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Weather conditions, climate change, and the price of electricity

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ABSTRACT

We estimate the effect of temperature, wind speed, solar radiation, and precipitation on wholesale electricity prices for six European countries, analyzing the full distribution of the weather variables. We provide evidence on nonlinear and extreme weather effects on electricity prices. In all countries, reductions in temperature below a certain threshold increase electricity prices, yet these thresholds tend to be lower for colder countries than for warmer ones. In addition, warmer countries have an upper threshold above which temperatures also increase prices. The precipitation threshold is near the maximum for countries with limited hydroelectric generation and much lower for others with high hydropower capacity, such as Norway. Wind speed has a similar effect on electricity prices across countries, while irradiance has a statistically significant effect in countries with the highest solar capacity and higher average irradiance. Ultimately, the impact of weather conditions on electricity prices is influenced by a country's initial climatic conditions, generation mix, policies, energy efficiency levels, and behavioral factors. Policies aimed at reducing the disproportionately negative impacts of climate change on vulnerable populations should ideally be informed by accurate quantification of the impact of weather on electricity prices.

1. Introduction

The further the energy transition progresses, the more dependent electricity prices will be on the weather. Yet, we still do not fully fathom the relationship between the two and, therefore, the effects we could expect climate change to assert on electricity provision and consumption in the medium term. Electricity is both an essential input for companies' production and a basic consumption good for households. Energy prices determine the general price level to a large extent, as recent surges in inflation around the world following spikes in the price of fuels have amply demonstrated; and also energy poverty, which is a consequence of the interplay between high energy needs due to inefficient energy housing, low household incomes, and expensive electricity (and fuels).

Here, we conduct a systematic empirical examination of the relationship between weather conditions and electricity prices. We consider two crucial aspects simultaneously, their nonlinearity and dynamics, while emphasizing the interpretability of the estimated impacts. Interpretation is facilitated in our study because, in socio-technical systems, such as energy markets, weather factors are exogenous to market variables, including prices and production quantities, at least at a high frequency.

We assess the total effect of weather on electricity prices, which requires excluding variables related to the supply or demand of electricity, such as net exports, load, or reservoir levels from the set of controls, as these variables are, in part, intermediate effects. Therefore, their inclusion may eliminate or attenuate the total impact of weather on electricity prices, which is incorrect, as they constitute mechanisms through which the effect of weather takes place rather than alternative explanations for price movements. We follow the general advice in the causal inference literature (Cinelli et al., 2022; Pearl, 2009) by excluding intermediate effects as controls from our models, which sets us apart from the previous literature (e.g., Gianfreda et al. (2016, 2019),

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Maciejowska (2020) and other references in what follows).

However, our models control for natural gas prices when estimating the impact of weather shocks on electricity prices. Gas-fired power plants are decisive in setting the market price, especially when electricity demand is high or renewable energy supply is low. Conversely, we exclude from our set of controls coal and oil prices, which may influence electricity pricing in certain circumstances, particularly in countries where the installed capacity of these generation sources is high, but to a much lesser extent than gas-fired power plants (Blume-Werry et al., 2021). Moreover, the linear correlation between coal and gas prices is high, meaning that including these variables along with natural gas prices could lead to multicollinearity issues in the model estimation.

These methodological issues have been overlooked in the previous literature. In fact, the existing literature has focused exclusively on using certain weather variables to improve the accuracy of forecasting electricity demand or supply. Yet, it has not analyzed the effects of different weather configurations on electricity prices in a way that can be understood and used for informing policy-making, optimizing individual consumption and production decisions, or even designing novel weather derivatives.

In the literature, weather is known to be a crucial determinant of wholesale electricity prices (Huurman et al., 2012; Maciejowska et al., 2021) and to impact electricity prices in a nonlinear fashion (Billé et al., 2022; Jasiński, 2020; Mosquera-López et al., 2017, 2018; Uribe et al., 2022). Recent studies have used Long Short-Term Memory (LSTM) neural networks (Azam and Younis, 2021; C. Zhang et al., 2020) or Generative Adversarial Networks (Lu et al., 2022) using weather variables to forecast electricity prices. Although weather conditions have been used for modeling or forecasting prices (Bigerna, 2018; Brancucci Martinez-Anido et al., 2016; Ludwig et al., 2015; Matsumoto and Endo, 2021), their use in the literature is mainly for forecasting electricity demand (Atalla and Hunt, 2016; Liddle and Huntington, 2021; Miller and Nam, 2022; Olivares-Rojas et al., 2021; G. Zhang and Guo, 2020) or supply (Brown and O'Sullivan, 2020; Stanger et al., 2019; Wang et al., 2019). Some studies evaluate the impact of weather on supply, demand, and prices simultaneously (Tanaka et al., 2022).

In the case of most studies that measure the direct effect of weather on prices, it is challenging to extract an interpretation of the relationship between them that can be used to determine, for example, how low or high temperatures must get to have a worrisome effect on prices; or from what precise wind speed or level of solar radiation renewable energy generation starts to significantly impact market prices; or up to what level of precipitation it remains determinant for electricity prices. This study emphasizes the different methodological needs of traditional forecasting and causal inference exercises.

There are a few exceptions to using black-box models to assess the relationship between weather and electricity (Mosquera-López et al., 2017; Uribe et al., 2022), which use quantile regressions to explain the impact of weather and fossil fuel prices on electricity prices. However, these studies focus on the effects of market or weather variables on the distribution of electricity prices. Nonlinearities are analyzed according to how expensive or cheap electricity is (according to the predicted variable) rather than the different configurations of weather variables in the explanatory equations (the predictor variables), which is the objective here. Focusing on weather variables is critical for, among other things, assessing the impact of climate change on electricity prices (Byers et al., 2020; Lin et al., 2022), identifying the effects of weather variables that put vulnerable consumers at risk (Feeny et al., 2021; Lee et al., 2022; Li et al., 2023), identifying weather thresholds that jeopardize investments during the energy transition (Gaudard et al., 2013; Sridharan et al., 2019), and for accurate ratemaking of weather derivatives (Mosquera-López and Uribe, 2022).

In general, we expect wind speed to negatively impact electricity prices due to increased generation from wind power. Precipitation is expected to negatively affect prices because it is an indicator of larger water reservoirs for hydraulic generation. The same relationship is expected between prices and solar radiation. The case of temperature is unique since, on average, its effect is expected to be positive for relatively warmer countries due to cooling requirements and negative for colder countries due to heating requirements. By the same logic, a nonlinear effect related to the season (summer versus winter) is also expected. For the first time, we analyze how the expected effects change according to the level of the variable in the predicting equation.

In this regard, we quantify the impact of temperature, wind speed, irradiance, and precipitation on wholesale electricity prices, using daily data from six European countries from January 1, 2015, to December 30, 2022, across the entire distribution of the explanatory variables (e.g., very high, medium, or very low temperatures) and also over different periods (i.e., from 1 to 20 days after the certain weather conditions were observed). Our method, originally developed in statistical medicine (Gasparrini et al., 2010), provides a new perspective on the relationship between weather and electricity, which can be used as a tool for risk monitoring and planning in the wake of the energy transition, as well as for assessing the expected impact of climate change on electricity prices.

We show that nonlinear and extreme weather effects on electricity are already a major concern in European electricity markets. However, as weather becomes an even more fundamental determinant of prices as fossil fuels are reduced from countries' generation mixes, the importance of this monitoring tool is expected to increase. In addition, the increase in variability and the greater frequency of extreme weather events that climate change is expected to bring (Orlov et al., 2020) further motivates this line of research.

Among other results, our analysis identifies thresholds at which the impact of temperature on electricity prices peaks, which governments could use to activate public programs to support families on the brink of (or already living in) energy poverty. Along the same lines, the fragments in the statistical distribution of wind speed, irradiance, and precipitation, where a nonlinear amplification effect of the transmission of weather on electricity prices is observed, can be used to design demand response programs so that households and businesses can adjust their consumption patterns and reduce their energy bills; and by generators interested in designing contingency plans to guarantee electricity production in anticipation of adverse weather conditions. Finally, although we are not primarily interested in forecasting, our results also provide useful information for increasing forecasting accuracy under different weather scenarios, adding to the current literature mainly based on machine learning models.

We identify significant heterogeneities at the country level, resulting from our sample's different generation mixes and diverse geographies. Such heterogeneities indicate the need to closely monitor the evolution of the energy transition and the dynamics of electricity prices on a country basis. In addition, according to our results, each country's volumetric energy risk associated with weather should be diversified away through greater market integration and larger international risk sharing of energy consumption.

The rest of this paper is organized as follows. In Section 2, we outline our main methods. In Section 3, we describe our data and data sources. In Section 4, we report and discuss our results for each weather variable. In Section 5, we conclude, summarize our main findings, and discuss the policy implications for energy markets, regulators, and practitioners.

2. Methodology

To measure the nonlinear effects in time and according to the level of the meteorological variables, we estimate a distributed lag nonlinear model (DLNM) following Gasparrini et al. (2010). This framework is able to simultaneously describe the nonlinear exposure-response dependency of electricity prices on weather variables and delayed effects several days after a weather event has been observed. In our case, we used 20 lags, which is sufficient to analyze the lagged effects of variables such as precipitation. In theory, precipitation must first be translated into water reservoir levels before it can affect prices.

