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On the Dynamics of Spot Power Prices across Western Europe in Pandemic Times

Luis María Abadie [1] and José Manuel Chamorro [2,*]

[1] Metroeconomica, Av. Zugazarte 8, 3rd Floor (Modules 5 & 6), 48930 Getxo, Spain; lm.abadie@outlook.es
[2] Department of Financial Economics II, Institute of Public Economics, University of the Basque Country UPV/EHU, Av. Lehendakari Aguirre 83, 48015 Bilbao, Spain
* Correspondence: jm.chamorro@ehu.eus

Abstract: Learning the dynamics of power prices in a given market is important for a number of players (e.g., producers, consumers, and policy makers) at both macro- and microeconomic levels. This paper analyzes the recent behavior of spot prices in eight Western European countries. The sample period coincides with the COVID-19 pandemic for the most part: it starts in April 2020 and runs until May 2023; it includes the start of the Russia–Ukraine war. We introduce a new model for the hourly spot price of electricity. The deterministic component includes yearly, weekly, and daily seasonalities; the stochastic component accounts for volatility, mean reversion, and discrete jumps. We estimate the model with publicly available hourly data. Regarding the development of the internal market for electricity, we find that core mainland power markets now move closer in step with one another than before, but the integration process of the Iberian Peninsula seems to have kicked into reverse. As for the dynamics of power prices, in the last part of the sample period the speed of reversion falls everywhere, and price volatility increases noticeably; the expected number of jumps per hour decreases, but their average size turns to positive and they become more volatile.

Keywords: spot power price; COVID-19 pandemic; seasonality; mean reversion; volatility; discrete jumps

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Citation: Abadie, L.M.; Chamorro, J.M. On the Dynamics of Spot Power Prices across Western Europe in Pandemic Times. *Energies* **2024**, *17*, 3420. https://doi.org/10.3390/en17143420

Academic Editor: Yuji Yamada

Received: 4 June 2024
Revised: 4 July 2024
Accepted: 7 July 2024
Published: 11 July 2024

1. Introduction

It has been a long time since the adoption of the Single European Act (28 February 1986) [1], which aimed to add new momentum to European integration and to complete the 'internal market' by 1 January 1993. As far as the power sector is concerned, there have been several milestones along the way [2–5].

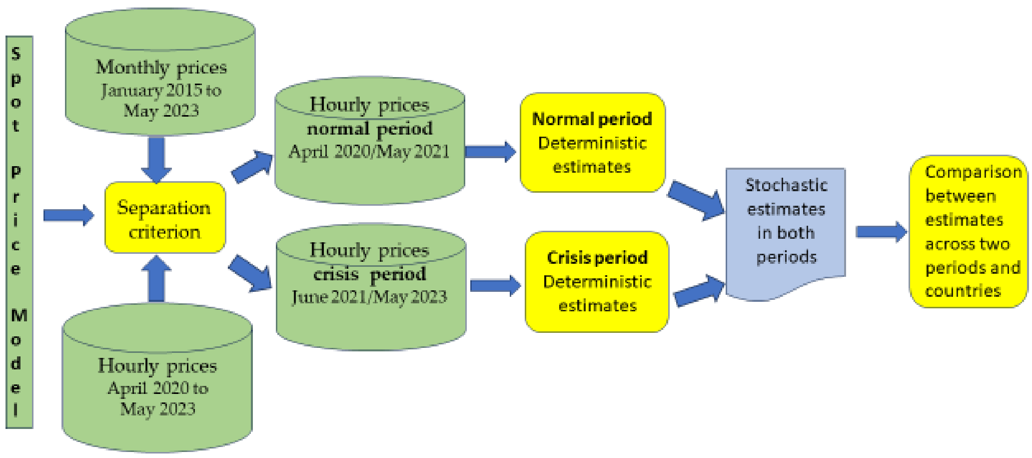
A number of researchers have assessed the extent to which the goal of completing 'an area with no internal borders and in which there is free movement' of electricity in particular has been accomplished. The assessment draws on the notion of market integration via price convergence; see for instance [6–8], among others. These two concepts are not to be confused. According to [9], the level of market integration at a particular time shows the (static) degree to which the single European market is attained. Instead, price convergence is the (dynamic) measure for the development of prices toward a single European price.

Other researchers look at power prices from a different perspective. They focus on the peculiar dynamics of electricity prices in day-ahead wholesale markets. Understanding price dynamics is necessary for the proper valuation and risk management of both real assets and financial contracts on electricity; see [10–13], to name a few. Ref. [14] provide a taxonomy of electricity price models applied to these purposes. As pointed out, the proposal of a particular model responds to the user's objectives, e.g., practical use, good price representation (of the main features of prices), price consistency (no arbitrage opportunities), or identifiability (liable to estimation from data).

No doubt, the impact of the COVID-19 pandemic has rippled way beyond global health concerns. Thus, a number of papers have addressed its impact on power systems, most of them from a physical or technical perspective, e.g., power demand and supply [15–17]. They usually adopt a top-down viewpoint (i.e., policy makers and system operators) and use metrics related to security of supply, system operation, frequency deviations, and the like. The Russia–Ukraine war has further compounded the global scenario. Ref. [18] adopts an economic perspective; in particular, the authors assess the ability of purchase power agreements to protect energy consumers from energy price spikes.

Arguably, the aftermath of the pandemic and the war may well run deeper than price levels. Specifically, have these events altered the inner dynamics of spot power prices? If so, is there any common pattern in the impact(s) across countries? From another perspective, have these events brought the internal market a bit closer or rather the opposite? Ref. [19] examines how the market anomalies caused by these events have affected European electricity markets. Following a novel approach, the authors convert time series into networks and then compare their degree distributions using the overlap coefficient. This transformation allows them to expand the set of properties analyzed simultaneously.

To our knowledge, no other paper explicitly addresses the above questions. Yet, our approach is quite different. Following previous research, we introduce a model for the hourly 'spot' price of electricity that encompasses four characteristics simultaneously: volatility, seasonality, mean reversion, and jumps. It comprises a deterministic component along with a stochastic component. The former accounts for seasonalities with different time frames. The latter combines mean reversion and discrete jumps. Next, we estimate our model, drawing on publicly available hourly data from eight Western European countries: Belgium, France, Germany, Italy, The Netherlands, Portugal, Spain, and the UK. The time horizon stretches from April 2020 through to May 2023, i.e., practically the whole COVID-19 pandemic and the outbreak of war. We are interested in the differential impact of these events across space and time. To this end, we analyze and then compare the behavior of the above markets before them and during them. See Scheme 1 below.



Scheme 1. Graphical representation of the process followed in developing the analysis.

Drawing on our data, we identify two sub-periods: April 2020–May 2021 and June 2021–May 2023 (end of the pandemic according to the WHO [20]); the first one covers the initial lockdowns and subsequent recovery toward the 'new normal', while the second one corresponds to the energy (price) crisis. Thus, Tables 4 and 5 show the deterministic estimates in the normal period and the crisis period, respectively; similarly, Tables 7 and 8 show the stochastic estimates in these periods. Relative to the first period, in the second one prices in the mainland markets show greater co-movement, whereas Iberian prices deviate from them. In addition, the speed of reversion falls everywhere, and price volatility increases noticeably; the expected number of jumps per hour decreases, but their average size turns to positive and they become more volatile.

The structure of the paper is as follows. Section 2 proposes the theoretical model for the spot price. Section 3 introduces two data sets; they include both hourly prices and monthly average prices, with each data set serving a different purpose. Section 4 provides numerical estimates of all the underlying parameters. The first ones correspond to the deterministic part in the two sub-periods. Next, the stochastic part is derived (as a residual, by subtracting the deterministic series from the price series). It is subsequently broken down into two series (corresponding to the mean-reverting process and the discrete-jumps process). Each series is used to estimate the parameters in the corresponding process in the two sub-periods. Section 5 discusses the main results, and Section 6 concludes.

2. Methodology (Stochastic Model for the Electricity Price)

Ref. [10] proposes a model for the natural logarithm of the day-ahead hourly price. Ref. [21] uses the logarithm of weekday medians (i.e., medians of 120 hourly observations). Logarithmic transformation has some advantages. Thus, log prices potentially mitigate the heteroscedastic properties of prices by minimizing the effects of high volatility and the outlier effects [22]. Nonetheless, a drawback is the inability to account for negative power prices, which some wholesale power markets allow (e.g., the Central Western Europe (CWE) market and the Irish Single Electricity Market (SEM)) and can be observed ever more frequently. Ref. [11] uses average daily prices (consequently, they only consider weekly and monthly seasonalities). Unlike these papers, we propose a model for the (absolute) spot price in levels and use hourly data. Absolute prices lead to straightforward interpretations, for instance when it comes to jumps' frequency and size. They allow for positive and negative values. In addition, hourly prices in particular allow analyze daily seasonality.

Specifically, we propose a process, P, for the (absolute) spot price in the physical world, which comprises a deterministic part, D, and a stochastic part, S:

$$P_t^i = D^i(t) + S_t^i \tag{1}$$

with $i =$ {Belgium, France, Germany, Italy, The Netherlands, Portugal, Spain, UK}. Time t appears in two different formats: as an argument, $Z(t)$ denotes a deterministic function of time; instead, as a subscript, Z_t stands for the value of a stochastic process at time t. Time (t) is measured in years on an hourly basis. For instance, the first hour in April 2020 is $t = (1/366/24)$; this is the first hour for which there are data from every country. Similarly to previous papers, this model includes the main features in wholesale power markets: seasonality, mean reversion, volatility, and jumps.

By assumption, the mathematical expectation of the stochastic part S^i is zero. Ref. [23] put it in a different way: "Based on the rather deterministic demand for electricity (which in turn is due to highly seasonal temperature patterns influencing the demand to a large extent), we assume that deviations from a deterministic seasonal function are temporary". Therefore, when it comes to forecasting mean or expected values, only D^i is relevant (for point values, instead, both parts–deterministic and stochastic–play a role):

$$D^i(t) = \beta_1^i + \beta_2^i t + \beta_3^i D_0(t) t^2 + YC^i(t) + WC^i(t) + DC^i(t) \tag{2}$$

Thus, the model for D^i includes an intercept, β_1^i, and a time trend, $\beta_2^i t + \beta_3^i D_0(t) t^2$ (where $D_0(t) = 0$ in the normal period and $D_0(t) = 1$ in the crisis period); we set both a linear and a quadratic time trend because, as displayed later on in Figures 1 and 2, there is a first period when prices are more or less stable, which is then followed by another one with an inverse U-shape. The model also includes the following:

(a) A yearly cycle, $YC^i(t)$: it encompasses different seasonal components (annual, semi-annual, quarterly, semi-quarterly, monthly, ...), as many as determined by statistical significance:

$$YC^i(t) = \sum_{j=1}^{5} [\beta_{2+2j}^i \sin(2j\pi t) + \beta_{3+2j}^i \cos(2j\pi t)] \tag{3}$$

Equation (3) represents the yearly cycle with up to five sine and cosine components. In principle, there are 10 beta coefficients, numbered from β_4 to β_{13}. If a specific coefficient turns out to be statistically non-significant (at standard confidence levels) in the estimation process, then it will be dropped (alternative model specifications and elimination procedures are available, e.g., [24]).

(b) A weekly cycle, $WC^i(t)$, according to the day of the week:

$$WC^i(t) = \beta^i_{14}D_1(t) + \beta^i_{15}D_2(t) + \beta^i_{16}D_3(t) + \beta^i_{17}D_4(t) + \beta^i_{18}D_5(t) + \beta^i_{19}D_6(t) \quad (4)$$

In Equation (4), there are six dummy variables. $D_1(t)$ equals 1 if it is Monday, and zero otherwise. $D_2(t) = 1$ on Tuesdays, and zero otherwise, and so on through to the sixth dummy variable. On the seventh day, Sunday, the six dummies are zero.

(c) A daily cycle, $DC^i(t)$, based on the particular hours, with their own seasonalities:

$$DC^i(t) = \sum_{j=1}^{5} [\beta^i_{18+2j}\sin(2j\pi\tau)/24 + \beta^i_{19+2j}\cos(2j\pi\tau)/24] \quad (5)$$

Equation (5) represents the daily cycle in hours. The index τ indicates the hour: τ = 1, 2, . . ., 24. There are 10 beta coefficients, from β_{20} to β_{29}.

Summing up, there are 29 beta parameters in the deterministic part $D^i(t)$: the constant, 2 time trends, 10 betas in the yearly cycle, 6 in the weekly one, and 10 in the daily one. As mentioned above, if any of them are not statistically significant, they will be suppressed, in which case the model is re-estimated again with fewer parameters.

