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The relationship between energy consumption and prices. Evidence from futures and spot markets in Spain and Portugal

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A B S T R A C T

Slow economic recovery, market concentration, and scant alternative energy sources make the Iberian energy market quite idiosyncratic when compared to the rest of the EU. This paper focusses on the Iberian energy market by dealing with the analysis of the relationship between energy consumption and energy prices by using fractional integration in the Iberian market. This technique is used in order to examine the degree of persistence of the series, looking at the spot and futures markets in Spain and Portugal. The results indicate that all the series are fractionally integrated, showing long memory and mean reverting behaviour. Moreover, a close relation between energy consumption and energy prices is found in the spot market whereas it is not found in the futures market. In fact, there is a weak relationship between the futures market and energy consumption. However, regarding energy pricing, the relationship is stronger but with the spot market itself.

1. Introduction

Energy is the cornerstone of modern economies not only for the suppliers of physical goods and services but also as a means of social welfare and comfort for people in general. Hence, it is crucial to know how price changes impact on the energy demand of suppliers and consumers. In the recent past, energy deregulation and sharp movements in the price of primary energy goods have stimulated an increased interest in this area. Most econometric studies in this field are focused on the price elasticities of energy demand with some other macroeconomic factors [1], helping us to gain a better understanding of the economic consequences of varying energy prices. Although the economic literature on energy demand dates back to the last century [2,3], in recent years numerous academic studies have used various techniques to estimate both the short and the long-term price elasticity demand of different energy products in different countries. This paper, however, departs from that literature in the sense that we first examine the degree of persistence in both energy consumption and energy prices using updated time series techniques based on fractional integration. In addition, the relationship between these two variables has been investigated in the spot and futures markets in the case of Spain and Portugal.

The Iberian business case has presented a number of regulatory specificities and competition constraints when compared to other European energy markets. The main issues to resolve today in the Spanish market are the scant competition, the tariff deficit, faulty tariff design, a raft of uncertainties, potential market integration and the introduction of new technologies [4]. In the Portuguese market, Amorim et al. [5] indicate that the two main issues to address are that of setting up balancing mechanisms to implement renewable energy sources and capacity incentives to allow new investments. These operational and financial constraints may be responsible for excessive volatility in pricing and energy consumption in the Iberian region. Ciarreta and Zarraga [6] found also relevant intra-day price and transmission volatility in the Iberian market, arguing how results are driven by market structure, market design and the regulation of renewable generation. Regarding the futures market, Capitán-Herraiz and Rodriguez-Monroy [7] documented its lack of liquidity in comparison with other North European markets.

Notwithstanding, the slow economic recovery experienced by the Iberian Peninsula following the global financial crisis of 2008 has also contributed to lack of investment in renewable sources. This earlier crisis has resulted in the absence of new players, which prefer to innovate in bigger and integrated markets, where future options and spot market trades can be transacted more easily, due to higher liquidity.

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This being the case, the energy market integration in the Iberian Peninsula, which is expected to take place from 2020 on, calls for more investigation on each country level current status. Although volatility in energy prices and consumption in spot and future markets might be mitigated due to variance pooling effects; future investment prospects could be affected by country-level market idiosyncratic conditions. The current COVID-19 crisis might highlight these weaknesses in the short future as has happened in the past.

In summary, this paper departs from that literature in the sense that it examines the degree of permanence in both energy consumption and energy prices using updated time series techniques based on fractional integration. In addition, the relationship between the two variables is investigated in the spot and futures markets in the case of Spain and Portugal. The rest of the paper is structured in seven sections. The literature review is presented in Section 2, while Section 3 focuses on the Iberian case. The major methodological steps adopted in this research are presented in Section 4. Data descriptive and sources are detailed in Section 5. Results are analyzed in Section 6 and discussed in Section 7. Conclusions follow in Section 8.

2. Literature review

The literature relating to energy models for demand forecasting and management in the last century is extensive, especially after the oil crisis during the 1970s. After the 1990s, as a result of the Kyoto Protocol, environmental problems were included in the equation and the relationship between social factors, natural resources consumption and dioxide emissions were also studied. A very popular contribution towards gaining an understanding of the different energy models is the that of Jebaraj and Iniyan [8] in which different types of models such as energy planning, supply-demand structure or forecasting models where reviewed and presented, as well as renewable and emission reduction policies.

A recent review of the different models for energy demand forecasting can be found in Suganthi and Samuel [1]. During the first decade of the 21st century several new techniques were introduced to accurately predict future energy needs. Traditional methods such as time series regressions as well as other computing techniques such as fuzzy logic, genetic algorithms and neural networks are being extensively used to study the demand side management.