Let us consider a general model specification describing the time series of electricity prices for a given market Y_t with $t = 1, \ldots, T$ expressed as:

$$g(\mu_t) = \alpha + \sum_{j=1}^{J} s_j(x_{tj}; \beta_j). \tag{1}$$

In Eq. 1, $\mu_t \equiv E(Y)$, g stands for a monotonic function, and Y is distributed following an exponential family. The functions s_j describe smoothed relationships between the linear predictor and the explanatory variables x_j. In the set of explanatory variables, we include: Temperature (Temp.lag), Wind Speed (Wind.lag), Precipitation (Prec.lag), Irradiance (Irra.lag), and natural gas prices (TTF.lag).[1] The relationship between the predicted prices and the predicting variables is defined by the parameters included in β_j[2] vectors.

In Eq. 1, s_j could be parametric or non-parametric functions. Our approach is parametric, as it relies on basis functions. The functions s_j identify the cross-basis.

A basis is a space of functions of which $s(x)$ is an element. Moreover, basis functions are a set of known transformations of the original variables x, which produce a new set of variables known as basis variables. The complexity and detail of the relationship between right-hand-side (RHS) variables and left-hand-side (LHS) variables depend on the basis function and its dimension. Polynomials or spline functions are popular alternatives in the literature.[3] A general specification can be expressed as follows:

$$s(x_t; \beta) = z_{t\cdot}^{T} \beta \,, \tag{2}$$

where $z_{t\cdot}$ is the t-th row of the $n \times v_x$ basis matrix Z, which results from applying the basis function to the covariates' vector, x. Note that Z can be made part of the matrix that contains the model (1) alongside unknown parameters β, which need to be estimated.

When we are interested in dynamic effects that occur with certain lags rather than only contemporaneously, we need to add a temporal coordinate to the analysis to consider past values of the covariates x_{t-l}. Here, l is the lag, and it denotes the time interval elapsed between the impulse-effect on RHS and the response on the LHS. This delayed relationship can be linear, in which case the extension of Eq. 2 becomes a distributed lag model (DLM). DLMs allow the effect of a single event to be distributed over time by the mean of various parameters that explain the contribution of different lags on the RHS variable to the overall effect on the LHS. A DLM model is expressed as follows:

$$s(x_t; \eta) = q_t^{T} C\eta. \tag{3}$$

In Eq. 3, C is a $(L+1)$ matrix of basis variables with elements $c_{\cdot k}$. This matrix derives from applying the basis functions to the lagged vector ℓ. η is a vector of parameters that needs to be estimated. Lastly, $q_{t\cdot}^{T}$ is a transposed vector of lagged values of the variables x at time $t-1$, which essentially captures the lagged effects of the variable x_t at different time intervals, which are then used to model the distributed lag effect on the response variable $s(x_t; \eta)$.

A generalization of DLM models allows for a nonlinear relationship between the prices on the LHS of Eq. 3 and the predictors on the RHS of the same equation, and can be described as follows:

$$s(x_t; \eta) = \sum_{j=1}^{\vartheta_x} \sum_{k=1}^{\vartheta_l} r_{tj\cdot}^{T} c_{\cdot k} \eta_{jk} = w_{t\cdot}^{T} \eta, \tag{4}$$

where r_{tj} is a vector of lagged impacts associated with time t converted by the basis function j. w_t is a vector that results from the application of the $\vartheta_x \bullet \vartheta_l$ cross-basis functions to x_t. As can be observed, the model in Eq. 3 is a special case of the model in Eq. 4, which considers linear and nonlinear relationships.

3. Data

We use daily data from Bloomberg and ENTOS-E for the six electricity prices of the markets of Denmark, France, Germany, Italy, Norway, and Spain, from January 1, 2015, to December 30, 2022, for a total of 2085 observations. All the prices are in EUR/MWh units. We use four weather variables: temperature (degrees Celsius), wind speed (m/s), precipitation (an integer in 100th mm), and solar irradiance (Wh/m^2). The first three variables were retrieved from Bloomberg, while the latter was from SoDa Service's sun radiation data. Lastly, we use the Title Transfer Facility (TTF) prices, the reference price of natural gas in Europe in EUR/MWh units, to control for natural gas prices in our models.

The six electricity markets in our sample were selected according to their different generation mixes to assess the impact of the weather variables on the electricity prices in markets with higher or lower shares of renewable generation. In addition, in the case of Denmark, we utilize the data for the largest geographical zone, as there is information available for the pricing of more than one zone in the country. Table 1 presents the summary statistics and the Augmented Dickey-Fuller (ADF) t-statistic of the electricity prices.

Fig. 1 shows the generation mix for each country in our dataset. The effect of weather on electricity prices depends strongly on the generation mix. Different levels of market competition in the provision of power characterize the diverse mixes, which are also linked to varied market structures and regulations. Dissimilar pricing dynamics result from the heterogeneities in the generation, variations in the physical transfer of power between markets, weather characteristics, and consumption patterns within each country.

4. Results

We used a distributed lag nonlinear model (DLNM) to estimate the effects of weather variables on electricity prices. These variables include temperature, precipitation, wind speed, and irradiance, which impact the supply and demand of electricity. As expected, these effects are nonlinear since they change according to the value taken by the explanatory variable. We present the descriptive statistics of temperature (see Section 4.1), precipitation (see Section 4.2), wind speed (see Section 4.3), and irradiance (see Section 4.4), and the thresholds or

[1] The names of the variables in the accompanying code are shown in brackets.

[2] Note that, as usual in electricity price modeling for day-ahead electricity markets, the explanatory variables are lagged one day with respect to the prices, but we omit this information in the equations to simplify the notation.

[3] In this respect, we have limited our analysis to the usual parameters found in the literature to describe such polynomials, with a similar number of variables and lags (e.g., Gasparrini et al. (2010) and Uribe and Chuliá (2023)), such as natural cubic splines with 7 degrees of freedom at 4 equally spaced knot intervals. Our results are invariant to reasonable changes in the specification of these hyper-parameters. We have also followed these previous contributions regarding the distributional assumption of Y and the corresponding estimation via a Generalized Linear Model, as implemented in the DLNM package by Gasparrini (2011).

Table 1
Electricity prices summary statistics and ADF test.

Country	Min	Mean	Max	Sds	Skewness	Kurtosis	t-ADF	t-ADF (drift)
Denmark	−3.93	44.94	464.54	38.88	4.75	36.06	−6.97***	−11.24***
France	3.68	57.22	540.66	52.57	3.83	21.14	−4.97***	−9.23***
Germany	−42.24	49.28	487.57	44.61	4.29	27.36	−5.34***	−8.31***
Italy	10.66	67.70	587.67	53.36	3.69	19.81	−1.60	−3.29**
Norway	0.94	37.81	387.45	31.99	3.14	19.16	−1.64	−3.24**
Spain	2.19	62.36	544.98	48.66	3.64	20.25	−2.26**	−4.25***

Note: the sample includes 2085 observations per country from January 1, 2015, to December 30, 2022. The electricity prices are in EUR/MWh units. The ADF unit root test was performed with and without drift, and *, **, and *** indicate that the null hypothesis of a unit root is rejected at 10%, 5%, and 1% levels, respectively.

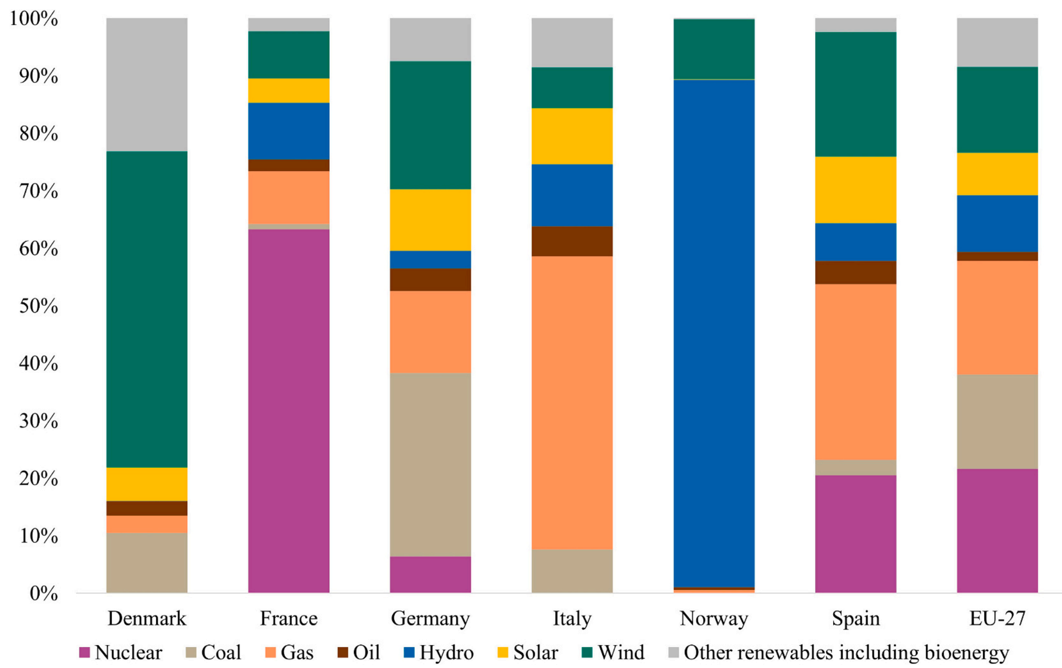

Fig. 1. Share of electricity generation by source in 2021.
Note: Drafted by the authors with information from ourworldindata.org.

ranges at which the relation between each meteorological variable and electricity prices significantly amplifies. The thresholds or ranges are selected using a contour plot, which shows the effect of each weather variable on electricity prices across the distribution of the explanatory variable at different lags. The threshold (range) is selected as the value (s) from which the expected effect of the weather variable on electricity prices is amplified. This value is adjusted, if necessary, according to the cumulative effect of the explanatory variable on electricity prices, which is the aggregated effect across all lags. The statistical significance of the thresholds (ranges) is assessed through the confidence intervals shown in the cumulative effect figures (see Appendix A).