On the other hand, the stochastic part, S^i_t, follows a continuous mean-reverting process with discrete jumps:

$$dS^i_t = \left(\alpha^i - \kappa^i S^i_t\right)dt + \sigma^i dW^i_t + J^i\left(\mu^i_j, \sigma^i_j\right)dq^i_j \quad (6)$$

Specifically, Equation (6) comprises three terms on the right hand. The first two of them constitute a so-called Ornstein–Uhlenbeck (OU) process; the third one is a Poisson process. Now, proceeding step by step in Equation (6), the first term is a function of S^i_t, while the other two are stochastic. Leaving the latter aside for a moment, the equation can be rewritten as $dS^i_t = \left(\alpha^i - \kappa^i S^i_t\right)dt = \kappa^i(\frac{\alpha^i}{\kappa^i} - S^i_t)dt$. Thus, the stochastic part of the electricity price in each country tends toward α^i/κ^i in the long term, with a reversion speed κ^i. If S^i_t falls below its long-run quilibrium level the parenthesis will be positive, which induces an increase in its value ($dS^i_t > 0$); conversely, if S^i_t rises above α^i/κ^i the parenthesis will be negative, pushing S^i_t downwards ($dS^i_t < 0$). In sum, when S^i_t departs from its long-term equilibrium (due to the impact of stochastic shocks, namely OU and jumps), the first term tends to restore the equilibrium (always subject to shocks). In addition, the higher the speed of reversion κ^i, the sooner S^i_t approaches its equlibrium value. Now, the second term generates a continuous random behaviour (without jumps): the volatility of the mean-reverting process is σ^i; dW^i_t is the increment of a standard Wiener process. The third term accounts for jumps in the electricity price with intensity λ^i (the mean rate of event occurrence); thus, if the time unit is an hour then λ^i jumps are expected per hour. The jump size is normally distributed with mean μ^i_j and volatility σ^i_j. Here, dq^i_j is a Poisson process such that $dq^i_j = 1$ with probability $\lambda^i dt$, and $dq^i_j = 0$ with probability $1 - \lambda^i dt$. We assume that dW^i_t and dq^i_j are independent.

Note that the earlier assumption $E(S^i) = 0$ implies that, in terms of average or expected values, the mean-reverting component and the discrete-jump component offset each other: if any one of them has a positive expected value then the other must have a negative one.

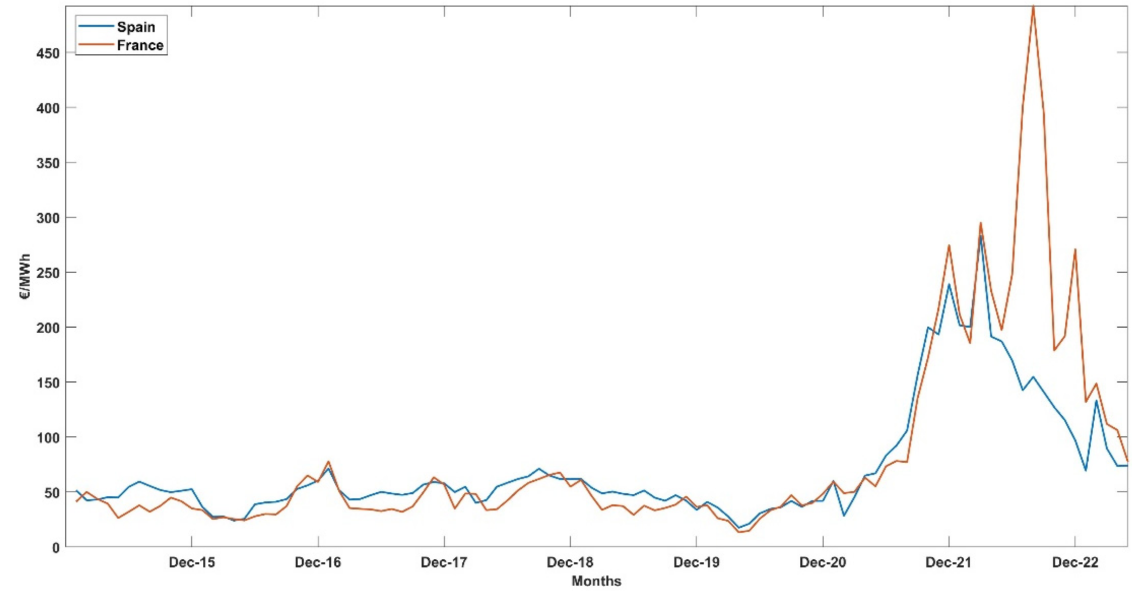


Figure 1. Electricity monthly spot prices in France and Spain during the 'normal' period (April 2020–May 2021) and the 'crisis' period (June 2021–May 2023).

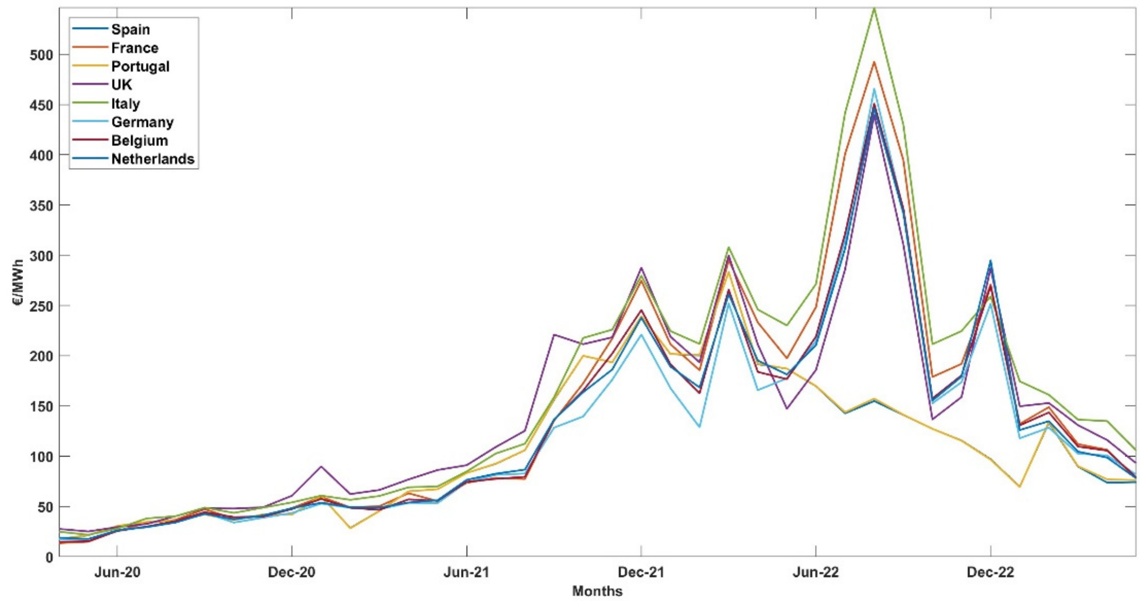


Figure 2. Monthly spot prices in eight European countries during the sample period.

3. Data

There are different definitions or notions of convergence. For example, in [25] price convergence means the reduction in international price level dispersion over time. According to [26], convergence is defined by convention as the percentage of hours during which absolute price differences are below 0.1 EUR/MWh. Ref. [7] distinguishes between partial convergence (prices in two markets approximate each other) and full convergence (law of one price holds). There are also definitions tailored to the particular econometric/theoretical model at hand, among them [7,9,22]. The empirical approaches include correlation analysis, regression analysis, cointegration analysis, Kalman filter analysis, principal components analysis, etc. Ref. [27] provides a list of them.

In our case, we keep the analysis simple and consider two different data sets. The first one includes three countries: France, Portugal and Spain. For each of them we have average monthly prices from January 2015 to May 2023 (i.e., 101 average prices for each country). A new inter-connector between Baixas (France) and Santa Llogaia (Spain) started operating in October 2015; its 2000 MW transmission capacity was ramped up progressively (Ref. [28] considers that on 1 January 2016 it was fully available). As a matter of fact, prices in Spain and Portugal are identical in many hours owing to the integration of both markets. Indeed, there is a joint Iberian power market operator, OMIE, for both Portugal and Spain.

The second set accounts for all the eight countries: the former three plus Belgium, Germany, Italy, The Netherlands, and the UK. It comprises hourly prices from April 2020 to May 2023 (i.e., 27,000 prices for each country). Thus, the two data sets overlap from April 2020 through to May 2023.

3.1. Monthly Overview

Monthly prices provide a first glimpse of the two sub-periods. Figure 1 shows their time path in France and Spain. Until early 2021, they fluctuate around a more or less stable level but then prices increase steeply.

Our first aim is to break down the time horizon into two parts: the normal period and the crisis period. Both hourly and daily electricity prices usually show high volatility. At this point, we stick to monthly prices; they are less volatile than hourly prices, which in turn makes it easier to reliably identify a structural break. The separation criterion draws on 24-month moving windows. We compute the price average and volatility for each month (starting from January 2017). Considering a standard normal distribution, the value that leaves 99.5% of the cumulative probability to its left (or, alternatively, 0.5% to the right) is 2.57583. We set the start of the crisis period when the monthly price is greater than the average plus 2.57583 times the volatility over 7 successive months; this happens in June 2021 (for both France and Spain). This result is in line with reports from the Spanish transmission system operator (TSO). According to Red Eléctrica de España [29]: "The average daily electricity market price in 2021 has been 111.93 €/MWh, the highest in history... more than triple that of last year (itself very low due to the pandemic)... with prices already above 90 €/MWh since the end of May".

The above result for France and Spain is assumed to apply to the eight countries. Thus, we split the spot price series into a normal period (running from April 2020 through to May 2021) and a crisis period (June 2021 to May 2023). Note that the normal period includes the initial months of the COVID-19 pandemic.

Figure 2 displays power prices in the eight countries over the whole sample period. Monthly prices are highest in Italy and France. They are lowest in Spain and Portugal; the latter are hard to identify because they are the same as the former very frequently.

3.2. Hourly Overview

Now, Table 1 shows the summary statistics of hourly prices in both sub-periods. Average levels and volatilities increase significantly from the first one to the second. The upward jumps are comparatively weaker in the Iberian Peninsula than in the other countries. Thus, percentage changes in Portugal and Spain fall short of 300%, but they surpass 400% and even 500% elsewhere.

Regarding skewness, the UK leads the sample in both the normal period (17.10) and the crisis period (3.81); second comes Portugal in the former (0.61) and France in the latter (2.08). Germany is the only place with negative skewness (−0.23, normal period). Positive skewness suggests that the probability mass is relatively more concentrated on the left of the distribution and the tail turns up on the right. This phenomenon is reinforced during the crisis period: skewness increases everywhere (except in the UK); the lowest rate is a non-negligible 31% (in Portugal).

When it comes to kurtosis, again the UK stands apart in the normal period (519.38); Germany (3.13) comes second, far behind. Italy is the only country with negative kurtosis (−0.24, normal period). As before, in the crisis period this statistic increases everywhere (except in the UK), with all the values above 3.0; this suggests that the probability distribution generates more outliers and/or more extreme outliers than the normal distribution. Kurtosis is minimum in Italy (3.68) and maximum in The Netherlands (25.12).

Table 1. Hourly electricity prices (EUR/MWh), April 2020–May 2023: summary statistics.

Country	**Normal Period (10,224 h)**		**Crisis Period (16,776 h)**		**% Change**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Spain	40.8	20	150	72.5	267.6%	262.5%
France	41.1	21.1	210	137	410.9%	549.3%
Portugal	40.8	20	150	72	267.6%	260.0%
UK	53.0	43.7	204	128	284.9%	192.9%
Italy	47.5	19.2	237	128	398.9%	566.7%
Germany	38.6	21.5	182	127	371.5%	490.7%
Belgium	39.8	21.7	192	124	382.4%	471.4%
The Netherlands	39.8	19.8	189	121	374.9%	511.1%
Country	Normal period (10,224 h)		Crisis period (16,776 h)		% Change	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
Spain	0.60	0.41	0.78	8.05	31.1%	1847.7%
France	0.31	1.26	2.08	6.97	571.8%	452.6%
Portugal	0.61	0.44	0.80	5.92	31.0%	1237.9%
UK	17.10	519.38	3.81	6.15	−77.7%	−98.8%
Italy	0.26	−0.24	1.35	3.68	412.9%	−1622.0%
Germany	−0.23	3.13	1.42	6.40	−724.7%	104.3%
Belgium	0.00	2.68	1.25	10.61	62,656.9%	296.6%
The Netherlands	0.41	2.14	1.33	25.12	226.6%	1073.4%

Tables 2 and 3 show the correlation coefficients between national hourly prices over both sub-periods; in a sense, the correlation coefficient provides a (static) measure of the level of market integration. Some markets show high correlations, among them those pertaining to the CWE electricity market. It is possible to distinguish two blocks. The first one comprises Portugal and Spain, where the correlation is almost perfect (99.8%) over both time horizons. In the other block, the correlations are not so extreme. Up to May 2021, they are higher than 75% between continental countries (France, Italy, Germany, Belgium, and The Netherlands), with the UK lagging behind (around 50%).

Table 2. Pearson correlation between hourly prices in normal period (April 2020–May 2021).