Regarding the drivers that can affect energy demand, York [9] analyzed the relationship between demographic trends and energy consumption for the period 1960–2000 in fourteen EU countries, concluding that the relationship between population size and energy consumption was highly elastic and close to one. The age structure of the population and its level of urbanization appear to play important roles in terms of energy consumption. Other studies suggest that price or economic activity also have an important relationship with energy demand. Sharimakin et al. [10] studied different European industries in the period 1995–2009 and concluded that long-run elasticity with respect to price is negative (−0.68), while long-run elasticity with respect to economic activity is positive (0.81). Adeyemi et al. [11] studied the asymmetric price responses and the underlying energy demand trends, concluding that changes in energy prices might induce asymmetric changes in the derived demand for energy. This process should depend upon whether the price falls, rises, or rises above a previous maximum, but the derived demand for energy might be driven by exogenous factors such as improvements in the efficiency of the capital or government regulations. A consequence of this is that the drivers of energy demand need not necessarily be the same for all countries in the estimation of demand models.

Analyzing energy consumption, Wong et al. [12] estimated the elasticities of changes in oil prices and income of twenty OECD countries for the period 1980–2010. Negative income elasticity was found for coal consumption but income elasticity for oil and gas was found to be positive, suggesting the importance of economic growth in the movement towards cleaner energy from coal to oil and gas. However, in the specific case of oil markets, its consumption fell significantly with higher oil prices. Bhattacharyya and Timilsina [13] studied other indirect aspects for developed economies, concluding that current models were not resolving conceptual issues regarding the existence of non-monetized transactions, such as the poor-rich or urban-rural structures. In addition, traditional energy resources or differentiation between commercial and non-commercial energy commodities were often poorly reflected in models. Other authors such as Beunder and Groot [14] concluded that the consumers' preferences cannot be simply taken as given, as is customary in standard economic models, and they should interact with the structure of financial incentives. In consequence, taxes and subsidies, or changing fixed or flexible rates in energy bills, were interacting and modifying with people's preferences.

Salisu and Ayinde [15] documented other emerging issues for energy demand, ranging from asymmetric price responses, time varying demand parameters, triangulation analyses to seasonal and climate change effects. They proposed models assuming symmetric, asymmetric energy prices or non-parametric techniques with Bayesian approaches, to make empirical captures using time-varying coefficient models such as rolling regressions. Figueiredo et al. [16] analyzed the effects of renewable energy output variations, particularly wind power, noting that its production is strongly influenced by weather conditions. A recent review of the latest current trends in energy systems can be found in Lopion et al. [17] as the requirements made on energy system models are changing due to the governments emissions regulation and the implementation of green energies. Along with the climate goals of the Paris Agreement, the national greenhouse gas strategies of industrialized countries involve the total restructuring of their energy systems.

In terms of the pricing discovery and the relationship between spot and futures markets, Figuerola-Ferretti and Gonzalo [18] studied the modelling of pricing in commodity markets, presenting an equilibrium model between spot and futures prices with finite elasticity of arbitrage services and convenience yields. This model was tested in non-ferrous metals prices traded in the London Metal Exchange (LME), concluding that most markets are in backwardation and futures prices are information dominant in highly liquid futures markets. Other studies, as that of Narayan and Sharma [19] proposed a time-varying price model structure based on a rolling-window error correction framework, showing that price discovery in nine general commodities is dominated by the spot market, while in another six, price discovery is dominated by the futures market. Therefore, challenging the well-established view in commodity markets that it is the futures market which dominates the spot price discovery process.

Regarding energy pricing, a review of the different techniques can be found in Weron [20] explaining the complexity of the available solutions, and this review has been recently updated in Nowotarski and Weron [21] focusing in a probabilistic perspective. Shrestha [22] analyzes empirically the price discovery process in the futures and spot markets for different types of energy, such as crude oil, heating oil and natural gas, discovering that almost all price discovery takes place in the futures markets for heating oil and natural gas but in the case of crude oil, price discovery takes place in both markets.

