International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2018, 8(5), 173-180.

Electricity and Natural Gas Prices Sharing the Long-term Trend: Some Evidence from the Spanish Market#

Dolores Furió[1]*, Javier Población[2]

[1]Department of Financial Economics, University of Valencia, Av. Los Naranjos, s/n 46022, Valencia, Spain, [2]D.G. Supervisión, Bank of Spain, C/Alcalá 48, 28014, Madrid, Spain. *Email: m.dolores.furio@uv.es

ABSTRACT

The relationship between electricity prices and fuel costs has been extensively studied. Many studies have analyzed the relationship between electricity and natural gas prices and found that electricity and natural gas futures prices are cointegrated. In this paper, using different factor models to jointly estimate the dynamics of both commodities, we show that natural gas and electricity prices are not only cointegrated but also share common long-term dynamics. This finding has crucial implications in terms of managing and hedging the risk faced by utilities, because the common long-term trend finding implies that the spark spread risk reflects only short-term effects. Moreover, these results indicate that by using prices from both commodities, it is possible to extract more information for estimation purposes.

Keywords: Stochastic Calculus, Natural Gas, Electricity
JEL Classifications: C32, C51, C60, G13

This paper is the sole responsibility of its authors, and the views represented here do not necessarily reflect those of the Bank of Spain.

1. INTRODUCTION

There has been a generalized trend toward the deregulation of energy markets at the EU level supported by Electricity and Gas Directives[1]. The changing regulatory framework has caused structural changes in the trading patterns and price formation of the electricity and natural gas industries that are being taken into account by traders and regulators. An important element of this transformation is the development of forward and spot electricity markets as well as natural gas trading hubs. In Spain, in line with many other European countries, the use of natural gas for power generation has experienced a huge increase in the Spanish generation system from 2002 onwards and combined cycle gas turbine (CCGT) plants usually set marginal prices in the Spanish electricity spot (day-ahead) market, thereby becoming strategic technology units. With the entrance of new renewable generating sources into the system, CCGT plants have sometimes been replaced by other generation technologies, above all during off-peak hours when nuclear and wind capacity are often sufficient to meet demand.

However, due to their flexibility, these CCGT plants are a major source of price-responsive peak power. Moreover, they are also considered to be among those necessary for providing backup power at times of either peak demand or low renewable output, acquiring a dominant role in managing intermittency from renewables. In this new context, a stronger coupling of gas and electricity market price dynamics would be expected, which should strengthen the level of correlation between both commodities.

In this paper, our focus is on measuring the extent of the relationship between the prices for Spanish electricity and National Balancing Point (NBP) natural gas. Our results are useful for improving the modeling of the so-called spark spread, which is the relevant issue for natural gas power plants. Note that the business of these

1 EU Directive 96/92/EC and EU Directive 98/30/EC on common rules for the internal electricity and gas market, respectively. They were revoked by EU Directive 2003/54/EC on the internal market in electricity and EU Directive 2003/55/EC on the internal market in natural gas.

plants depends on the difference between electricity and natural gas prices, given that the latter is used in their power generation process. In this way they are exposed to price risk from electricity but also from natural gas and, apart from individually hedging each of these risks in their corresponding forward market, they can also directly hedge their global risk position by trading spark spread derivatives contracts. Thus, selling the forward spark spread is equivalent to selling electricity forward and buying natural gas forward. The payoff from a short position in the forward spark spread is the difference between the contractual delivery price and the spot spark spread at maturity. On the other hand, a spark spread option is an option with the underlying asset being a two-commodity portfolio (i.e., electricity and natural gas), in which the holder has the right but not the obligation to enter into a forward or spot spread contract. Therefore, a natural gas power plant can be somewhat viewed as a spread option. If the spark spread is positive, then the plant should be run, and otherwise it should not. In fact, in this latter case, it would be better not to generate power but rather buy the electricity in the market to meet their generation commitment. Of course, spark-spread derivatives contracts can also be traded with the aim of taking advantage of favorable changes in the difference in prices of the two commodities.

The relationship between electricity prices and fuel costs has been extensively studied in the literature. Mjelde and Bessler (2009) examine the interrelationships between electricity prices and four fuel sources Natural gas, crude oil, coal and uranium. Their results, among others, conclude that peak electricity prices react to shocks in natural gas prices. Serletis and Shahmoradi (2006) test for causal relationships between natural gas and electricity price changes. Their results indicate that there is causality between both series of prices. Bosco et al. (2010) find strong evidence of common long-term dynamics between electricity prices from European power markets and the natural gas Zeebrugge index. Furió and Chuliá (2012) investigate the causal linkages between prices for Spanish electricity, Brent crude oil and Zeebrugge (Belgium) natural gas. Their findings reveal that Brent crude oil and Zeebrugge natural gas forward prices play a prominent role in the Spanish electricity price formation process. Emery and Liu (2002) analyze the relationship between electricity and natural gas futures prices and find that electricity and natural gas futures prices are cointegrated.

