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ABSTRACT
Renewable generation has increased exceptionally its weight in power markets, and its relevance is due to increase with the introduction of recent climate policies in Europe. The merit-order effect ranks first on the direct impacts of renewables on electricity markets. However, in order to analyse its impact, it is important to control for the different forces driving electricity prices. As a result, the analysis through a structural model of demand and supply of electricity is interesting to capture price drivers and therefore measure correctly the merit-order effect. The objective of this paper is to introduce this framework on the Spanish day-ahead market, using weekly data for the period 2013-2019. The empirical analysis is carried out using structural vector autoregressive models (SVAR) and autoregressive distributed lag models (ARDL) to each equation, with the addition of GARCH models to control for the possible autoregressive volatility behaviour of the residuals. In line with previous literature, we obtain that demand of electricity is elastic to economic growth, price-inelastic and shows a significant level of substitution between electricity and natural gas. The supply function is also price-inelastic, after controlling for capacity factors, inputs prices and external balance, that are shown to be significant. The estimated values of the merit-order effect is aligned with previous literature. We obtain that a 10% increase in the average quantity generated by the special regime technologies (wind, solar and CHP) is associated with a 5 % reduction in electricity prices, around 2.35€/MWh of the average price for the analysed period.

JEL: L94, L51, L52, L13.

Keywords: Demand of electricity, Supply of electricity, Merit-Order, Renewable generation, Capacity Factor, Day-ahead Power market.

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1. Introduction

The renewable energy industry around the world has experienced an unprecedented development in recent years, and its contribution to electricity generation has increased significantly. It will play an even more significant role in the transition to carbon-efficient economies. The Spanish National Integrated Plan for Energy and Climate 2021-2030 (PNIEC by the Spanish acronym) establishes the objective to reduce emissions in 23% by 2030 in comparison to 1990.[1] To do so, renewable generation is expected to make up over 70% of electricity generation by 2030 and over 35% of primary energy consumption.

In Spain, renewable generation grew fast due to the incentives given through feed-in tariffs and feed-in premiums. With these policies implemented, wind and solar energy increased their installed capacities significantly after 2007, when these incentives were introduced (Bianco et al., 2019). Such policies aim is to increase investment by reducing the risk of renewable projects, ensuring a minimum threshold of revenue to generators.

The main research line about the effects of renewable energy sources in wholesale markets is a down-pressure in electricity equilibrium prices. In order to obtain the equilibrium of demand and supply, bids from generators are ordered increasingly following the *merit-order* to build supply. One of the principles supply formation could follow is to define the merit-order in terms of the marginal cost of each generating technology (Bhattacharyya, 2011), which is the case of the Spanish market.

Since the marginal cost of operating renewable technologies is close to 0, they are placed at the bottom of the merit order. Therefore, an increase of renewable energies will shift supply outwards, displacing the least efficient sources and meeting the demand at a lower price. This is the merit-order effect of Renewable Energy Sources (RES).

However, the increased penetration of RES could also present problems on its own. The volatility and uncertainty on wind generation may create a concern regarding security of supply and the need for thermal generation to cover-up the unexpected drops in RES, given the expected phase-out of the nuclear power plants by 2035. There is a substantial body of literature analysing such concerns. Although most of these analyses are theoretical (Ambec and Crampes, 2012; Green et al., 2011), analysing the need to determine the complexity of capacity payments and how to establish them in the future. While renewable energies will decrease equilibrium prices, there is also a smaller room for thermal units like coal or CCGT to produce. A significant increase in renewable energies could displace thermal units out of the market, leading to their shut down, which justifies the existence of capacity payments in the system to ensure security of supply (Böckers et all., 2013).

The main idea to acknowledge heading to this analysis is that the share increase of renewable energies will improve welfare if and only if the profits from such an increase overcome the different payments (Newbery et al., 2018). Savings from increased renewable generation come from thermal units' fuel costs and reduced capacity payments as renewable generation increases. Besides, capacity payments

1 All the information and analysis previous to the publication of the PNIEC can be found in MITECO's website.

to thermal units will vanish when renewable capacity is large enough to sustain demand alone (Newbery et al., 2018).

In the Spanish day-ahead market, there are several analyses dealing with these topics (Marques et al., 2019; Roldán-Fernandez et al., 2018; Cabello et al., 2014; Espinosa and Pizarro-Irizar, 2018; Gerres et al., 2019). Furthermore, Bianco et al. (2019) expose the impact of the increased renewable sources share on total generation of combined cycle plants (CCGT) and thermal units. The increased deployment of RES on the system decreased equilibrium prices and therefore the competitiveness of thermal units, making the investment on thermal units unprofitable. For that reason, Ciarreta et al. (2016) explains that the increased penetration of RES forced some thermal plants, mainly combined cycles, to use more competitive strategies.

To understand the impact of RES generation on electricity prices, it is necessary to have a broad view of the main drivers in electricity markets. As a result, this analysis will cover the determinants of the demand and supply curve shifters, so we can understand price formation in the equilibrium and focusing specially in the merit-order effect.

This paper will be structured as follows: section 2, includes a literature review of relevant analysis done on the Spanish day-ahead electricity market, together with references to other markets that are relevant for the analysis of the merit-order effect using a structural approach. Section 3, discusses the structural approach and the challenges that we may face applying the structural analysis to the case of electricity markets in Spain. Furthermore, we describe the main variables of our database and the econometric strategy used in the specification, estimation and testing of the equilibrium dynamic system of equations in structural form. Section 4, presents the empirical analysis of the system of equations in reduced form estimating a vector autoregressive (VAR) model and their corresponding impulse response functions (IRF) and the forecast errors variances. Section 5, discusses the empirical results from single-equation dynamic models in structural form of demand and supply equations. Finally, section 6 includes the main conclusions of our analysis and possible extensions.

2. Literature review of electricity markets

This section will be divided into two parts. Firstly, we introduce the analysis of electricity markets through structural analysis, showing the different approaches found in the literature. After that, we will focus on the literature review of the Spanish market to support our empirical analysis.

The application of structural analysis to electricity markets was introduced in economic analysis after the liberalization process, since the freely traded commodity prices were now closer to be determined by the interaction between supply and demand (Fezzi and Bunn, 2010). Weron (2014) gathers the most relevant approaches to analyse electricity markets and establishes five different categories for methodologies: multi-agent, fundamental, reduced-form, statistical, and computational intelligence models (Ziel and Steinert, 2016). Structural analysis falls under the category of fundamental models since we are analysing exogenous drivers. In the literature, different techniques and approaches can be found. Although they usually receive the name of structural analysis, the denomination of supply-demand framework is very popular because the analysis uses information from both "sides" of the market.

One of the techniques exploiting the demand-supply framework is the X-Model. It was introduced in the financial analysis of electricity prices, following the first steps taken by Barlow (2002) in the introduction of diffusion models to analyse electricity prices. This model covers a broad range of techniques that do not directly analyse the process of price formation. Instead, they analyse the sale and purchase curves defined in the auction process in electricity market exchanges (Ziel and Steinert, 2016), obtaining the supply and demand functions, and then analysing the electricity price formation under the equilibrium assumption that supply and demand must match.

The main advantage of these techniques is a better capture of price spikes, see Escribano et al. (2011), coming from the intersection of a complex supply mix and/or a given load/demand. However, the main drawback of this approach is that it requires a large amount of micro-level data. Furthermore, in order to define the supply and demand functions from the auction data, these papers usually impose certain restrictions for equilibrium-curves generation or assume a predefined form for either demand or supply functions. The most usual restriction is defining a perfectly inelastic demand function, which grants the opportunity to capture the supply curve and the merit order more carefully (Carmona et al., 2013; Kulakov, 2020; Shah and Lisi, 2020).

Some examples of crucial variables to define supply are input prices, emission prices and capacity availability. The lessons from this framework are still followed in the application of reduced-form analysis. The reduced-form analysis of the market is only focusing on the analysis of quantities and prices, so while it is still exploiting drivers of demand and supply, it loses the identification of these demand and supply curves. Carmona and Coulon (2014) present a deep explanation of the discussion around the use of both approaches and explain some advantages of the structural model over the reduced form. These are usually related to the identification of sources for the randomness in prices due to jumps or diffusion processes. To put it briefly, the broader view of the market helps to understand the different mechanisms in price formation and explaining extreme events.

Fezzi and Bunn (2010) used this approach to analyse the PJM day-ahead market following an Asymmetric VAR model. They focus on a static model of supply and demand, controlling for nonlinear reactions in the short-term. Their results show that demand is inelastic to prices, but it reacts to past positive shocks in supply. Buzoianu et al. (2005) provides an extension of the framework using dynamic models of supply and demand, analysing equilibrium prices by including latent supply and demand curves that vary over time. Their demand analysis establishes for the first time in this literature review the non-linear impact of temperature on demand, with the use of a comfort zone defined by thresholds. Boogert and Dupont (2008) analyse the Dutch market, focusing on the impact of capacity availability to estimate price spikes. As it is usual, they assume that demand is insensitive to prices, so that they can focus on the behaviour of supply. They introduce the concept of reserve margin index, which represents the fraction of the supply available to cover demand. Their results show that the available capacity is closely connected to capacity utilization, and forecasting is improved when taking the margin into account.

The only example of the reduced-form model applied in the Spanish market is Marques et al. (2010). Their period of analysis covers the last years before the formation of the Iberian Market (MIBEL). However, their approach is not to understand electricity price drivers but analyse the exercise of market power in the framework of "New Industrial Economics". Their demand equation takes a linear function, controlling for oil prices, temperatures, and a tourism variable. Their results show an aggregated elasticity of demand close to -0.1. Their supply equation, apart from input prices and hydro capacity, takes estimates of the average collusiveness of conduct. Their results show the market was not pricing consistently over marginal cost. Their control variables of the supply would be nowadays considered too restrictive for our analysis since they do not control for RES.

Our analysis, although following the fundamental analysis of electricity equilibrium prices through a well identified structural model of demand and supply, it is close to the category "statistical analysis" defined by Weron (2014), since it is based on aggregated data for the wholesale electricity market, without observing more detailed data on individual marginal costs or on the complex definition of aggregate demand and supply from individual agent information. On the other hand, the possible application of non-linear structural models can even be extended through GARCH models of the residuals. This is an important issue, given the clear evidence found in price spikes through regime-switching or jump-diffusion (Ziel et al., 2015; Escribano et al., 2011).

For the rest of the section, we focus on the literature review in the Spanish day-ahead market. We hope to justify the selection of the main drivers to include in our empirical analysis. Energy consumption and growth are usually closely related, which is the discussion of coupling (Bhattacharyya, 2011). This discussion is especially relevant in the Spanish case, since the income-elasticity in Spain is one of the highest in the European Union (Pérez-García and Moral-Carcedo, 2017). One of their main results is that the income-elasticities for electricity consumption are converging across Europe and have been decreasing due to the reduction of industrial activities weight in GDP.

However, the relationship between economic growth, and energy demand is not so clear-cut. On the one hand, efficiency gains could lead to a decoupling of energy demand and growth, but the relationship is still relevant due to the rebound effect (Rausch and Schwerin, 2016). On the other hand, both are endogenous processes since energy availability is necessary for economic development (Toman and Jemelkova, 2003). Besides, there are certain future issues that may affect non-residential electricity consumption, such as electrification of the economy (substituting fossil-fuelled assets with electric), and energy efficiency policies (Pérez-García and Moral-Carcedo, 2017). A further look into reasons behind the energy consumption growth in Spain can be found in Pérez-García and Moral-Carcedo (2016), which shows through a decomposition analysis the impact of economic structure (as in the distribution of production by sector) and cyclic behaviour (GDP). For the period 1970-2012, 44% of energy demand growth was caused by economic growth itself. Other relevant factors are non-residential intensity, households, and demographic changes.[2] One exercise analysing the decoupling effect in Spain is García-Gusano et al. (2018) comparing different techniques to forecast demand for

2 The analysis of energy consumption from the household sector can be found in (Escobar et al., 2020).

long horizons. Their results suggest that it is important to take into account the endogeneity between growth and energy to analyse a decoupling effect.

Another of the main variables in aggregate electricity demand is temperature. One of the first studies for Spain to this regard is Pardo et al. (2002), which introduces the use of derived temperature variables to capture outdoor air temperature, Cooling Degree Days (CDD), and Heating Degree Days (HDD). Although their goal is to forecast prices given past values of temperature, their results show that load is indeed affected by contemporaneous and past temperatures, with HDD having a higher impact. Romero-Jordán et al. (2014) and Blázquez et al. (2013) provide analysis for the impact of these variables on household electricity consumption. Moral-Carcedo and Pérez-García (2015) is an example of that analysis in the industrial sector, defining that Retail trade, Public administration, Accommodation, Health, Water collection, and Manufacturing are especially sensitive to temperatures.

Ballester and Furió (2015) analyses the stylized facts of prices. Their results show a negative relationship between renewable generation share and day-ahead market prices, but that it also increases price volatility. The problem is that their regression of prices is only include a constant and the renewable share, without more control variables, and therefore are subject to omitted variables biases. On the other hand, they find that increases in this share of renewables reduce the probability of jumps in peak prices. Furthermore, they also find a negative relationship between this share and the number of times combined cycle plants (CCGT) set marginal equilibrium prices.