In the specific case of the electricity market, Malo [23] studied electricity spot and futures price dependence with a multifrequency approach for modeling spot and weekly futures price dynamics. Garcia-Martos et al. [24] worked with unobserved components, proposing a differential model to extract seasonal common factors from the vector of general electricity prices. Lisi and Pelagati [25] considered the market time series comparing deterministic and stochastic approaches, and concluding that both approaches may give good results. Le et al. [26] proposed an algorithm to simulate the clearing of the integrated European intra-day market coordinating the discrete auction with the continuous trading, helping to solve the different intra-day market situations. Monteiro et al. [27] presented a probabilistic price forecasting model for day-ahead hourly price forecasts in electricity markets, based on a Gaussian density estimator function for each input variable, allowing the parameters of a Beta distribution to be calculated for the hourly price variable. De Marcos et al. [28] proposed a short-term hybrid electricity price forecasting model combining a cost-production optimization model with an econometric neural network model. Manner et al. [29] proposed a dynamic multivariate binary choice model, following a vector autoregressive (VAR) process. Finally, Lago et al. [30] used deep learning algorithms with neural networks, and in Lago et al. [31] they improved the model results associating this specific focus with market integration.

Finally, regarding the specific usage of fractional integration in the context of energy, there are some studies that have used this methodology, including the contributions of Elder and Serletis [32] regarding energy future prices, Barros et al. [33] focusing on U.S. renewable energy consumption, Weron [20,34] and Gil-Alana et al. [35] in the field of electricity prices, and Barros et al. [36] on energy prices.

3. The Iberian case

This section focuses on the cases of Spain and Portugal. To understand the specific Iberian business case, an interesting analysis of the Spanish market can be found in Duarte et al. [4] focusing in the specific disaggregation of the electricity industry into the generating, transmission, distribution and marketing businesses, which were decoupled in 1997 under legislation prohibiting any single company from conducting more than one of these businesses. Conventional thermal and hydropower generating together make up more than 50% of total output, wind power produces 19% and nuclear power accounts for only 7% where almost all demand is covered by domestic production. The main issues to be resolved in the Spanish market concern the scant competition, the tariff deficit, faulty tariff design, a raft of uncertainties, potential market integration and the introduction of new technologies. In the Portuguese market, Amorim et al. [5] indicate that the two main issues to address are that of fulfilling balancing mechanisms to be able to manage more than 50% of renewable energy sources and the capacity incentives to allow new investments. In this line, as in Portugal there is a commitment for the renewable electricity share to reach 60% by 2020. Several authors have worked in this industry green-renewal process. Figueiredo et al. [37] explain the issues around replacing traditional coal-based power plants with photovoltaics, while Pereira and Saraiva [38] explain the implications of the penetration of wind power, since this process is putting the profitability of traditional stations under pressure. Distributional costs of wind energy production in Portugal under the liberalized Iberian market regime can be found in Prata et al. [39].

Another issue in the Iberian market is the interconnection needs between different countries. As explained by Rubino and Como [40]; current EU energy policy calls for a well-integrated internal energy market by 2020 achieving interconnection of at least 10% of the installed electricity production capacity for all EU member states, with a 15% target in 2030. Figueiredo et al. [41] track the Iberian case, showing that Iberia has already surpassed this value reaching 25.6% and is aiming to achieve 3000 MW in the near future, which will represent 32% of the maximum demand considered in this study. An adequate cross-border interconnection capacity should avoid the internal development of dispatchable reserve capacity, helping balancing and grid security purposes.

Several studies have tried to explain the electric consumption and price evolution in the Iberian market. Ciarreta and Zarraga [42] studied the dynamic relationship between electric consumption and GDP in Spain for the period 1971 to 2005 using a VAR model with differenced series in a unidirectional causality relationship. Their results show a linear relationship running from GDP to electric consumption with no evidence of a non-linear relationship. In Ciarreta and Zarraga [6]; the same authors studied the volatility of hourly pricing from the Iberian intra-day electricity market for the period 2002–2014, concluding that the results show significant volatility transmissions between the sessions, arguing how results are driven by the market structure, the market design and the regulation of renewable generation. Regarding the futures market, Capitán-Herraiz and Rodriguez-Monroy [7] documents its lack of liquidity compared with other North European markets, mentioning that the main significant drivers are the traded volumes in the OTC trading and auctions. Thus, it would be advisable to attract new players in order to increase liquidity and price efficiency.

Regarding pricing models, Lagarto et al. [43] studied the market power of generating firms in the day-ahead Iberian Electricity Market (MIBEL) using a model where data on power plants, fuels, CO_2 and the day-ahead electricity market are provided as input data, and measuring the direct influence of the external market price drivers, such as fuel and CO_2 prices, renewable generation, or power plants availability. They conclude that major firms behaved much more competitively in off-peak than in peak periods, in some cases generating at market prices below marginal costs. Monteiro et al. [27] recently proposed another specific pricing model for the day-ahead price forecasting in the MIBEL market. Input variables include hourly time series records of weather forecasts, previous prices, and regional aggregation of power generations and power demands.