In this paper, the methodology employed allows us to go a step further by showing that natural gas and electricity are not only cointegrated but also exhibit common long-term dynamics, implying that the spark spread reflects only short-term effects, which extends the empirical evidence presented above. In other words, two random processes are cointegrated if they are not stationary, but a linear combination of them is. With regard to having a common trend, we are referring to the situation where both dynamics have the same long-term factor. Following Cortázar et al. (2008) and García et al. (2012b), we estimate models in which several commodities can exhibit both common and specific factors, and assess the relative performance of several factor models to jointly explain the dynamics of commodity prices. According to the obtained results, the most suitable model in terms of simplicity and fit is the one that assumes a common long-term trend for natural gas and electricity.

This common long-term trend model for natural gas and electricity belongs to the family of multi-factor models proposed by Schwartz (1997) and a related series of papers, including those by Schwartz and Smith (2000), García et al. (2012a), García et al. (2012b) and Lucia and Schwartz (2002). In all of them, it is assumed that the spot price is the sum of both short- and long-term components. Long-term factors account for the long-term dynamics of commodity prices, which are assumed to follow a random walk, whereas the short-term factors can be identified with the mean-reverting components in commodity prices. Moreover, a deterministic seasonal component is added as suggested by Sorensen (2002), Lucia and Schwartz (2002) and García et al. (2012b)[2]. The fact that natural gas and electricity share a common long-term trend will have straightforward implications for managing and hedging the spark spread risk. As far as we know, this is the first time this sort of methodology is used in natural gas and electricity prices.

The remainder of this paper is organized as follows. Section 2 presents the data. In section 3 we provide the theoretical models that we are going to use in the following section to obtain concrete results. In section 4 we show that natural gas and electricity prices exhibit common long-term trends, implying that the spark spread only reflects short-term effects. Finally, section 5 concludes with a summary and discussion.

2. DATA

It is generally known that electricity cannot be economically stored at any significant scale. This lack of inventories together with the fact that power generation and consumption need to be coincident with each other means that prices react quickly to supply and/or demand disruptions. As a consequence, spot prices for electricity are highly volatile. Within this framework, forward markets play a crucial role to the extent they provide a tool for participants to manage the risk derived from the volatility of spot prices. In Spain, the volume of the electricity forward OTC financial contracts has grown at a high rate, up to exceeding the electricity demand for the first time in 2010 (CNE, 2012).

There are two main wholesale trading gas hubs in Western Europe Zeebrugge in Belgium and the NBP in the United Kingdom, linked through the so-called Interconnector. Both the NBP and Zeebrugge hubs provide open access to spot (and forward) markets with competitive pricing of natural gas.

The data set used in this paper comprises weekly average observations of Spanish OTC electricity forward prices and NBP Natural Gas OTC forward prices, with maturities from 1-month-ahead to 3-month-ahead and from two-quarter-ahead to four-quarter-ahead in the case of natural gas and two-quarter-ahead, three-quarter-ahead and 1-year-ahead in the case of electricity, from 10/10/2008 to 28/07/2017, yielding 460 quotations for each contract. Because we are using models with more than one commodity, we have chosen to maintain a consistent time to maturity between forward contracts to avoid decompensating

2 In Lucia and Schwartz (2002) and García et al. (2012a) we can find that electricity and natural gas exhibit seasonal behavior.

the short-term/long-term relations[3]. F1 (F2, F3) is for the 1 (2, 3)-month-ahead, whereas F6 (F9, F12) is for the 6 (9, 12)-month-ahead, though due to the lack of liquidity for monthly contracts with maturity longer than 3 months, quarterly and yearly contracts are used as a proxy for the price series of the last three above mentioned contracts. In particular, the two-quarter-ahead contract price and the three-quarter-ahead price is used as a proxy for the F6 contract price and the F9 contract price, respectively, whereas the four-quarter-ahead contract price is used as a proxy for the F12 contract price in the case of natural gas and the 1-year-ahead contract price is used as a proxy for the F12 contract price in the case of electricity. The data have been taken from the database of the Thomson Reuters Eikon platform. The price series for natural gas was originally quoted in pence sterling per therm. For the analysis in this study, natural gas prices have been converted into euros per MWh using the corresponding exchange rate from the Thomson Reuters Eikon platform and a conversion factor of 29.3071 kWh per therm. The main descriptive statistics of the series are summarized in Table 1.

The table shows the mean and the annualized volatility of the two commodity series prices by maturity. Mean prices are expressed in Euros per MWh. The volatility is calculated as the standard deviation of log returns. F1, corresponding to the 1-month-ahead forward contract closest to maturity, F2 to the 2-month-ahead forward contract and so on.

As observed in Figure 1, natural gas and electricity month-ahead forward prices display rather similar overall patterns, following a decreasing trend in 2008 and the first half of 2009, increasing from the second half of 2009 to mid-2012, and remaining quite stable from that date to the end of the sample. The notable decreases in electricity prices in the months of February-March correspond to wet years, which contrast with prices for these months during dry years. The drops in prices in the month of February from 2014 on can also be explained by the increase in wind and—though to a lesser extent—solar generation. At this stage, it is evident that both prices show rather strong co-movement.