Country	**Spain**	**France**	**Portugal**	**UK**	**Italy**	**Germany**	**Belgium**	**The Netherlands**
Spain	1.000							
France	0.743	1.000						
Portugal	0.998	0.738	1.000					
UK	0.465	0.526	0.463	1.000				
Italy	0.749	0.858	0.745	0.532	1.000			
Germany	0.623	0.892	0.618	0.474	0.776	1.000		
Belgium	0.679	0.930	0.675	0.536	0.807	0.927	1.000	
The Netherlands	0.639	0.896	0.634	0.518	0.816	0.91	0.939	1.000

Table 3. Pearson correlation between hourly prices in energy crisis period (June 2021–May 2023).

Country	**Spain**	**France**	**Portugal**	**UK**	**Italy**	**Germany**	**Belgium**	**The Netherlands**
Spain	1.000							
France	0.454	1.000						
Portugal	0.998	0.454	1.000					
UK	0.437	0.755	0.439	1.000				
Italy	0.404	0.925	0.406	0.737	1.000			
Germany	0.380	0.889	0.380	0.751	0.869	1.000		
Belgium	0.443	0.912	0.443	0.782	0.882	0.954	1.000	
The Netherlands	0.445	0.896	0.444	0.778	0.880	0.953	0.972	1.000

Nonetheless, from June 2021 onwards correlations get stronger (Table 3): above 85% between continental countries, and higher than 70% for the UK. Thus, the energy crisis has contributed to further integrating these power markets. Instead, the evidence for the Iberian Peninsula is the opposite: hourly prices have de-coupled from those beyond the Pyrenees, as shown by correlations falling from over 60% in the normal period to under 40% in the crisis period.

4. Numerical Estimates of National Price Processes

Regarding empirical analyses, Ref. [10] considers three European wholesale power markets: the APX (The Netherlands), EEX (Germany), and PPX (France). The same number of European markets applies to [11]: Amsterdam Power Exchange (APX, The Netherlands), NordPool (Scandinavia) and Spain. In [21], the number grows to six: APX (The Netherlands), EEX (Germany), EXAA (Austria), NordPool (Scandinavia), Omel (Spain), and Powernext (France). The authors of [22] use data from seven markets: European Energy Exchange (EEX, Germany), Belgian Power Exchange (BELPEX, Belgium), Energy Exchange Austria (EXAA, Austria), Amsterdam Power Exchange (APX, The Netherlands), Nord Pool Power Exchange (ELSPOT, Scandinavia), Single Electricity Market (SEM, Northern Ireland and Republic of Ireland), and APX Power UK (former UKPX, Great Britain). We estimate our model drawing on hourly data from eight Western European countries.

4.1. Deterministic Parts

Tables 4 and 5 display the estimation results during the 'normal' and 'crisis' periods, respectively. Full details for each country in each period appear in Supplementary Materials. We run an OLS linear regression analysis with heteroskedasticity-consistent (HAC) robust standard errors.

Table 4. Deterministic parameters in the normal period (April 2020–May 2021).

Parameters	Spain	France	Portugal	UK	Italy	Germany	Belgium	The Netherlands
β_1	3.19	4.00	3.56	14.00	11.40	5.20	5.17	9.74
β_2	47.49	44.02	47.39	55.37	46.81	36.29	41.43	36.94
β_3	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
β_4	−5.25	−4.85	−5.24	n.s.	−2.86	−3.18	−4.93	−3.07
β_5	−6.72	n.s.	−6.63	3.78	−0.87	n.s.	n.s.	1.18
β_6	−3.34	2.72	−3.40	n.s.	0.88	2.22	1.71	1.17
β_7	4.40	2.46	4.52	4.01	0.87	1.85	2.33	1.92
β_8	n.s.	n.s.	n.s.	3.68	−1.06	n.s.	1.20	0.90
β_9	5.65	3.37	5.73	7.15	2.34	2.29	3.09	2.28
β_{10}	1.59	n.s.	1.66	2.90	n.s.	n.s.	n.s.	n.s.
β_{11}	4.32	2.69	4.37	3.01	1.00	n.s.	1.90	0.95
β_{12}	4.25	n.s.	4.34	2.52	n.s.	n.s.	n.s.	n.s.
β_{13}	n.s.	−3.67	n.s.	n.s.	−2.51	−3.42	−3.12	−2.75
β_{14}	10.96	13.85	10.53	5.54	10.03	13.91	11.75	9.90
β_{15}	13.00	16.62	12.66	7.94	11.89	17.01	15.30	12.19
β_{16}	13.44	17.54	13.07	12.43	12.80	17.27	16.38	12.30
β_{17}	14.15	16.63	13.82	9.49	12.30	17.34	15.11	12.77
β_{18}	11.57	14.15	11.23	8.45	11.28	16.22	13.45	11.02
β_{19}	4.45	6.29	4.27	2.77	4.75	7.71	6.02	4.71
β_{20}	−2.76	−4.11	−2.80	−12.44	−4.71	−3.58	−3.78	−3.84
β_{21}	0.54	−1.05	0.55	n.s.	−0.50	n.s.	0.76	n.s.
β_{22}	−5.83	−7.84	−5.69	−9.87	−7.50	−8.69	−8.71	−8.40
β_{23}	1.24	−0.66	1.25	n.s.	−1.01	−1.53	n.s.	−1.18
β_{24}	−0.49	1.53	−0.50	3.30	1.51	1.72	1.97	2.05
β_{25}	−0.67	−0.55	−0.70	−6.42	−0.20	−0.78	−0.72	−0.62
β_{26}	1.00	2.03	0.94	5.52	1.40	1.71	1.84	1.72
β_{27}	−0.66	0.35	−0.63	−0.70	−1.00	−0.48	−0.39	−0.57
β_{28}	n.s.	−0.69	n.s.	n.s.	n.s.	−0.58	−0.45	−0.58
β_{29}	n.s.	0.26	n.s.	3.69	n.s.	0.16	0.63	0.38

n.s. = not significant at the 10% level.

Table 5. Deterministic parameters in the energy crisis period (June 2021–May 2023).

Parameters	Spain	France	Portugal	UK	Italy	Germany	Belgium	The Netherlands
β_1	−347.52	−1229.5	−345.44	−660.4	−1214.4	−949.4	−953.53	−933.10
β_2	550.37	1328.36	549.31	828.20	1342.57	1017.06	1047.56	1035.03
β_3	−143.14	−297.21	−142.77	−190.7	−297.86	−223.53	−232.80	−231.27
β_4	−23.82	26.72	−23.35	n.s.	35.33	31.75	17.80	19.40
β_5	23.13	−43.88	23.25	−35.71	−51.82	−46.54	−42.30	−39.47
β_6	n.s.	−34.12	n.s.	−39.40	−37.03	−27.27	−27.01	−28.28
β_7	19.94	−12.49	20.16	0.00	−13.68	−12.98	−11.65	−8.67
β_8	−4.78	n.s.	−4.61	19.83	10.00	14.14	9.86	13.35
β_9	2.99	36.62	3.22	33.83	33.55	30.33	30.10	28.73
β_{10}	−13.28	−33.51	−13.10	−37.46	−26.06	−33.79	−34.53	−32.41
β_{11}	−3.84	7.56	−3.88	7.03	8.69	n.s.	n.s.	n.s.
β_{12}	n.s.	24.09	n.s.	14.41	12.31	15.15	20.55	15.73
β_{13}	−11.69	−8.76	−11.72	−6.78	−9.24	−8.88	−8.49	−7.44
β_{14}	23.08	52.75	21.77	28.26	33.10	53.14	47.12	42.84
β_{15}	24.94	66.76	23.51	33.61	42.06	70.89	57.76	51.98
β_{16}	22.91	65.03	21.31	25.32	41.22	66.41	53.62	47.87
β_{17}	24.76	63.19	23.54	30.67	44.69	60.15	53.13	47.78
β_{18}	21.38	56.24	19.92	27.88	41.69	49.00	45.95	42.52
β_{19}	9.43	22.08	8.07	n.s.	15.55	17.72	14.23	13.25
β_{20}	−3.88	−18.65	−4.23	−34.23	−19.44	−16.60	−16.60	−15.72
β_{21}	10.43	−7.05	10.02	−4.39	−2.40	n.s.	3.17	5.57
β_{22}	−21.12	−31.69	−20.78	−32.99	−27.81	−31.65	−33.13	−33.77
β_{23}	1.22	−6.27	1.30	n.s.	−12.71	−17.75	−14.71	−16.91
β_{24}	−1.49	5.85	−1.46	13.95	7.18	7.73	8.41	9.71
β_{25}	−1.51	n.s.	−1.48	−11.19	n.s.	n.s.	n.s.	1.72
β_{26}	4.25	8.65	4.12	11.09	6.96	6.97	7.42	6.10
β_{27}	−3.68	n.s.	−3.56	−2.34	−1.98	0.89	n.s.	n.s.
β_{28}	n.s.	−2.12	n.s.	−1.49	n.s.	−2.37	−1.93	−1.93
β_{29}	n.s.	n.s.	n.s.	5.69	0.79	n.s.	0.66	n.s.

n.s. = not significant at the 10% level.

Table 4. The regression intercept (β_1), which is statistically significant everywhere, varies markedly across markets. It is highest in the UK (14.00 EUR/MWh) and Italy (11.40), while the lowest values correspond to Portugal (3.56) and Spain (3.19). The linear time trend (β_2) is positive everywhere and shows less dispersion. Again, the UK (55.37 EUR/MWh over a year) stands out, followed by Spain (47.49) and Portugal (47.39). The minimum value corresponds to Germany (36.29). As for the quadratic time trend, β_3 is not statistically significant anywhere at the 10% level in this period (which is not surprising in view of the left part in Figures 1 and 2).

Regarding the yearly cycle (β_4 through β_{13}), some coincidences arise. For example, there is at least one non-significant parameter in every country (though it is never the same for every one). Yet, some groupings show up. For instance, β_8 is non-significant in France–Germany–Spain–Portugal. Instead, β_{10} and β_{12} are non-significant in Belgium–France–Germany–Italy–The Netherlands. There are also parameters that are significant in every market and even show the same sign, e.g., β_7 and β_9, both positive. Conversely, β_4 is consistently negative (except in the UK, where it is not significant).

Unlike the former, the weekly cycle (β_{14} through β_{19}) is statistically significant every day in all of the markets. Across space, the lowest estimates correspond to the UK, and the highest ones to Germany and France. Across time, the estimates are highest on Wednesdays and Thursdays, and lowest on Saturdays.

When it comes to the daily cycle (β_{20} through β_{29}), France is the only country where all of the estimates are statistically significant (at the 10% level). Similarly to the yearly cycle, some parameters are significant in every market and even show the same sign, either negative (β_{20}, β_{22}, and β_{25}) or positive (β_{26}). On the other hand, a few groups turn up. For instance, both β_{28} and β_{29} are non-significant in Portugal–Spain–Italy.

Table 5. In the energy crisis period, some results change dramatically. Thus, the numerical estimates of the regression intercept (β_1) bear no resemblance to the

earlier ones. They turn negative and quite sizeable: around (−1200) in UK–Italy, and (−350) in Portugal–Spain. The linear time trend (β_2) remains positive but jumps above 1000 in Belgium–France–Germany–Italy–The Netherlands, while reaching 500 in Portugal–Spain. The quadratic time trend, β_3, which was not significant anywhere in the normal period, now becomes statistically significant and shows a negative sign, with Belgium–France–Germany–Italy–The Netherlands at one end (between −223.53 and −297.86) and Portugal–Spain at the other (around −143).

The estimates of the yearly cycle are very different too (relative to the normal period). The number of non-significant estimates drops from 23 before to 9 now. Some estimates switch from negative to positive or the other way round. The absolute values increase noticeably, sometimes by a factor of 10 or more. Still, other findings remain, e.g., β_9 is significant and positive in all of the markets. Conversely, now β_{10} is significant everywhere and negative (no longer positive).

Concerning the weekly cycle (β_{14} through β_{19}), the main difference is the size of the estimates, which increases across both space and time, sometimes by a factor of five or more. Again, the highest values correspond to Germany and France. The lowest ones arise in Portugal and Spain (not the UK). Across time, now the estimates are highest mostly on Tuesdays; again, the lowest are on Saturdays.

As for the daily cycle (β_{20} through β_{29}), now the number of non-significant coefficients grows from 12 to 17. As before, β_{20} and β_{22} remain significant and negative everywhere, while β_{26} continues to be positive in every market. β_{25} ceases to be significant in Belgium–France–Germany–Italy. Similarly to the above parameters, the absolute values jump upward: in Table 4 just one of them reaches 10; now, values above 20 and even 30 are common. Again, β_{28} is non-significant in Portugal–Spain–Italy. β_{29} continues non-significant in Portugal–Spain but now France–Germany–The Netherlands join the list.

