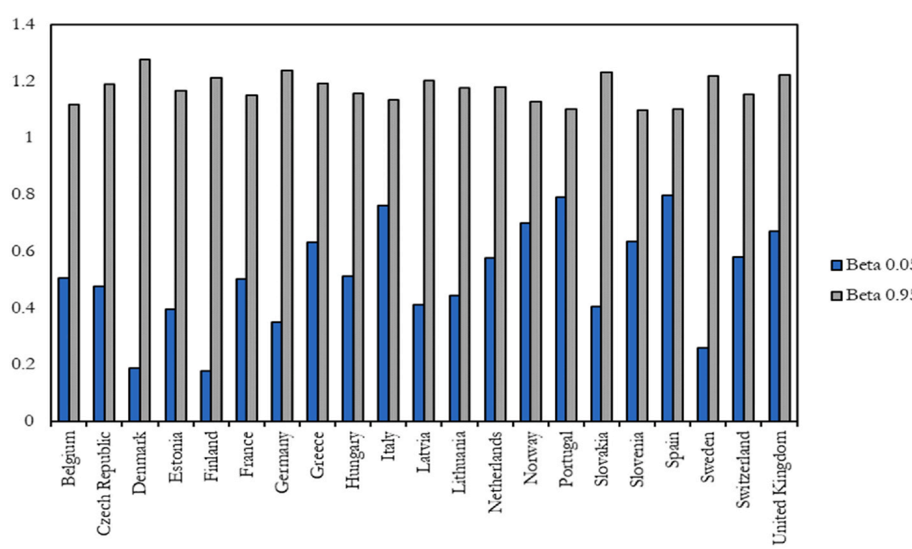
Note: This figure shows the indicators I_2 (left side) and I_3 (right side) of the transmission from gas to electricity prices at high quantiles ($\theta = 0.9\ 9$) over low quantiles ($\theta = 0.01$), respectively.

Appendix F. I_2 and I_3 for 0.90 and 0.10 quantiles



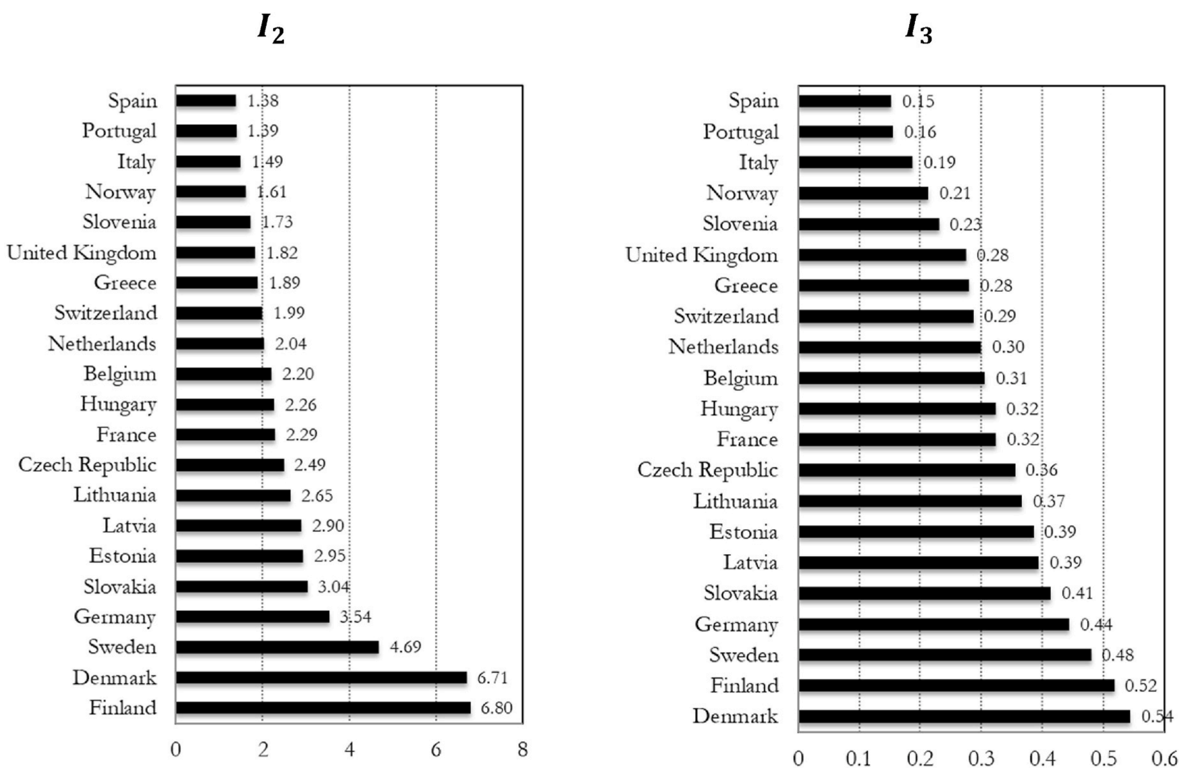
Note: This figure shows the indicators I_2 (left side) and I_3 (right side) of the transmission from gas to electricity prices at high quantiles ($\theta = 0.90$) over low quantiles ($\theta = 0.10$), respectively.