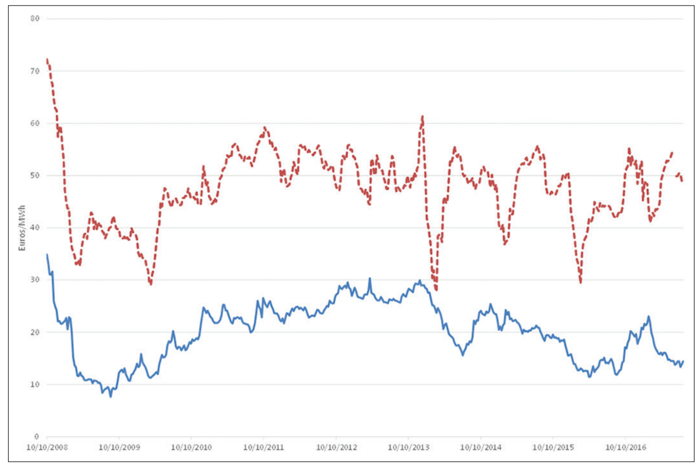
3. THEORETICAL MODELS

In this section, based on the models proposed by Cortázar et al. (2008) and García et al. (2012b), we use different factor models with or without assuming common long-term trends for natural gas and electricity. These comparisons will demonstrate that the most suitable model in terms of both simplicity and fit is the one that assumes a common long-term trend for both commodities. This result suggests that both commodities are not only cointegrated, as shown in previous studies, but also share a common long-term trend. This finding will have straightforward implications for managing and hedging the spark spread risk[4].

Table 1: Descriptive statistics

Forward	Gas		Electricity	
Maturity	Mean	Volatility (%)	Mean	Volatility (%)
F1	20.1	15.0	47.5	13.6
F2	20.5	14.0	47.1	14.7
F3	20.9	12.9	47.4	10.9
F6	20.7	29.2	47.6	8.1
F9	21.8	18.0	47.1	6.3
F12	22.9	11.7	48.2	5.0

Figure 1: Gas and electricity forward prices. Spanish electricity and national balancing point natural gas 1-month-ahead forward prices (October 2008–July 2017)



As stated by García et al. (2012b), modeling each commodity separately is likely the way to obtain the best fit for a given data set. If we were to obtain a similar goodness of fit when modeling both commodities jointly with a common long-term trend, the conclusion would be that both commodities share a common long-term trend. It is also possible to compare the results obtained from modeling the commodities jointly with and without the assumption of a common long-term trend; if there is a common long-term trend, the results should be comparable.

3.1. The Three Models Proposed

Within the context of the two-factor model proposed by Schwartz and Smith (2000), here we present three different models for the stochastic behavior of both commodities under study. In this model, the log-spot price (χ_t) is assumed to be the sum of two stochastic factors A short-term deviation (χ_t) and a long-term equilibrium price level (ξ_t). Thus,

$$X_t = \xi_t + \chi_t \tag{1}$$

The stochastic differential equations (SDEs) for these factors are as follows:

$$d\xi_t = \mu_\xi dt + \sigma_\xi dW_{\xi t}$$

$$d\chi_t = -\kappa\chi_t dt + \sigma_\chi dW_{\chi t} \tag{2}$$

Where $dW_{\xi t}$ and $dW_{\chi t}$ can be correlated ($dW_{\xi t}dW_{\chi t} = \rho_{\xi\chi}dt$) and $\rho_{\xi\chi}$ represents the coefficient of correlation between long- and short-term factors.

3 Schwartz (1997) realized that mean-reversion effects tend to be smaller for contracts with longer maturities. García et al. (2012a) found evidence suggesting the same conclusion in the case of natural gas.

4 Given what is said above, the possibility of modeling the spark spread directly instead of modeling each price series as a stochastic system has been considered. However, by modeling each commodity as a stochastic system, we use richer information than directly modeling the price differences.

In this model, κ and σ_χ represent the speed of adjustment and volatility, respectively, of the short-term factor, whereas μ_ξ and σ_ξ represent the trend and volatility, respectively, of the long-term factor.

Furthermore, a deterministic seasonal component is added, as suggested by Sorensen (2002)[5]. Therefore, the log spot price (X_t) is assumed to be the sum of two stochastic factors (χ_t and ξ_t) and a deterministic seasonal trigonometric component (α_t) (i.e., $X_t = \xi_t+\chi_t+\alpha_t$). The SDEs for ξ_t and χ_t are given by Eq. (2) and by

$$d\alpha_t = 2\pi\phi\,\alpha_t^* dt \text{ and}$$

$$d\alpha_t^* - 2\pi\phi\alpha_t dt$$

Where is the other seasonal factor that complements α_t, and φ is the seasonal period.

To value the derivatives contracts, we must rely on the "risk-neutral" version of the model. The SDEs for the factors under the equivalent martingale measure can be expressed as:

$$d\xi_t = (\mu_\xi - \lambda_\xi)dt + \sigma_\xi dW_{\xi t}$$

$$d\chi_t = (-\lambda_\chi - \kappa\chi_t)\chi_t dt + \sigma_\chi dW_{\chi t} \qquad (3)$$

The models we are going to propose here are similar to the ones presented in García et al. (2012b); however, there will be significant differences. One of them is the fact that, to avoid unnecessary parameters, we are going to use just one set of seasonal factors for both commodities when estimating them jointly[6].