To gain additional insights, the following figures display some of the above results for the three types of seasonalities. Regarding yearly patterns, Figures 3 and 4 show $YC^i(t)$ over the two periods in Germany (core) and Spain (periphery), respectively. A cursory look allows the observation that the energy crisis has led to much wilder swings in the former than in the latter (as suggested in Tables 4 and 5 by the changes in β_4 through β_{13}). An absence of pattern changes in the yearly cycle would imply perfect positive correlation (+1.00) across the two periods. In Spain it is 0.3783. In Germany it is −0.30643.

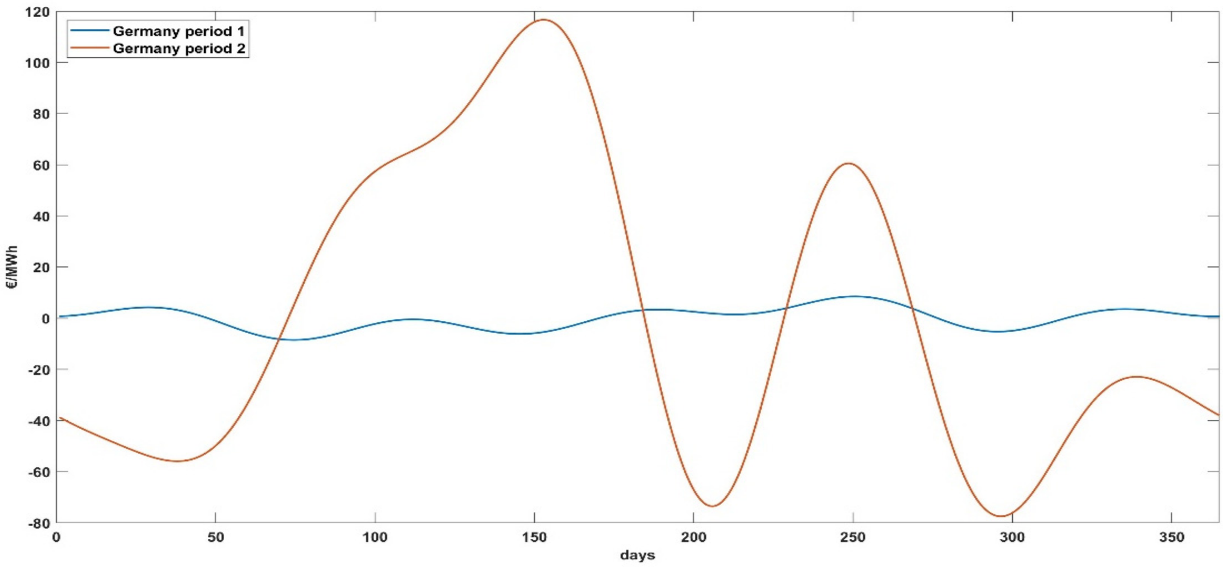


Figure 3. Germany: yearly seasonal effect, $YC(t)$, during the two periods.

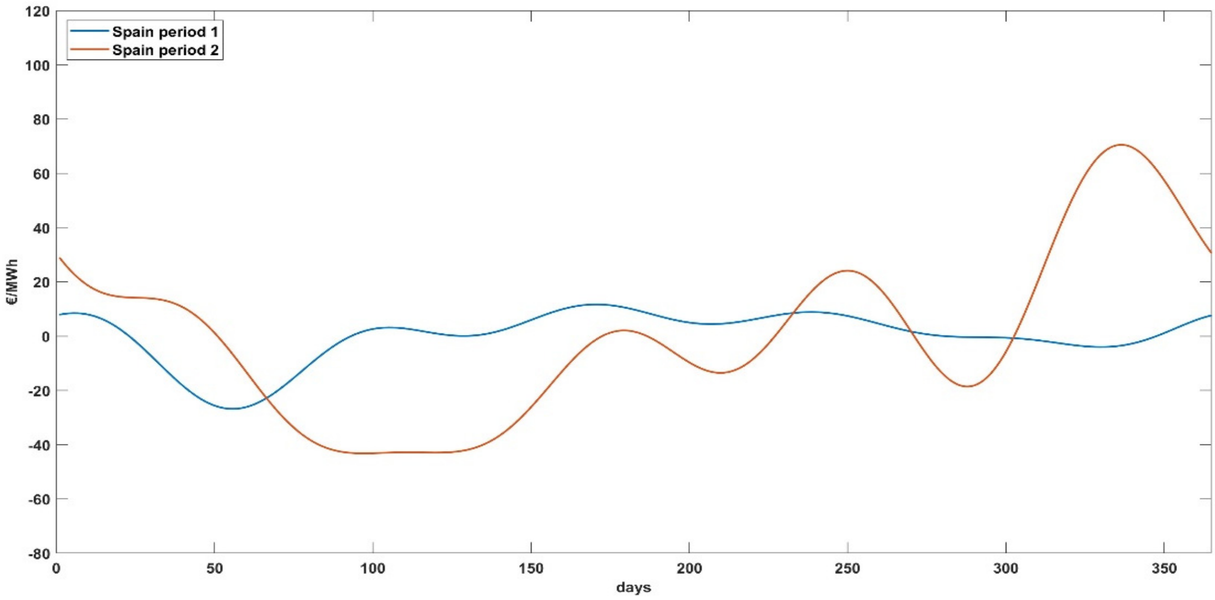


Figure 4. Spain: yearly seasonal effect, $YC(t)$, during the two periods.

Figure 5 focuses on the energy crisis period specifically. The two national cycles are very different during the first part of the year; in the second, instead, they describe similar paths. At any time, the German yearly cycle displays wider amplitude than the Spanish one.

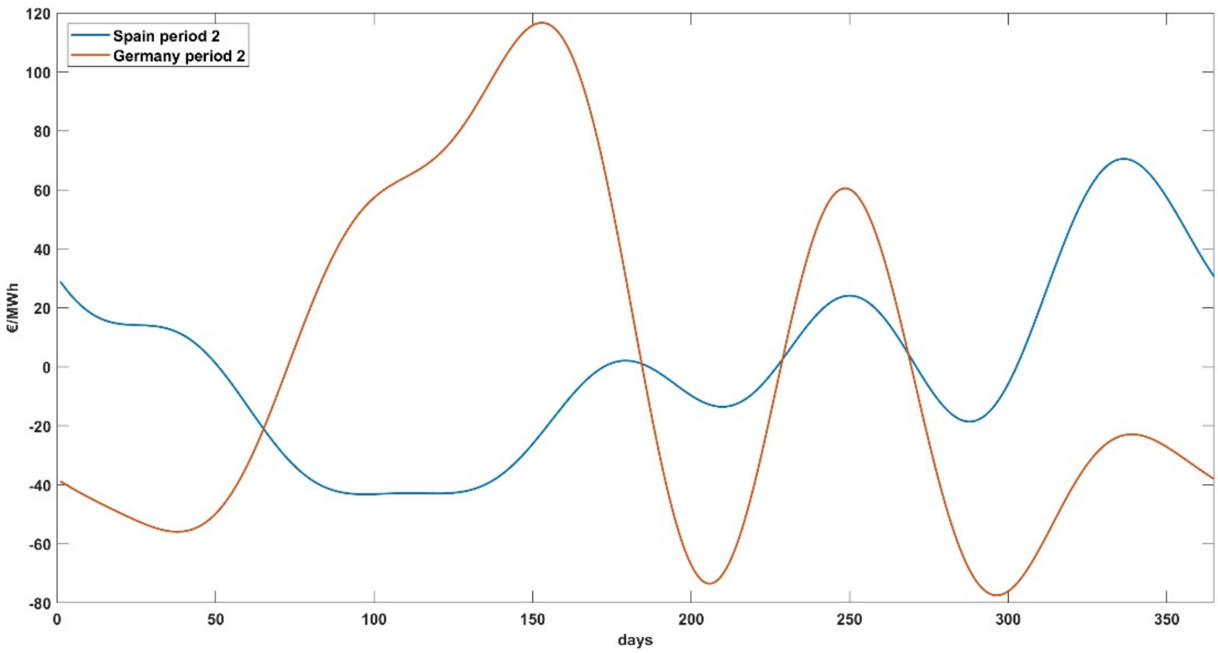


Figure 5. Germany and Spain: yearly seasonal effect, $YC(t)$, during the crisis period.

As for the weekly effects, Figures 6 and 7 show that $WC^i(t)$ get more prominent in both Germany and Spain during the crisis period. As before, the changes are much bigger in the former than in the latter. On the other hand, Saturday stands apart from the working days.

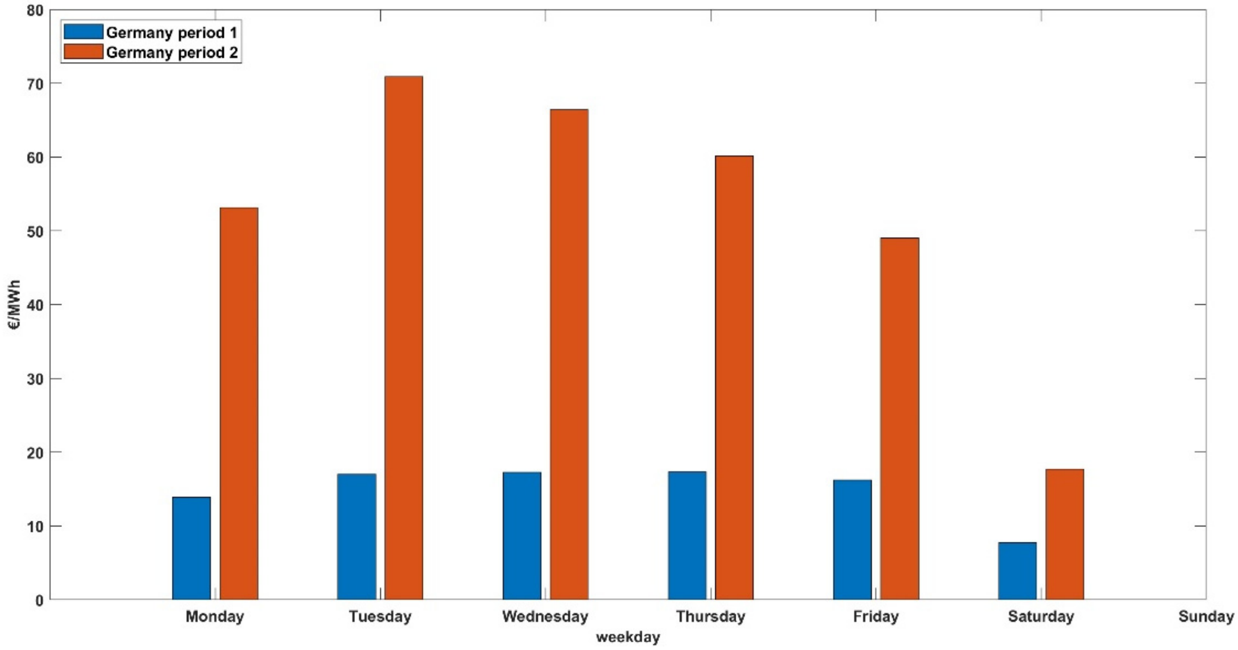


Figure 6. Germany weekly effects, $WC(t)$, during the two periods.

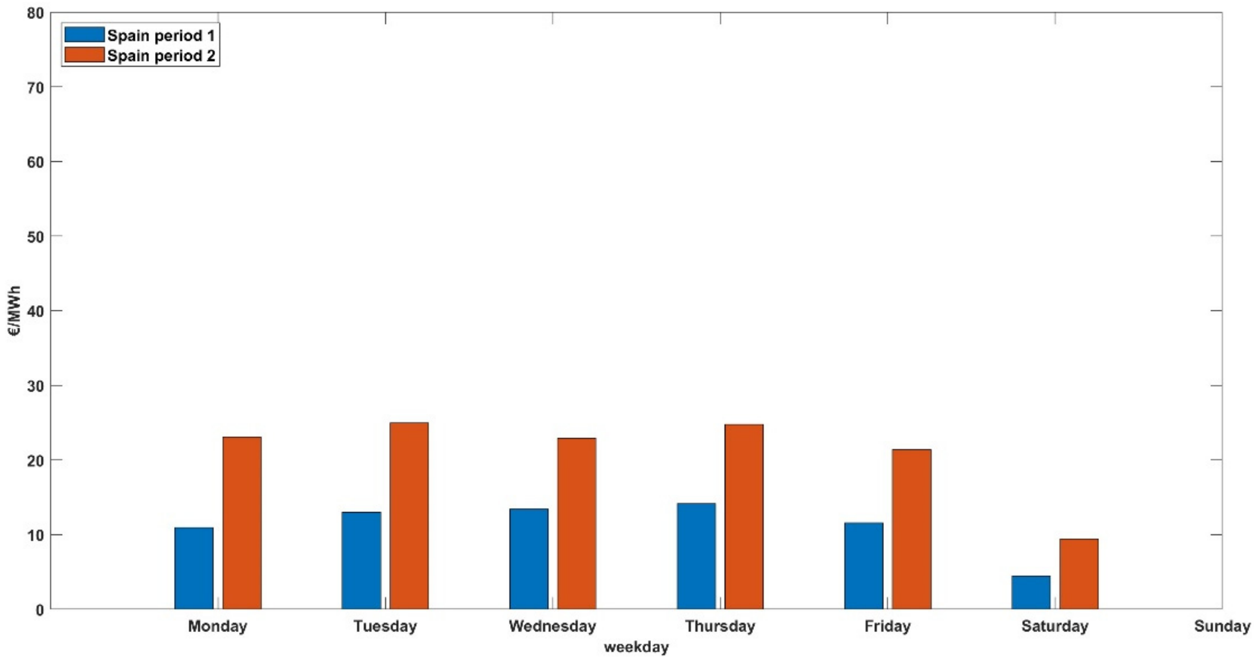


Figure 7. Spain weekly effects, $WC(t)$, during the two periods.