Pereira da Silva and Horta (2019) analyses the impact of variable RES on price volatility. Their results show, once more, that price volatility is expected to rise as a consequence of wind and solar penetration. However, their results have interesting results for solar production. In some cases, they find a negative impact of solar generation on price volatility, which could be connected to the fact that solar generation often coincides with peak demand and it reduces the jump between peak and valley periods.

Gelabert et al. (2011) use a multiple regression of prices on quantities for different technologies and they do not take into account the endogeneity coming from the simultaneous process of demand and equilibrium prices since they focus on cointegration. An important difference from our approach is that they only focus on price equation, and they do not identify the differences between the demand and supply effects. Their results show that a 1 GWh increase in electricity production leads to a reduction of 1.9€ in prices (4% of average daily price between 2005 and 2010).

Böckers et al. (2013) estimate the merit-order effect of renewable energies and the displacement of other technologies with a structural VAR. The main driver of renewable generation is wind, with mid-merit technologies being more affected than peak-load plants, specially CCGT generation. Their estimations show that a 1 GWh increase in electricity production leads to a reduction of 3.1% in electricity prices.

Azofra et al. (2014) analyses the impact of wind on electricity prices through scenarios of production. Their estimates show that wind generation reduced prices in 9 €/MWh and a 10% a reduction in wind generation would lead to 7.42 €/MWh of saving.

Lastly, there are exercises to forecast prices in the Spanish market using machine learning and nonlinear functions, which show that including renewable generation improves forecasting accuracy (Romero et al., 2018; Yang et al., 2017; Cruz et al., 2011).

3. Methodology: Structural modelling and data

This section will define the framework for the structural analysis of the aggregate day-ahead market equilibrium and present the data used in the empirical analysis.

3.1 Structural Modelling

The approach our estimations will try to apply is to analyse the Spanish day-ahead market is the structural analysis, studying the system of equations formed by demand, supply, and prices. This approach allows us to have an overall look at the market, analysing both demand and supply individually to increase our understanding of price's behaviour. The structural demand function for electricity evaluated at the market equilibrium:

$$\phi_{qd}(L)logQE_t = \phi_0 + \theta_{pd}(L)logPE_t + \delta'_{rd}(L)X_{dt} + \varepsilon_{dt} \quad (1)$$

where the corresponding polynomials in the lag operator L are given by; $\phi_{qd}(L) = 1 + \sum_{i=1}^{q1} \phi_{id} L^i$, $\theta_{pd}(L) = \theta_{0d} + \sum_{i=1}^{q2} \theta_{id} L^i$ and similarly with $\delta'_{rd}(L)$.

The structural supply function (inverse) of electricity evaluated at the market equilibrium:

$$\rho_{ps}(L)logPE_t = \alpha_0 + \alpha_{qs}(L)logQE_t + \pi'_{rs}(L)X_{st} + \varepsilon_{st} \quad (2)$$

where the corresponding polynomials in the lag operator L are now given by; $\rho_{ps}(L) = 1 + \sum_{i=1}^{p1} \rho_{is} L^i$, $\alpha_{ps}(L) = \alpha_{0s} + \sum_{i=1}^{p2} \alpha_{is} L^i$ and similarly with $\pi'_{rs}(L)$.

For identification purposes of those demand and supply equations of electricity, we require that the vector of explanatory variables in X_{dt} and X_{st}, should have some different components, although some will overlap Woolridge (2002). For example, the variable income should only be a component of the demand variables (X_{dt}) and certain inputs affecting the cost of production should only be a component of the supply variables (X_{st}).

From the total, or long-run, multipliers of the autoregressive distributed lag (ARDL) models, equations (1) and (2), we obtain the long-run *price-elasticity of demand* as $\varepsilon_{q,p}^{d} = \theta_{pd}(1)/\phi_{qd}(1)$ and the long-run *price-elasticity of supply* as $\varepsilon_{q,p}^{s} = \alpha_{pd}(1)/\rho_{qd}(1)$.

In order to write ARDL of equations (1) and (2) as a simultaneous equation system it is convenient to write them more explicitly as in (3) and (4),

$$logQE_t = \phi_0 + \widetilde{\phi_{qd}}(L)logQE_{t-1} + \theta_{0d}\log PE_t + \widetilde{\theta_{pd}}(L)\log PE_{t-1} + \delta'_{rd}(L)X_{dt} + \varepsilon_{dt} \quad (3)$$

$$logPE_t = \alpha_0 + \widetilde{\rho_{ps}}(L)logPE_{t-1} + \alpha_{0s}\log QE_t + \widetilde{\alpha_{qs}}(L)logQE_{t-1} + \pi'_{rs}(L)X_{st} + \varepsilon_{st} \quad (4)$$

Solving this system of equations will, in result, grant the opportunity to analyze factors that will determine equilibrium prices. The reduced form function of equilibrium prices (PE), by substituting (3) into (4) we get,

$$\log PE_t = \gamma_0 + \widetilde{\gamma_p}(L)\log PE_{t-1} + \gamma'_{rd}(L)X_{dt} + \pi'_{rs}(L)X_{st} + u_{pt} \quad (5)$$

where the new gamma-parameters of (5) are linear combinations of the structural parameters of equations (3) and (4).

The reduced-form coefficients can be interpreted as the net effect of each variable on equilibrium prices, since we are differentiating the variables X_s that shifts the supply curve and the variables X_d that shifts the demand curve, relative to the price elasticities of these two functions.

Since most of our variables are only included in the demand or the supply, we could already classify the previously commented controls in these two categories. For example, the variable Capacity factor would fall in the first category. However, the variables Balance, GDP, CDD and HDD would be an example of the second category.

The analysis of structural equations is a typical example of a simultaneous equation model, and a specific example of autonomous equations, since both demand and supply have an economic interpretation and relevance on their own. Firstly, the identification of demand and supply functions is coming from the variables affecting only the demand function (income, etc.) and only the supply functions (mainly variables related to the cost of production, etc.). The data on quantity and prices that we observe are the equilibrium values of the market, equations (1) and (2) simultaneously. As a result, a simple regression analyzing only the relationship between quantities and prices we cannot directly identify if the price-elasticities estimated corresponds to the demand or the supply. Therefore, identification is accomplished by exploiting shifts in only one of the equations, say a demand curve to identify the supply curve, and vice versa. It is important to understand that the empirical analysis done in this paper with aggregate data of the market, we are studding changes affecting the equilibrium values of these two equations.

Nevertheless, we cannot simply discard the fact that the real data generation process for supply quantities is, indeed, stepping. Consequently, to get a better grip on our estimations, we need to bear in mind that in the equilibrium, the price-elasticity of supply might be small. Secondly, the simultaneous determination of these equations raises an endogeneity problem in the electricity price series, in the demand and supply equations which we must address of to avoid estimation biases. In a regression of quantity (Q) on prices (P), any shock in demand or supply will affect both the regressor (P) and the error term of the regression. The usual econometric technique employed in the literature is instrumental variables. The advantage of this kind of formulation of the equilibrium is that supply shifters can be used in order to identify instruments for prices in the demand function, and vice versa. The discussion about the instruments used in each model will be presented in following sections. Thirdly, the estimation of simultaneous equations raises the question so as to whether it is interesting to estimate the equations simultaneously or separately. A system of equations estimation is more efficient whenever all the equations of the system are correctly specified. However, a more robust procedure is to use single-equation estimation methods, such as 2SLS, which is consistent estimator if the instruments are exogenous, independently of the misspecification of the other equation of the system. Therefore, we will estimate the two equations separately.

As for the specification of the models, both linear and log-linear specifications are likely to provide valid but different elasticity estimates. Due to the volatility and spiky behavior of prices observed in our sample, our estimations will consider the estimation of log-linear functions, which is helpful to reduce volatility and possible effects of outliers. Furthermore, the approach using all variables in logs will directly provide the estimation of constant elasticities, simplifying the interpretation of the main implications.

The only paper found applying a similar approach to the Spanish market is Marques et al. (2010). However, they do not have the objective to analyze electricity drivers of the equilibrium variables, and therefore they do not address the analysis of the merit-order effect of RES and it is only based on a reduced-form approach. In particular, their supply analysis uses prices as the dependent variable, thus differing from the application in this paper.

In order to analyze the equilibrium dynamic interactions between quantities and prices at the equilibrium, we will use the following structural form vector autoregressive model with exogenous variables. Writing the system of equations (3) – (4) as a *Structural Vector Autoregressive* model with X-exogenous variables (SVAR-X), we get,

$$\begin{bmatrix} 1 & -\theta_{0d} \\ -\alpha_{0s} & 1 \end{bmatrix}\begin{bmatrix} \log QE_t \\ \log PE_t \end{bmatrix} = \begin{bmatrix} \phi_0 \\ \alpha_0 \end{bmatrix} + \begin{bmatrix} \tilde{\phi}_{qd}(L) & \tilde{\phi}_{pd}(L) \\ \tilde{\alpha}_{qd}(L) & \tilde{\alpha}_{pd}(L) \end{bmatrix}\begin{bmatrix} \log QE_{t-1} \\ \log PE_{t-1} \end{bmatrix} + \begin{bmatrix} \delta'_{rd}(L) & 0 \\ 0 & \pi'_{pd}(L) \end{bmatrix}\begin{bmatrix} X_{dt} \\ X_{st} \end{bmatrix} + \begin{bmatrix} \varepsilon_{dt} \\ \varepsilon_{st} \end{bmatrix}$$

Which can be written in matrix notation as in (6),

$$BY_t = \gamma_0 + \mathrm{P}_{qp}(L)Y_{t-1} + \Pi' X_t + \varepsilon_t \tag{6}$$

where $E[\varepsilon_t \varepsilon_t'] = D$ is a diagonal matrix variance-covariance matrix with the variance elements, $var(\varepsilon_{dt})$ and $var(\varepsilon_{st})$, in the diagonal.

The *reduced form VAR* from (5) is obtained,

$$Y_t = B^{-1}\gamma_0 + B^{-1}\mathrm{P}_{qp}(L)Y_{t-1} + B^{-1}\Pi' X_t + B^{-1}\varepsilon_t \tag{7}$$

or

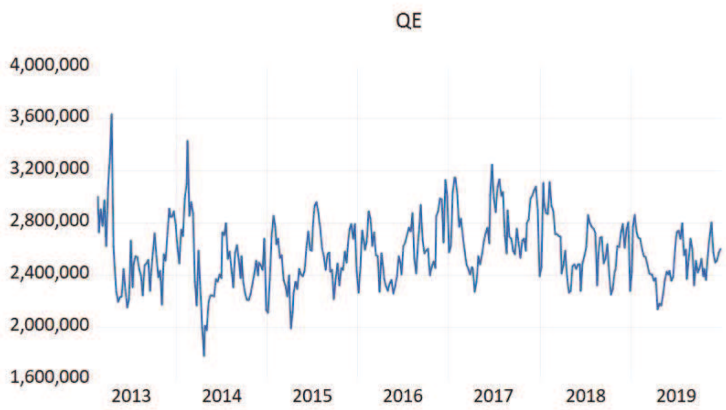
$$Y_t = a_0 + A_{qp}(L)Y_{t-1} + \widetilde{\Pi'} X_t + u_t \tag{8}$$

where the new variance-covariance matrix $E[u_t u_t'] = \Omega$ is not diagonal anymore. The degree of contemporaneous correlation of the u_t terms depends on the off-diagonal elements of the matrix B in the structural form (6). After estimating the reduced form VAR of equation (8), we will be able to: a) calculate Granger-causality tests, b) obtain the corresponding forecast-error variance decomposition and c) calculate the impulse response functions (IRF) to evaluate how shocks from electricity prices and quantities are transmitted through time.

3.2 Data Description

In the empirical analysis use weekly data from February 2013 to December 2019, accounting for 360 weeks. In fact, due to the fact that most of our international price variables did not present data for weekends, the variables take into account only weekdays. Through the aggregation to obtain weekly data we avoid the problem of having missing observations, especially in commodity prices. In the final sample have 359 weekly observations, where data from the first week of 2020 was removed. Data from the day-ahead market is public and available at websites of the market's operator, OMIE, and from the infrastructure operator, REE. More precisely, information about total demand and energy exchanged from the different generating technologies came from OMIE and they were obtained aggregating hourly data.

Figure 1. Equilibrium quantities in the Spanish Day-Ahead Power Market (QE, MWh)



The information about renewable energies, such as wind, PV and thermal solar, or other renewable sources such as cogeneration of heat and power (CHP), are included under the group special regime in this source. In order to disaggregate different sources and analyse renewable energies individually, we took information about the total daily generation from REE to generate weekly data. Weekly data on electricity prices are obtained as the average of the non-weighted daily prices (*€/MWh*), extracted from OMIE.

Figure 2. Electricity price series (PE, €/MWh, Weekday Weekly average)

The prices for other inputs were obtained from REE, which provided us with information about the relevant European markets. Coal prices came from Amsterdam's API2 (*€/t*) and they were translated to euros using the official daily exchange rate from Banco de España. Carbon prices came from Sendeco2 (*€/TCO₂eq*). The natural gas prices considered are Dutch's TTF future prices (€/MWh) and were obtained using Bloomberg. Even though we are comparing a future market with the spot variables, there is evidence that whenever markets are efficient, future and spot prices are cointegrated (Modjatahedi and Movassagh, 2005; Emery and Liu, 2002; Maslyuk and Smyth, 2009). As a consequence, we could take future prices as a fair proxy for spot prices since they will follow a common trend, based on Granger´s representation theorem (Engle and Granger, 1987). The analysis done on the order of integration shows that it is I(1) and we consider the TTF's growth rate instead of the level series. Data on Installed Capacities (IC) is published with annual frequency by REE (*MW*). In order to increase the frequency of the data, we have interpolated these variables in order to have quarterly data (see Table 11).