Appendix G. I_1 indicator for 0.95 quantile with NBP gas prices



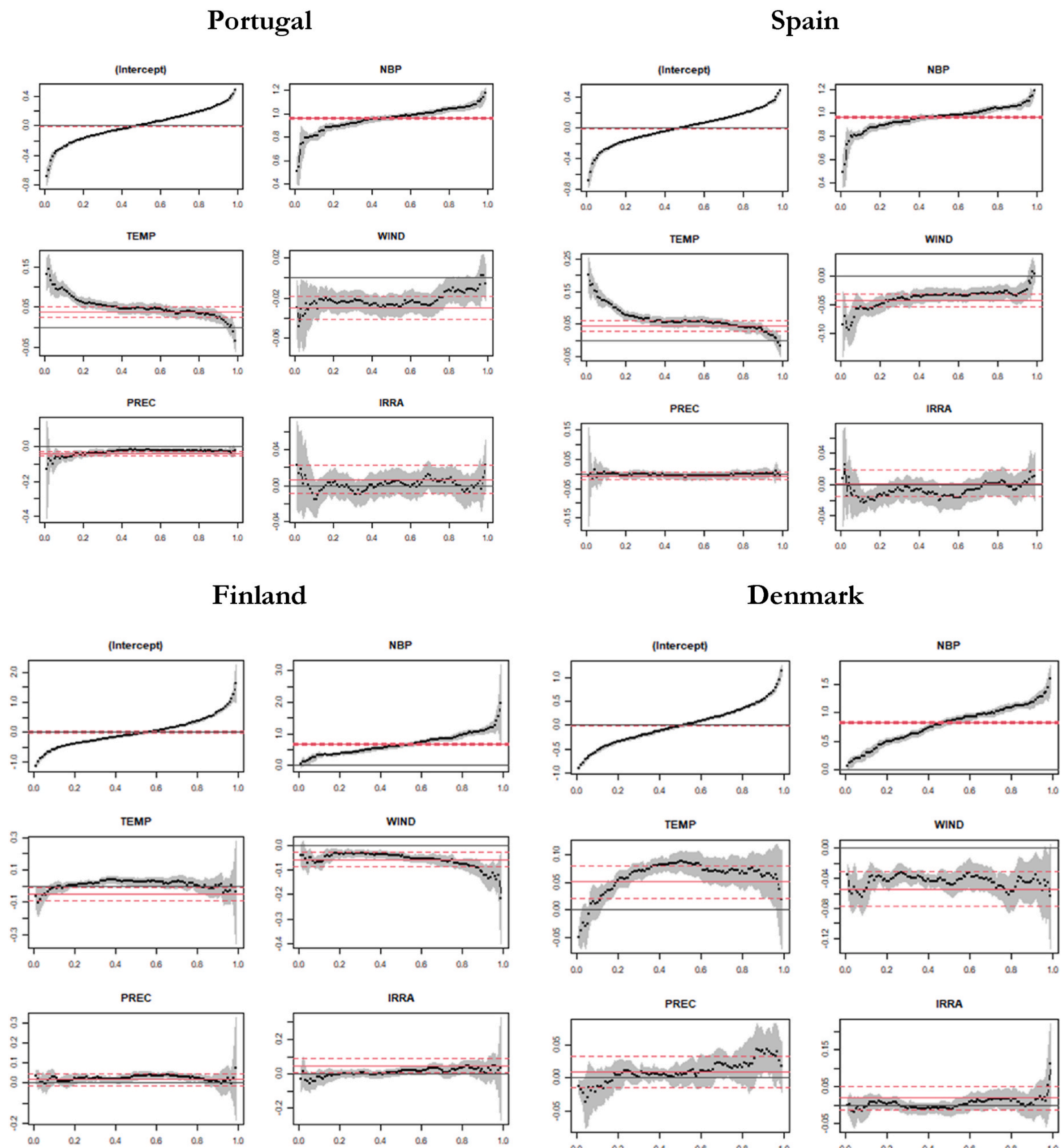
Note: This figure presents the beta estimates of regression slopes for 0.95 (I_1 indicator) and 0.05 quantile of the regressions with NBP gas prices.