Concerning hourly effects over the day, $DC^i(t)$, here the differences between the two countries are smaller than before. In Germany, the correlation of the hourly cycles during the two periods is 0.9355; see Figure 8. In Spain it is slightly lower, 0.9087; see Figure 9. In both countries the swings become wider during the crisis period.

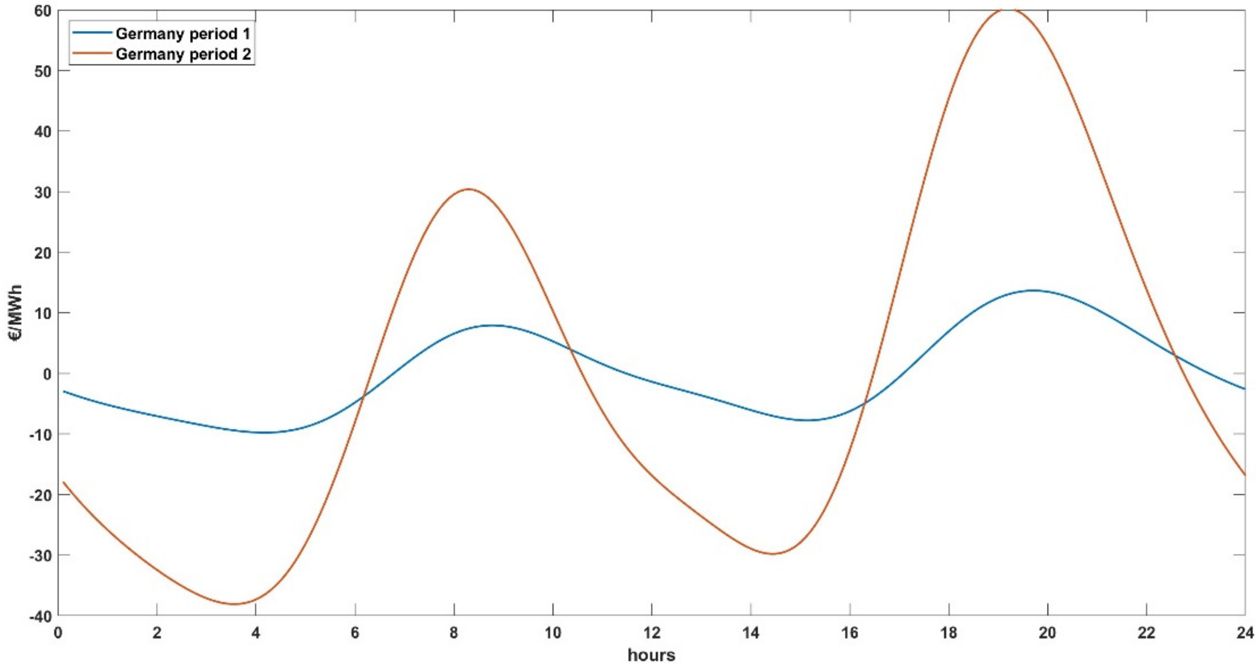


Figure 8. Germany, daily effects, $DC(t)$ over the 24 h, during the two periods.

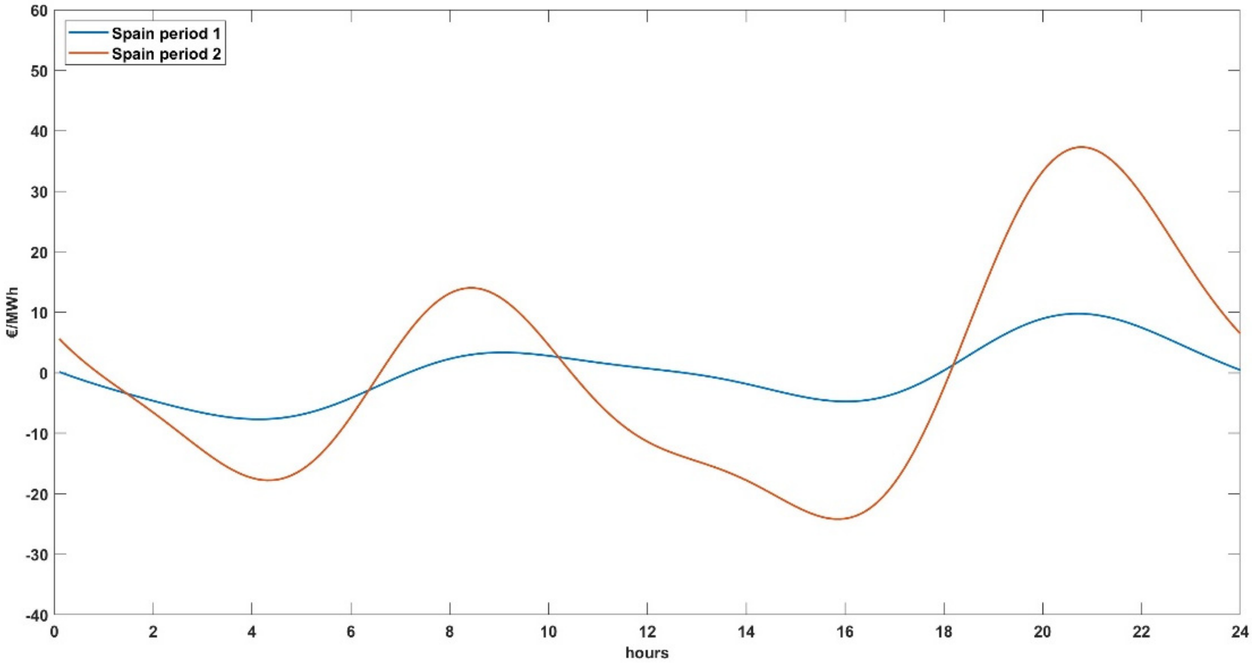


Figure 9. Spain, daily effects, $DC(t)$ over the 24 h, during the two periods.

Figure 10 displays the national hourly cycles during the energy crisis period. The paths are similar, with Spanish patterns following German ones with a delay of 1 to 2 h in the second part of the day.

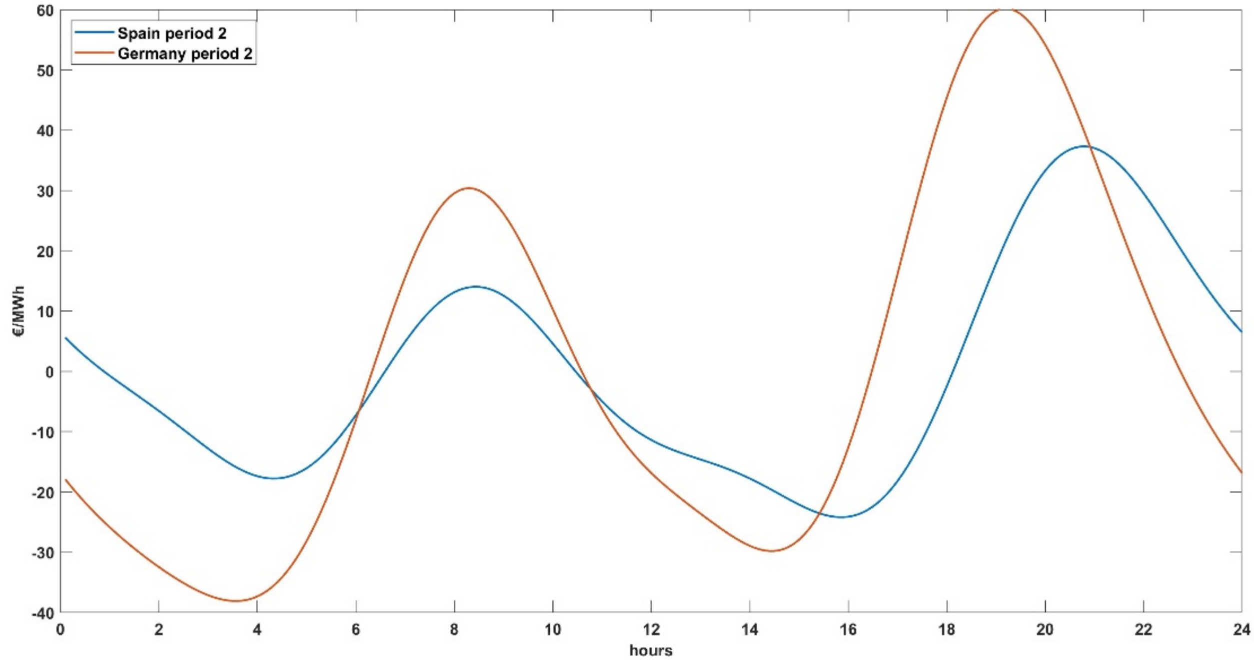


Figure 10. Germany and Spain, daily effects, $DC(t)$ over the 24 h, during the crisis period.

For further comparison purposes, Figures 11 and 12 show hourly spot prices in Germany and Spain over the energy crisis period along with the respective deterministic components. There is evidence of (yearly) seasonality, volatility, jumps, and mean reversion, especially in the particular case of Germany.

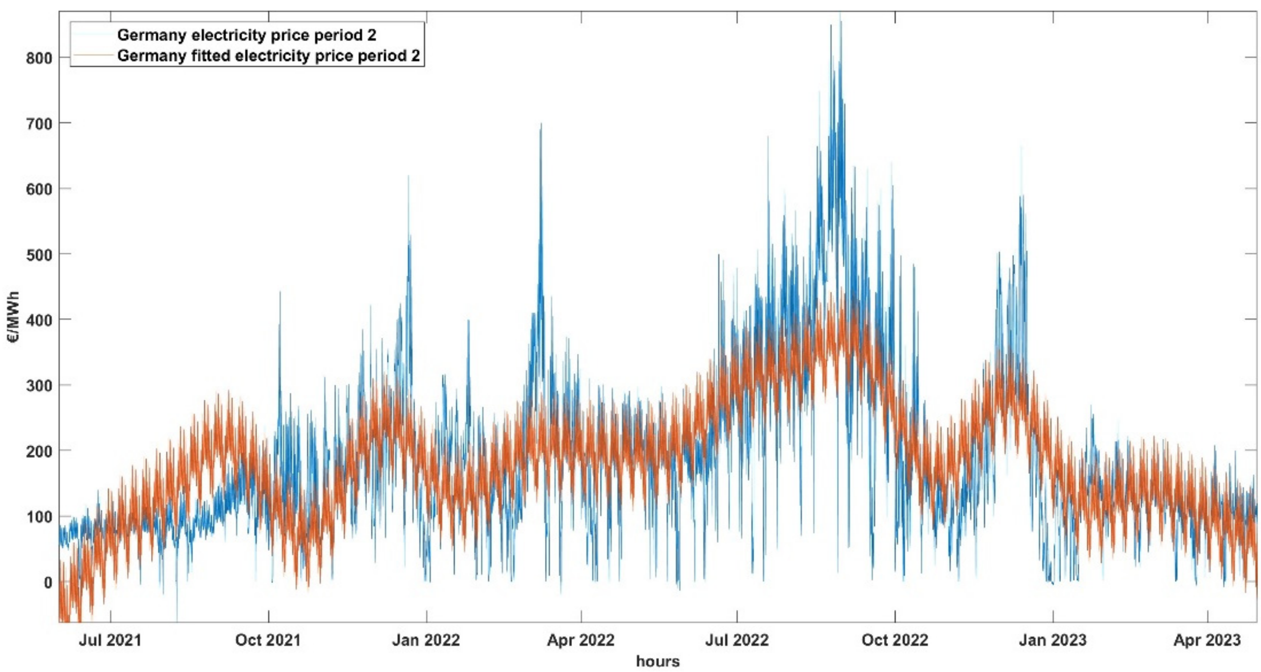


Figure 11. Germany, electricity prices (blue) and deterministic part (red) in crisis period.