The first specification, in which each commodity is modeled separately, will be the simplest one; it is represented by a four-factor model with no correlation between the factors. This model, however, is not very realistic.

To solve this problem, we propose a second four-factor model, a joint model for both commodities that allows for correlation between factors. In this model, the log-spot price of each commodity is assumed to be the sum of two stochastic factors, a short-term deviation (χ_{it}) and a long-term equilibrium price level (ξ_{it}), i =1, 2, where subscripts 1 and 2 refer to natural gas and electricity, respectively, and a deterministic seasonal component (α_t). Therefore, the log-spot price will be $X_{it} = \xi_{it}+\chi_{it}+\alpha_t$, $i = 1, 2$. The SDEs of the factors for this joint model without a common long-term trend are

$$\left.\begin{aligned} d\xi_{it} &= \mu_{\xi i}dt + \sigma_{\xi i}dW_{\xi it} \\ d\chi_{it} &= -\kappa_i\chi_{it}dt + \sigma_{\chi i}dW_{\chi it} \end{aligned}\right\} i = 1,2$$
$$d\alpha_t = 2\pi\phi\alpha_t\,dt$$
$$d\alpha_t = -2\pi\phi\alpha_t dt \qquad (4)$$

5 Sorensen (2002) suggested introducing a deterministic seasonal component into models for agricultural commodities. Here, we use Sorensen's proposal for natural gas and electricity, which exhibits strong seasonal behavior (see, for example, Lucia and Schwartz (2002)).

6 The results do not change significantly if we use García et al. (2012b) models and are available at the reader's request.

Where $dW_{\xi 1t}$, $dW_{\xi 2t}$, $dW_{\chi 1t}$ and $dW_{\chi 2t}$ can show any correlation structure, resulting in six correlation parameters.

This model requires an additional parameter to account for the variability in seasonality of the commodities. Because the seasonal factor is the same for both commodities, this factor will be multiplied by a different constant (Cs_i) for each commodity; however, because we have only two commodities, we can normalize Cs_1 to one in order to avoid identification problems.

Therefore, the spot price for natural gas can be calculated as $P_{1t} = exp(\xi_{1t}+\chi_{1t}+\alpha_t)$ $P_{1t} = exp(\xi_{1t}+\chi_{1t}+\alpha_t)$, whereas the electricity spot price will be $P_{2t} = exp\ (\xi_{2t}+\chi_{it}+Cs\square\alpha_t)$.

As stated in García et al. (2012b), this second model does account for the relationships between series, but it does so in a somewhat ambiguous way. First, we have six correlations to consider, none of which is negligible. Second, we have two correlated long-term trends. Finally, we cannot take this correlation as the only measure because the long-term trend for one commodity is also correlated with the short-term trend for the other commodity. Moreover, questions regarding subjects such as the general market trend cannot be answered.

This problem can be solved by means of a third specification with only one long-term trend for both commodities. In addition, the (isolated) influence of one series on another can be directly determined by observing the short-term/short-term correlation coefficient. In this model, the log-spot price (X_{it}) is assumed to be the sum of two stochastic factors, a short-term deviation (χ_{1t}), which is different for each commodity, and a common long-term equilibrium price level (ξ_t), and a deterministic seasonal component, α_t. Therefore, the log-spot price (X_{it}) will be $X_{it} = \xi_t+\chi_{it}+\alpha_t$, i = 1, 2. The SDEs of the factors for this joint model with a common long-term trend are:

$$d_{\xi t} = \mu_\xi dt + \sigma_\xi dW_{\xi t}$$

$$d\chi_{it} = -\kappa_i\,\chi itdt + \sigma_{\chi t} dW_{\chi it}, i=1,2$$

$$d\alpha_t = 2\pi\phi\alpha_t dt$$

$$d\alpha_t = -2\pi\phi\alpha_t dt \qquad (5)$$

Where $dW_{\xi t}$, $dW_{\chi 1t}$ and $dW_{\chi 2t}$ can show any correlation structures resulting in 3 correlation parameters.

This common long-term trend model, which also contains common seasonality factors, requires three additional parameters to account for the variable quality of the commodities. Therefore, even if their long-term dynamics are the same, their price levels and the effects of the long-term factor on their prices may differ. Consequently, it is necessary to introduce a constant (K_i) in the price level to account for this fact. Furthermore, these quality differences might lead to differences in the way that this common long-term trend and seasonal factor affects the price dynamics of each commodity. Thus, because the long-term factor is the same for both commodities, this factor will be multiplied by a different

Table 2: The two-factor model for each commodity separately

Parameters and other relevant information	Natural gas	Electricity
Contracts	F1, F2, F3, F6, F9 and F12	F1, F2, F3, F6, F9 and F12
Period	10/10/2008 to 28/07/2017	10/10/2008 to 28/07/2017
Number obs.	460	460
μ_{ξ}	−0. 3560** (0.1593)	−0.1820* (0.1077)
κ	0.4522*** (0.1200)	10.0000*** (0.0000)
$\sigma_{\square}$	0.7801*** (0.2012)	0,2723*** (0.0285)
σ_{χ}	1.0096*** (0.1900)	1.5478*** (0.1090)
$P\square\chi$	−0.9375*** (0.0334)	−0.6582*** (0. 0532)
λ_{ξ}	−0.9276*** (0.1891)	−0.0960 (0.1050)
λ_{χ}	2.0000*** (0.0000)	−1.8908*** (0.5963)
φ	0.9956*** (0.0009)	1.1260*** (0.0032)
σ_{η}	0.0775*** (0.0012)	0.1198*** (0.0018)
Log-likelihood	5309.45	4300.38
AIC	5291.45	4282.38
SIC	5254.27	4245.20