4. Methodology

Fractional integration is a time series technique that allows investigators to determine the dynamic specification of the data in a more flexible way than other approaches based on integer degrees of differentiation. It belongs to a broader category named long memory, characterized because the spectral density function is unbounded in at least one frequency on its spectrum. Within this group of processes, a very popular analysis model within the time series studies is the fractional integration that is described in the following paragraph and that is characterized because its spectral density function tends to infinity as the frequency approaches 0.

We say that a given process $\{x_t, t = 0, \pm 1, \ldots\}$ is integrated of order d, and denoted as I(d) (where d can be any real value) if it can be represented as:

$$(1 - L)^d x_t = u_t\ , \ t = 1, 2, \ldots\ , \tag{1}$$

where L is the lag operator ($Lx_t = x_{t-1}$) and u_t is integrated of order 0, i.e., I(0), defined as a covariance stationary process with a positive and bounded spectrum. Thus, u_t can be a white noise but also a weakly autocorrelated process, for example, of the AutoRegressive Moving Average (ARMA) form.[1]

The estimation of the differencing parameter d is crucial. Thus, if $d = 0$, $x_t = u_t$ in (1), and x_t is said to be short memory as opposed to the case of long memory that takes place when $d > 0$. From a statistical viewpoint, the borderline point is 0.5. Thus, if $d < 0.5$, x_t is covariance stationary; however, if becomes nonstationary for $d \geq 0.5$, and it is more nonstationary as we increase the value of d, noting that the variance of the partial sum increases in magnitude with d; finally, from a policy perspective, mean reversion occurs if $d < 1$ and shocks will have permanent effects if $d \geq 1$.

We estimate the value of d using the Whittle function based on the frequency domain [45], and, for this purpose, we use a version of a testing procedure developed in Robinson [46] that is very convenient in the context of the series examined here, noting that it permits us to test any real value of d, including thus values in the nonstationary range ($d \geq 0.5$). Using this method, we test the null hypothesis:

$$H_o: \quad d \quad = \quad d_0\ , \tag{2}$$

[1] Thus, if u_t in (1) is ARMA(p, q), x_t is said to be a fractionally integrated ARMA, i.e., an ARFIMA(p, d, q) process. See, [44].

in (1), where x_t can be the errors in a regression model of form:

$$y_t = \beta' z_t + x_t, t = 1, 2, \ldots, \tag{3}$$

where z_t can be either exogenous regressors or deterministic terms such as an intercept and/or a linear time trend. The test statistic proposed in Robinson [46] contains several important features. Thus, its limiting distribution is standard normal (N(0, 1)), so that we do not need to rely on critical values based on Monte Carlo simulation studies. Moreover, the test statistic and its asymptotic behaviour remain valid for any real value d_0 in (2), including nonstationary cases, and thus, it does not require preliminary differencing to render the series stationary prior to the performance of the test; finally, it is the most efficient method in the Pitman sense against local departures from the null.[2] Using alternative methods (also based on fractional integration) produced essentially the same results as those reported in this work.

5. Data description

The dataset encompassing spot and futures daily prices and energy consumption was obtained from the OMIP website (http://www.omip.pt/Downloads/tabid/104/language/pt-PT/Default.aspx) for Portugal and Spain, during the period encompassed from 2007 to 2017. Table 1 presents the descriptive statistics for these time series, while Table 2 presents the Kendall's Tau correlation coefficient.

While Table 1 suggests that price and demand time series are, somehow, asymmetrically distributed, although dispersion maybe considered low – with the exception of future energy demand -, Table 2 reveals a moderately strong correlation between future and spot prices and a very weak correlation between spot energy and spot prices. Time series are depicted in Figs.1 and 2 for both energy and prices.

6. Empirical results

This section starts with the analysis of the individual series. The initial point is to estimate the value of d in the model given by (3) and (1) with $z_t = (1,t)^T$, i.e.,

$$y_t = \beta_0 + \beta_1 t + x_t; (1 - L)^d x_t = u_t, t = 0, 1, \ldots, \tag{4}$$

where y_t refers to each of the observed time series (energy consumption and prices in the spot and future markets); β_0 and β_1 are unknown coefficients referring, respectively, to an intercept and a linear time trend, while x_t is supposed to be I(d), where d can be any real value; finally, u_t is I(0), expressed in terms of both uncorrelated and autocorrelated (Bloomfield) errors. Bloomfield [50] proposed an alternative to the ARMA modelling in a non-parametric way. It is non-parametric because there is no explicit form for the model since it is exclusively presented in terms of its spectral density function. He showed that the log of that function approximates very well the log spectrum of AR processes, producing also autocorrelations that decay exponentially fast as in the AR model. In all cases, we present the results for the original data as well as for the log-transformed values.