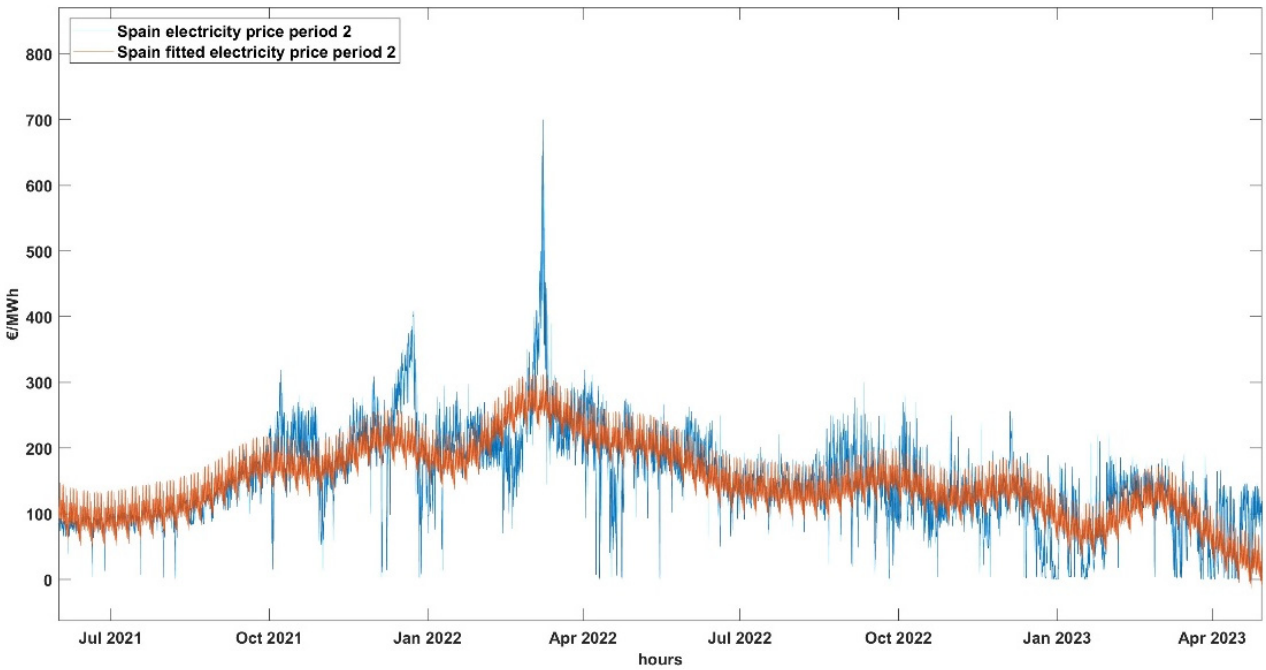


Figure 12. Spain, electricity prices (blue) and deterministic part (red) in crisis period.

4.2. Stochastic Parts

Now, moving on to the stochastic part of the hourly spot price entails getting the series of S_t^i residuals ($S_t^i = P_t^i - D^i(t)$, i.e., the residuals of the OLS regression). As expected, during the energy crisis (June 2021–May 2023) its volatility grows significantly (see Table 6). This fact renders future prices less predictable than in normal times. The biggest percentage increases take place in Italy and France; the opposite is true in the Iberian Peninsula and the UK, where it is smallest.

Table 6. Hourly volatility (EUR/MWh) of the S_t^i series in both periods for the sample countries.

Volatility	Spain	France	Portugal	UK	Italy	Germany	Belgium	The Netherlands
Normal	12.17	12.32	12.14	36.16	8.83	15.12	14.35	12.93
Crisis	45.52	88.19	45.34	96.52	72.61	86.85	84.09	81.89
% Change	274.1%	616.1%	273.6%	167.0%	722.3%	474.5%	485.9%	533.5%

According to Equation (6), the stochastic component S_t^i comprises two parts: an OU process and a Poisson process. We separate the mean-reverting part and the discrete-jumps part following a recursive approach. Starting from the initial series of S_t^i residuals, we consider that there is jump at a particular time when (the absolute value of) the residual at this time exceeds three times the standard deviation ('volatility') of that series; the same metrics is used by [6,14], among others. After this first residual is filtered out, the volatility of the initially considered mean-reverting part will be lower; thus, it is possible that new values turn up as jumps (in which case they are treated accordingly). The process finishes when the volatility of the mean-reverting part does not change and therefore no new jump arises. The number of iterations changes across countries and periods. The minimum number is six, and the maximum is nine; Ref. [9] performs a filter and smoother algorithm up to five times, the same number as [6]. In the end, starting from the S_t^i series the recursive procedure leads to two series: one corresponds to the OU process and the other to the Poisson process. Each series allows the derivation of numerical estimates of the parameters underlying it.

Figure 13 displays the decomposition of the S_t^i series for Germany during the energy crisis period. The upper graph shows the original series, i.e., the sum of the OU process and the Poisson process. The (discrete) series of jumps, whether negative or positive, is represented in the middle. The bottom graph shows the (continuous) series of mean-reverting changes. Clearly, whenever the S_t^i residual approaches 400 EUR/MWh in the upper graph the reason is a jump, not mean reversion; just look at the units along the vertical axes of the middle and bottom graphs.

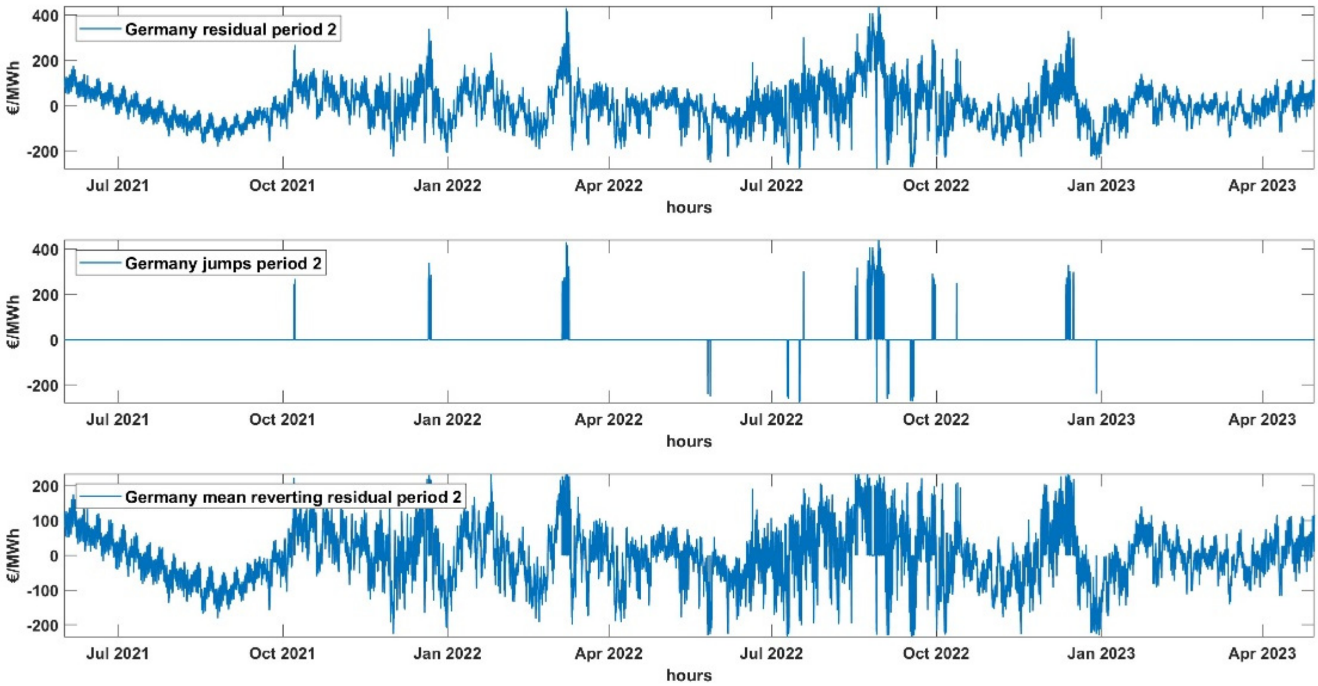


Figure 13. Germany's stochastic part over the crisis period: jumps and mean reversion.

At this point, it is worth remembering that, by assumption, $E\left(S_t^i\right)$ is zero. This applies to the upper series in Figure 13. Therefore, the averages of the other two series below must sum to zero. The graph in the middle shows more positive jumps than negative ones (i.e., the mean is positive). This in turn implies that the mean-reverting series in the lower graph must have a negative mean.

Similarly, Figure 14 displays the decomposition of the S_t^i series for Spain during the energy crisis period. The upper graph shows the original series. It is more stable than the German one (as suggested by Figures 11 and 12). The jumps in the middle graph are more abundant; nonetheless, their size is smaller. Interestingly, positive jumps in Spain synchronize well with the German ones, but this is not true for negative jumps, which are more frequent in Spain. The bottom graph of mean-reverting changes shows a similar size reduction: the range in Germany is [−200 EUR/MWh; 200 EUR/MWh], while in Spain it is [−100 EUR/MWh; 100 EUR/MWh].

The next step is to derive numerical estimates of the parameters underlying S_t^i in both periods. We use the residuals of the OLS regression (their average is zero). Upon identification of the jump series, parameter estimation is straightforward. Table 7 shows the results; note that $\Delta t = 1/(365 \times 24)$.

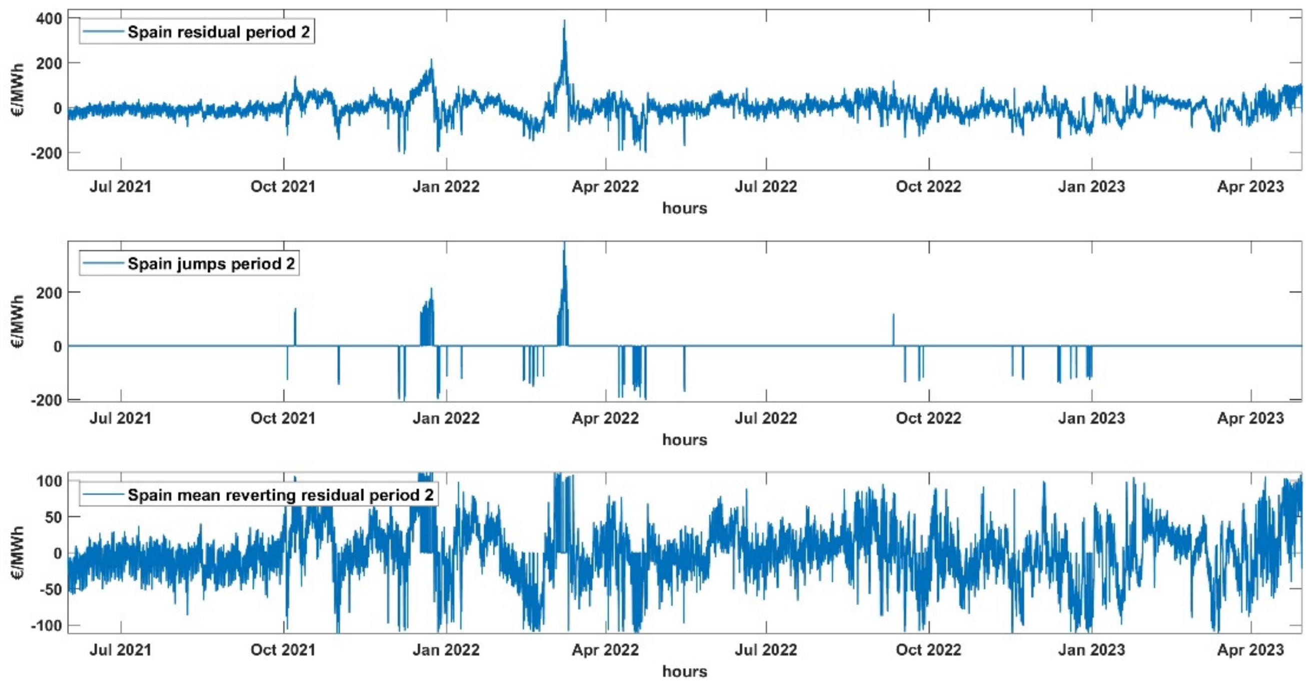


Figure 14. Spain's stochastic part over the crisis period: jumps and mean reversion.

Table 7. Stochastic part S_t^i: parameter estimates of the jump process.