Important control variables for our analysis are related to climate, which are relevant for both demand and supply conditions. For these variables we take the average of daily precipitation (*mm*), sun hours (*h*), wind speed (*Km/h*) and temperature (*ºC*). To construct these variables, we have taken the average data from four stations (Madrid Airport, Valencia Airport, Jaén and A Coruña Airport) covering different areas of the Iberian Peninsula, which can be found published in AEMET's (Spanish Climatology Agency) database. Other information that is usually used in this kind of models to control for hydro generation is hydraulic reserves (in *%*). Since this information is published with monthly frequency by REE, we have interpolated this variable to obtain the weekly frequency, (see Table 11). In order to do this, we used the information on dammed water from the Spanish Ministry for Ecological Transition and Demographic Challenge.[3]

The interpolation done to generate weekly data of key variables was possible due to the use of lower frequency variables (factors) that are not available when working with daily data. Examples of those

3 The website of the reports can be found here.

relevant control variables are given by the Gross Domestic Product (GDP in million €) and the seasonal adjusted Industrial Production Index (IPI). Both data are coming from the National Statistics Institute (INE). GDP is usually measured at a quarterly frequency, however using different variables at higher frequency, related to energy consumption, Brent prices and IPI itself, it has been interpolated to a weekly frequency (see Table 11). Other interesting variables in relation to electricity demand are the service and industrial sector index for electricity demand, normalized to 100 points in 2010. These indices are published with monthly frequency in REE's website. These variables were only relevant for the interpolation process.

In order to compare the generation between different sources and the state of the system in a given week, it is important to take into account how the installed capacity is being used. For that instance, we measure it by capacity factors, which are defined as the actual energy output for a given source divided by the theoretical total generation if the installed capacity was used fully at every hour of the week.[4] Although renewable energy generation will depend on the climate conditions on a given day, these capacity factors are usually considered a good measure of efficiency (Urbina, 2014).

4. Estimation of a structural vector autoregression (SVAR) of electricity demand and supply

The analysis of nonstationarity of the variables considered is done by combining the time series plots with the autocorrelation function (ACF), the partial autocorrelation function (PACF) and unit-roots tests based on the augmented test of Dickey and Fuller (ADF). Focusing on the evolution of price and quantity series, introduced in the previous section (see Figures 1 and 2), it is clear that they are not trending in mean and/or variance, despite the existence of some outliers and the changing observed in the volatility in the price series, as was well documented by Escribano et al. (2011). The ADF tests of Table 13 confirm the stationarity of those two variables, PE and QE.

To provide a preliminary look of the degree of contemporaneous correlation (simultaneity) a VAR analysis of the supply and demand functions is implemented. VARs are popular to account for dynamic effects in a system of equations and has been used in the past to analyse electricity markets. For example, Paschen (2016) uses a Structural VAR to estimate the impact of wind and solar power on prices in the German market. His shows that accounting for interactions of the dynamics processes in these generating technologies is important not to underestimate the merit-order.

Our goal with the VAR is different. We want to estimate the system of demand and supply equations, to evaluate the degree of simultaneity between equilibrium prices and quantities. For that, in our initial VAR analysis we consider quantity and prices to be the main simultaneous/endogenous variables of our structural analysis. In order to properly identify the supply and demand functions, we

4 For the 5-day week, the divisor of the fraction is computed as the installed capacity times 120.

must impose some exclusion restrictions on the exogenous determinants. For that reason, we impose that the demand shifters (X_{dt}) will have no impact on the price equation of the supply function (except for TTF prices) and that the supply shifters (X_{st}) will have no impact on the quantity equation.[5] In the initial VAR model, we always include constant terms, seasonal monthly dummy variables and up to 4 lags of the endogenous variables to make sure that the residuals are white noise. The correlogram (ACF) of the residuals shows no significant serial correlation and the Portmanteau test (Q-Stat) of no serial correlation up to lag 6 in Table 1, shows that there is no evidence against white noise residuals.

With this estimated VAR(4) model, we address three main issues: (a) Granger-causality tests, (b) Forecast-error variance decomposition and (c) Impulse response functions (IRF).

The results of the Granger-Causality tests computed with Eviews are shown in the next table.

Table 1. Granger-causality test in Reduced-Form VAR

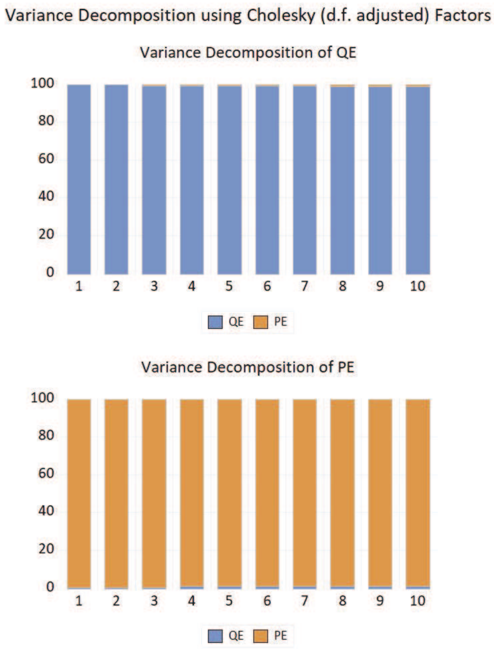
Dependent: QE	**Chi-sq**	**P-value**	Dependent: PE	**Chi-sq**	**P-value**
PE	2.900	0.575	QE	5.413	0.248
Portmanteau test (6 lag)	P-value	0.235			

The result on Granger-causality test, confirm the idea that there is a lack of feedback between our weekly prices and quantities. This result might be due to the fact that we have weekly data information between 2013 and 2019. This empirical regularity, lead us to search for important factors that shift the demand and the supply curves, anticipating therefore future changes in the equilibrium values of both variables, PE and QE.

The next step is to study a possible causality in variance of electricity prices and quantities. As we observed before, in equilibrium the variance of electricity prices is higher than variance in the quantities. However, it is relevant to confirm the forecast error variance between both. The next figure shows the estimated forecast-error variances of QE and PE, under 10 weekly horizons of each series. It is clear that the forecast-error variance of each variable, depends solely on its own past and not on the past of the other.

5 We also estimated the SVAR without imposing restrictions on the lags of those exogenous variables. The estimation results did not change much.

Figure 3. Forecast-error variance decomposition



These results are consistent with the Impulse response functions (IRF). Our results suggest the relationship between quantity and prices in the equilibrium, when considering dynamic effects, are temporally independent with dynamic cross-correlations equal to zero.[6]

In fact, the result is only in one direction, none of the lags of prices is relevant to explain demand, while demand lags are relevant to determine prices. This preliminary result indicates that the aggregate demand of electricity is quite inelastic to prices; however, supply could be more responsive than the demand due to the fact that different technologies are competing to enter the mix as the marginal unit.[7]

As a final check, we present the estimated contemporaneous correlation matrix of the variables QE and PE related to the off-diagonal elements of the matrix B in equation (6). Our estimations results suggest the contemporaneous correlation between equilibrium prices and quantities of electricity is low and equal to 0.045. Therefore, the variance-covariance matrix of the reduced form residuals of the VAR(4) is close to be a diagonal matrix.

Furthermore, following a similar VAR modelling approach, we can evaluate the degree of the dynamic and contemporaneous correlations among the variables of the supply function of electricity. These additional variables are the capacity factors for hydro generation (CF-Hydro) and thermal generation (CF-Thermal) which covers the use of coal and CCGT capacity jointly. The new SVAR is

6 The IRF results do not change when altering the ordering of the variables in the VAR(4) and using the Cholesky decomposition of the var-cov matrix of the residuals.

7 The result of a simple OLS model of equations (3) and (4) was aligned with this idea: the price slope in the demand function was not significant, while supply had a positive and significant slope with respect to prices. However, as we will see later on, these results are not reliable due the simultaneous equation bias.

form using the system of two equations (8), with QE and PE variables, and adding the two capacity factors, CF-Hydro and CF-Thermal, forming a VAR of four variables. The estimated results are the following. Firstly, the Portmanteau serial correlation tests, shows no clear evidence of serial correlations for lags lager than 6, see Table 2.

Table 2. Granger-causality test in Reduced-Form VAR

Dependent: QE	**Chi-sq**	**P-value**	Dependent: CF Hydro	**Chi-sq**	**P-value**
CF Hydro	17.328	0.004	QE	8.453	0.132
CF Thermal	1.894	0.863	CF Thermal	33.488	0.000
PE	1.899	0.862	PE	1.361	0.928
All	21.489	0.121	All	39.254	0.001
Dependent: CF Thermal	**Chi-sq**	**P-value**	Dependent: PE	**Chi-sq**	**P-value**
CF Hydro	8.879	0.114	CF Hydro	4.954	0.467
QE	9.147	0.103	CF Thermal	2.171	0.824
PE	1.397	0.924	QE	2.411	0.789
All	15.380	0.424	All	9.896	0.826
Portmanteau test (6 lag)	P-value	0.039			

The interaction results between QE and PE, obtained before, are still relevant now and we cannot find evidence of Granger-causality. However, the introduction of these capacity factors provides an interesting insight on the supply function. QE is Granger´s caused by the hydro capacity factor with p-value of 0.004 in Table 2. Th explanation is that hydro generation is a mid-merit technology usually setting marginal prices, since it is displacing more expensive technologies such as pumping and thermal generation, and it has great modulling capabilities for supply. However, thermal capacity is not Granger´s causing QE at the equilibrium, with a p-value of 0.86, since this is a marginal technology mainly covering peaks. The substitution of hydro and thermal generation is evident by the results of Granger-causality test. Hydro generation is Granger´s caused by thermal generation, with a p-value of 0.00, but not the other way around with ap-value of 0.10. We may argue that hydro generation is negatively correlated with thermal generation, since these are substitutes as marginal technologies.

Again, our results show PE is close to be contemporaneously uncorrelated with the rest of the factors considered in our supply VAR. The results are consistent with the correlation matrix.

Table 3. Contemporaneous cross-correlations

	QE	CF Hydro	CF Thermal	PE
QE	1	0.311	0.348	0.067
CF Hydro	0.311	1	0.128	-0.038
CF Thermal	0.348	0.128	1	0.069
PE	0.067	-0.038	0.069	1

The results are similar when analysing the Impulse Response Functions (Figure 4) and the forecast-error variance decompositions (Figure 5).