In the case of temperature, we present the threshold from which lower or higher temperatures significantly increase electricity prices. We find that reductions in temperature below a certain threshold increase electricity prices, yet these thresholds tend to be lower for colder countries than for warmer ones. Some countries are even starting to display upper thresholds above which temperatures also increase prices, indicating that global warming may be altering the relationship between temperature and electricity prices.

For precipitation, wind speed, and irradiance, we show the range at which the weather variable decreases electricity prices, indicating that, most likely, renewable generation with hydro, wind, or solar is setting the price of electricity (if demand is low, as discussed in Durante et al. (2022)). In such a case, the higher the renewable deployment, the higher the expected decrease in electricity prices.

We find that precipitation negatively impacts electricity prices. We

Table 2
Descriptive statistics and thresholds of temperature.

Country	Minimum	Mean	Maximum	Threshold	Significance
Denmark	−7.3	10.0	25.2	< 5	YES
France	−15.6	12.4	30.1	< 0	YES
Germany	−9.4	10.6	28.1	< 5	YES
Italy	−0.6	16.1	29.6	< 10 & > 24	YES
Norway	−11.2	6.8	23.8	< 5	YES
Spain	2.1	16.5	29.4	< 10 & > 20	YES

Note: The table shows the minimum, mean, maximum, and threshold temperature (degrees Celsius) at which the relationship between the weather variable and electricity prices amplifies. The significance of the effect on electricity prices is estimated at a 95% confidence level. The statistical significance and cumulative effect of temperature are graphically presented in Appendix A, Fig. A.1.

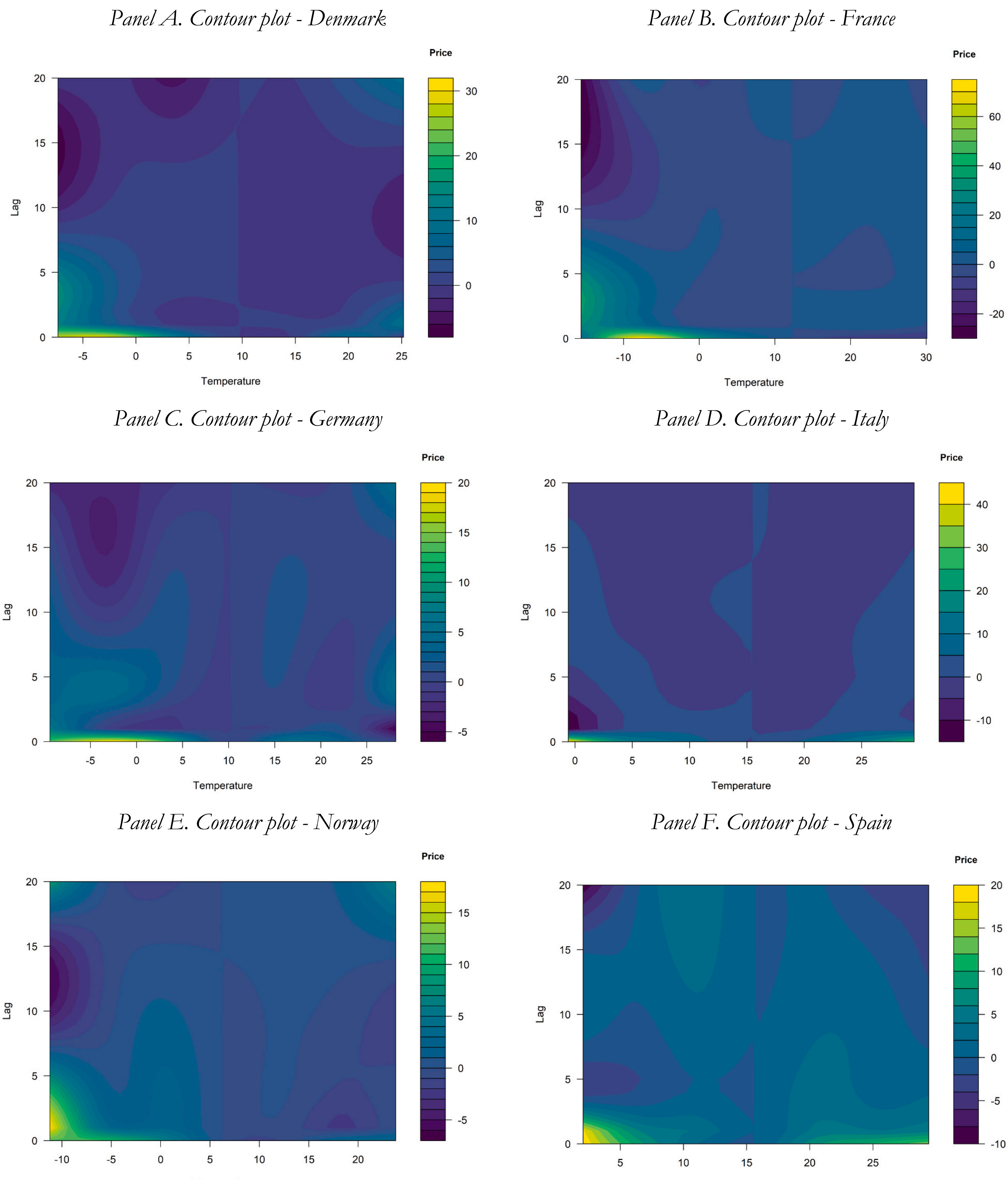

Fig. 2. Effect of temperature on electricity prices.
Note: The figure shows the contour plots of the nonlinear effect of temperature on electricity prices. The effect varies across the different values of temperature and lags.

document high thresholds associated with this impact for countries with limited hydro generation and much lower thresholds for other countries with high hydropower capacity, such as Norway.

Wind speed has a similar effect on electricity prices across countries. The thresholds from which this weather variable and electricity prices share a negative relationship range from 7 to 20 m/s. Irradiance has a statistically significant effect in countries with the highest solar capacity and higher average irradiance in our sample, as is the case of Spain and Italy.

Given the changes in the energy markets during the pandemic and the recent energy crisis, we also conducted a robustness check of our results by estimating our model with data until January 2020. Section 4.5 presents the effect of the weather variables on electricity prices from January 1, 2015, to January 31, 2020, and discusses the overall results found.

4.1. Temperature

Temperature significantly increases electricity prices when it falls below certain thresholds, which vary across countries (see Table 2). In general, the colder the country, the lower the threshold. For warmer countries, the threshold is higher; some also have an upper threshold at which higher temperatures positively affect prices. This is the case for the warmest countries in our sample, such as Italy and Spain, where the usage of air conditioning increases electricity demand, especially as temperatures increase.

Fig. 2 depicts the whole distribution of temperature and its effect on electricity prices. The lowest threshold is 0° in the case of France (see Panel B), with the highest effect between −5° and − 15° degrees. Although France has the lowest recorded minimum temperature, Denmark (see Panel A), Germany (see Panel C), and Norway (see Panel E) have lower average temperatures but have a higher threshold temperature of 5°. However, in the results for the sample until January 2020, Denmark and Germany have the lowest threshold (0°), while France has a threshold of 5°. These results can be rationalized by the fact that France has lower minimum temperatures in 2020–2022, suggesting that the effects of climate change are passed through to electricity prices. However, these results are also sensitive to the exceptional events that occurred between 2020 and 2022; on the one hand, the reduced demand for electricity (industrial and residential) due to the lockdowns during the pandemic, and, on the other hand, the increased demand once the restrictions were lifted and economies began to recover, as well as the rise of the energy crisis in late 2021.

For the colder countries (Denmark, France, Germany, and Norway), the effect of temperature on prices above the threshold is practically zero. In Italy (see Panel D) and Spain (see Panel F), the threshold is higher, 10°, and the effect is also statistically significant for warmer temperatures above 20°. These results also explain further increases in electricity prices when temperatures are high, although with less intensity than in the lower temperature ranges.