Country	Parameter	Period 1		Period 2	
		Value	95% Confidence Int.	Value	95% Confidence Int.
Spain	λ^i	0.0441	(0.0318, 0.0564)	0.0264	(0.01836, 0.0344)
	μ_j^i	−14.4427	(−17.7146, −11.1708)	18.5654	(3.6591, 33.4717)
	σ_j^i	35.3564	(33.1898, 37.828)	159.637	(149.772, 170.904)
France	λ^i	0.0443	(0.0342, 0.0544)	0.0169	(0.0109, 0.0230)
	μ_j^i	−12.2928	(−15.9278, −8.6578)	278.116	(251.293, 304.938)
	σ_j^i	39.3675	(36.96, 42.1129)	229.641	(212.18, 250.257)
Portugal	λ^i	0.0442	(0.0317, 0.0567)	0.0260	(0.0180, 0.0341)
	μ_j^i	−14.3919	(−17.6526, −11.1313)	21.7014	(6.7194, 36.6833]
	σ_j^i	35.2744	(33.115, 37.7373)	159.351	(149.44, 170.68)
UK	λ^i	0.0247	(0.0180, 0.0315)	0.0255	(0.0183, 0.0326)
	μ_j^i	60.4514	(34.7452, 86.1576)	302.743	(272.567, 332.919)
	σ_j^i	207.616	(190.964, 227.473)	317.244	(297.298, 340.081)
Italy	λ^i	0.0246	(0.0179, 0.0313)	0.0157	(0.0093, 0.0221)
	μ_j^i	1.37807	(−2.4449, 5.2010)	219.776	(202.397, 237.156)
	σ_j^i	30.8143	(28.3383, 33.768)	143.414	(132.135, 156.814)
Germany	λ^i	0.0506	(0.03959, 0.0615)	0.0165	(0.0106, 0.0224)
	μ_j^i	−22.9209	(−26.7685, −19.0734)	199.309	(174.505, 224.114)
	σ_j^i	44.5307	(41.9718, 47.4244)	209.709	(193.579, 228.795)
Belgium	λ^i	0.0512	(0.0403, 0.0620)	0.0183	(0.0124, 0.0242)
	μ_j^i	−14.7873	(−18.6988, −10.8759)	162.406	(136.437, 188.375)
	σ_j^i	45.5337	(42.9313, 48.4744)	231.236	(214.277, 251.132)
The Netherlands	λ^i	0.0432	(0.0336, 0.0528)	0.0212	(0.0149, 0.0274)
	μ_j^i	−5.56887	(−9.6148, −1.5229)	135.724	(110.714, 160.734)
	σ_j^i	43.2802	(40.6028, 46.3386)	239.605	(223.181, 258.658)

Regarding Table 7, we focus specially on Germany and Spain (the analysis can be extended easily to the other markets in the sample). Starting with the former in the two periods, the expected number of jumps per hour (λ^i) drops by two-thirds from the normal period to the crisis period (namely, from 0.0506 to 0.0165). This may be a consequence of more volatile power prices in the crisis period: the higher the volatility, the higher the threshold to overcome (three times) in order to qualify as a jump. The jumps become more acute. The average size (μ_j^i) switches from (−22.9209) to 199.309 EUR/MWh, and volatility (σ_j^i) jumps from 44.5307 to 209.709 EUR/MWh, a factor of 4.7. In the case of Spain, the jumps undergo similar changes, but these are milder. The expected jumps per year (λ^i) decrease by less than one-half (from 0.0441 to 0.0264). Their average size (μ_j^i) reverses from (−14.4427) to 18.5654, and volatility (σ_j^i) increases by a factor of 4.5 (from 35.3564 to 159.637). These increases in jump sizes and volatilities are consistent with Table 6: S_t^i is more volatile in Germany than in Spain and becomes more so (see also Table 1).

The above patterns are broadly similar across all the sample markets. The expected number of jumps per year drops everywhere (except in the UK, where it is almost constant). In the normal period, the average jump size is negative in six (out of eight) markets (the exceptions being the UK and Italy). However, it is positive in all of them during the crisis period; for one, in Italy the average jump rises from 1.37807 to 219.776 EUR/MWh. As for jump volatility, in the normal period the UK is at the top (207.616) and Italy at the bottom (30.8143). They both keep their positions in the crisis period, but the gap compresses noticeably (317.244 and 143.414, respectively).

When it comes to the OU process, the parameters are estimated by OLS with HAC robust standard errors; see Table 8. Again, we look in particular to Germany and Spain; regarding the absolute parameter estimates, note that in Equation (6) the first parenthesis is multiplied by dt, which equals (1/8760) here. As explained in Section 2, the joint parameter α^i/κ^i is the level toward which the mean-reverting part of the electricity price in country i tends in the long term; further, it does so at a reversion speed κ^i. During the normal period, the long-term level of S_t^i is positive in both Germany (1.1574) and Spain (0.6410), both measured in EUR/MWh. Nonetheles, it switches to negative in the crisis period (−3.2956 and −0.4108, respectively). On the other hand, remember that, by assumption, $E\left(S_t^i\right) = 0$: the averages of the two underlying processes must sum to zero. In this regard, whenever the value of μ_j^i in Table 7 is negative, the corresponding α^i/κ^i on Table 8 is positive, and the opposite is also true. Overall, the results are consistent with those in Table 6, namely the higher volatility levels in Germany (whatever the period considered) and also the bigger increase in volatility.

The reversion speed κ^i falls in both countries: by around two-thirds in Germany (from 1431.94 to 507.31) and less than one-fifth in Spain (from 900.05 to 737.42). Note that $k = ln2/t_{1/2}$, where $t_{1/2}$ is the expected half-life of the (deseasonalized) stochastic part, i.e., the time required for the gap between S_0^i and the long-term level α^i/κ^i to halve. A lower speed of reversion means that, when a shock to S_t^i strikes, the impact takes longer to disappear (or S_t^i takes longer to stabilize). In other words, the anchoring effect of long-run levels α^i/κ^i weakens. In turn, intuition suggests that more observations far from the average (because of the slower reversion) will lead to higher volatility in the series. Table 8 shows that the volatility of the mean-reverting process (σ^i) doubles in the crisis period: in Germany from 219.36 to 480.02, and in Spain from 187.94 to 362.41. Again, this is consistent with the results in Table 6.

Now at the sample level, in the normal period, the long-term level α^i/κ^i is negative in just two countries, namely the UK (−1.5009) and Italy (−0.0354). All other countries are somewhere between The Netherlands (0.2383) and Germany (1.1574). Perhaps a possible interpretation is that even in this period, the UK was already hard-pressed in terms of power prices (in Table 1 it tops the rank with the highest average price, 53.0 EUR/MWh, followed by Italy, so the 'natural' path forward is downward). Yet, in the second period all of them display negative values of α^i/κ^i. The lowest ones correspond to the UK (−7.6989) and France (−4.7273). In the opposite extreme, we find Spain (−0.4108) and Portugal (−0.4869). The biggest drops take place in the UK and France, and the smallest ones in Spain and Portugal.

Table 8. Stochastic part S_t^i: parameter estimates of the mean-reverting process.

Country	Parameter	Period 1		Period 2	
		Value	95% Confidence Int.	Value	95% Confidence Int.
Spain	α^i	576.92	(−82.96, 1236.79)	−302.94	(−2145.33, 1539.46)
	k^i	900.05	(789.28, 1010.81)	737.42	(653.18, 821.65)
	σ^i	187.94	(186.67, 189.25)	362.41	(360.48, 364.36)
France	α^i	722.81	(−57.06, 1502.68)	−2668.79	(−5643.07, 305.49)
	k^i	1336.16	(1216.69, 1455.64)	564.55	(485.44, 643.64)
	σ^i	201.44	(200.07, 202.83)	480.17	(477.63, 482.76)
Portugal	α^i	551.88	(−87.67, 1205.88)	−354.12	(−2177.74, 1469.51)
	k^i	872.89	(762.38, 983.4)	727.29	(645.87, 808.71)
	σ^i	186.31	(185.04, 187.6)	360.71	(358.8, 362.66)
UK	α^i	−2916.67	(−4275.61, −1557.73)	−6064.53	(−9442.32, −2686.73)
	k^i	1943.31	(1818.22, 2068.39)	787.72	(706.02, 869.42)
	σ^i	260.43	(258.66, 262.23)	489.85	(487.25, 492.49)
Italy	α^i	−55.61	(−736.76, 625.54)	−1910.29	(−4408.36, 587.77)
	k^i	1570.10	(1457.43, 1682.8)	542.41	(469.32, 615.5)
	σ^i	192.30	(190.99, 193.63)	442.67	(440.32, 445.04)
Germany	α^i	1657.33	(712.19, 2602.47)	−1671.86	(−4724.35, 1380.61)
	k^i	1431.94	(1302.63, 1561.25)	507.31	(436.22, 578.39)
	σ^i	219.36	(217.88, 220.88)	480.02	(477.48, 482.61)
Belgium	α^i	1230.48	(281.95, 2179.01)	−2221.93	(−5894.06, 1450.2)
	k^i	1636.34	(1499.6, 1773.09)	745.24	(661.05, 829.44)
	σ^i	241.23	(239.6, 242.91)	514.47	(511.74, 517.25)
The Netherlands	α^i	431.50	(−528.79, 1391.79)	−2455.92	(−6258.76, 1346.96)
	k^i	1810.56	(1669.2, 1951.93)	853.33	(769.38, 937.28)
	σ^i	221.68	(220.18, 223.22)	518.87	(516.12, 521.67)

Regarding the reversion speed, κ^i falls the most in Italy (65.45%) and Germany (64.57%). It falls the least in Portugal (16.68%) and Spain (18.07%). As before, the volatility of the mean-reverting process (σ^i) increases significantly in the crisis period. It rises by 138.37% in France and 134.06% in The Netherlands. Instead, it does so only by 88.09% in the UK and 92.83% in Spain.

5. Discussion

Looking at hourly prices in both sub-periods, we found that price averages and volatilities rise noticeably from the first one to the second (with the increases comparatively weaker in the Iberian Peninsula). Skewness is also reinforced in the crisis period (except in the UK, where it reaches the highest levels). The same applies to kurtosis, which increases everywhere (except in the UK), well above 3.0 in every market. On the other hand, correlation analysis shows a fragmented market. In the first period, correlation between the five mainland countries is higher than 75%. It falls to around 50% between them and the UK, and somewhere between 62% and 74% between them and Portugal and Spain (which display an almost perfect match, 99.8%). In the second period, we identify two distinct dynamics: the correlation between core countries increases above 85%, and above 70% between them and the UK; instead, between core countries and the two Iberian countries, it falls to somewhere between 38% and 45% (which suggests de-coupling with the mainland). To some extent, these results resemble those in [19]: they too find strong similarities among most markets, while the Spanish and Portuguese electricity exchanges exhibit the weakest similarity to the broader European market.

Then, we estimated the model with hourly data from the above countries over the two periods. Regarding the deterministic component, we ran a linear OLS regression. In the normal period, the intercept is statistically significant everywhere, ranging between 14.00 EUR/MWh in the UK and 3.19 EUR/MWh in Spain. The linear time trend is also significant everywhere and positive (around 50). The quadratic time trend, instead, is not significant anywhere. Not surprisingly, some regularities arise in terms of seasonalities across countries. In the crisis period, there are several dramatic changes. Thus, the regression intercept remains significant but becomes negative and huge (between −1229.5 EUR/MWh in France and −345.44 EUR/MWh in Portugal). The linear time trend remains significant and positive, but jumps above 1000 in some countries. The quadratic time trend now becomes significant and negative. There are also changes in the seasonalities parameters. Common to all of them is a sizeable increase in their absolute values.

When it comes to the stochastic component, the starting point is the series of residuals of the earlier OLS regression. Its volatility grows significantly in the crisis period. As for estimation, the first step is to break the single series down into two, namely the continuous mean-reverting series and the discrete-jumps series. For this purpose we follow a recursive approach (it filters out the residuals whose absolute value exceeds three times the series volatility). The number of iterations ranges between six and nine; it changes across countries and periods.

The series of jumps lends itself to straightforward estimation of the underlying parameters. Overall, in the second period the expected number of jumps per hour decreases across all the markets (apart from the UK, where it is essentially constant). The reason may be higher price volatilities in it, which raise the threshold to qualify as a jump (namely three times volatility). In addition, in the normal period the average jump is negative in most countries, but turns to positive everywhere in the crisis period. Jump volatility also rises in all of the markets, with the UK at the top and Italy at the bottom.

Unlike the former, the mean-reverting process is estimated from the corresponding series by OLS regression. In the normal period, the long-term level of the stochastic component is positive in most of the countries. However, it switches to negative in all of them in the crisis period; the extreme values are found in the UK (−7.6989 EUR/MWh) and Spain (−0.4108 EUR/MWh). The reversion speed falls everywhere in the second period, with the highest drop taking place in Italy (65.45%) and the lowest in Portugal (16.68%). The opposite happens with volatility, which increases significantly in the second period (the most in France and The Netherlands, and the least in the UK and Spain).

In short, the road toward an integrated EU internal market for electricity is far from over. As the impacts of the COVID-19 pandemic have faded away and the economies return to 'normal', core power markets have gotten more correlated; in a sense, it has brought the EU goal closer to fulfillment. Nonetheless, regarding the Iberian Peninsula, the pandemic seems to have put it farther apart from the mainland. This unexpected setback jeopardises ongoing efforts to bridge structural isolation from the main markets.