The table presents the results for the Schwartz and Smith (2000) two-factor model for each commodity separately (first specification). Standard errors are in parentheses. The estimated values are reported with * denoting significance at 10%, ** denoting significance at 5%, and *** denoting significance at 1%

Table 3: The joint model without a common long-term trend for both commodities

Natural gas and electricity Contracts F1, F2, F3, F6, F9 and F12 Period 10/10/2008 to 28/07/2017 Number Obs. 460			
$\mu_{\xi\ Gas}$	0.1690 (0.4474)	$\lambda_{\chi\ Electricity}$	1.1839 (0.7988)
$\mu_{zElectricity}$	−0.2980 (0.6815)	φ	1.0012*** (0.0011)
κ_{Gas}	0.1700*** (0.0151)	Cs	8.0451*** (0.8941)
$\kappa_{Electricity}$	0.1177*** (0.0079)	$P_{\xi Gas\xi Electricity}$	0.4030*** (0.0066)
$\sigma_{\xi\ Gas}$	1.1192*** (0.0772)	$P_{\chi Gas\chi Electricity}$	0.3890*** (0.0001)
$\sigma_{\xi\ Electricity}$	1. 9560*** (0.0135)	$P_{\xi Gas\chi Gas}$	− 0.9814*** (0.0001)
$\sigma_{\chi\ Gas}$	1.3187*** (0.0674)	$P_{\xi Electricity\chi Electricity}$	− 0.9989*** (0.0002)
$\sigma_{\chi Electricity}$	2.1808*** (0.0000)	$P_{\xi Electricity\chi Gas}$	− 0.3877*** (0.0063)
$\lambda_{\xi\ Gas}$	−1.1563** (0.4834)	$P_{\xi Gas\chi Electricity}$	− 0.3985*** (0.0000)
$\lambda_{\xi\ Electricity}$	−1.0150 (0.7230)	σ_{η}	0.0578*** (0.0006)
$\lambda_{\chi\ Gas}$	1.4539*** (0.5496)		
Log-likelihood	12354.53		
AIC	12312.53		
SIC	12225.77		

The table presents the results obtained using the Schwartz and Smith (2000) two-factor model without a common long-term trend for the two commodities (second specification). Standard errors are in parentheses. The estimated values are reported with *denoting significance at 10%, **denoting significance at 5% and ***denoting significance at 1%

constant (C_i) for each commodity, and because the seasonal factor is the same for both commodities, this factor will be multiplied by a different constant (Cs_i) for each commodity. As we just have two commodities, we can normalize K_1 to zero and C_1 and Cs_1 to one in order to avoid identification problems. Therefore, the spot price for natural gas can be calculated as $P_{1t} = exp(\xi_t+\chi_{1t}+\alpha_t)$, whereas the electricity spot price will be $P_{2t} = K+exp(C\cdot\xi_t+\chi_{it}+Cs\cdot\alpha_t)$.

This third model (i.e., the joint model with a common long-term trend) is preferable to the second one (i.e., the joint model without a common long-term trend); it contains fewer parameters and is therefore simpler.

4. ESTIMATION RESULTS

The data set used in this section consists of weekly average observations of natural gas in NBP and electricity in Spain as described in Section 2.1. We choose weekly data because daily data are generally affected by high levels of noise caused by local market supply or demand shocks, possible overreaction to unexpected news, etc. A number of papers choosing weekly data can be found in the prior literature, such as in Schwartz (1997), Schwartz and Smith (2000) or Cortázar and Schwartz (2003), among others. Additionally, because we are using models with more than one commodity, we have chosen to maintain a consistent time to maturity between forward contracts to avoid decompensating the short-term/long-term relations[7].

The models presented in Section 3.1 have been estimated using the Kalman filter methodology. Detailed accounts of Kalman filtering are given in Harvey (1989) and García et al. (2012b). The ways these models should be discretized are developed in García et al (2008)[8].

Tables 2 and 3 respectively present the results for the first specification (i.e., the two-factor model by Schwartz and Smith

7 Schwartz (1997) realized that mean-reversion effects tend to be smaller for contracts with longer maturities. García et al. (2012a) found evidence suggesting the same conclusion in the case of natural gas.