For all the countries, the positive effect of lower temperatures (and higher temperatures for the warmer countries) on electricity prices is mainly contemporaneous (see contour plots in Fig. 2) and statistically significant (see Appendix A, Fig. A.1).

Overall, low and, in some cases, high temperatures have a statistically significant effect on electricity price increases. Our findings underscore that the expected impacts of climate change on electricity prices will be influenced not only by physical factors, such as the current average temperature in a country or energy efficiency levels, but also by behavioral factors, such as the perceived threshold at which individuals tend to use heating or cooling, leading to increased electricity demand.

4.2. Precipitation

Unlike wind speed or irradiance, for example, the effect of precipitation on electricity prices is not directly transmitted to electricity prices because most hydropower generation depends on reservoir levels. For this reason, Table 3 shows not only the precipitation thresholds but also the lags for which the negative relationship between precipitation and electricity prices persists.

The thresholds at which higher rainfall leads to lower electricity prices are close to the maximum precipitation in the case of Denmark, which has limited generation capacity from hydro sources (see Table 3). The precipitation threshold for Denmark is above 4000 in 100th mm, which is close to the maximum recorded rainfall of 4493 in 100th mm.

Conversely, Norway has a markedly lower precipitation threshold, reflecting the fact that hydropower represents the country's primary source of electricity generation, accounting for 88% of the total in 2022, and that it has the highest average precipitation of the sample (although not the maximum levels). The precipitation interval at which rainfall decreases electricity prices is 500–2000 in 100th mm, with the lowest value almost corresponding to Norway's average precipitation. In the case of France, which relies on hydropower as the second-largest source of electricity generation after nuclear power, with a share of 10%, the precipitation threshold is considerably lower than the maximum, yet not as close to the average rainfall as in Norway. The same behavior is found in Germany and Spain, which have a share of hydro generation in their electricity mixes, but it accounts for <10%.

Table 3
Descriptive statistics and thresholds of precipitation.

Country	Minimum	Mean	Maximum	Threshold	Lags	Significance
Denmark	0	261.3	4494.3	> 4000	10–20	YES
France	0	328.4	8313.3	4000-5000	< 15	YES
Germany	0	210.7	2719.7	400–1100	< 20	YES
Italy	0	265.0	13,799.7	< 8000	< 20	NO
Norway	0	449.5	3274.9	500–2000	< 20	YES
Spain	0	180.8	2791.8	1500-2500	< 20	YES

Note: The table shows the minimum, mean, maximum, and threshold precipitation (an integer in 100th mm) at which the relationship between the weather variable and electricity prices amplifies. The table also shows the lags at which this relationship amplifies. The significance of the effect on electricity prices is estimated at a 95% confidence level. The statistical significance and cumulative effect of precipitation are graphically presented in Appendix A, Fig. A.2.

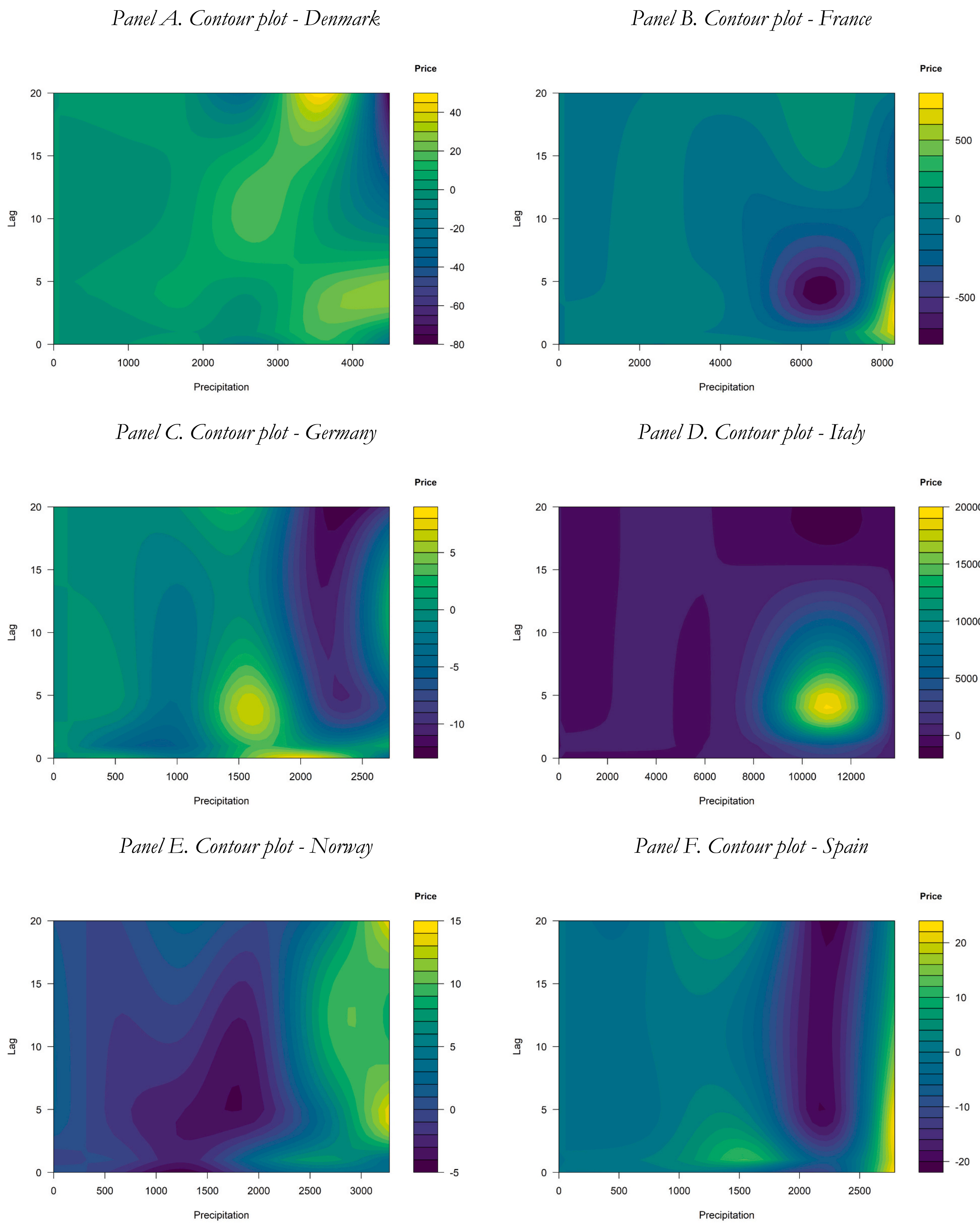

Fig. 3. Effect of precipitation on electricity prices.
Note: The figure shows the contour plot of the nonlinear effect of precipitation on electricity prices. The effect varies across the different values of precipitation and lags.

Table 4
Descriptive statistics and thresholds of wind speed.

Country	Minimum	Mean	Maximum	Threshold	Significance
Denmark	2.2	9.8	24.0	15–20	YES
France	2.0	7.1	17.3	10–16	NO
Germany	2.5	6.9	22.6	7–13	YES
Italy	2.8	5.5	14.9	> 13	YES
Norway	2.4	7.3	18.2	> 14	YES
Spain	2.3	6.0	17.1	> 15	YES

Note: The table shows the minimum, mean, maximum, and threshold wind speed (m/s) at which the relationship between the weather variable and electricity prices amplifies. The significance of the effect on electricity prices is estimated at 95% confidence levels. The statistical significance and cumulative effect of wind speed are graphically presented in Appendix A, Fig. A.3.

Fig. 3 depicts the effect of precipitation on electricity prices for the six countries. In Norway, the relationship between precipitation and prices becomes negative around the average rainfall, with a higher negative effect on prices between 1000 and 2000 in 100th mm (see Panel E). Moreover, this effect lasts about 20 days, reflecting the level of dispatchability of reservoir hydro generation and storage-related sources.

Although hydropower also represents an important share of the French generation mix, as mentioned earlier, the effect is quite different to the case in Norway. In France, precipitation decreases electricity prices at higher levels of rainfall, around 4000 in 100th mm, with the effect lasting up to 15 days and only statistically significant until around 5000 in 100th mm (see Appendix A, Fig. A.2, Panel B).

The cases of Germany (see Panel C) and Spain (see Panel F) exhibit a similar graphical pattern, with the negative effect of precipitation at the upper right distribution of the weather variable and with the effect lasting 20 days. Italy (see Panel D) displays a different dynamic, with a negative effect observed below the threshold and for all lags. Nevertheless, the effect is not statistically significant (see Appendix A, Fig. A.2, Panel D), reflecting the following facts of the Italian electricity market: (i) the majority of hydro generation is located in the north of the country, however, the single national price is hardly affected by hydro, given that it is a weighted average of zonal prices; (ii) the hydro share in the mix is low (or at least hydro being marginal in the day-ahead market) compared to thermal sources; (iii) hydro generators have shown to prefer to withhold their capacity in the wholesale market to sell electricity in the balancing market session (Gianfreda et al., 2018, 2019; Gianfreda and Grossi, 2012). Finally, for Denmark (see Panel A), the negative effect is only present at the upper end of the precipitation distribution, and the effect is present from lags 10 to 20. This is consistent with the country's scarce generation with hydropower sources.