Figure 4. Impulse Response Function

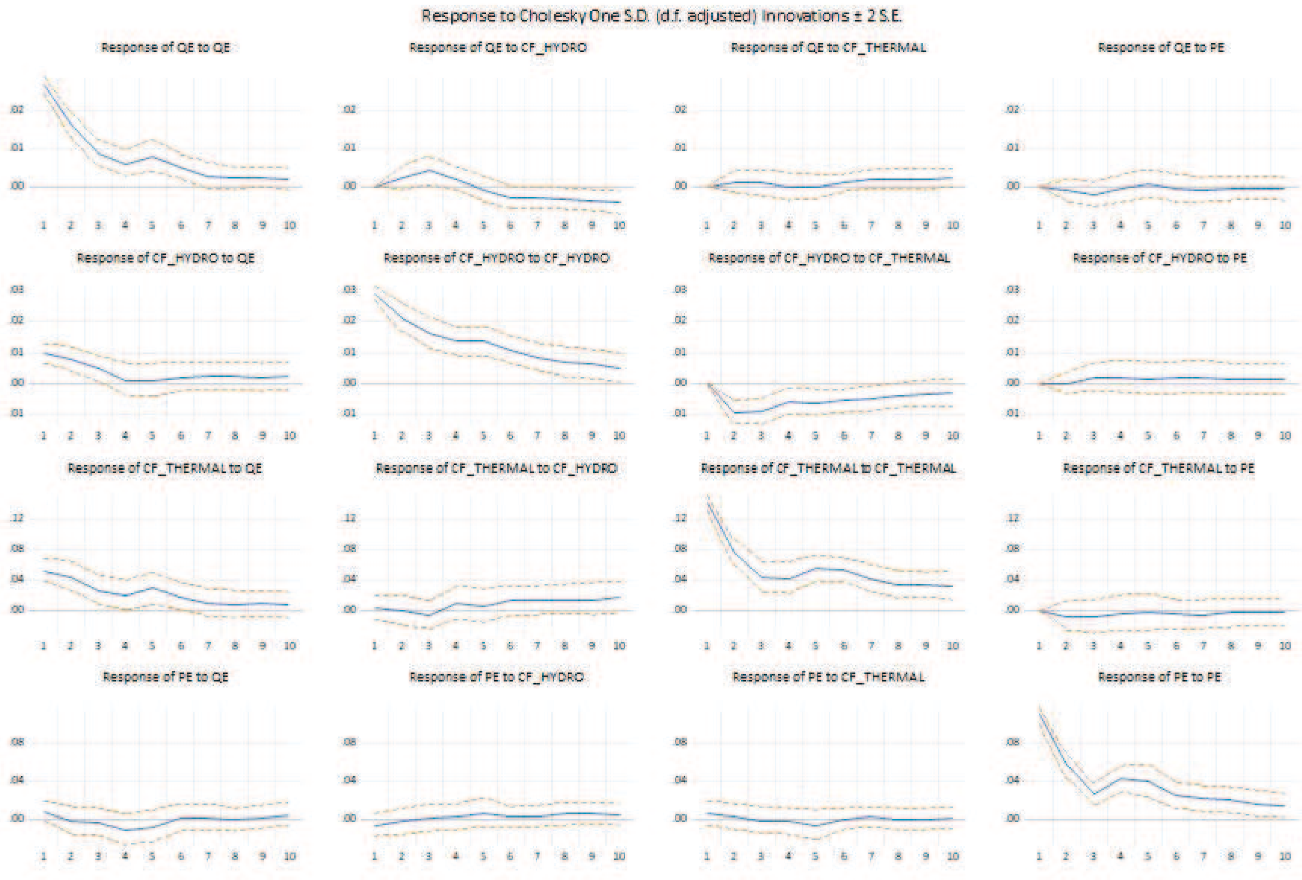
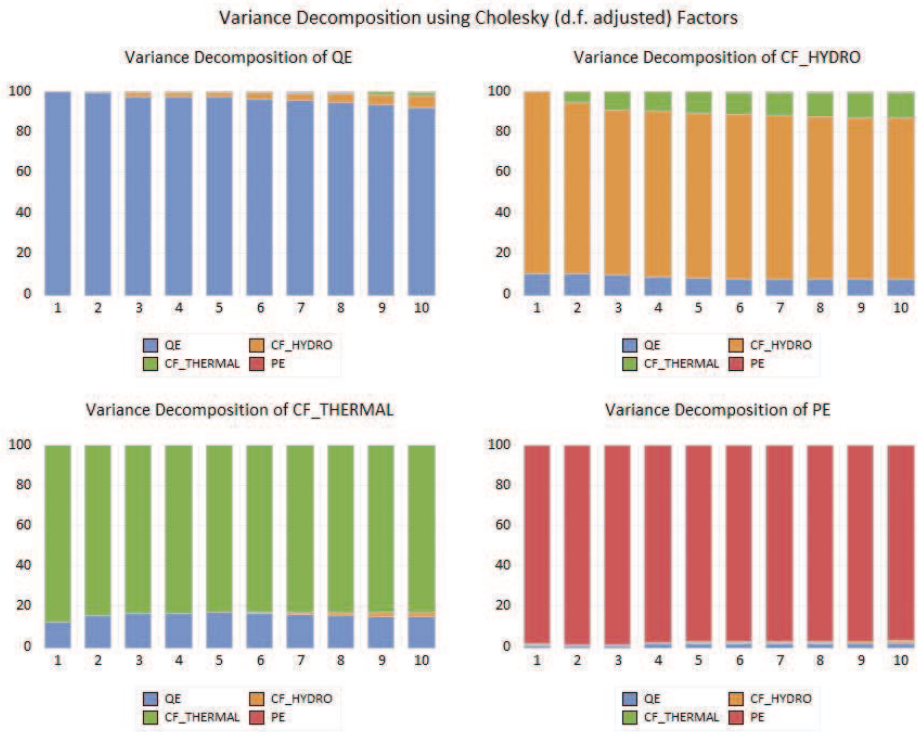


Figure 5. Forecast-error variance decomposition



The estimation of our structural VARs shows that the demand and supply function will be very inelastic, almost vertical. This result implies that the PE and QE in the equilibrium will mainly be affected by the supply and demand shifters and not so much by the corresponding price-elasticities of demand and supply (inelastic). There are different implications to these preliminary results:

- The introduction of dynamic models (VAR) for QE and PE do not represent an upside relative to the use of single-equation models.

- However, instrumental variables (IV) may still be needed in single equation models with contemporaneous variables, in order to control for the small (endogeneity) but relevant contemporaneous correlation between QE and PE.

In summary, in the following sections, we focus on the equation-by-equation approach to estimate the system of equations (6). However, instrumental variables will be used in the estimation, since prices (PE) and quantities (QE) are endogenous by construction of the structural demand and supply analysis. Notice that this is true, even if the degree of simultaneity (or contemporaneous correlation) is small in our weekly dataset of PE and QE.

5. Single-equation models of demand and supply of electricity

5.1 Electricity Demand

On the demand side, there are different variables that may define the behaviour of consumption of electricity. A classical discussion on energy economics involves the de-coupling of economic development and energy consumption (Bhattacharyya, 2011). Demand functions estimates are usually related to income and prices, especially when analysing households' demand. In an aggregated exercise with annual, quarterly o monthly data, income is usually measured through economic activity indexes or variables such as Gross Domestic Product or the Industrial Production Index, which are closely tied to electricity consumption (cointegrated). In fact, the inclusion of GDP's growth is important for the Spanish data as was shown by Perez-García and Moral-Carcedo (2017).

The problem of these variables is that they are not measured at the weekly frequency. However, this can also be taken as an advantage, since we may assume that GDP is exogenous to weekly electricity demand, thus reducing the problem of endogeneity and avoiding the omitted variable bias generated when we do not control for income. As we will see later on, see Table 11, we address this issue by using interpolation techniques at the weekly frequency, similar to the ones used by National Institute of Statistics to build quarterly GDP from annual data. There seasonality of our data is controlled in our models through monthly dummies.

One of the main demand shifters at the aggregated level is temperature, which raises electricity demand generally in summer and winter. In order to capture this effect on the market, instead of including directly the temperature series, we have defined the cooling and heating degree days (*ºC*) as CDD_t=Max[log(T-18),0]$_t$ and HHD_t=Max[log(15-T),0]$_t$ where *T* is the weekly average temperature.[8] Both thresholds together define the comfort zone where neither cooling nor heating are needed (between 15 ºC and 18 ºC). Where to put the thresholds has been discussed previously for the household segment in Blázquez et al. (2013) and Romero-Jordán et al. (2014).

On the other hand, in the analysis of demand, it is usually necessary to account for close goods to our commodity of interest, which may be substitutes or complements. In the case of demand electricity, we will only account for natural gas prices, which is a close substitute in households and buildings. Since our dataset contains international prices since we do not observe the direct price faced by Spanish consumers, the relationship could be subject to measurement errors. Moving ahead of the estimations, we observe that contemporaneous gas prices are not significant in the demand equation, but there is a significant delay in the relationship. If this is the case, demand would not be adjusting to prices in the same week of a shock but in the following weeks, which can be explained due to the fact that we are not using data from the Virtual Trading Point (PVB).

8 The thresholds of 15 degrees and 18 degrees, are commonly used in the literature. None of them take negative values or zeros. Therefore, there is no problem taking logarithms.

Finally, the series of electricity prices is endogenous by constructions of the equilibrium of the market and therefore must be treated with instrumental variables. Good instruments are highly correlated with prices (PE) but uncorrelated with the error term of the demand equation. For our demand estimations, we have taken two supply factors related to renewable generation that are independent of electricity demand. The variables chosen are:

- Wind flow speed. This instrument will be relevant because it is related to electricity prices through wind generation. Higher wind flow speed will lead to higher renewable generation, thus reducing prices through the merit-order effect. It is true that speed of wind may be an imperfect measure of wind generation since the production of wind energy is possible within a threshold of speeds.[9] However, this may be a fair exogenous proxy, which is also uncorrelated with the error term of the demand equation. Electricity consumers cannot choose directly the generation mix of their bill, so how the energy they receive was generated is irrelevant to how much they consume.[10]

- Capacity factor for solar generation (computed as the sum of photovoltaic and thermosolar sources). This variable has similar good properties as the previous instrumental variable. A higher use solar installed capacity means that there is more electricity being generated from solar sources in the market, thus reducing prices via the merit-order effect. Endogeneity could be an issue if the capacity factor is built using the actual quantity generated from solar sources, but not in the equilibrium. Renewable energy generation is considered exogenous since it will depend on climate and technical exogenous factors.

Apart from these explanatory variables, we need to include lags of electricity prices and quantities in order to get a demand function with uncorrelated residuals (white noise). These lags can also be interpreted as instruments, so the fact that we are using more than one instrument could lead to an overidentification of the price-elasticity parameter.

Although different specifications will be applied in the empirical analysis through an iterative process of the ARDL model, the basic final specification for equation (1), taking into account the order of integration of the variables,[11] is:

$$\phi_{qd}(L)\log QE_t + \phi_0 + \theta_{pd}(L)\log PE_t + \delta'_{rd}(L)X_{dt} + \varepsilon_{dt} \tag{9}$$

where X_{dt} includes, seasonal monthly dummies, the rate of growth of prices of gas (TTF), the rate of growth of gross domestic product (GDP), cooling degree days (CDD) and heating degree days (HDD). These last three variables only enter in the demand function and not in the supply and therefore identifies de demand curve.

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9 According to IRENA, maximum power is generated at 15 m/s, while at least 3-5 m/s wind flow speed is necessary to start generating electricity.

10 The authors would like to thank Shanshan Yuan for the discussion related with this instrument. Some unpublished research meant that wind flow speed introduces uncertainty in the market, and distributors may shift their demand from the Day-Ahead Market (DAM), thus leaving wind flow speed to be endogenous. We think uncertainty on wind generation is always present since there is perfect foresight. The usual behaviour is to deal with these real-time issues in markets that come after the DAM, like technical restrictions or intra-day markets. As a result, we consider that this instrument is not endogenous with demand in the DAM.

11 The Augmented Dickey-Fuller tests are presented in Table 9.

The result of the estimation of the demand functions is shown in Table 3 and the first stage of the 2SLS model in Table 4. Our first structural analysis of the previous section, using a VAR, showed that the degree of endogeneity of prices (PE) is small. However, since prices to be endogenous by construction of the structural analysis, consequently, we estimate the demand function by both ordinary least squares (OLS) and two stage least squares (2SLS).

Since there is no definition or threshold to set peak demand in weekly data, we take the 90th percentile threshold as "extreme events". As a consequence, we included a dummy variable that takes value 1 if the demand in a given week is between the 90th percentile of the whole sample. The relevance of this dummy is to control our model for overestimating the sensitivity of demand to prices.

Table 3. Demand first stage regressions of 2SLS's model

	Dependent variable: Electricity Prices (PE)
C	0.509*** (0.154)
PE(-1)	0.506*** (0.082)
PE(-3)	0.260** (0.114)
ΔTTF	-0.077 (0.123)
ΔTTF(-1)	-0.214* (0.119)
ΔGDP	1.135 (0.810)
CDD	0.024* (0.014)
HDD	0.033 (0.031)
CF Solar	-0.027* (0.042)
Wind Speed	-0.106** (0.043)
Seasonal controls	Monthly
Percentile 90	Yes
N	356
Adj. R-Sq.	0.543
AIC	-1.1538
BIC	-1.288
Durbin-Watson	2.023
Serial Correl. Test	0.890

The analysis of our first stage, Table 3, of the 2SLS, showed our instruments were relevant and aligned with the arguments implied previously; wind flow speed and the capacity factor for solar are significant and showed a negative sign. To check for possible weak instruments, we follow the usual rule of thumb, the F-statistics is higher than 10 (Stock and Watson, 2015). Since we are using four instruments for prices (CF Solar, Wind Speed and the two lags of prices), we need to check for over-identifying restrictions. We have included the J-statistics for the demand equations in table 4, which follow a χ^2 distribution. The critical value at 95% confidence level is 7.81 (Stock and Watson, 2015). The null hypothesis of the overidentification test is that both instruments are exogenous. Since none of the J-statistics sit above the critical value, we cannot reject the null hypothesis that our instruments are exogenous.[12]

Table 4. Dynamic electricity demand estimations

Variable	OLS	ARCH	IV	IV-ARCH
Dependent variable: Quantity of Electricity (QE)				
Conditional expectation equation				
Q(-1)	0.478***	0.470***	0.432***	0.418***
	(0.043)	(0.042)	(0.044)	(0.005)
ΔTTF	-0.026	-0.027	-0.041	-0.036
	(0.034)	(0.048)	(0.032)	(0.030)
ΔTTF(-2)	0.049	0.044	0.099**	0.091***
	(0.043)	(0.033)	(0.045)	(0.034)
ΔGDP	0.668***	0.552***	0.900***	0.786***
	(0.301)	(0.200)	(0.312)	(0.267)
CDD	0.015**	0.014***	0.025***	0.023***
	(0.005)	(0.005)	(0.006)	(0.005)
HDD	-0.005	-0.001	0.007	0.010*
	(0.006)	(0.004)	(0.006)	(0.006)
PE	0.023**	0.022*	-0.421***	-0.401***
	(0.011)	(0.011)	(0.081)	(0.063)
PE(-1)	-0.028***	-0.027**	0.274***	0.263***
	(0.010)	(0.014)	(0.072)	(0.064)
C	3.346***	3.395***	3.856***	3.928***
	(0.272)	(0.272)	(0.409)	(0.016)
Seasonal controls	Monthly	Monthly	Monthly	Monthly
Percentile 90	Yes	Yes	Yes	Yes
Conditional Variance equation				
σ^2		0.00041		0.00038
		(4.20e-5)		(4.08e-5)
$u^2(-1)$		0.192		0.215
		(0.079)		(0.077)
N	356	356	355	355
Adj. R-Sq	0.702	0.699	0.717	0.715
AIC	-4.623	-4.637	-4.676	-4.687
BIC	-4.383	-4.376	-4.436	-4.425
Durbin-Watson	2.509	2.027	2.031	1.981
J-Statistic			3.386	3.268
Serial. Cor.	0.402		0.471	
LM ARCH	0.009	0.906	0.076	0.884

We started evaluating models with 3 lags for the controls and 4 for the dependent variable, the models presented are the product after the iterated removal of non-significant lags. All regressions used White robust standard error (except for those including GARCH)

12 However, it is important to remember that we may not have the power to check the exogeneity of our instruments in our sample (Stock and Watson, 2015).