8 https://link.springer.com/article/10.1057/palgrave.jdhf.1850079

Table 4: The joint model with a common long-term trend for both commodities

Natural gas and electricity Contracts F1, F2, F3, F6, F9 and F12 Period 10/10/2008 to 28/07/2017 Number Obs. 460			
μ_ξ	1.3598*** (0.0149)	φ	1.0004*** (0.0018)
κ_{Gas}	0.2298*** (0.0001)	$P_{\xi\chi Gas}$	−0.9876*** (0.0014)
$\kappa_{Electricity}$	0.4136*** (0.0000)	$P_{\xi\chi Electricity}$	−0.9864*** (0.0000)
σ_ξ	0.5427*** (0.0000)	$P_{\chi Gas\chi Electricity}$	0.9872*** (0.0006)
$\sigma_{\chi Gas}$	0.4436*** (0.0211)	K	−51.7237*** (1.0060)
$\sigma_{\chi Electricity}$	0.7807*** (0.0000)	C	0.7177*** (0.0000)
λ_ξ	1.3683*** (0.0000)	Cs	9.5861*** (1.0577)
$\lambda_{\chi Gas}$	−1.1721*** (0.0000)	σ_η	0.0349*** (0.0004)
$\lambda_{\chi Electricity}$	−2.0000*** (0.0000)		
Log-likelihood	15171.93		
AIC	15137.93		
SIC	15077.70		

The table presents the results for the Schwartz and Smith (2000) two-factor model assuming a common long-term trend for all three commodities (third specification). Standard errors are in parentheses. The estimated values are reported with *denoting significance at 10%, **denoting significance at 5%, and ***denoting significance at 1%

(2000)) and the second specification (i.e., the joint model without a common long-term trend), whereas the results of the estimation of the third specification (i.e., the joint model with a common long-term trend for all three commodities) are presented in Table 4.

The first notable observation is that the speed of adjustment (κ) is significantly different from zero in all cases, implying long-term growth and mean reversion in the commodity prices.

It is also interesting to notice that in most cases, short-term volatility (σ_χ) is higher than long-term volatility (σ_ξ). This result is consistent with the results obtained by Schwartz and Smith (2000) for oil, García et al. (2012a) for natural gas, heating oil and gasoline and García et al. (2012b) for oil, heating oil and gasoline.

In general, the market prices of risk associated with the short-term factors, λ_χ, are significantly different from zero, mainly in the case of natural gas, whereas the prices of risk associated with the long-term factors, λ_ξ, tend to be non-significantly different from zero. These results suggest that the risk associated with long-term factors can be more easily diversified than the risk associated with short-term factors. Additionally, as in García et al. (2012b), the values of the market prices of risk are generally higher when the factor models are estimated separately (Table 2) than when the model is estimated jointly, with or without a common long-term trend (Tables 3 and 4). These results suggest that the risk associated with the long- and short-term factors is more difficult to diversify when we ignore the relationships among factors.

As expected, the seasonal period (φ) is roughly 1 year in all cases; this result is consistent with the findings of García et al. (2012a) and García et al. (2012b).

If we define the Schwartz Information Criterion (SIC) as $ln(L_{ML})–qln(T)$, where q is the number of estimated parameters, T is the number of observations and L_{ML} is the value of the likelihood function using the q estimated parameters, then the fit is better when the SIC is higher. The same conclusions are obtained with the Akaike Information Criterion (AIC), which is defined as $ln(L_{ML})–2q$.

According to the values of the SIC and the AIC in Table 2, the Schwartz and Smith (2000) model fits natural gas prices better than electricity prices. The adjustments in the joint models (Tables 3 and 4) are considerably higher than the two individual ones, meaning that modeling the dynamics of both commodities jointly is better that doing so separately. In other words, it is better to use data from the other commodity in modeling the dynamics of one of these two commodities.

Comparing the adjustment (AIC and SIC) of both the joint model with and the joint model without the common long-term trend, it can be concluded that results are notably better in the case of the model with the common long-term trend, clearly evidencing that both commodities exhibit the same long-term trend. Therefore, we do not need a second long-term factor when jointly modeling both commodities and the joint model that assumes common long-term trends (the simplest one) arises as the one that better fits the data.

In addition, the relative fit of the models to both commodity price series can be assessed as well by evaluating their predictive ability. The in-sample 1-day predictive ability is presented in Table 5 for the three specifications considered in Section 3.1. Firstly, it is found that the joint models clearly provide better results than the two-factor models for each commodity separately. Secondly, from the comparison of the two joint models, the one incorporating a common trend overwhelms the model without a common trend in most of the cases according to the RMSE criterion, confirming the results obtained from the AIC and SIC values[9].

Consequently, according to the obtained results, both commodities exhibit the same long-term trend and thus we do not need a second long-term factor when jointly modeling both commodities.

9 It is of note that the ME values for the natural gas price estimates associated with most maturities are lower in the case of the joint model without a common trend. However, ME values should be interpreted cautiously because positive and negative errors can cancel out, being opposite to RMSE values, which also measure the average magnitude of the error but by averaging the squared differences between estimation and actual observations.