4.3. Wind speed

The countries with the highest share of wind power in their generation mix are Denmark, Germany, and Spain. In 2022, wind power accounted for 55%, 22%, and 22% of their generation mix, respectively. While Denmark is the only country in the sample where wind power is the primary source of electricity generation, wind power is a relevant technology in the generation mix for all six countries, with Italy and France having the lowest shares, but still accounting for 7% to 8% of their generation mix. Hence, the thresholds at which wind speed and electricity prices have a negative relationship are similar across the countries, with values ranging from 7 to 20 m/s (see Table 4). These ranges reflect that wind turbines reach their maximum power output at around 15 m/s, and that turbines are shut down at wind speeds above 25 m/s to avoid damage. However, we find that, for France, which has a relatively low share of wind power generation, wind speed does not lead to a decrease in electricity prices at any value.

The biggest decreasing effect of wind on electricity prices is present mainly contemporaneously or lasting a few days (see Fig. 4). This outcome can be explained by the fact that non-conventional renewables, such as wind and solar, are as-available resources, which means that they cannot adjust their output power supplied to the electrical grid according to the demand or flexibility requirements of the system.

4.4. Irradiance

Not a single country in our sample relies on solar power as its primary source of electricity generation. However, the installed capacity has recently increased across European countries, with Spain, Germany, and Italy leading the way, reaching a solar generation share between 10% and 12% of their mix in 2022. Furthermore, Spain and Italy have the highest average, maximum, and minimum irradiance levels in the sample. As expected, both countries exhibit a statistically significant negative effect of irradiance on electricity prices (see Table 5), which is mainly contemporaneous (see Fig. 5). However, for Spain, the negative effect starts at a lower threshold (4500 Wh/m^2), below the average irradiance, and persists above this value throughout the upper tail of the variable distribution. In Italy, the effect begins at 6000 Wh/m^2 and ends at 8000 Wh/m^2. Furthermore, the absolute value of the effect's magnitude is higher in the case of Spain (see Panel D and F).

Although Germany also has a high share of solar generation, its average irradiance is considerably lower than the average in Spain and Italy, and the weather variable does not have a statistically significant effect. Nevertheless, the irradiance has a negative and statistically significant effect on German electricity prices when the sample ends in January 2020 (see Section 4.5).

Regarding the countries with a lower share of solar generation, such as Norway, the point at which irradiance has an impact on prices is close to the maximum values of the variable, or the effect is not statistically significant, as in Denmark and France.

4.5. Robustness and discussion

Given the changes in the energy markets during the pandemic and the recent energy crisis, we conducted a robustness check of our results by estimating our model with data up to January 2020 (see Appendix B for the descriptive statistics and thresholds of the weather variables in this period and the Online supplementary material for the graphical results). Overall, the dynamics, thresholds, and statistical significance of the relationship between weather variables and electricity prices are comparable to those observed in the complete sample. Nevertheless, the absolute value of the effects' magnitudes is higher in the case of the full sample.

Specifically, the effect of low and high temperatures on electricity prices is statistically significant for the six countries in both samples. There are changes in the lower thresholds, with Denmark and Germany showing lower values in the subsample (Jan 2015 to Jan 2020). Additionally, Germany and Norway display an upper threshold. These changes may be indicative of climate change and the impact of heat and cold waves on electricity prices.

Precipitation has a statistically significant decreasing effect on prices over different ranges for five out of the six countries in both samples. The weather variable has no effect on electricity prices in Italy in the full sample, and in Denmark in the subsample. Denmark produces <1% of its electricity with hydropower, which explains the lack of effect in the subsample or its high threshold for the full sample. In the case of Italy, as mentioned in Section 4.2, the non-significance in the full sample precipitation reflects the fact that the national prices are not very sensitive to the price formation of the northern zone, the low number of times that hydro is marginal in the day-ahead market, and the preferences of hydro generators. However, the effect becomes significant when the last three years of our sample are excluded.

The decreasing effect of wind speed on prices is statistically

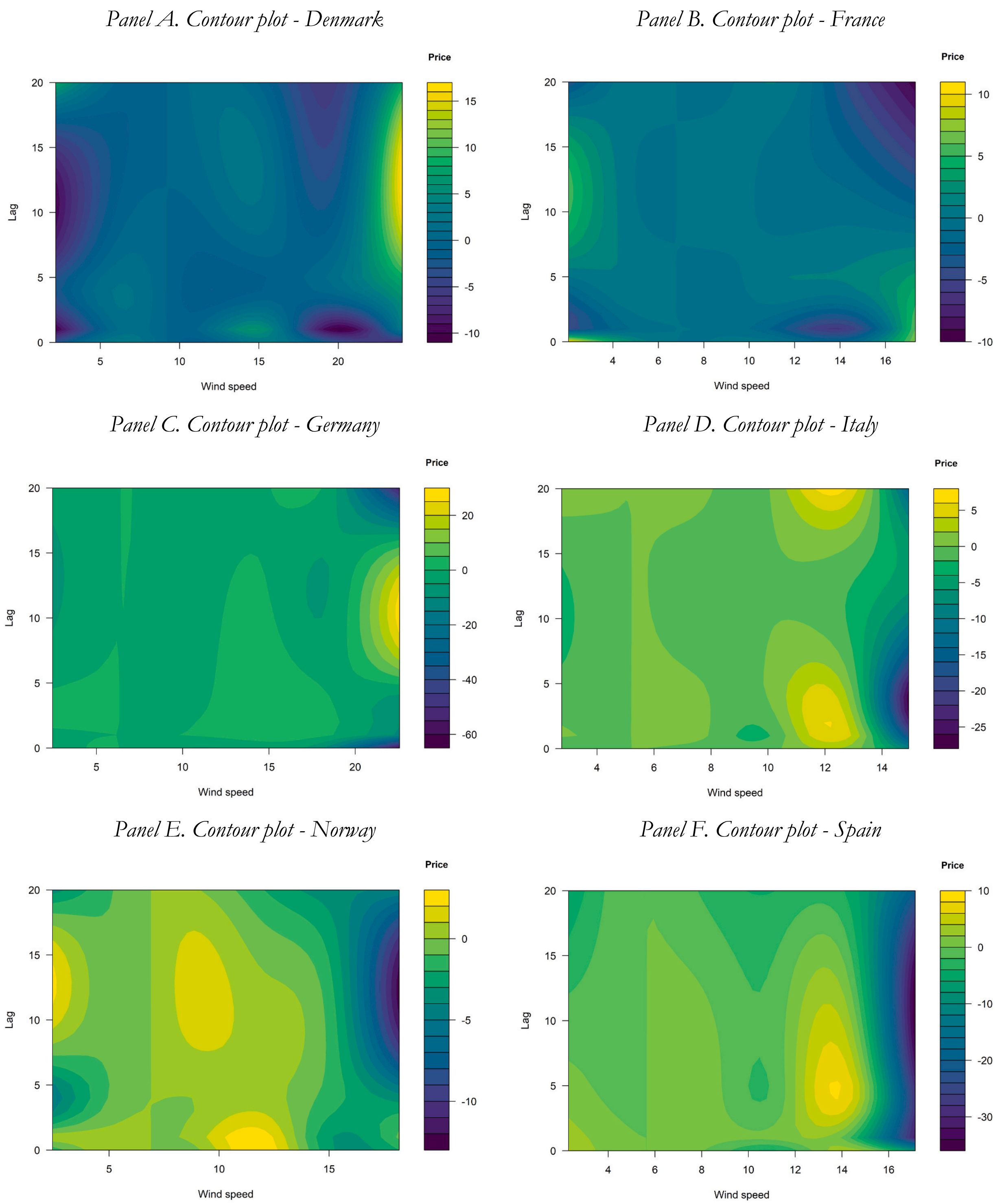

Fig. 4. Effect of wind speed on electricity prices.
Note: The figure shows the contour plot of the nonlinear effect of wind speed on electricity prices. The effect varies across the different values of wind speed and lags.

Table 5
Descriptive statistics and thresholds of irradiance.

Country	Minimum	Mean	Maximum	Threshold	Significance
Denmark	133	2886	8363	> 6000	NO
France	219	3369	8681	4000 - 7000	NO
Germany	152	3077	8476	> 6000	NO
Italy	312	4551	8766	6000 - 8000	YES
Norway	82	2686	8414	> 7000	YES
Spain	406	4845	9243	> 4500	YES

Note: The table shows the minimum, mean, maximum, and threshold irradiance (Wh/m^2) at which the relationship between the weather variable and electricity prices amplifies. The significance of the effect on electricity prices is estimated at 95% confidence levels. The statistical significance and cumulative effect of irradiance are graphically presented in Appendix A, Fig. A.4.

significant for five out of the six countries in both samples. The range in which the relationship between the variables is negative in the subsample is 8 to 20 m/s. Irradiance exhibits a significant decreasing effect for half the countries in the full sample, while, in the subsample, the effect is significant for five markets. The non-significance of irradiance for Denmark and Germany throughout the full sample may indicate that during the recent energy crises, natural gas was marginal on more occasions, setting the price more times and displacing renewable generation.