Our findings can be adressed from different perspectives, e.g., empirical and theoretical. Thus, Ref. [7] mentions several reasons for deviations from uniform spot prices, among them limited inter-connection capacities and differences in market design (e.g., auction design, pricing rules, closing hours. . .). Because of these 'imperfections', market coupling can play an important role in fostering market integration. But constraints loom. For instance, Ref. [26] finds a convergence of power prices in France and Germany in 2010 and 2011 (in the wake of market coupling). Nonetheless, since 2012 they have diverged; renewable generation in Germany is so high in certain hours that inter-connectors tend to get congested. Ref. [7] considers 25 European electricity market areas and finds similar results.

According to our results, policy makers face two opposing trends (convergence/divergence) behind recent events. Fortunately, this does not necessarily mean that they must take some mutually offsetting measures. For one, increasing inter-connection capacity bodes well both for the center and the periphery. Enhanced inter-connections not only contribute to integrating markets, but to the green energy transition as well. Consistent with this view, the European Commission published the fifth list of Projects of Common Interest (PCI) in November 2021. As it turns out, the majority of PCI projects involve just four countries, namely France, Germany, Spain, and Portugal. The largest one in particular concerns the French–Spanish border; Ref. [30] assesses the economics of the French–Spanish inter-connector over the period 2020–2022. Despite these projects, even in 2030 up to eight countries will fall short of the minimum inter-connection requirement (15%), among them France, Germany, Italy, and Spain; see Ref. [31]. Thus, additional investments in inter-connectors are needed. As suggested above, progress must be made in market harmonization as well.

In addition to the above factual issues, our results are also dependent on the particular price model adopted, which has some limitations. Thus, the parameters underlying mean reversion and discrete jumps are time-independent. This precludes any seasonal behavior, which can be restrictive; for instance, jumps may be more frequent at peak hours, or in winter (this is an empirical issue). Maybe continuous changes and discrete jumps revert to their starting levels at different speeds; imposing a single speed can lead to overestimation for the former and underestimation for the latter. In a more general model, they would be time-dependent; volatility would also be stochastic and account for jumps. Our treating national price series independently (as opposed to jointly) is another limitation of the paper. These venues are left for future research.

6. Conclusions

This paper focuses on spot power prices in Western Europe during the COVID-19 pandemic and the outbreak of the Russia–Ukraine war. It aims to assess whether these events have changed the inner dynamics of these prices (and, if so, how).

We introduce a new model for the hourly spot price of electricity. It comprises a deterministic component (with a time trend plus yearly, weekly, and daily seasonalities) and a stochastic component (with both a continuous- and a discrete-time process).

Our sample comprises Belgium, France, Germany, Italy, The Netherlands, Portugal, Spain, and the UK. Drawing on publicly available market prices, within the sample period we identify a 'normal' or 'pre-crisis' period (April 2020–May 2021) and an (energy prices) 'crisis' period (June 2021–May 2023).

A cursory look at hourly prices shows that all of the usual descriptive statistics (price averages, volatilities, skewness, and kurtosis) increase noticeably in the second period (relative to the first one). On the other hand, in the second period the correlation between core countries rises, while it falls between them and the two Iberian countries (which suggests de-coupling). In short, the pandemic and the war seem to have had two opposing impacts on the bumpy road toward an integrated EU internal market for electricity; while core power markets are getting more correlated (thus bringing the EU goal closer to fulfillment), the Iberian Peninsula is farther apart from the mainland.

Regarding estimation of the price model, we start from the deterministic component. In the first period, we find a positive linear time trend which, in the second one, shows up accompanied by a negative quadratic time trend. Not surprisingly, some regularities arise in terms of seasonalities across countries. In the crisis period, all of the seasonality parameters undergo a sizeable increase in their absolute values. Concerning the stochastic component, in the second period the expected number of price jumps per hour decreases everywhere, the average jump turns from negative to positive, and jump volatility rises. On the other hand, the long-term price level switches from positive to negative everywhere, the reversion speed falls, and volatility increases.

Our findings are partly owing to market 'imperfections', which call for further market harmonization. Increasing inter-connection capacity is another venue for improvement. Be that as it may, both private and public agents have prominent roles to play.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/en17143420/s1, Table S1: Spain deterministic parameters during normal period. Table S2: France deterministic parameters during normal period. Table S3: Portugal deterministic parameters during normal period. Table S4: U.K. deterministic parameters during normal period. Table S5: Italy deterministic parameters during normal period. Table S6: Germany deterministic parameters during normal period. Table S7: Belgium deterministic parameters during normal period. Table S8: Netherlands deterministic parameters during normal period. Table S9: Spain deterministic parameters during the energy crisis period. Table S10: France deterministic parameters during the energy crisis period. Table S11: Portugal deterministic parameters during the energy crisis period. Table S12: U.K. deterministic parameters during the energy crisis period. Table S13: Italy deterministic parameters during the energy crisis period. Table S14: Germany deterministic parameters during the energy crisis period. Table S15: Belgium deterministic parameters during the energy crisis period. Table S16: Netherlands deterministic parameters during the energy crisis period.

Author Contributions: Conceptualization, L.M.A. and J.M.C.; Methodology, L.M.A.; Software, L.M.A.; Validation, L.M.A.; Formal analysis, L.M.A. and J.M.C.; Investigation, L.M.A. and J.M.C.; Resources, L.M.A. and J.M.C.; Data curation, L.M.A.; Writing—original draft, J.M.C.; Writing—review & editing, J.M.C.; Visualization, L.M.A.; Supervision, J.M.C.; Project administration, L.M.A. and J.M.C.; Funding acquisition, J.M.C. All authors have read and agreed to the published version of the manuscript.

Funding: The authors gratefully acknowledge support from the Basque Government (IT1777-22−Environmental and Resources Economics Policy Group) and the Low Carbon Programme.

Data Availability Statement: The authors have drawn on the database of the Spanish power transmission and distribution system operator (Red Eléctrica de España), which is publicly available: https:/www.esios.ree.es/ (accessed on 31 October 2023).

Acknowledgments: The authors thank two anonymous referees for their helpful remarks. The authors remain responsible for any errors.

Conflicts of Interest: Author Luis María Abadie is employed by the Metroeconomica company. Author José Manuel Chamorro declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. EUR-Lex. Single European Act. Available online: https://eur-lex.europa.eu/eli/treaty/sea/sign (accessed on 1 November 2023).
2. EUR-Lex. Directive 96/92/EC of the European Parliament and of the Council of 19 December 1996 Concerning Common Rules for the Internal Market in Electricity. Available online: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:31996L0092 (accessed on 1 November 2023).
3. EUR-Lex. Directive 2003/54/EC of the European Parliament and of the Council of 26 June 2003 Concerning Common Rules for the Internal Market in Electricity and Repealing Directive 96/92/EC—Statements Made with Regard to Decommissioning and Waste Management Activities. Available online: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:32003L0054 (accessed on 1 November 2023).
4. EUR-Lex. Directive 2009/72/EC of the European Parliament and of the Council of 13 July 2009 Concerning Common Rules for the Internal Market in Electricity and Repealing Directive 2003/54/EC (Text with EEA Relevance). Available online: https://eur-lex.europa.eu/legal-content/en/TXT/?uri=CELEX:32009L0072 (accessed on 1 November 2023).
5. EUR-Lex. Directive (EU) 2019/944 of the European Parliament and of the Council of 5 June 2019 on Common Rules for the Internal Market for Electricity and Amending Directive 2012/27/EU (Recast) (Text with EEA Relevance). Available online: https://eur-lex.europa.eu/legal-content/en/TXT/?uri=CELEX:32019L0944 (accessed on 1 November 2023).
6. De Menezes, L.M.; Houllier, M.A. Reassessing the integration of European electricity markets: A fractional cointegration analysis. *Energy Econ.* **2016**, *53*, 132–150. [CrossRef]
7. Gugler, K.; Haxhimusa, A.; Liebensteiner, M. Integration of European Electricity Markets: Evidence from Spot Prices. *Energy J.* **2018**, *39*, 41–66. [CrossRef]
8. Ioannidis, F.; Kosmidou, K.; Makridou, G.; Andriosopoulos, K. Market design of an energy exchange: The case of Greece. *Energy Pol.* **2019**, *133*, 110887. [CrossRef]
9. Zachmann, G. Electricity wholesale market prices in Europe: Convergence? *Energy Econ.* **2008**, *30*, 1659–1671. [CrossRef]
10. Huisman, R.; Huurman, C.; Mahieu, R. Hourly electricity prices in day-ahead markets. *Energy Econ.* **2007**, *29*, 240–248. [CrossRef]
11. Escribano, A.; Peña, J.I.; Villaplana, P. Modelling electricity prices: International evidence. *Oxf. Bull. Econ. Stat.* **2011**, *73*, 622–650. [CrossRef]

12. Gudkov, N.; Ignatieva, K. Electricity price modelling with stochastic volatility and jumps: An empirical investigation. *Energy Econ.* **2021**, *98*, 105260. [CrossRef]
13. Ioannidis, F.; Kosmidou, K.; Savva, C.; Theodossiou, P. Electricity pricing using a periodic GARCH model with conditional skewness and kurtosis components. *Energy Econ.* **2021**, *95*, 105110. [CrossRef]
14. Deschatre, T.; Féron, O.; Gruet, P. A survey of electricity spot and futures price models for risk management applications. *Energy Econ.* **2021**, *102*, 105504. [CrossRef]
15. Hauser, P.; Schönheit, D.; Scharf, H.; Anke, C.P.; Möst, D. COVID-19's impact on European power sectors: An econometric analysis. *Energies* **2021**, *14*, 1639. [CrossRef]
16. Navon, A.; Machlev, R.; Carmon, D.; Onile, A.E.; Belikov, J.; Levron, Y. Effects of the Covid-19 pandemic on energy systems and electric power grids: A review of the challenges ahead. *Energies* **2021**, *14*, 1056. [CrossRef]
17. Bompard, E.; Mosca, C.; Colella, P.; Antonopoulos, G.; Fulli, G.; Masera, M.; Poncela-Blanco, M.; Vitiello, S. The immediate impacts of COVID-19 on European electricity systems: A first assessment and lessons learned. *Energies* **2021**, *14*, 96. [CrossRef]
18. Kapral, K.; Soetaert, K.; Castro, R. An off-site power purchase agreement (PPA) as a tool to protect against electricity price spikes: Developing a framework for risk assessment and mitigation. *Energies* **2024**, *17*, 2161. [CrossRef]
19. Szeberényi, A.; Bakó, F. Electricity market dynamics and regional interdependence in the face of pandemic restrictions and the Russian-Ukrainian conflict. *Energies* **2023**, *16*, 6515. [CrossRef]
20. World Health Organization. Coronavirus Disease (COVID-19) Pandemic. Available online: https://www.who.int/europe/emergencies/situations/covid-19 (accessed on 1 June 2024).
21. Bosco, B.; Parisio, L.; Pelagatti, M.; Baldi, F. Long-run relations in European electricity markets. *J. Appl. Econom.* **2010**, *25*, 805–832. [CrossRef]
22. Nepal, R.; Jamasb, T. Interconnections and market integration in the Irish Single Electricity Market. *Energy Policy* **2012**, *51*, 425–434. [CrossRef]
23. Christensen, T.S.; Benth, F.E. Modelling the joint behaviour of electricity prices in interconnected markets. *Quant. Financ.* **2020**, *20*, 1441–1456. [CrossRef]
24. Çanakoğlu, E.; Adiyeke, E. Comparison of electricity spot price modelling and risk management applications. *Energies* **2020**, *13*, 4698. [CrossRef]
25. Engel, C.; Rogers, J.H. European product market integration after the Euro. *Econ. Policy* **2004**, *19*, 347–384. [CrossRef]
26. Keles, D.; Dehler-Holland, J.; Densing, M.; Panos, E.; Hack, F. Cross-border effects in interconnected electricity markets—An analysis of the Swiss electricity prices. *Energy Econ.* **2020**, *90*, 104802. [CrossRef]
27. Mas Urquijo, I.; Paraschiv, F. Cross-border Effects between the Spanish and French Electricity Markets: Asymmetric Dynamics and Benefits in the Light of European Market Integration. *Energy J.* **2023**, *44*, 241–276. [CrossRef]
28. REE. Available online: https://www.sistemaelectrico-ree.es/2021/informe-del-sistema-electrico/mercados/mercado-diario (accessed on 1 June 2024).
29. Keppler, J.H.; Phan, F.; Le Pen, Y. The impacts of variable renewable production and market coupling on the convergence of French and German electricity prices. *Energy J.* **2016**, *37*, 343–359. [CrossRef]
30. Abadie, L.M.; Chamorro, J.M. Evaluation of a cross-border electricity interconnection: The case of Spain-France. *Energy* **2021**, *233*, 121177. [CrossRef]
31. Mezősi, A.; Kácsor, E.; Diallo, A. Projects of common interest? Evaluation of European electricity interconnectors. *Util. Policy* **2023**, *84*, 101642. [CrossRef]