Table 5: Predictive ability

Panel A: Model for the commodities separately					
Gas			Electricity		
Contract	ME	RMSE	Contract	ME	RMSE
F1	−0.0424	0.0755	F1	0.0296	0.0666
F2	−0.0218	0.0619	F2	0.0016	0.1105
F3	−0.0043	0.0626	F3	−0.0057	0.1257
F6	−0.0401	0.1374	F6	0.0042	0.1354
F9	−0.0228	0.0830	F9	0.0032	0.1387
F12	−0.0136	0.0870	F12	0.0295	0.1293
Panel B: Joint model without a common long-term trend					
F1	−0.0211	0.0619	F1	−0.0062	0.0508
F2	−0.0014	0.0551	F2	−0.0043	0.0735
F3	0.0154	0.0655	F3	−0.0029	0.0446
F6	−0.0298	0.1109	F6	0.0055	0.0583
F9	−0.0134	0.0825	F9	−0.0105	0.0513
F12	−0.0046	0.0596	F12	−0.0020	0.0416
Panel C: Joint model with a common long-term trend					
F1	−0.0007	0.0194	F1	0.0162	0.0194
F2	0.0023	0.0171	F2	0.0125	0.0171
F3	0.0053	0.0211	F3	0.0091	0.0211
F6	−0.0070	0.0266	F6	0.0075	0.0266
F9	−0.0019	0.0241	F9	−0.0119	0.0241
F12	0.0053	0.0251	F12	−0.0012	0.0251

The table presents the mean error (ME), calculated as real minus predicted values, and the root mean squared error (RMSE), to analyze the predictive power ability of the Schwartz and Smith (2000) two-factor model for both commodities separately (Panel A), and jointly, both without a common long-term trend (Panel B) and with a common long-term trend (Panel C). The time period is 10/10/2008 to 28/07/2017 (460 weekly observations for each commodity)

It is also worth noting that although previous studies have found that the prices of these two commodities are cointegrated, this conclusion is extended in the present work because we find that they also exhibit a common long-term trend. Moreover, to the best of our knowledge, this is the first time that a factor model with a common long-term trend for the prices of natural gas and electricity has been proposed and estimated. Additionally, the results of the estimation of this common long-term trend model suggest that the price-level re-scaled differences between gas and electricity (spark spread) are stationary, given that the long-term trend is the same for both commodities and hence what differentiates their dynamics are short-term factors, namely, mean reversion factors.

Finally, the fact that natural gas and electricity prices share a common long-term trend has important implications for managing and hedging the spark spread risk because with a single long-term trend, the spark spread reflects only short-term effects. If we assume different long-term trends for each commodity, however, the spark spread would reflect long- and short-term effects, implying higher volatility, which is crucial in VaR calculations or in spark spread option valuation. Moreover, given that if the utility decides to hedge its spark spread with forward contracts, choosing a short position in electricity and a long position in natural gas, the joint model with the long-term trend would be the suitable tool for anticipating the future benefit that the utility would have in order to calculate the utility market price, to expand capacity or to open a new plant.

5. CONCLUSION

In this paper, we explore the relationships between Spanish electricity forward prices and NBP forward natural gas prices. Our results suggest that the spark spread only reflects short-term effects. We have used different factor models to jointly estimate the dynamics of both commodities, and have found that among different factor models with and without common long-term trends, the most suitable model in terms of simplicity and fit is the one that assumes a common long-term trend for both commodities. This finding has important implications in terms of both pricing and hedging the risk faced by utilities. As far as we know, this is the first time that a factor model with a common long-term trend for the prices of natural gas and electricity has been estimated. One of the consequences of market liberalization is the appearance of price variation risk, which is notable in electricity markets. In fact, extreme values usually appear more often than in other commodities markets[10]. This characteristic makes forward markets, where huge trading volumes occur, especially useful as a hedging tool. However, depending on the market, it can be very difficult to hedge long-term positions, since beyond a specific time in the future the liquidity of the forward market dries up. In such cases, cross-hedging strategies are frequently explored. To do so, one needs to identify the right commodity, since the success of cross hedging depends completely on how strongly correlated the instrument being hedged is with the instrument underlying the forward contract. In this paper, we find evidence that Spanish electricity and NBP natural gas forward prices are not only cointegrated, as shown in previous papers, but also share common long-term dynamics. The obtained results are also useful in terms of pricing. Firstly, one common approach to estimating a forward contract is given by the well-known cost-of-carry relationship. This standard forward pricing model provides a link between forward and spot prices, under the assumption of the absence of arbitrage opportunities. Therefore, taking positions in both markets and storing the underlying asset until the expiration date of the forward contract, the no-arbitrage condition leads to an estimate of the forward price. However, in contrast to financial assets and most commodities, electricity is not economically storable. Thus, in this particular setting, the supposed link between forward and spot prices is not straightforward and the no-arbitrage argument referred to above cannot hold. In such a case, alternative pricing methodologies must be employed, such as using information from another commodity market whose prices are related. The daily average of the 24 hourly spot prices is the benchmark at which forward positions are cash settled on maturity. CCGT plants are flexible enough in their operation, with fast starting and load ramping, so as to act strategically in the market, becoming one of the key generation technologies that can set electricity marginal prices. Therefore, natural gas prices may be a good candidate for being used to price electricity, whenever it can be proved that both commodities move together. As previously indicated, the analysis made goes beyond correlation and even to cointegration between the series involved in the study to rigorously show that they also share common long-term dynamics. A second way in which the results are useful with regard to pricing is that, because the goodness of fit of the joint models is higher than that of the two individual ones, modeling the dynamics of both commodities jointly is better that doing so separately. In this way, it is possible to extract more information for estimation purposes by using