Table 3 displays the estimates of d (and their associated 95% confidence intervals) under the assumption of white noise errors. The results for the three standard cases of: i) no deterministic terms (i.e., $\beta_0 = \beta_1 = 0$ in (4)), ii) an intercept ($\beta_1 = 0$ in (4)), and iii) an intercept with a linear time trend (β_0 and β_1 unknown) have been displayed, marking in bold in the table the selected model for each series, based on the t-values of the estimated coefficients on the d-differenced series.

The first thing that can be observed in Table 3 is that the time trend is not required in any single case, and the intercept is sufficient to describe the deterministic terms. While focusing on the estimated values of d, it can be seen that in all cases the values are constrained between 0 and 1 and both hypotheses (I(0) and I(1)) are decisively rejected in favour of fractional integration. Starting with the spot market, it is observed that the estimated value of d is 0.72 for consumption and 0.64 for the energy prices, and the values are slightly smaller (0.70 and 0.54) in the case of the log transformed data. For the futures market, the values are much smaller, being 0.24 (and 0.27 for the logged values) in the case of the energy consumption and 0.54 (0.48) for prices. Thus, evidence of long memory (d > 0) and mean reversion (d < 1) is obtained in all cases, and thought consumption seems to be nonstatonary (d ≥ 0.5), prices follow a stationary path (d < 0.50)

In Table 4 we allow the error term to be autocorrelated. However, instead of imposing a specific modelling assumption for u_t in (4), we use here a non-parametric method due to Bloomfield [50]. It is called non-parametric in the sense that no functional form is explicitly presented for u_t in (4). The model is exclusively defined in terms of its spectral density function throughout an expression that approximates fairly well highly parameterized ARMA process. Moreover, this approach accommodates extremely well in I(d) models (see Ref. [51]. The results using this approach are very similar to those given in Table 3 in the sense that all values are constrained between 0 and 1 implying fractional integration and mean reverting behaviour. Thus, shocks affecting these series will have transitory though persistent effects.

Thereafter, the relationships between the two variables (in logs) were analyzed by taking a regression of one of the variables against the other. Based on the fractional nature of the two series, one possibility here is to conduct a regression model under the assumption that the independent variables are exogenous to the system, allowing the errors to be potentially fractional. Thus, the following regression model was considered first,

$$\log\ C_t = \gamma_0 + \gamma_1 \log P_{t-k} + x_t; (1 - L)^d x_t = u_t\ ,\ t = 0, 1, \ldots, \tag{5}$$

where C refers to energy consumption and P to energy prices, and with k = 0, 1, 2, 3, 4 and 5. Once more, we present the results for the two cases of uncorrelated (white noise) and autocorrelated (Bloomfield) errors, in Tables 5 and 6 respectively.

The most noticeable feature observed in these two tables is that contemporaneously the slope is statistical significant in the two (spot and futures) markets, however, allowing for lags (k > 0) the coefficient only remains significant in the case of the spot market, implying that prices affect the behaviour of energy consumption in this market.

Finally, the same experiment was carried out but in the opposite way, by testing energy prices against energy consumption, while still maintaining the possibility of long memory errors, i.e,

$$\log\ P_t = \gamma_0\ +\ \gamma_1 \log C_{t-k} + x_t; (1 - L)^d x_t = u_t, t = 0, 1, \ldots, \tag{6}$$

The results for the two cases of uncorrelated and autocorrelated errors are respectively reported in Tables 7 and 8. It can be seen that similar to the previous tables, only lag effects are statistically significant in the case of the spot market. Thus, energy prices and energy consumption are both related in a bi-directional way in the case of the spot market. However, this relationship does not hold in the futures market.

7. Discussion of results

These results suggest that the energy spot market in Portugal and Spain presents the price-elasticity of demand expected behaviour of micro-economics, where higher prices induces lower consumption and vice-versa, in a feedback process that is temporally persistent. This temporal persistence within the ambit of a feedback process of prices and consumption in the spot markets is consistent with results presented in Table 1, where readers can easily note that variable dispersion is lower in spot markets, possibly as a consequence of a tied joint

[2] See Ref. [47] for an application using the same version of the tests of [46] as the one used in this work. The same version of the tests has been used in Refs. [48,49]; etc.

Table 1
Descriptive statistics.