However, the effects of weather variables on electricity prices are more pronounced in the full sample. In other words, our model captures the impact of a higher number of extreme weather events in the last three years, along with the higher deployment of variable renewable generation. Moreover, it remains a baseline for future assessments of the impact of climate change and RES penetration, influenced by public policies and regulations.

Our base model shows that weather has a nonlinear effect on electricity prices. Temperature changes substantially impact electricity prices, especially when they drop below specific thresholds, which differ across countries. In general, colder countries tend to have lower thresholds, while warmer countries have higher ones. In some instances, warmer countries also have an upper threshold, at which higher temperatures increase electricity prices.

Precipitation levels also affect electricity prices, with countries not reliant on hydroelectric power, like Denmark, showing that higher rainfall does not lower electricity prices. Conversely, in nations with greater hydroelectric power in their energy mix, such as Norway, precipitation is statistically significant, and the negative effect is present in almost two-thirds of the distribution of the weather variable.

The negative relationship between wind speed and electricity prices remains consistent across countries, with thresholds generally falling within the range of 8 to 20 m per second. This range corresponds to the point at which wind turbines reach their maximum power output, and exceeding 25 m per second leads to turbine shutdown to prevent damage. Regarding irradiance, Spain and Italy, which have the highest average solar radiation levels in our sample and rely significantly on solar power, unsurprisingly exhibit a statistically significant negative correlation between irradiance and electricity prices.

Finally, the effect of wind and irradiance on electricity prices is present mainly contemporaneously or lasting a few days. This effect is consistent with the inability of non-conventional renewables to adjust their output power supplied to the electrical grid according to the system's demand or flexibility requirements. However, this outcome can change with the deployment of storage systems, which can alter the dynamics of the effect of weather variables on prices.

5. Conclusions

We analyze the nonlinear relationship between weather and electricity prices. Not only do we estimate the effect of climate conditions on prices, but also offer new information to electricity market participants. Our results could enable electricity consumers and producers to better hedge climate risk. At the same time, we provide valuable information for public policy design to support affordable and reliable energy for consumers and foster the necessary investments for the energy transition.

The thresholds that we identify from which higher or lower temperatures increase electricity prices can be used by governments to activate public programs to support vulnerable households suffering or close to suffering from energy poverty.[4] This is particularly important as climate change has increased the volatility of weather, rising temperatures in the warmer months and decreasing them in the colder months, increasing the likelihood that vulnerable energy consumers will be unable to heat or cool their homes. Additionally, the temperature thresholds we estimate can be used to design hedging mechanisms for industrial consumers to reduce their exposure to high electricity prices, which are activated when the temperature reaches these levels. Moreover, the thresholds for wind speed, irradiance, and precipitation provide crucial information for designing demand response programs so that households and companies can adapt their demand to reduce energy bills.

In addition, new weather derivatives can be designed for generators to hedge low electricity prices when weather conditions enable high levels of renewable electricity generation, which can compromise cash flow and investment return. The information about thresholds and ranges in the statistical distributions of weather variables can also be used by developers and energy communities for optimal decisions on where to allocate their renewable projects. Lastly, our results are also useful for the ratemaking of weather insurance products.

Overall, our findings highlight that the expected impact of climate change on electricity prices is influenced not only by a country's initial climatic conditions, such as average precipitation, temperature, or wind speed, but also by policy decisions related to the generation mix, energy efficiency levels, and consumer behavior regarding heating and cooling technologies and the temperature thresholds at which they are required. The latter point is also closely tied to the energy efficiency of the residential sector, which is a government-actionable area. Our approach and results offer a straightforward yet comprehensive monitoring system for tracking the effects of weather on electricity prices, enabling anticipation of the impacts of climate change on electricity markets.

CRediT authorship contribution statement

Stephania Mosquera-López: Writing – review & editing, Writing –

[4] Although the energy component is not the only component of retail prices, and most electricity is traded at fixed prices through bilateral contracts, wholesale price spikes eventually affect retail prices. This happens when the terms of bilateral contracts or forward instruments incorporate higher spot prices or through dynamic retail tariffs that some consumers face.

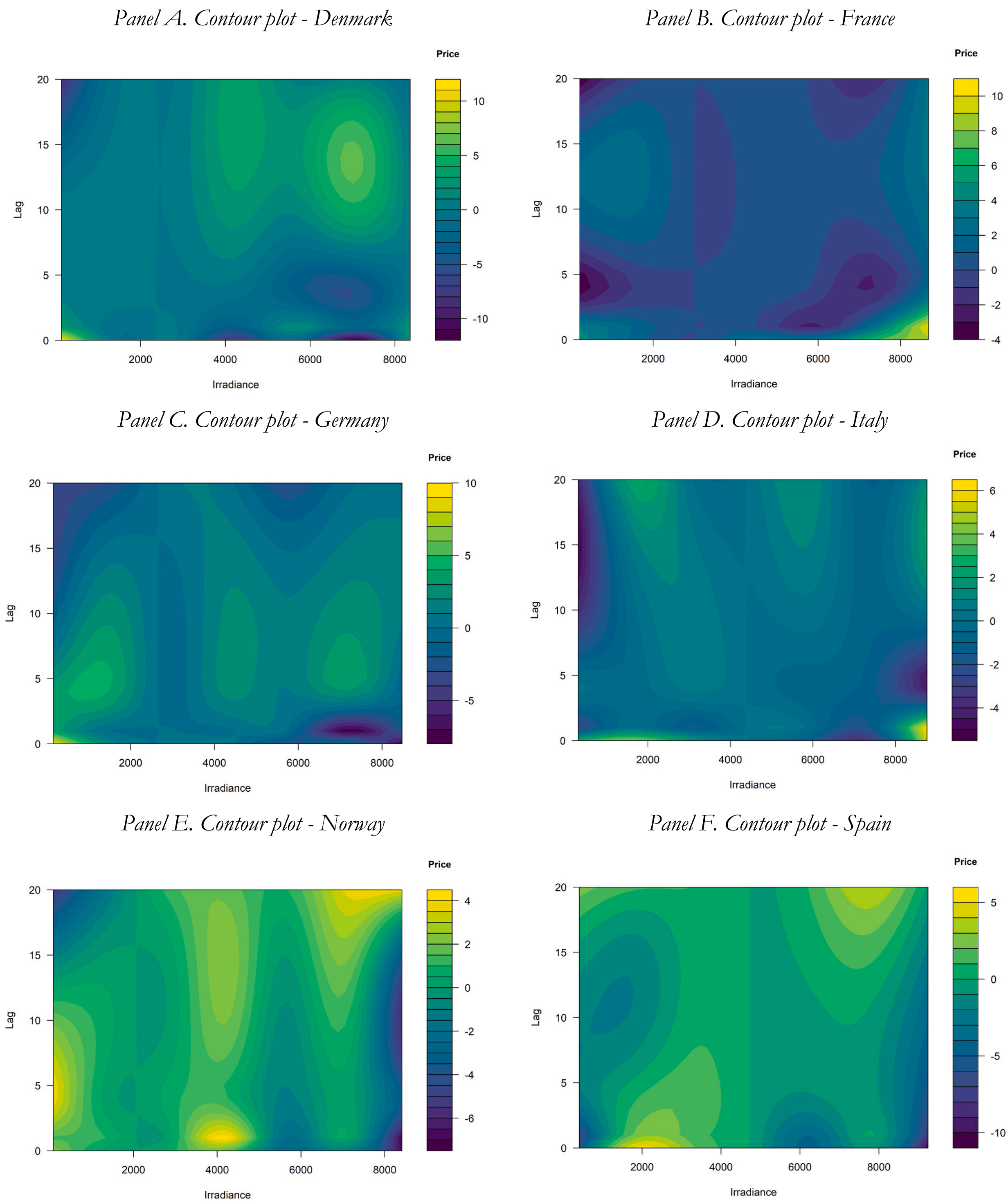

Fig. 5. Effect of irradiance on electricity prices.
Note: The figure shows the contour plot of the nonlinear effect of irradiance on electricity prices. The effect varies across the different values of irradiance and lags.

original draft, Investigation, Formal analysis, Data curation, Conceptualization. **Jorge M. Uribe:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Orlando Joaqui-Barandica:** Visualization, Software, Methodology, Data curation.

Declaration of competing interest

None.