Since our dynamic demand function has an autoregressive distributed lag, ARDL (p,q) specification, we could interpret both the simultaneous/contemporaneous effect (at L=0) or the total multiplier (at L=1) of demand after controlling for the rest of the explanatory variables. For our models to be compared, we focus on the total multiplier. The following Table 5 displays the results for our long-run demand estimates.

Table 5. Demand function: Total multipliers (L=1)

	(OLS)	(IV)	(IV-ARCH)
ΔGDP	1.281	1.584	1.350
ΔTTF	-0.413	0.174	0.156
CDD	0.028	0.044	0.039
HDD	-0.010		0.017
PE	-0.011	-0.339	-0.237

Furthermore, our models have been extended using an autoregressive conditional heteroskedasticity model (GARCH). Apart from the correlogram of the squared residuals, we use the ARCH heteroskedasticity test. In OLS, we clearly have an issue of heteroskedasticity of ARCH type, and a conditional heteroskedasticity process is estimated for the residuals of the ARDL demand model[13]. We can see that the coefficients do not change much when including the ARCH, only TTF changes. Notice that in the OLS model and in the OLS-ARCH model, Table 4, we get a positive price-elasticity of demand in the contemporaneous impact, indicating a clear evidence of a simultaneous equation bias.

The dynamic specification in all models is the same since all the estimated demand functions show no evidence serial correlation (white noise residuals).[14] At first sight, we see that accounting for the conditional variance, GARCH equation, significantly reduces the values of the estimated parameters.[15] The electricity demand function shows a high value of the estimated income-elasticity of demand (1.35), and the total multiplier ranges in a wide interval among the different models, see Table 4.

The temperature variables pose a small impact on demand compared to the other variables, but their coefficients are consistent through our estimations (with the exception of HDD, although it is only significant in the IV-ARCH model), see Table 4. The variable controlling for the use of air conditioning has a higher impact on demand compared to heating, which is an interesting finding,

13 The inclusion of these models showed that there was no significant lag in the correlogram of the squared-residuals and we would not reject the homoskedasticity hypothesis in the ARCH test.

14 The correlogram of residuals showed no sign of autocorrelation up to 36 lags. Besides, the Durbin-Watson statistic is close to 2 in all models and the Breusch-Godfrey test is shown in the table 11.

15 Even though we do not present all models, the inclusion of the peak dummy reduced the estimated coefficients for all variables, confirming our suspicions of overestimation.

since electricity is the first source of heating in Spanish households.[16] A 1% increase on average temperature during summer (over 18ºC) leads to an increase in the equilibrium quantity demanded around 0.04%. Meanwhile, a 1% decrease in the average temperature during winter (below 15ºC), leads to an increase in the quantity demanded in the equilibrium close to 0.02%.

The estimated coefficient for the international price for natural gas shows that it is not significant in the contemporaneous week, but the effect is aged once. This is consistent with the fact that a price shock may not be perfectly measured since we are not observing the natural gas price faced in the Spanish market. Even with this limitation, the elasticity estimated in the total multiplier is positive in the 2SLS models, showing these commodities are substitutive products at the aggregate level.[17] On average, an increase of 1% increase in the price of natural gas leads to an increase in the equilibrium demand for electricity of 0.16%, see Table 4.

Finally, the estimated price-elasticities present evidence of the inelastic behaviour of demand (-0.23). Even though these parameters change between both specifications. 2SLS models show similar parameters for the own-price elasticity, 1% increase in electricity prices would lead to a reduction in demand in the range of 0.23% and 0.33%, ceteris paribus.

5.2 Electricity supply

For supply function of electricity, apart from it own equilibrium price (PE), the other explanatory variables are related to the cost of production or to the prices of other commodities, which are generally used as inputs in the different sources of electricity generation. In this regard, we include natural gas and coal prices. Carbon prices are also included since all the electricity generation firms have no free allocation of emission rights. This means all the thermal unit generations (such as coal, CHP or CCGT plants) must always pay a price for their emissions. These commodity prices are treated as exogenous in our estimations since they are stablished at international markets. Therefore, in that sense, we are assuming that the Spanish electricity generation sector is not big enough to influence international (European) prices for natural gas, coal, and carbon emissions.

In order to control for renewable energy generation, we directly include the Special Regime generation, which accounts for all the renewable generation and CHP in the system. Even though we have information about aggregate wind and solar production, we decide not to include these variables to understand the overall merit-order effect. Although this variable is directly included in the quantity of supply, renewable generation is considered exogenous since it will depend on climate variables and technical constraints.

16 IDAE (2019). Household sector energy consumption in Spain, p. 14.

17 We decide to ignore the negative sign in the OLS model since none of the coefficients are statistically significant and thy are biased.

One of the main contributions of this paper is the inclusion of capacity factors. Firstly, there is a high correlation between these factors since different generating types of energy are competing to cover demand. Although loading allows for different sources, there is high substitutability between different generating technologies, therefore estimations must be done carefully. Figure 7 shows the correlation matrix of our capacity factors and other relevant variables for supply, showing key results for estimation. Coal and Combines Cycles generation show a high complementarity, instead of the substitution that we would expect if these two sources were competing to enter into the market. However, we must also bear in mind that this substitution depends on the share of renewables that is in the system. Peak demands increase the likelihood of this sources to be complementary. In fact, Urbina (2014) finds a positive correlation between load and CCGT capacity factors, which could be found in Figure 7, with the high correlation between residual demand (this is computed as the difference between total demand and generation from renewable energy sources) and CCGT and Coal capacity factors. For the purpose of this paper, we gather these factors together to represent the capacity factors for thermal generation. Secondly, the construction of these variables includes the quantity for each generation source in the numerator. Since these quantities are part of the equilibrium quantities, they create a simultaneous equation issue in each of the capacity factor that are based on non-renewable technologies. Our VAR analysis done with this variables in previous sections, found that hydro capacity factor was having a high impact on the equilibrium quantity, while the impact of thermal capacity was lower. Therefore, in the estimation of the supply function, we control for their endogeneity using instrumental variables.

Once we have selected the capacity factors (CF) that we want to include in our analysis, CF Hydro and CF Thermal, we need to discuss the instrumental variables used for them.

CF Hydro. The degree of usage of hydraulic installed capacity depends directly on the level of hydraulic reserves, so it is a good idea to use this variable to instrument such capacity factor. To achieve higher usage of capacity hydro, we need higher levels of hydraulic reserves, so the relevance condition is met. For the exogeneity condition to be met, we need the instrument to have a relevant impact on supply, but only through its effect on the capacity factor. Since the capacity factor is closely tied to the reserve level, we might think that the factor is taking all relevance in the supply equilibrium, and reserves are only important in a previous stage of the formation of the equilibrium. Furthermore, the availability of hydro generation should not be a determinant of the equilibrium supply quantity, but rather what the producers finally decide to produce with that availability. Another instrument we used for the hydro CF is the average level of precipitations. A higher level of precipitations will increase the hydraulic reserves, and the effect might not only be contemporaneous but also past weeks precipitations can have an impact. The exogeneity of precipitations should be of no concern since supply is only dependent on this aspect of climate through hydraulic generation.

CF Thermal. Since this variable is computed as the sum of coal and CCGT capacity factors, any variable affecting any of them can be used as an instrument. Following Figure 7, there is a relevant negative correlation between both capacity factors and hydraulic reserves. The relevance condition is then tied to the fact that a higher hydraulic reserve level is tied to a higher hydraulic generation, thus reducing the room for thermal generation in the equilibrium. Besides, we can use the lags of coal and CCGT capacity factors as instruments for the contemporaneous percentage of capacity being used. In this case, we are assuming individual technologies will not determine quantity of supply but rather the thermal gap. This is reasonable since coal generation's relevance declined during 2019, but the effect could be relevant for the rest of our analysed period.

After controlling for the electricity generation in Spain, it is important also to control for imports and exports of electricity to have a complete overview of the aggregated supply equilibrium. Instead of including both exported and imported quantities separately, we decide to include the ratio of exports over imports. Since our estimations use log-linear specifications, the variable is capturing the difference between exported and imported quantities. The objective of this variable is to control whether Spanish generation was able to just-cover, undercover or exceeded the total demand. As a consequence, the expected sign for the parameter is negative. If the log of the ratio is positive, it means that the supply in that week is higher than demand, and the excess supply is not consumed in the Spanish market. On the contrary, the variable will be negative in a given week, meaning that the market was a net-imported and the quantity generated needs extra support from Morocco, France or Portugal.

Finally, it is important to mention that few generating plants have not been included in the analysis, such as nuclear, pump and other waste and residual sources. However, the impact of these variables is limited since they are very stable,[18] so their generation is only constrained by technical issues. Maybe, the only generating source missing in the analysis would be pump, but its relevance is quite smaller compared to hydro in our sample. As a result, these contributions will be included in the constant term of our estimations.

As a parallel analysis to what was done estimating the demand function, we will still consider electricity prices (PE) to be endogenous by construct and part of the instruments will be taken from the demand equation.

Degree days, this variable is taken as the sum of the CDD and HDD variables that are included in the demand equations. Firstly, these variables are exogenous to energy generation and so they are not correlated with the equation's errors. Secondly, temperatures are relevant to explain demand, so an increase in temperature shifts demand upwards, pressuring prices to rise. As a consequence, we expect this variable to be relevant and a good instrument for electricity prices in the supply equation.

The final ARDL(p,q) specification selected for the supply function is given by:

$$\alpha_{qs}(L)logQE_t = \widetilde{\alpha_0} + \widetilde{\rho_{ps}}(L)logPE_t + \widetilde{\pi_{rs}'}(L)X_{st} + \widetilde{\varepsilon_{st}} \qquad (10)$$

where X_{st} includes, seasonal monthly dummies, the rate of growth of prices of gas (TTF), CF Hydro, CF Thermal, Balance, the rate of growth of the price of Carbon and the rate of growth of the price of Coal. These last five variables only enter in the supply function, an not in the demand function, and therefore identifies the supply curve.

18 CNMC (2020) report.

Table 6. Supply first-stage regressions of 2SLS's model

Dependent variable:	PE	CF Hydro	CF Thermal
PE(-1)	0.501^{***} (0.067)		
PE(-3)	0.243^{**} (0.105)		
ΔTTF		0.112^{*} (0.048)	0.368^{*} (0.208)
ΔTTF(-1)	-0.189^{*} (0.111)	0.109^{***} (0.039)	0.143 (0.204)
ΔP Carbon	0.042 (0.212)	0.104 (0.103)	
ΔP Carbon (-1)			-0.460 (0.279)
ΔP Coal	0.945^{*} (0.567)	0.022 (0.120)	0.422 (0.507)
ΔP Coal	-0.321^{***} (0.117)	-0.136 (0.128)	-0.776 (0.507)
DD	0.030^{*} (0.015)		
ΔRes. Hydro		0.276^{***} (0.095)	-1.342^{***} (0.449)
ΔRes. Hydro(-1)		0.346^{*} (0.181)	
Precipitation		0.007^{*} (0.003)	
CF Coal (-1)			0.575^{***} (0.072)
CF Coal (-4)			0.102^{**} (0.044)
CF CCGT (-1)			1.053^{***} (0.389)
CF CCGT (-3)			0.885^{***} (0.266)
C	0.199 (0.616)	-0.128 (0.222)	1.708^{***} (0.007)
Trend	$-1.28e^{-4*}$ $(6.67e^{-5})$	$-3.75e^{-5}$* (2.12e-5)	-
Seasonal controls	Monthly	Monthly	Monthly
N	356	357	355
Adj. R-Sq.	0.543	0.769	0.824
AIC	-1.543	-4.233	-1.440
BIC	-1.281	-3.950	-1.145
Durbin-Watson	1.937	2.057	2.055
Serial Correl. Test	0.902	0.572	0.127

All regresions used White robust standard errors

Table 7. Dynamic electricity supply estimations

Variable	OLS	ARCH	IV	IV-ARCH
Dependent variable: Quantity of Electricity (QE)				
Conditional expectation equation				
Q(-1)	0.657^{***}	0.655^{***}	0.621^{***}	0.550^{***}
	(0.056)	(0.020)	(0.055)	(0.001)
Q(-4)				0.070^{***}
				(0.014)
ΔPCarbon	-0.061	-0.059	-0.041	-0.208^{***}