Variables	Min	Max	Mean	SD	CV
Spot Energy (MWh)	465,578.300	922,465.000	654,659.647	71,056.337	0.109
Future Energy (MWh)	48,000.000	1,055,730.000	103,750.166	112,060.387	1.080
Spot Price (Euro/MWh)	5.779	94.128	49.649	11.455	0.231
Future Price (Euro/MWh)	11.250	75.148	48.732	6.871	0.141

Table 2
Kendall's Tau correlation matrix.

	Future Energy	Future Price	Spot Energy	Spot Price
Future Energy (MWh)	1			
Future Price (Euro/MWh)	−0.006103973	1		
Spot Energy (MWh)	−0.064405016	0.070074661	1	
Spot Price(Euro/MWh)	−0.038958766	0.510570069	0.14204931	1

* Kendall's Tau correlation was preferred over the traditional Pearson's correlation coefficient since it is better able to capture extreme, joint tail variation, being widely used for modeling bi-variate distributions by using the copulas technique. Significant results at $p < 0.05$ are highlighted in bold.

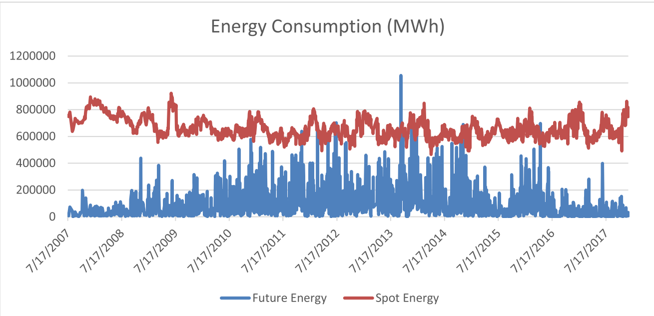

Fig. 1. Energy consumption time series.

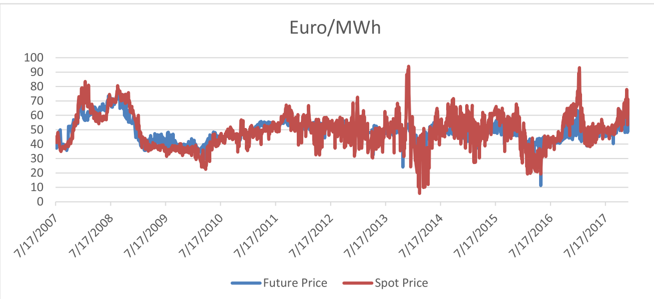

Fig. 2. Energy price time series.

behaviour.

On the other hand, results for the future energy markets are counterintuitive. Not only is temporal persistence not significant, but higher (lower) levels of energy prices tend to stimulate higher (lower) energy consumption levels and vice-versa. This behaviour is typical of speculative movements, where economic agents anticipate their purchases due to fear of future supply shortages. As long as energy supply in Portugal and Spain is controlled by a few companies with insufficient funding for generation and distribution capacity expansion, and which are scarcely integrated with other EU countries, this speculative behaviour in futures markets is quite justifiable.

Finally, it can be said that the main challenge of governments and

Table 3
Estimated values of d under no autocorrelation for the error term.

i) Original data			
Spot market			
Series: Original	No terms	An intercept	A linear trend
Energy consumption	0.82 (0.79, 0.85)	**0.72 (0.70, 0.75)**	0.72 (0.70, 0.75)
Energy prices	0.68 (0.65, 0.71)	**0.64 (0.61, 0.67)**	0.64 (0.61, 0.67)
Futures market			
Series: Original	No terms	An intercept	A linear trend
Energy consumption	0.24 (0.21, 0.26)	**0.24 (0.21, 0.26)**	0.24 (0.21, 0.26)
Energy prices	0.65 (0.63, 0.67)	**0.52 (0.50, 0.54)**	0.52 (0.50, 0.54)
ii) Logged data			
Spot market			
Series: Logged	No terms	An intercept	A linear trend
Energy consumption	0.99 (0.96, 1.03)	**0.70 (0.67, 0.73)**	0.70 (0.67, 0.73)
Energy prices	0.76 (0.74, 0.79)	**0.54 (0.51, 0.57)**	0.54 (0.51, 0.57)
Futures market			
Series: Logged	No terms	An intercept	A linear trend
Energy consumption	0.46 (0.44, 0.48)	**0.27 (0.24, 0.29)**	0.27 (0.24, 0.29)
Energy prices	0.85 (0.82, 0.88)	**0.48 (0.46, 0.50)**	0.48 (0.46, 0.50)

The values in parenthesis report the 95% confidence bands for the values of d, i.e., the values of d where the null hypothesis cannot be rejected at the 5% level. In both, the selected model in relation with the deterministic terms.