Appendix H. I_2 and I_3 indicators for 0.95 and 0.05 quantiles with NBP gas prices



Note: This figure shows the indicators I_2 (left side) and I_3 (right side) of the transmissions from NBP gas prices to electricity prices at high quantiles ($\theta = 0.95$) over low quantiles ($\theta = 0.05$), respectively.

Appendix I. Effect of NBP natural gas prices and weather covariates on electricity prices at different quantiles of the price distribution for Portugal, Spain, Finland, and Denmark



Note: The horizontal axis presents the quantiles of electricity prices (5th and 95th), while the vertical axis is the effect of the explanatory variable. The dotted black lines are the varying influences across quantiles, alongside 95% confidence intervals. The red solid line is the effect at the mean of the price distribution, with associated confidence intervals. The explanatory variables are GAS through the NBP, TEMP is the average temperature, WIND is the average wind speed, PREC is the average precipitation, and IRRA is the irradiance of the capital of the respective country.

Appendix J. Wald test and Pseudo R^2 of the quantile regressions with NBP natural gas prices

Country	Belgium	Czech Republic	Denmark	Estonia	Finland	France	Germany
NBP	35.743***	56.158***	67.19***	96.340***	33.18***	46.348***	66.046***
Temperature	1.132	6.842***	6.411***	1.029	1.229	3.077***	0.610
Wind Speed	0.377	3.901***	0.701	6.752***	1.103	0.517	2.154*
Precipitation	1.303	0.433	2.000*	0.388	0.924	4.329***	2.478**
Irradiance	1.680	1.718	0.642	1.598	0.885	2.453**	1.104
Pseudo-R2	0.670	0.666	0.514	0.521	0.375	0.694	0.631
Country	**Greece**	**Hungary**	**Italy**	**Latvia**	**Lithuania**	**Netherlands**	**Norway**
NBP	76.089***	40.776***	32.447***	36.515***	45.881***	38.300***	37.043***
Temperature	2.670**	0.087	1.379	1.951*	3.180***	4.696***	5.886***
Wind Speed	2.119*	0.768	1.412	4.908***	15.466***	0.840	3.064***
Precipitation	10.784***	6.851***	0.607	0.598	1.485	3.714***	1.302
Irradiance	4.057***	0.812	1.208	1.255	3.081***	3.949***	3.693***
Pseudo-R2	0.698	0.657	0.774	0.537	0.488	0.739	0.619
Country	**Portugal**	**Slovakia**	**Slovenia**	**Spain**	**Sweden**	**Switzerland**	**United Kingdom**
NBP	29.023***	65.583***	198.014***	77.377***	132.798***	40.030***	30.124***
Temperature	13.236***	0.936	3.035***	18.845***	1.849*	5.379***	1.854*
Wind Speed	0.486	1.040	0.966	5.534***	3.126***	2.032*	1.380
Precipitation	1.417	3.962***	0.633	0.152	2.847**	1.632	0.088
Irradiance	1.347	0.453	4.057***	1.116	1.043	1.586	0.382
Pseudo-R2	0.748	0.593	0.681	0.749	0.445	0.725	0.724

Note: This table presents the Wald statistic for all the regressions estimated at different quantiles of electricity prices distribution to test the hypothesis of equal slopes across the quantiles. The table also shows the Pseudo R^2 of the degree of fit of the models.

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