	(0.057)	(0.061)	(0.085)	(0.062)
ΔPCoal	0.077	0.071	-0.019	-0.174*
	(0.097)	(0.098)	(0.121)	(0.105)
ΔPCoal(-1)	-0.268**	-0.284**	-0.274**	-0.218**
	(0.105)	(0.097)	(0.117)	(0.099)
ΔTTF(-1)	0.071**	0.055**	0.111**	0.101**
	(0.032)	(0.024)	(0.048)	(0.035)
RES	0.116***	0.105***	0.122***	
	(0.025)	(0.017)	(0.029)	
RES(-1)	-0.087***	-0.084***	-0.98**	
	(0.029)	(0.017)	(0.042)	
ΔRES				0.106***
				(0.023)
Balance	-0.004*	-0.004*	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
CF Hydro	0.334***	0.295***	0.416**	0.392***
	(0.050)	(0.067)	(0.764)	(0.109)
CF Hydro(-1)	-0.272***	-0.245***	-0.229	-0.242**
	(0.049)	(0.056)	(0.163)	(0.115)
CF Thermal (-2)	0.005	0.009	0.020	0.014**
	(0.006)	(0.006)	(0.008)	(0.005)
PE	0.018**	0.019**	0.155**	0.238***
	(0.009)	(0.009)	(0.067)	(0.056)
PE(-3)	-0.022**	-0.025***	-0.143*	-0.103*
	(0.009)	(0.009)	(0.061)	(0.054)
C	2.017***	2.074***	2.227***	2.185***
	(0.435)	(0.041)	(0.420)	(0.027)
Trend	$6.18e^{-5}$	$3.68e^{-5}$	$3.18e^{-5}$	$3.52e^{-5*}$
	($1.38e^{-5}$)	($2.01e^{-5}$)	($2.33e^{-5}$)	($1.94e^{-5}$)
Seasonal controls	Monthly	Monthly	Monthly	Monthly
Conditional Variance equation				
σ^2		0.00017**		0.0003**
		($7.01e^{-5}$)		($8.45e^{-5}$)
$u^2(-1)$		0.189		0.494
		(0.123)		(0.261)
GARCH		0.524***		
		(0.152)		
N	357	357	353	353
Adj. R-Sq	0.659	0.656	0.627	0.605
AIC	-4.479	-4.179	-4.388	-4.487
BIC	-4.196	-4.196	-4.092	-4.169
Durbin-Watson	25.587		23.815	
J-Statistic			3.686	8.378
Serial. Cor.	0.015		0.530	
LM ARCH	0.008	0.278	000	0.409

We started evaluating models with 3 lags for the controls and 4 for the dependent variables, the models presented are the product after the iterated removal of non-significant langs.All regressions used White robust standard errors (except for those including GARCH).

The results of the OLS and the 2SLS estimation of the supply models are shown in Table 7 and the first stage for the IV model is included in Table 7. We rejected homoskedasticity in both OLS and simple 2SLS models. However, the 2SLS-ARCH model presents a different specification than OLS. The special regime (RES) generation had a negative total multiplier, which would be interpreted as an increase in renewable generation affects equilibrium supply negatively since the lagged variable's coefficient is higher than the contemporaneous. Therefore, we could take the first difference of the variable assuming that the two coefficients are equal in magnitude but with different sign. In the case of supply, we do not use the peak demand dummy variable, because supply must always meet the demand, and it is reacting rather than creating the peaks. The first step in this procedure is to test whether the contemporaneous variables are endogenous, although the VAR analysis done previously suggested that maybe only one of them is relevant, the hydro capacity factor. However, we will apply the Hausman test of endogeneity to both the capacity factors. The inclusion of the residuals on the capacity factors from the first stage are included in the OLS equation of the supply function, and they are individually significant at the 99% confidence level. Furthermore, we also did the Wald exclusion restriction test with the null hypothesis that both coefficients are equal to zero, and obtained a value of 213.898 for the χ^2 and a p-value equal to 0.00. Therefore, we can conclude that both capacity factors are endogenous in the supply function. First stage regressions of the 2SLS estimation showed our instruments were relevant for the different variables.[19] In this case, we have used a total of 9 instruments for three variables, so it is relevant to check the over-identification of the coefficients in the supply equations. In Table 6, we have added the J-statistic and χ^2 critical value. The results in both equations are that we cannot reject the null hypothesis that our instruments are exogenous. Anyhow, we also include the OLS results to compare the different specifications.

Table 8. Supply total multipliers (L=1). Long run impacts

	OLS	IV	IV-ARCH
Balance	-0.012	-0.013	-0.021
$\Delta PCarbon$	-0.178		-0.547
$\Delta PCoal$	-0.557	-0.722	-1.031
ΔTTF	0.0207	0.294	0.265
CF Hydro	0.181	1.097	0.394
CF Thermal	0.015	0.052	0.036
RES	-2.199	0.063	0.278
PE	-0.012	0.031	0.355

The use of coal and CCGT installed capacity is having a significant but small impact on equilibrium quantities, see Table 4. Even though we estimated the expected a positive sign for these technologies, the small parameter could mean that the use of these technologies relies somehow on the quantity demanded, so their impact on supply is small due to the fact that these are usually the marginal technology. This result could raise the question of how these impacts change, depending on the degree of penetration of renewable generation on the total quantity generated.

The impact of hydraulic capacity is significantly higher, although changing depending on the estimator used. Due to the fact that the ARCH process is significant and improved the information criteria, we set in IV-ARCH of Table 8 that the estimated impact of a unitary percent increase in the

19 The coefficient for the variable adding CDD and HDD is, although small, significant and positive in the price first-stage equation. For the capacity factor for hydro we settled with the use of hydraulic reserves, its lag, and the weekly average level of precipitations. As for the thermal capacity factor, we decide not to include lags of the dependent variable, but rather use the lagged components of the variable so we can, first, account for dynamics in the past of the variable, and second, have relevant instruments. All regressions complied with the rule-of-thumb for weak instruments and no serial correlation was found. An interesting result of the first stage was that the inclusion of hydraulic reserves showed a negative coefficient in the thermal capacity factor equation, confirming the substitution of hydro and thermal generation in line with our Reduced VAR analysis shown in the previous section.

use of hydraulic capacity is related to an average increase of 0.4% in the supplied quantity of electricity.

Renewable generation (RES) has a significant and positive effect on quantity if we are controlling for the endogeneity of certain variables, using the IV-ARCH models. Notice that since the OLS is not considering endogeneity of the three variables RES has the opposite sign. On average, if renewable generation was increased 1% (compared to the average), the quantity in the equilibrium is increased by 0.28% on average. On the other hand, balance has a low impact on equilibrium quantities, but its impact and sign are consistent in the three models. This means that supplied quantity is lower when the ratio exports to imports increases.

As for the variables controlling for input prices, the estimations obtain mixed results. Coal prices do present a negative impact on supply, as we would suggest, since a higher coal price will make coal plants to bid higher prices, thus reducing the quantity of coal-fired generation in the equilibrium. In fact, supply shows an elastic behaviour when we look at the elasticity of the coal price growth rate in the ARCH model.

A similar interpretation could be given to European emission prices. An increase in these prices will increase the marginal price for emission-intensive technologies, usually thermal plants. As a consequence, this fact can be sustained with the negative coefficient. However, the pass-through to supply is rather inelastic, a 1% increase in the growth rate of carbon will lead to a decrease of 0.5% in the equilibrium supply.[20] This coefficient shows that the impact of carbon prices is lower to that of coal prices, which could be explained by the fact that carbon is not a primary input for electricity supply, and the pass-through of an increase in carbon prices depends on the ability of thermal generation plants to get in the equilibrium mix.

On the other hand, natural gas prices are significant but present a positive coefficient, which goes against the usual argument of an input price. At first, it is difficult to establish a certain argument for this result. Due to the fact that natural gas is usually supplied in long-term contracts, at least annual,[21] an increase in the growth rate of future prices gives more incentives to natural gas-fired plants to achieve higher shares in the equilibrium. Since spot and futures are cointegrated, we could also interpret an increase in the growth rate of futures as an expected increase in spot prices (Steven Errera, 2002). When we expect prices to increase, suppliers are encouraged to try to provide as much energy as possible, since they need to cover their gas contract and their investment in the plant.

The price-elasticity increases with the inclusion of the GARCH process, which is fitting for the spiky behaviour of prices. Besides, the estimated parameters are somewhat higher than those estimated for demand. This result is aligned with our initial findings and is consistent with the fact that supply is more disaggregated than demand. The quantity supplied could be more elastic due to the fact that

20 The result is interesting but not surprising. The pass-through of EUA prices to electricity depends on: (i) The fact that a thermal unit must be the marginal, (ii) The emission factor of the marginal unit; and (iii) the efficiency of the marginal unit.

21 The authors acknowledge gas procurement in shorter periods is possible, but these contracts are mostly used as a complement to avoid possible penalties whenever there are deviations from contracted capacity.

higher prices lead to the entrance of more technologies and diversifies the mix. As a result, we can gather that the more inelastic demand will have a bigger role when determining prices. On average, the own-price elasticity of the day-ahead equilibrium is close to 0.36, ceteris paribus.

The results show our supply estimations could be improved since the implied total multipliers change drastically between the different models, so our results may have an issue of multicollinearity. However, the inclusion of non-significant lags in the models lead to even bigger changes in both the magnitude and significance of the variables. As a result, we decided to include those variables that made our results reasonable and without serial correlation issues.

5.3 Reduced-Form for equilibrium prices

The reduced-form or analysis of equilibrium prices will gather all the variables in both demand and supply. However, as we have mentioned before, the coefficients depend on the estimated parameters of the two previous steps.

However, there are further concerns about the analysis of the price equation. Mean reversion may come from demand shifts, increasing economic activity will lead to more expensive generators to enter into the market, and the contrary when demand decreases. Besides, the impact of cyclical weather could also have this impact on equilibrium prices through demand (Escribano et al., 2011).

Price volatility is usually connected to extreme events, like higher/lower than expected volumes of demand, shocks on energy input prices, or issues in the transmission network (Forrest and MacGill, 2013). However, the increase in price volatility can also be caused by the increased participation of renewable energies. Whenever climate conditions are not favourable for renewable generation, the void left by these technologies is filled with expensive but flexible thermal plants (Pereira da Silva and Horta, 2019).

Electricity markets there are different dynamics that could non-linear, with one of them being a strong dependence of the volatility on its own past (Weron, 2014). In this context, we consider the ARCH model of Engle (1982).

Even if the VAR analysis showed that electricity prices were independent from the capacity factors and demand, there are some arguments to consider these variables to be endogenous.

There is a simultaneous relationship between prices and thermal generation. On the one hand, higher prices lead to more technologies into the generating mix, and also make way for more expensive thermal generation units like CCGT and Coal, which are specifically controlled in this variable. On the other hand, higher capacity factors lead to higher prices, because it means that these technologies are taking a bigger share of the generation mix.

In the case of the hydraulic capacity factor, the simultaneous generation still applies since hydraulic reserves can be stored. As a result, generators may be waiting to bid their bigger quantities when prices are higher at little opportunity cost. The Spanish competition authority (CNMC) sued Iberdrola for this kind of behaviour in the past.[22] In the literature there are other examples of hydraulic

22 Find the official document issued by CNMC here.

generation as a competition driver in the Nordic market (Huisman et al., 2014), however, the share of this technology was at 53% in their sample and it averaged 7% in ours.

It is important to remind that we are merely analysing drivers of electricity prices in the equilibrium, and as a result, our estimation should not be considered an analysis of market power even when using capacity factors, since for that we should rely on more disaggregated data from firms. Good examples of this kind of analysis can be found in Ciarreta et al. (2016) and Moutinho et al. (2014).

Table 9. Reduced-form first-stage regression of 2SLS's model

Variable	CF Hydro	CF Thermal
PE(-1)	0.001	-0.097*
	(0.011)	0.048
PE(-3)	-0.002	0.048
	(0.011)	(0.050)
ΔGDP	1.367*	0.855
	(0.796)	(1.121)
CDD(-2)	0.000	-0.012*
	(0.004)	(0.022)
HDD	0.006	0.041*
	(0.005)	(0.021)
ΔPCarbon	0.115*	-0.304
	(0.066)	(0.278)
ΔPCarbon(-2)	0.106	0.066
	(0.066)	(0.277)
ΔPCoal	0.045	0.242
	(0.119)	(0.505)
ΔPCoal(-2)	-0.228*	-0.578
	(0.121)	(0.509)
ΔTTF(-1)	0.007	0.010
	(0.005)	(0.211)
ΔTTF(-2)	0.084	0.144
	(0.050)	(0.211)
ΔRES	-0.183***	-1.059***
	(0.022)	(0.094)
Balance	-0.010***	0.042***
	(0.003)	(0.013)
Balance(-4)	-0.012***	-0.031**
	(0.003)	(0.014)
CF Hydro(-1)	0.770***	
	(0.052)	
CF Hydro(-2)	0.039***	
	(0.050)	
ΔRes. Hydro	0.447***	1.719***
	(0.108)	(0.437)
ΔRes. Hydro(-2)	0.046	-1.584***
	(0.102)	(0.431)
Precipitation	0.008***	
	(0.003)	
CF CCGT (-2)		-0.236*
		(0.120)
CF CCGT(-4)		0.3085
		(0.384)
CF Coal		0.124**
		(0.059)
C	0.037	0.131
	(0.023)	(0.097)
Trend	$-6.45e^{-5}$***	$3.68e^{-5}$***
	($2.26e^{-5}$)	($2.01e^{-5}$)
Seasonal controls	Monthly	Monthly
N	356	355

Adj. R-Sq	0.768	0.819
AIC	-4.212	-1.400
BIC	-3.875	-1.051
Durbin-Watson	2.051	2.195
Serial. Cor.	0.319	0.024
LM ARCH	0.029	0.565

All regressions used White robust standard errors.