Table 4
Estimated values of d under autocorrelation (Bloomfield) for the error term.

i) Original data			
Spot market			
Series: Original	No terms	An intercept	A linear trend
Energy consumption	0.83 (0.79, 0.87)	**0.70 (0.65, 0.77)**	0.70 (0.65, 0.77)
Energy prices	0.70 (0.65, 0.73)	**0.62 (0.58, 0.68)**	0.62 (0.58, 0.68)
Futures market			
Series: Original	No terms	An intercept	A linear trend
Energy consumption	0.30 (0.27, 0.34)	**0.30 (0.27, 0.34)**	0.30 (0.27, 0.34)
Energy prices	0.83 (0.80, 0.86)	**0.70 (0.67, 0.74)**	0.70 (0.67, 0.74)
ii) Logged data			
Spot market			
Series: Logged	No terms	An intercept	A linear trend
Energy consumption	0.99 (0.94, 1.03)	**0.68 (0.64, 0.72)**	0.69 (0.64, 0.73)
Energy prices	0.84 (0.81, 0.88)	**0.60 (0.55, 0.64)**	0.60 (0.55, 0.64)
Futures market			
Series: Logged	No terms	An intercept	A linear trend
Energy consumption	0.57 (0.54, 0.60)	**0.30 (0.27, 0.33)**	0.30 (0.27, 0.33)
Energy prices	0.96 (0.92, 1.01)	**0.65 (0.62, 0.69)**	0.65 (0.62, 0.69)

The values in parenthesis report the 95% confidence bands for the values of d, i.e., the values of d where the null hypothesis cannot be rejected at the 5% level. In both, the selected model in relation with the deterministic terms.

regulators should be to use this anticipatory consumption that triggers price increases to stimulate new energy projects related to capacity expansion, especially with green energies. Recent events such as the announcement of Iberdrola to build a new "mega" photovoltaics plant in Usagre – Extremadura (an investment of 290 € million, to be in service in September 2020), which will be the largest plant in Europe, is a clear example. Reductions in production costs and increases in the efficiency of solar panel plants are accelerating this process of green energy expansion.

Table 5
Estimated coefficients in the model in (5) under no autocorrelation.

k	Spot market		Future market	
	γ_1 (t-value)	d (95% band)	γ_1 (t-value)	d (95% band)
0	**−0.0615 (-8.33)**	0.70 (0.67, 0.73)	**1.0956 (3.49)**	0.27 (0.24, 0.29)
1	**−0.0615 (-8.33)**	0.70 (0.67, 0.73)	−0.1809 (−0.57)	0.27 (0.24, 0.29)
2	**−0.0617 (-8.35)**	0.70 (0.67, 0.73)	−0.5933 (−1.49)	0.27 (0.24, 0.29)
3	**−0.0620 (-8.40)**	0.70 (0.67, 0.73)	−0.4132 (−1.31)	0.27 (0.24, 0.29)
4	**−0.0620 (-8.39)**	0.70 (0.67, 0.73)	0.1035 (0.32)	0.27 (0.24, 0.29)
5	**−0.0621 (-8.41)**	0.70 (0.67, 0.73)	0.4214 (1.36)	0.27 (0.24, 0.29)

In bold, significant coefficients at the 5% level.

Table 6
Estimated coefficients in the model in (5) under (Bloomfield) autocorrelation.

k	Spot market		Future market	
	γ_1 (t-value)	d (95% band)	γ_1 (t-value)	d (95% band)
0	**−0.0605 (-8.16)**	0.68 (0.64, 0.74)	**1.2069 (3.75)**	0.30 (0.27, 0.34)
1	**−0.0604 (-8.15)**	0.68 (0.64, 0.74)	−0.1771 (−0.54)	0.30 (0.27, 0.34)
2	**−0.0606 (-8.18)**	0.68 (0.64, 0.74)	−0.6054 (−1.61)	0.30 (0.27, 0.34)
3	**−0.0615 (-8.32)**	0.69 (0.64, 0.74)	−0.4103 (−1.27)	0.30 (0.27, 0.34)
4	**−0.0615 (-8.30)**	0.69 (0.64, 0.75)	0.1374 (0.42)	0.30 (0.27, 0.34)
5	**−0.0616 (-8.32)**	0.69 (0.64, 0.75)	0.4833 (1.49)	0.30 (0.27, 0.34)

In bold, significant coefficients at the 5% level.