10 For more details about the characteristics of electricity prices see Bessembinder and Lemmon (2002).

prices from both commodities. Finally, the Spanish electricity market is in a stimulated state of flux. It is challenging to price a commodity whose price is so heavily affected by the intervention of government policy. Uncertainty with regard to, for instance, the support policy for renewables or domestic coal, or the introduction or removal of term auctions can make market participants hedge forward electricity exposure through other markets that are liquid, reliable and relatively more stable, such as the NBP natural gas forward market, on the basis that the two commodities are strongly correlated. In a context such as the one described, it is of great relevance to shed light on the short- and long-term relationships between the price of electricity and one of its main determinants, such as the price of natural gas[11], which is traded in an international market that is not affected by changes in the Spanish regulations of the electricity market. In this work, the dynamics of Spanish electricity forward prices and NBP natural gas forward prices have been jointly estimated so as to determine the extent of their interactions. The study is carried out over a long enough period to be able to extract the true nature of the relationship between both price series beyond the changes in regulation that have affected the operation of the Spanish electricity market. Last but not least, spread contracts themselves are widely used all over the world as powerful risk management tools. It is clear that those generation plants using natural gas to produce electricity should be especially interested in the results of an analysis involving both commodities, since the business of these plants depends on the difference between electricity and natural gas prices. According to Eydel and Wolyniec (2003), "the spread, both as a product and as a concept, is probably the most useful, prevalent and important structure in the world of energy." The insights derived from the joint modeling of both commodities are useful for a proper valuation of the spark spread. In fact, if those insights were ignored, the theoretical value of a spark spread option would be overvalued since not only short-term effects but also long-term ones would be considered, implying higher volatility (which is translated into higher prices), though just the latter effects should be taken into account when valuing the option according to the results found.

REFERENCES

Bosco, B., Parisio, L., Pelagatti, M., Baldi, F. (2010), Long-run relations in European electricity prices. Journal of Applied Econometrics, 25, 805-832.

CNE. (2010), Informe Sobre la Relación de Los Precios del Mercado Spot y el de Los Mercados a Plazo. Madrid Comisión Nacional de Energía.

CNE. (2012), Informe Sobre el Sector Energético Español. Parte III. Medidas Sobre los Mercados Mayoristas de Electricidad. Madrid Comisión Nacional de Energía.

Cortázar, G., Milla, C., Severino, F. (2008), A multicommodity model for futures prices Using futures prices of one commodity to estimate the stochastic process of another. Journal of Futures Markets, 28(6), 537-560.

Cortázar, G., Schwartz, E. (2003), Implementing a stochastic model for oil futures prices. Energy Economics, 25(3), 215-238.

Emery, G.W., Liu, Q. (2002), An analysis of the relationship between electricity and natural-gas futures prices. Journal of Futures Markets, 22, 95-122.

Eydel, A., Wolyniec, K. (2003), Energy Power Risk Management New Developments in Modeling, Pricing, Hedging Wiley Finance. Butte, Montana National Center for Appropriate Technology.

Furió, D. Chuliá, H. (2012), Price volatility dynamics between electricity fuel costs Some evidence for Spain. Energy Economics, 34, 2058-2065.

García, A., Población, J., Serna, G. (2008), A note of commodity contingent valuation. Journal of Derivatives and Hedge Funds, 13(4), 311-320.

García, A., Poblacion, J., Serna, G. (2012a), The stochastic seasonal behaviour of natural gas prices. European Financial Management, 18(3), 410-443.

García, A., Poblacion, J., Serna, G. (2012b), Analyzing the dynamics of the refining margin Implications for valuation and hedging. Quantitative Finance, 12, 1839-1855.

Harvey, A.C. (1989), Forecasting Structural Time Series Models and the Kalman Filter. Cambridge (U.K.) Cambridge University Press.

Lucia, J., Schwartz, E. (2002), Electricity prices and power derivatives Evidence from the nordic power exchange. Review of Derivatives Research, 5, 5-50.

Mjelde, J.W., Bessler, D.A. (2009), Market integration among electricity markets and their major fuel source markets. Energy Economics, 31, 482-491.

Schwartz, E.S. (1997), The stochastic behavior of commodity prices Implication for valuation and hedging. The Journal of Finance, 52, 923-973.

Schwartz, E.S., Smith, J.E. (2000), Short-term variations and long-term dynamics in commodity prices. Management Science, 46(7), 893-911.

Serletis, A., Shahmoradi, A. (2006), Measuring and testing natural gas and electricity markets volatility Evidence from Alberta's deregulated markets. Studies in Nonlinear Dynamics and Econometrics, 10(3), 10.

Sorensen, C. (2002), Modeling seasonality in agricultural commodity futures. The Journal of Futures Markets, 22, 393-426.

Bessembinder, H., Lemmon, M.L. (2002), Equilibrium pricing and optimal hedging in electricity forward markets. The Journal of Finance, 57(3), 1347-1382.

11 The Spanish Comisión Nacional de Energía states that together with the expected demand and the CO2 allowance prices, forward fuel prices, and in particular the forward natural gas price, form the basis for the Spanish electricity forward prices (CNE, 2010).