For the reduced form equation, the first relevant step we must take is to check the need for instruments in the capacity factors for hydraulic and thermal generation due to their possible simultaneous endogeneity with prices. The Hausman test showed capacity factors were exogenous, which is aligned with our previous VAR analysis. However, we will still estimate the 2SLS, as a robustness check on our OLS estimation (the F statistic is higher than 10, complying with the usual rule of thumb, so we can compare both models since our instruments were significant.).[23] \footnote{When applying the Hausman test, the residuals for both parameters are not significant, with p-values of 0.907 for thermal and 0.388 for hydro. Besides, the joint test with the null hypothesis of coefficients being equal to zero gives (following a χ^2 distribution) a p-value of 0.687.}

On the other hand, the electricity price series has two big drops for the weeks of the dates 9/12/2018 and 3/11/2019, so our estimations include two dummy variables to control for the possible impact of these outliers on the estimations.

Table 10. Dynamic electricity equilibrium prices estimation

Variable	OLS	IV
PE(-1)	0.491***	0.482***
	(0.067)	(0.067)
PE(-3)	0.223**	0.223**
	(0.103)	(0.101)
ΔGDP	1.367*	1.323*
	(0.796)	(0.809)
CDD(-2)	0.026*	0.026*
	(0.014)	(0.014)
HDD	0.010	0.017
	(0.020)	(0.020)
ΔPCarbon	0.019	0.063
	(0.197)	(0.211)
ΔPCarbon(-2)	0.162	0.180
	(0.203)	(0.205)
ΔPCoal	0.626	0.614
	(0.436)	(0.438)
ΔPCoal(-2)	0.512	0.375
	(0.407)	(0.425)
ΔTTF(-1)	-0.207	-0.214*
	(0.127)	(0.125)
ΔTTF(-2)	0.239	0.278
	(0.149)	(0.174)

23 The estimated price drops in these two dates were 71% and 100\% from the average. In fact, average prices fell close to 0 in these two weeks, because demand was below the average of each year and renewable energies meant over 50% of the total supply. This kind of behaviour arises the question of whether it was necessary to control for possible non-linear effects in the pricing equation depending on the penetration rate of renewable generation on supply. However, we settle with the analysis of linear models.

Balance	-0.007	-0.004
	(0.010)	(0.011)
Balance(-4)	0.022**	0.023**
	(0.010)	(0.011)
ΔRES	-0.143	-0.232
	(0.068)	(0.125)
CF Hydro	-0.262	-0.699
	(0.161)	(0.562)
CF Hydro(-1)	0.180	0.614
	(0.139)	(0.467)
CF Thermal	-0.033	-0.069
	(0.026)	(0.059)
C	0.488***	0.513***
	(0.146)	(0.157)
Date 9/12/18	-0.761***	-0.769***
	(0.045)	(0.041)
Date 3/11/19	-1.052***	-1.045***
	(0.042)	(0.042)
N	355	355
Adj. R-Sq	0.735	0.735
AIC	-2.063	-2.063
BIC	-1.724	-1.725
Durbin-Watson	2.089	2.086
Serial. Cor.	0.313	0.351
LM ARCH	0.000	0.000

The variables included in the reduced-form estimations come from the analysis of the previous step. Due to the fact that renewable generation was found to be stationary in mean, but the difference was significant in the supply models, we consider the difference in this step. Furthermore, we account for conditional heteroskedasticity in the model. For the OLS model, the p-value for the one-lag test on the squared residuals, following a χ^2 , was below 0.000, so we rejected the null hypothesis for homoskedasticity and taking into account the autoregressive process in the volatility of electricity prices was necessary.[24]

Table 11. Reduced-form total multipliers (L=1)

	OLS	IV
CDD	0.090	0.186
HDD	-0.800	0.049
ΔGDP	4.107	3.857
Balance	0.076	0.057
$\Delta PCarbon$	0.527	0.712
$\Delta PCoal$	3.317	2.885
ΔTTF	0.095	0.186
CF Hydro	-0.239	-0.249
CF Thermal	-0.962	-0.201
RES	-0.500	-0.678

24 Including a GARCH(1,1) was enough to reject the null hypothesis of an ARCH process up to 32 lags (following a χ^2) with a p-value equal to 0.233, but the parameters had problems of their own. The GARCH(1,1) were not compelling with the desired behaviour and the roots were above the unity value, which implied volatility is explosive. We decide to stick without these.

The estimations of the ARDL takes Huber-White robust standard errors to reduce the impact of the persistence in the variance. For the interpretation of the total multipliers, we must take into account the coefficients in the previous demand and supply estimations, especially for the prices of natural gas prices, since it is the only variable showing up in both functions. The estimated coefficient in demand was close 0.16 when we integrated the ARCH process, meanwhile, it was between 0.27 and 0.29 for supply. The estimated total multiplier is small but show that natural gas prices had a positive impact on electricity prices, although the coefficient is only significant in the 2SLS model. In average, 1% increase in the growth rate of natural gas prices will increase prices in 0.19%.

From the demand-side equation, temperatures show a positive coefficient since they are pure demand shifters. Increases by 1% in average temperatures above 18ºC and a decrease below 15ºC lead to price increases of 0.1%-0.2%. Besides, we can see that the effect of high temperatures is not significant, which is aligned with previous results in the demand function.

On the other hand, we have the growth rate of GDP, which shows a very big impact on electricity prices. In fact, a 1 percentage point increase in the growth rate of economic activity will increase electricity prices by 3.9%, showing the coupling of energy markets and overall economic activity. This result is showing that a relevant increase in economic activity will increase demand significantly, and will, therefore, be met with higher prices since installed capacity is not flexible in the short-term.

The estimations for the supply-side variables continue to be consistent with the expected coefficients, although we find some significance issues. The price for carbon-emission in the EU ETS is not significant in any of our models, despite the fact that it was relevant in equilibrium supply. This result is a particular example of the issues faced when estimating the reduced-form equation.

The growth rate of coal prices is not significant in any of our models, which may be explained due to the lower impact of this technology in the generation mix.

On the other hand, the use of hydraulic installed capacity is also not affecting prices in our period of analysis, as the VAR analysis found. The coefficient between equations changes significantly. Hydro generation is very flexible, which grants the chance for producers to only use their capacity whenever prices are very high. To get this situation we need (i) a very high demand in a given week or (ii) a very low amount of renewable generation in the system, so again the implementation of non-linear effects could be interesting. Anyhow, the fact that hydro is not affecting prices is also related to its flexibility, since the use of its installed capacity will be used to fill gaps between demand and supply, not having a huge effect on prices.[25]

The capacity factor for CCGT and Coal generation is not significant in either model. It presents a negative sign, as it was expected to see it was a supply shifter with a positive coefficient. Since we know that thermal generation is usually closely tied to peak demand and higher prices, we may conclude that the capacity factor may not be the best way to capture the positive impact of thermal generation units in prices. In fact, we can derive that the use of installed capacity is a pure analysis of supply, and we would need a new approach to capture the increase in price with thermal generation.

25 A downside of using the capacity factor and weekly data is that the analysis cannot capture the hourly peak-shaving of hydro generation.

The main variable of our analysis is the quantity of renewable energy generated. The coefficients for both the level and the differenced variable give similar results. Through-out our sample, a 1% increase in the quantity of renewable energy generated led to a 0.5%-0.7% decrease in electricity prices, ceteris paribus. This result is aligned with the concept of the merit-order effect since in the equilibrium we are shifting outwards the supply curve.

Moreover, the estimated coefficients for balance are aligned with their negative impact on supply, thus showing a positive impact on electricity prices in the equilibrium. We could interpret a positive coefficient by showing the example of both cases. Whenever demand cannot be met by national generation, it means that prices are not so high so at to include thermal units and energy is cheaper in either Morocco, Portugal or France (Spain is a net-exporter to Andorra, so we left it out of this thought), so we have to import electricity. On the other hand, higher prices are related to net-export weeks, higher prices lead to more generation (since the elasticity of supply to price is significant and positive) and the extra generated electricity can be sold in other markets.

5.4. Main empirical results and the merit-order effect: A international comparison

This section compares our estimated magnitudes to previous literature. For the demand function estimations, in all the explanatory variables obtain the expected signs. Our results show that income is indeed connected to electricity demand in the short term, and with an elastic relationship (income-elasticity higher than 1) as was found in Pérez-García and Moral-Carcedo (2017). Alternative income-elasticity estimation approaches are focused on lower frequencies and long-term modelling (Pérez-García and Moral-Carcedo, 2016; Toman and Jemelkova, 2003).

The derived temperature measures are significant, but their effect is not aligned with the first estimates for the aggregate market (Pardo et al., 2002; Blázquez et al., 2013) since the effect of cooling effects is double than heating. However, our results are aligned with more recent research. This change in the structural behaviour could be caused by recent changes in the demand composition (Pérez-García and Moral-Carcedo, 2015).

The estimated parameters for natural gas shows there is a substitution effect at the economy level. For households, these commodities are usually substitutes since they are both used for similar appliances (Blázquez et al., 2013; Romero-Jordán et al., 2014). However, there is evidence of this aggregate substitution effect in some papers (Labandeira et al., 2012), even in the household sector (Labandeira et al., 2006). In summary, our results suggest that there is indeed a substitution between electricity and natural gas.

As for the price-elasticity of demand, our final estimations show that it ranges between -0.26 and -0.34. Although this is far from the -0.1 estimated in Marques et al. (2010), it is close to estimates in aggregated exercises for the household sector (Romero-Jordán et al., 2014; Labandeira et al., 2012). Again, the increase in the sensitivity of aggregate demand to prices could be due to a change in the structure of the Spanish economy, and to an increased in the control of prices through improved technology and modern metering.

This approach is the first to analyse the supply function estimating the equation using the equilibrium quantity as the dependent variable, since previous papers used the reduced-form analysis (Marques et al., 2010). Our explanatory variables were selected after doing a literature review. As a result, apart from input prices, the capacity factors were relevant to identify the supply equilibrium quantity, showing a positive relationship. For hydraulic generation, the coefficient is much bigger than thermal generation. This could be explained by the fact that this technology has a lower marginal price, so it is more frequently in the mix. On the other hand, thermal generation is usually more relevant for peak periods. The fact that our analysis losses this kind of analysis, due to the weekly frequency, may explain why that the total multipliers are close to 0.

In order to control for the possible imbalance between demand and supply, we included the ratio of exported over imported energy. This coefficient, despite being small is significant and aligned with the pre-established idea of a negative coefficient to obtain net balance.

The prices for inputs, such as coal and emissions, are relevant and show a negative sign, showing that a positive shock would shift supply inwards or, increasing the price for the same quantity. However, the parameter with natural gas prices is a source of concern. Even though we may have financial reasons to explain a positive shock on supply, the expected sign would be a negative relationship with equilibrium supply, following the same arguments as the previous input prices.

As for the price-elasticity of supply, its estimated elasticity is around 0.36 in the final IV-ARCH model. The fact that this elasticity is slightly higher than that of the demand equation could be consistent with the fact that supply is more disaggregated than demand. Thus, the quantity supplied could be more elastic due to the fact that higher prices lead to the entrance of more technologies in the equilibrium.

Finally, in the reduced-form price equation the coefficients in these equations follow the explained rule of structural analysis. Demand-side variables are pushing prices to rise, especially due to the coupling of energy demand and economic growth. As for international prices, increases in coal prices are passed through to electricity prices. However, the same cannot not said about carbon prices, which are not significant to explain electricity prices. To the discussion of emission price pass-through to electricity prices, previous literature has found differing results. Some papers find a full pass-through (Fabra and Reguant, 2014), while others do not find such a relationship (Jouvet and Solier, 2013; Mosquer-López and Nursimulu, 2019). Our results would contribute to the latter group.

The capacity factor for hydraulic generation is not significant. It might be the case that these plants are taking advantage of their capacity for storage to sell when prices are higher. In the end, our estimations cannot provide any result on this discussion. As for Coal and CCGT generation, we know as well they would be higher for higher prices, but again, our results do not prove this to be the case. Due to the fact that it is a supply variable, we find a negative impact on prices.

The different estimations are robust when analysing the merit-order effect of renewable generation since all point to an elasticity around 0.5 (we take the conservative estimation). Thus a 10% decrease in renewable generation in the equilibrium would lead, on average, to a 5% increase in prices. Applying this percentage to the average price in our sample, this 10% decrease in RES generation would lead to an increase of 2.35 €/MWh. This result is higher than that found by Azofra et al. (2014)

which found a 10% decrease in wind production would lead to a 1.58 €/MWh increase in prices. However, their result is only measuring wind generation, so a higher estimate is consistent. Another reason our results may reach a higher merit-order effect is due to the fact that we use more recent data, and the installed capacity was higher and more stable than in previous papers. The results from linear-linear or log-linear estimations cannot be compared since we cannot make that computation in our application (Böckers et al., 2013; Gelabert et al., 2011).

Table 12. Merit-order estimation in the Spanish Day-Ahead Market

Author(s)	Model	Period	Frequency	Variable	Measurement
Böckers et al. (2013)	VAR	2008-2012	Daily	Special Regime	$\uparrow 1GWh \Rightarrow -3.1\%$
Gelabert et al. (2011)	OLS	2005-2009	Hourly	Special Regime	$\uparrow 1GWh \Rightarrow -2€/MWh(-3.7\%)$
Azofra et al. (2014)	Decision Tree	2012	Hourly	Wind Generation	$\downarrow 10\% \Rightarrow +1.58\,€/MWh$
Escribano & Ortega (2021)	ARDL	2013-2019	Weekly	Special Regime	$\downarrow 10\% \Rightarrow +5\%$ $(2.35\,€/MWh)$

On the other hand, the quantity for special regime includes cogeneration together with renewable generation. Since these technologies include a higher cost than renewables (Gelabert et al., 2011), our merit-order effect could be underestimated. For that, including information about individual technologies can be interesting as an extension of our models.