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Appendix A. Cumulative effects and significance

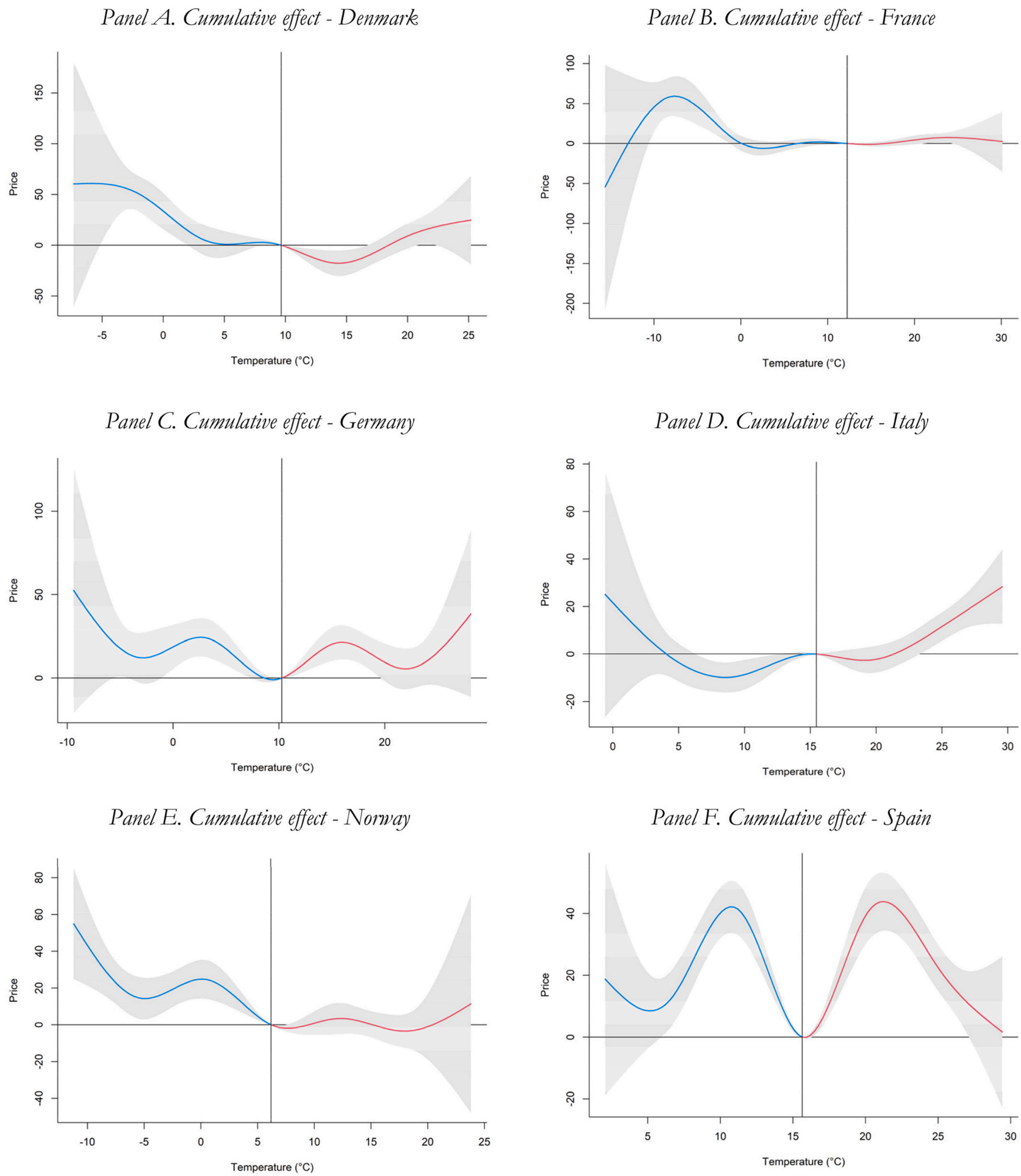

Fig. A.1. Cumulative effect of temperature on electricity prices.
Note: The figure shows the cumulative effect of temperature on electricity prices. The blue line represents the cumulative effect before the median temperature, while the red line is after the median temperature. The grey area depicts the confidence interval at the 95% level.

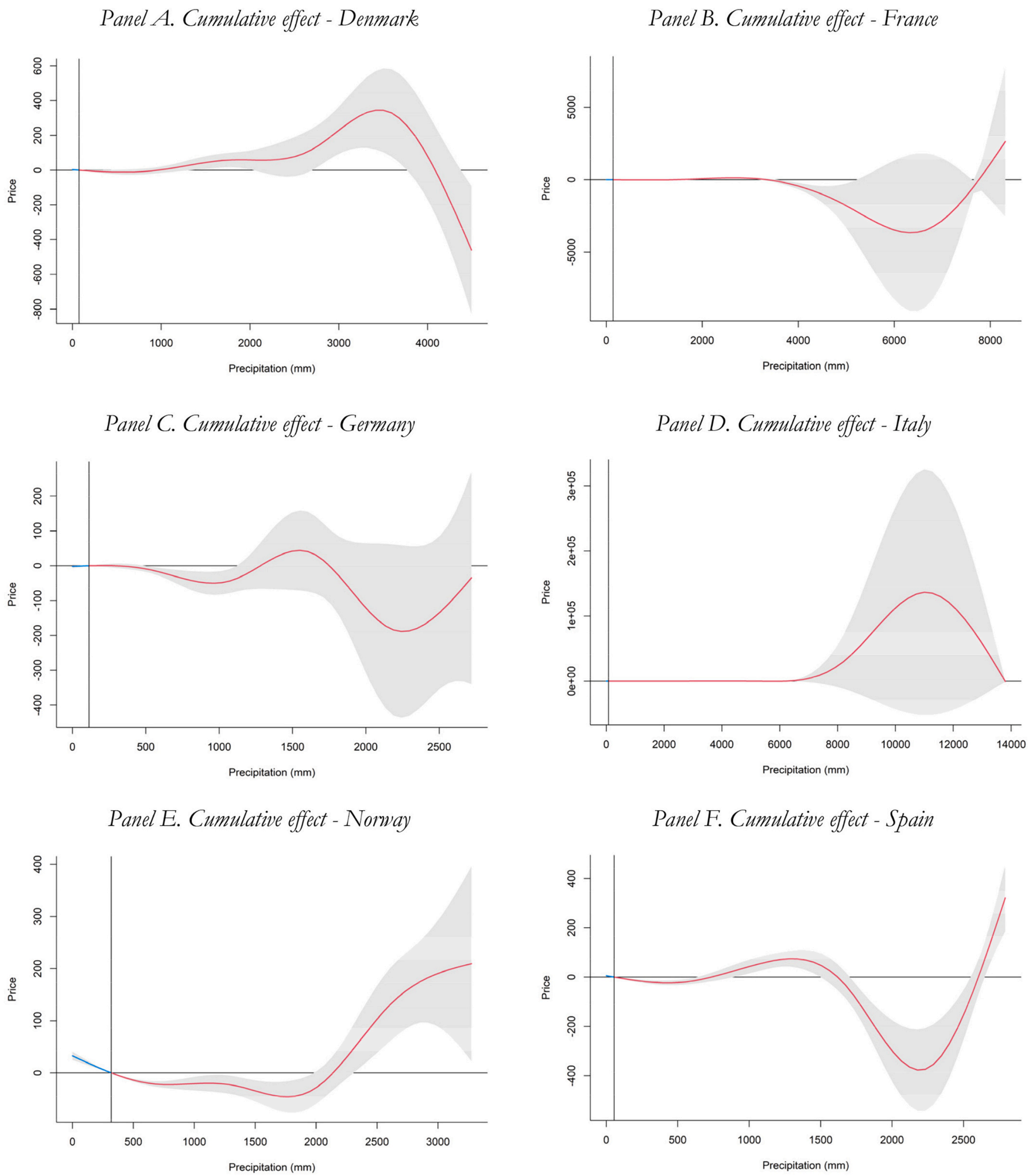

Fig. A.2. Cumulative effect of precipitation on electricity prices.
Note: The figure shows the cumulative effect of precipitation on electricity prices. The blue line represents the cumulative effect before the median precipitation, while the red line is after the median precipitation. The grey area depicts the confidence interval at the 95% level.