Table 7
Estimated coefficients in the model in (6) under no autocorrelation.

k	Spot market		Future market	
	γ_1 (t-value)	d (95% band)	γ_1 (t-value)	d (95% band)
0	**−0.3680 (-6.34)**	0.54 (0.52, 0.57)	**0.0056 (4.43)**	0.47 (0.45, 0.50)
1	**−0.3680 (-6.34)**	0.54 (0.52, 0.57)	−0.0008 (−0.68)	0.48 (0.46, 0.50)
2	**−0.3689 (-6.36)**	0.54 (0.52, 0.57)	−0.0023 (−1.05)	0.48 (0.46, 0.50)
3	**−0.3710 (-6.41)**	0.54 (0.52, 0.57)	−0.0014 (−1.15)	0.48 (0.46, 0.50)
4	**−0.3704 (-6.39)**	0.54 (0.52, 0.57)	−0.0007 (0.61)	0.48 (0.46, 0.50)
5	**−0.3706 (-6.38)**	0.54 (0.52, 0.57)	0.0022 (1.15))	0.48 (0.46, 0.50)

In bold, significant coefficients at the 5% level.

8. Conclusion and policy implications

Throughout this paper the stochastic properties of energy consumption and energy prices in Spain and Portugal have been examined by using fractional integration or I(d) techniques in the spot and futures markets. The following points can be concluded according to this study:

1. The univariate results clearly indicate that all the examined series display long memory patterns with mean reverting behaviour and thus the effects of the shocks disappear in the long run. In the multivariate setting we show that both variables are linked together in a bi-directional way in the case of the spot market, but this pattern does not hold in the futures market.

Table 8
Estimated coefficients in the model in (6) under (Bloomfield) autocorrelation.

k	Spot market		Future market	
	γ_1 (t-value)	d (95% band)	γ_1 (t-value)	d (95% band)
0	**−0.4264 (-7.26)**	0.60 (0.55, 0.64)	**0.0056 (4.75)**	0.65 (0.61, 0.69)
1	**−0.4263 (-7.26)**	0.60 (0.55, 0.64)	−0.0012 (−1.02)	0.65 (0.61, 0.69)
2	**−0.4276 (-7.28)**	0.60 (0.55, 0.64)	−0.0022 (−1.89)	0.66 (0.60, 0.70)
3	**−0.4213 (-7.18)**	0.59 (0.56, 0.63)	−0.0013 (−1.13)	0.66 (0.62, 0.70)
4	**−0.4200 (-7.16)**	0.59 (0.55, 0.63)	−0.0006 (−0.58)	0.65 (0.62, 0.69)
5	**−0.4206 (-7.17)**	0.59 (0.55, 0.63)	−0.0020 (−1.72)	0.65 (0.62, 0.69)

In bold, significant coefficients at the 5% level.

2. There is a weak relationship between the futures market and energy consumption, however regarding the energy pricing, there is a stronger relationship with the spot market itself.
3. In the case of energy consumption, our study is in line with other energy consumption studies, such as Wong et al. [12] for oil pricing that concluded higher oil prices lead to lower oil consumption. Our results have shown that energy consumption behavior could be similar in the spot pricing, with no strong relationship in terms of future pricing, as final consumers are not directly affected by future energy price changes.
4. Regarding energy pricing, our study seems to be in line with that of Narayan and Sharma [19] completed for 15 general commodities, which concluded that in 60% of these commodities the stock market was dominant while in the other 40% it is the futures market which is dominant.
5. Finally, according to our study, it can be said that in the Iberian energy market, spot dominates the futures market but both markets have a certain relationship in terms of electricity pricing. Furthermore, correlation shows a direct relationship between both markets. This result might make sense, as the futures market is used to hedge peaks of the spot market production pull, while these peaks usually happen only at certain specific demand events (for instance, cool spells or heat waves), where fewer energy sources are entering in the energy pull increasing the spot price.
6. Our results could be used by policy-makers to draw some regulatory changes, since the energy supply in Portugal and Spain is controlled by only a few suppliers. Therefore, investment marks should be created so that speculative behaviour in futures markets could be avoided due to capacity expansion and better integration with EU energy lines. This being the case, the main challenge of a novel regulatory mark is to capture energy consumption in anticipation – and the consequent price increase - to trigger new energy projects related to capacity expansion, especially with green energies, with other EU players.

Credit author statement

Prof. Luis Alberiko GIL-ALANA is the primary researcher in this work. He has contributed in all sections in this work, making special attention to the methodological part and the implications of the series. Prof. Peter WANKE proposed the idea of this work. He obtained the data and contributed on the introduction, literature review and the implications of the results. Prof. Miguel MARTIN-VALMAYOR contributed with the introduction, literature review and the geographical context on Section 3 (The Iberian case). Also, with the implications of the results. For the revision, the three authors have jointly worked on it.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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