6. Conclusions

The analysis of the impact of the main renewable drivers on electricity prices, the merit-order effect in the day-ahead markets, has attracted a lot of attention. However, the analysis of literature focusing on Spanish markets did not follow the structural approach of demand and supply.

The analysis is exercised exploiting weekly data for the period from February 2012 to December 2019. The selection of this frequency posed some problems since some of the most relevant variables, such as GDP or installed capacities, are available at least quarterly. For that, an interpolation process was used to improve the number of observations without needing to reduce further the frequency of our dataset. Increasing the frequency of the observations usually face important bias of the estimates due to omitting relevant variables affecting the demand and the supply of electricity.

We confirm that temperature is an important determinant of electricity demand, with a higher impact of temperatures during the summer. The demand of electricity function has an income-elasticity higher than 1, supporting the idea of energy consumption coupling with economic cycles (Perez-García and Moral-Carcedo, 2017) while price-elasticity of demand is inelastic. Our results show an increase in the sensitivity compared to the previously available analysis in the day-ahead market (Marques et al., 2010).

On the other hand, the estimation of the supply function including as explanatory variables input prices, capacity factors, renewable generation and the external balance. The last one is added to control for those events when total demand of electricity is not matched with national supply. Clearly, the introduction of capacity factors was relevant, even without controlling for technical constraints.

Those input prices affecting both demand and supply (like gas, etc.) generally showed a negative relationship with quantities demanded and positive relationship with the supply. In relation to the price-elasticity, our estimations show that in absolute value, the price-elasticity of supply is higher than the price-elasticity of demand, but both are inelastic. This result could be pointing towards the fact that the supply mix is quite complex, and price increases allow to enter more technologies into the equilibrium.

The main goal of this analysis was to estimate the merit-order effect of renewable generation. This approach considers the impact on the quantity generated, rather than on penetration. We do not disaggregate this variable in more renewable technologies in order to focus on the aggregated market impact of these technologies (Gelabert et al., 2011). Even though our results cannot be directly compared to previous estimations, we obtain a merit-order effect close to 0.5, that is, a 10% decrease in RES generation in our analysed period would have led to an average increase of 2.35€/MWh in prices.

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Figures and tables

Figure 7. Correlation matrix of supply factors

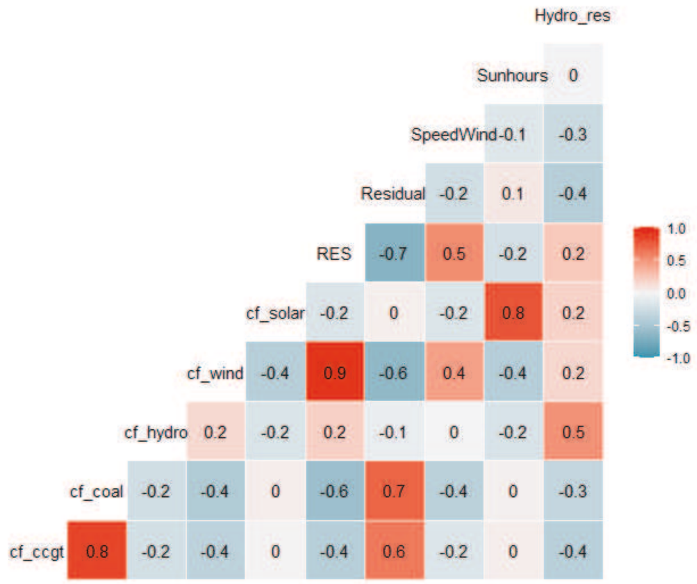

Table 13. Interpolation results

Series	Frequency (Original)	R-Squared	Variables
IC CCGT	Quarterly (Annual)	80.79	Service Index (REES), GDP, Natural Gas Consumption (INE), IPI, IPI2 , Dummy Y18
IC Coal	Quarterly (Annual)	90.31	Industry index (REEI), REII2 , GDP, Natural Gas Consumption (INE), Gasoline Consumption (INE), Dummy Y18, IPI Capital Goods
IC Solar PV	Quarterly (Annual)	90.67	Industry index (REEI), REII2 , GDP,GDP^2 , Total Oil consumption, Dummy Y19, IPI, IPI^2
IC CSP	Quarterly (Annual)	97.57	Industry index (REEI), REII2 , GDP,GDP 2 , Total Oil consumption, Dummy Y19, IPI, IPI^2
GDP	Weekly (Quarterly)	98.89	Monthly and Yearly dummies, Price of Brent, IPI, Total Oil Consumption (INE)
Hydro reserves	Weekly (Monthly)	95.30	Precipitation, Precipitation^2 , Temperature, Temperature^2 ,Sunhours, Sunhours^2 ,Speedwind, Dammed water

Sources: REE (System Operator), INE, Ministry for Ecological Transition and Demographic Challenge

Table 14. Data Descriptions

Series	Source	Description
IC CCGT	REE/Computed	Installed capacity for CCGTs taken yearly and interpolated by doing a regression over quarterly aggregated data. It was used to compute the weekly capacity factor for thermal generation.
IC Coal	REE/Computed	Installed capacity for Coal plants taken yearly and interpolated by doing a regression over quarterly aggregated data. It was used to compute the weekly capacity factor for thermal generation.
IC Solar PV	REE/Computed	Installed capacity for solar PV generation taken yearly and interpolated by doing a regression over quarterly aggregated data. It was used to compute the weekly capacity factor for solar generation.
IC CSP	REE/Computed	Installed capacity for Concentrated Solar Power generation taken yearly and interpolated to quarterly data. It was used to compute the weekly capacity factor for solar generation.
GDP	INE	Data from aggregated accounting, interpolated by doing a regression over weekly data (week variable: Brent, the rest was monthly).The goal is to increase volatility and have a proxy of GDP in demand.
Hydro reserves	Embalses.net (MITECO)	Data from MITECO registry. This variable was monthly and interpolated to weekly frequency using climate variables. Hydro reserve is a good measurement on the capacity of hydro generation and is used as an instrument.
Electricity Price	OMIE	Arithmetic average of hourly prices each week in the Day-Ahead Market during weekdays.
EUA Prices	Sendeco2	Arithmetic average of daily spot prices each week.
TTF Prices	Bloomberg	The TTF is the natural gas market in the Netherlands that is used in Europe as a reference market for natural gas. The series are computed as the arithmetic average of daily Month-Ahead quotations in the TTF market and converted to €/MWh automatically by Bloomberg.
Coal Prices	Bloomberg	API2 Coal is an index for the coal price in Europe. The series are computed as the arithmetic average of daily Month-Ahead quotations of API2 in USD/T. The data was provided by REE and converted to €/t using the exchange rate from Banco de España.
Brent Prices	Bloomberg	The price of Brent is the physical exchange of oil barrels, which is usually used as a reference price for oil products in Europe. The series are computed as the arithmetic average of daily Month-Ahead quotations for Brent barrels converted to €/MMBtu automatically by Bloomberg.
Wind Generation	REE	Sum of hourly busbar generation of wind on-shore installations. The series differ from Day-Ahead scheduling since it includes balancing services and real time generation.
Solar PV Q	REE	Sum of hourly busbar generation of all the Solar Photovoltaic plants in Spain. The series differ from Day-Ahead scheduling since it includes balancing services and real time generation.
Solar CSP Q	REE	Sum of hourly busbar generation of all the Concentrated Solar Power plants in Spain. The series differ from Day-Ahead scheduling since it includes balancing services and real time generation.
Total Solar	Computed	Sum of Solar PV and Solar CSP.
Coal Q	OMIE	Sum of hourly scheduled generation in the Day-Ahead Market for coal plants. The information in OMIE separates imported coal plants and national coal plants. We use the sum of both series..

CCGT Q	OMIE	Sum of hourly scheduled generation in the Day-Ahead Market by Combined-cycle gas turbines..
Hydro Q	OMIE	Sum of hourly scheduled generation in the Day-Ahead Market of UGH and non-UGH hydro generation. Hydro plants in the same river basin are usually managed jointly (Unión de Gestión Hidráulica), so information for a single plant is not available. Non-UGH hydro plants are managed independently..
Special Regime Q	OMIE	Sum of hourly scheduled generation in the Day-Ahead Market of all plants included in the old Special Regime, including CHP, mini-hydro, wind, solar PV and other renewable energy sources receiving the special remuneration scheme.
Balance	OMIE	The variable is computed as the ratio of exported to imported energy. The series for imports and exports were computed as the sum of hourly scheduled energy exchanges scheduled in the Day-Ahead Market with all neighbour countries (PT, FR, MR, AN).
Quantity	OMIE	Sum of hourly scheduled demand in the Day-Ahead Market, which includes pumping, cross-border energy exchanges and conventional demand.
Temperature	AEMET/Comp.	Information on daily temperature in: Madrid Airport, Valencia Airport, Jaén and A Coruña Airport. Computed as the average of daily information provided by AEMET.
CDD	Computed	Computed as Max[log(Temperature-18);0]
HDD	Computed	Computed as Min[log(15-Temperature);0]
Speedwind	AEMET/Comp.	Information on daily windspeed (m/s) in: Madrid Airport, Valencia Airport, Jaén and A Coruña Airport. Computed as the average of daily information provided by AEMET.
Precipitation	AEMET/Comp.	Information on daily precipitations (m^3) in: Madrid Airport, Valencia Airport, Jaén and A Coruña Airport. Computed as the average of daily information provided by AEMET.
CF Thermal	Computed	Computed as the sum of Coal + CCGT over the sum of their installed capacities times the number of hours each week (120).
CF Hydro	Computed	Computed as weekly sum of Hydro generation over its installed capacity times the number of hours each week (120).
CF Solar	Computed	Computed as weekly sum of Solar PV and Solar CSP over their installed capacities times the number of hours each week (120).
CF Wind	Computed	Computed as weekly sum of wind generation over its installed capacity times the number of hours each week (120), taken as a proxy since we cannot observe directly information on wind quantities in the Day-Ahead Market.

Table 15. ADF Unit-Root tests

Series	Trend + Constant	Constant	Neither	I(d)
Electricity Price	-5.1*** (0.000)	-4.65*** (0.000)	-0.245 (0.597)	I(0)
EUA Price	-1.92 (0.641)	-0.45 (0.896)	1.02 (0.92)	I(1)
TTF Price	-2.31 (0.423)	-1.89 (0.333)	-0.87 (0.335)	I(1)
Coal Price	-2.11 (0.534)	-2.13 (0.230)	-0.82 (0.359)	I(1)
Wind	-6.49*** (0.000)	-6.51*** (0.000)	-0.000 (0.681)	I(0)
Solar PV	-6.78*** (0.000)	-6.78*** (0.000)	-0.06 (0.658)	Trend-Stationary
CSP	-6.50*** (0.000)	-6.51*** (0.000)	-0.37 (0.549)	Trend-Stationary
Total Solar	-7.27*** (0.000)	-7.28*** (0.000)	-0.174 (0.622)	Trend-Stationary
Coal	-3.98** (0.010)	-3.81*** (0.003)	-0.58 (0.463)	Trend-Stationary
CCGT	-2.67 (0.246)	-2.26 (0.184)	-1.09 (0.248)	I(1)
Hydro Q	-3.84** (0.015)	-3.80*** (0.003)	-0.02 (0.672)	Trend-Stationary
Special Regime Q	-6.52*** (0.000)	-6.53*** (0.000)	-0.12 (0.641)	Trend-Stationary
Balance	-6.09*** (0.000)	-4.73*** (0.000)	-4.09*** (0.0001)	I(0)
Quantity	-6.06*** (0.000)	-5.95*** (0.000)	0.03 (0.693)	I(0)
CDD	-5.99*** (0.000)	-5.92*** (0.000)	-4.94*** (0.000)	I(0)
HDD	-5.79*** (0.000)	-5.77*** (0.000)	-3.97*** (0.000)	I(0)
Hydro Res.	-4.591*** (0.001)	-3.92*** (0.002)	-0.97 (0.293)	I(1)
Speedwind	-4.27*** (0.003)	-2.10 (0.242)	0.11 (0.719)	I(1)
Precipitation	-3.71** (0.022)	-2.23 (0.195)	-1.99* (0.091)	I(0)
GDP	-4.92*** (0.000)	-0.16 (0.940)	4.78 (1.000)	I(1)
CF CCGT	-3.58*** (0.032)	-3.61*** (0.006)	-2.07** (0.036)	I(0)
CF Hydro	-5.04** (0.000)	-5.385*** (0.000)	-1.48 (0.129)	I(0)
CF Coal	-7.45** (0.045)	-3.37 (0.012)	-1.92** (0.052)	I(0)
CF Solar	-7.85*** (0.000)	-7.76*** (0.000)	-2.21** (0.026)	I(0)
CF Wind	-5.08*** (0.000)	-5.11*** (0.000)	-0.94 (0.306)	I(0)

The number of lags was determined using Akaike Criteria (max. 16 lags, as default in Eviews 10). The t-statistic and MacKinnon one-sided p-values (in parenthesis) are presented. One of the variables showed the need for a second difference. Series for installed capacities were stationary.