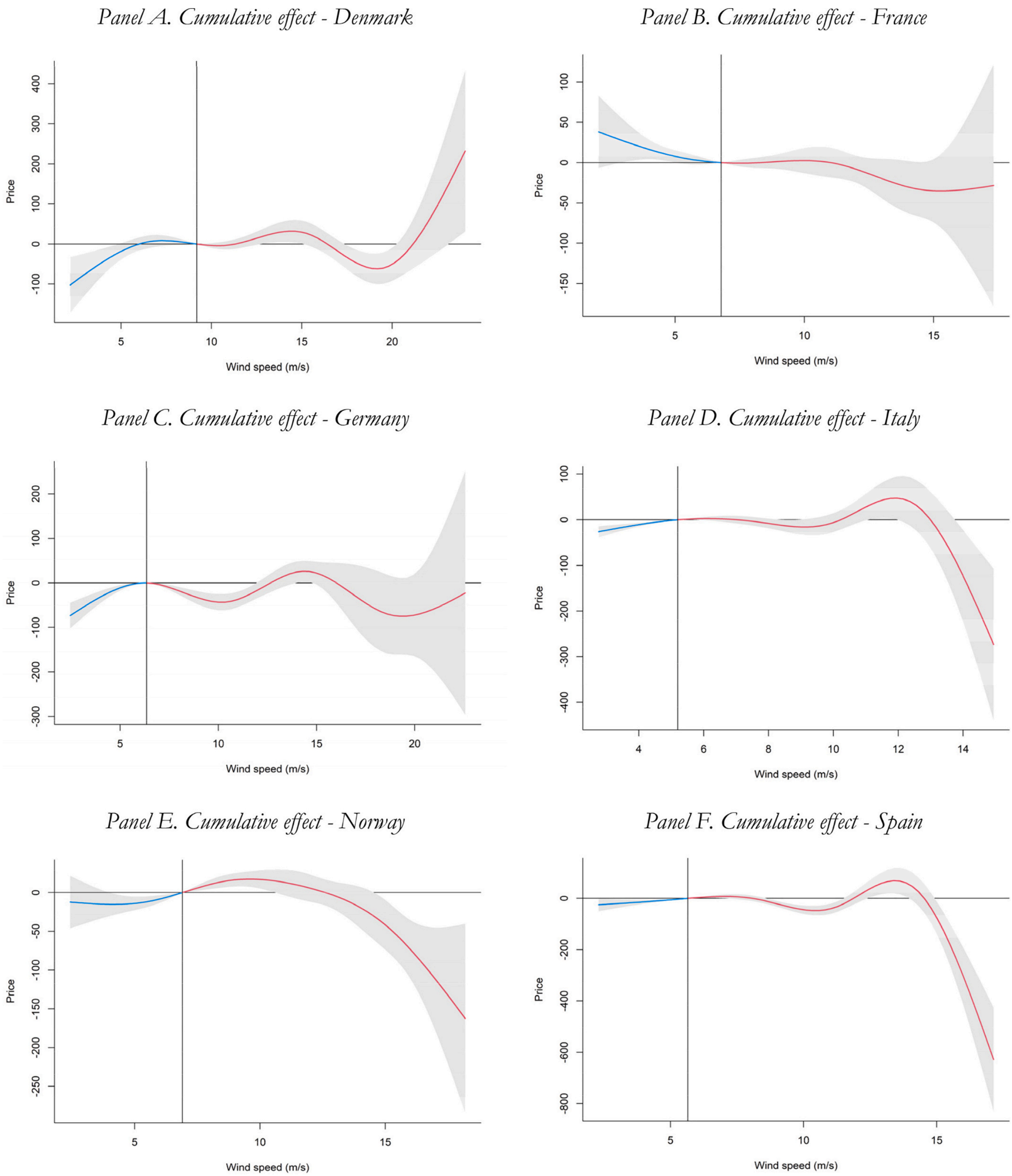

Fig. A.3. Cumulative effect of wind speed on electricity prices.
Note: The figure shows the cumulative effect of wind speed on electricity prices. The blue line represents the cumulative effect before the median wind speed, while the red line is after the median wind speed. The grey area depicts the confidence interval at the 95% level.

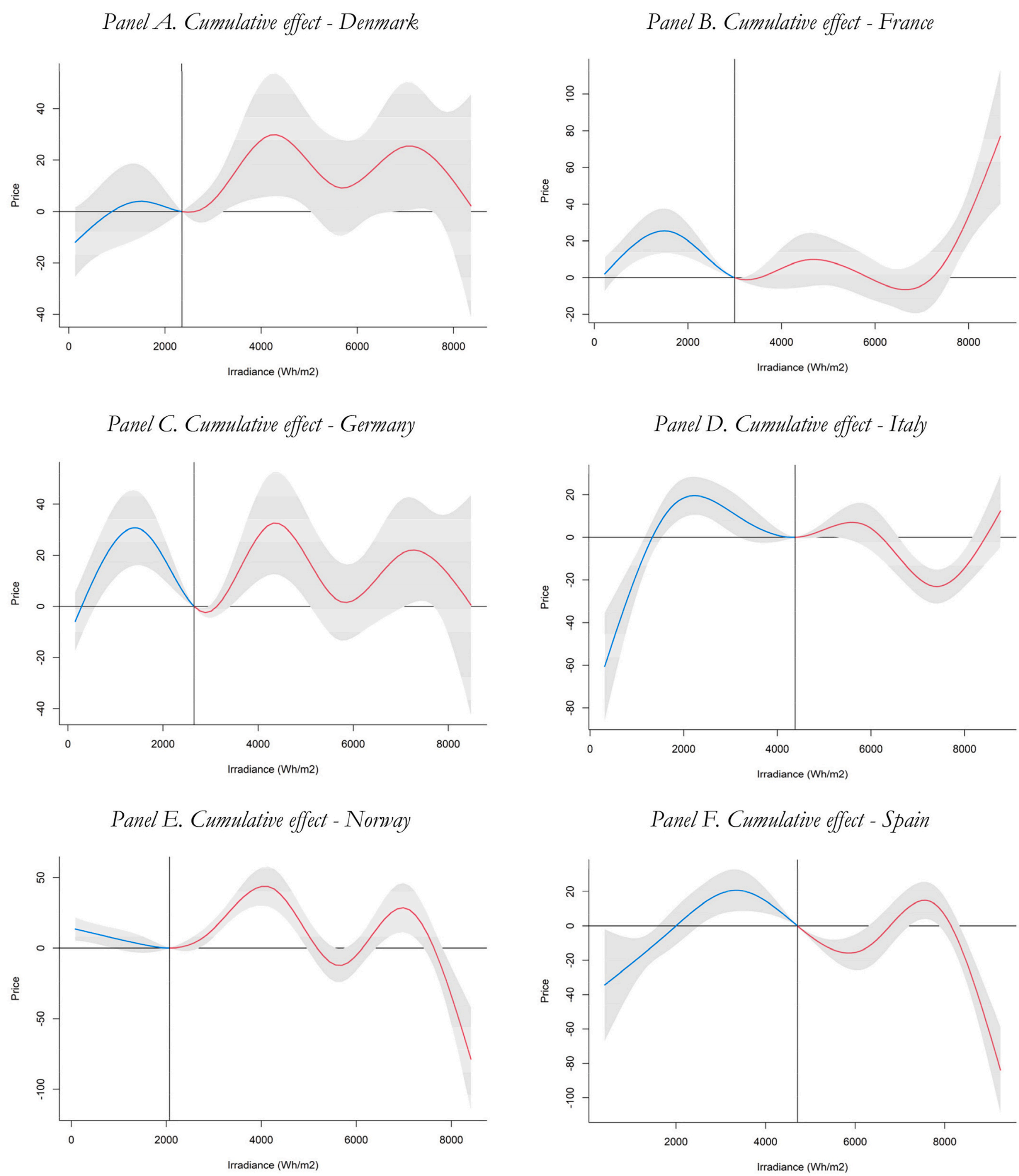

Fig. A.4. Cumulative effect of irradiance on electricity prices.
Note: The figure shows the cumulative effect of irradiance on electricity prices. The blue line represents the cumulative effect before the median irradiance, while the red line is after the median irradiance. The grey area depicts the confidence interval at the 95% level.

Appendix B. Descriptive statistics and thresholds of weather variables, sample period January 2015–January 2020

Panel A. Temperature					
Country	Minimum	Mean	Maximum	Threshold	Significance
Denmark	−7.3	9.8	25.2	< 0	YES
France	−3.4	13.2	30.1	< 5	YES
Germany	−9.4	10.5	28.1	< 0 & > 20	YES
Italy	−0.6	15.9	29.6	< 5 & > 24	YES
Norway	−11.2	6.6	23.8	< 5 & > 20	YES
Spain	2.7	16.1	29.4	< 10 & > 20	YES

Panel B. Precipitation						
Country	Minimum	Mean	Maximum	Threshold	Lags	Significance
Denmark	0	257.0	3349.7	> 2500	< 20	NO
France	0	272.1	2939.1	1500 - 2000	< 10	YES
Germany	0	227.0	2719.7	1000 -1600	< 15	YES
Italy	0	257.1	3047.5	< 2000	< 20	YES
Norway	0	481.0	3274.9	500–2500	< 20	YES
Spain	0	173.6	2791.9	1400 - 2000	< 10	YES

Panel C. Wind speed					
Country	Minimum	Mean	Maximum	Threshold	Significance
Denmark	2.4	9.9	24.0	15–20	YES
France	2.4	7.0	17.3	10–14	YES
Germany	2.5	7.0	20.7	> 17	YES
Italy	2.8	5.6	14.9	> 8	NO
Norway	2.4	7.3	17.7	13–16	YES
Spain	2.3	6.0	15.5	> 12	YES

Panel D. Irradiance					
Country	Minimum	Mean	Maximum	Threshold	Significance
Denmark	145	2800	8339	2500 - 4500	YES
France	289	3258	8393	> 4000	NO
Germany	152	3014	8348	> 8000	YES
Italy	402	4456	8654	6000 - 8000	YES
Norway	82	2606	8414	5000 - 7000	YES
Spain	483	4830	8921	> 8000	YES

Note: The table shows the minimum, mean, and maximum of the weather variable and the threshold at which its relationship with electricity prices amplifies. The significance of the effect on electricity prices is estimated at 95% confidence levels. The weather variable statistical significance, cumulative effect, and contour figures are presented in the online supplementary material.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107789.

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