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CAMPUS OF INTERNATIONAL EXCELLENCE

MASTER IN ECONOMICS
Empirical Applications and Policies

The relation between electricity and natural gas spot prices in Spain:

cointegration and volatility spill-over analysis

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Abstract

The relation between electricity and natural gas prices got increased attention recently, after their joint rise in many European countries. The present Master Thesis explains the theoretical relation between both markets in Spain given the significant amount of natural gas devoted to electricity generation. Our main contribution is the analysis of the natural gas Iberian hub, not explored in the literature yet, whose liquidity is also an element of the analysis. In order to quantify the relation between these two markets, we carry out a cointegration analysis, by means of a Johansen and Juselius Cointegration test and a VECM approach. The results show that there are strong common long-term dynamics between both price series, and that, in the short-term, gas prices have a larger impact on electricity prices than electricity prices on natural gas prices. Additionally, we study the volatility spill-over between the markets using three different extensions of the Multivariate GARCH. The results show that there is a strong volatility spill-over between the markets, but the models turn out to be non-stable, so further research in this sense is needed.

Key words: electricity, natural gas, cointegration, volatility spill-over

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List of Abbreviations

ACER	Agency for the Cooperation of Energy Regulators
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heteroskedastic
Bcm	Billion cubic meters
BIC	Bayesian Information Criterion
CCC	Constant Conditional Correlation
CNMC	*Comisión Nacional de Mercados y Competencia*
DCC	Dynamic Conditional Correlation
GARCH	Generalised Autoregressive Conditional Heteroskedastic
GDP	Gross Domestic Product
GWh	Gigawatt per hour
LNG	Liquified Natural Gas
MA	Moving Average
MGARCH	Multivariate Generalised Autoregressive Conditional Heteroskedastic
MIBEL	*Mercado Ibérico de la Electricidad*
MIBGAS	*Mercado Ibérico del Gas*
MWh	Megawatt per hour
NBP	National Balancing Point
OMIE	*Operador del Mercado Ibérico de Energía – Polo Español*
OMIP	*Operador del Mercado Ibérico de Energía – Polo Portugués*
PP	Phillip Peron
PVB	*Punto Virtual de Balance*
TTF	Title Transfer Facility
TVB	*Tanque Virtual de Balance*
VAR	Vector Autoregressive
VCC	Varying Conditional Correlation
VECM	Vector-Error Correction Model

1. Introduction

Electricity and natural gas are key energy products in all countries. They also play a paramount role in the decarbonisation and transition goals to reach net cero emissions. The steady electrification of societies leads to an exponential increase of electricity demand and renewable technologies have not reached self-sufficiency. Combined cycle plants burn natural gas as back up for renewable technologies, a logic that has been especially present in Spain for the past 20 years.

The present paper aims to study the strength of the relation between electricity and natural gas markets by analysing the cointegration and volatility spill-over between their prices overtime. There are competing arguments about whether the relation has increased or diminished, considering that from 2004 onwards natural gas appeared as the solution and future of cleaner electricity generation. On the one hand, against the hypothesis of a strong relation between both prices, an argument is that in the past years the high penetration of renewable technologies has led to the decay of natural gas importance leaving combined cycled plants as subsidised backup plants close to disappearing. On the other hand, in favour of the hypothesis, a different argument is that due to technical limitations of renewable technologies, natural gas is an indispensable back up resort that is, in any case, one of the major marginal technologies in the electricity price formation, and therefore with a high importance in electricity prices.

The social and economic context of Spain, which this paper focuses on, could hardly make this analysis more pertinent. From April 2021 to the present time, that is, September 2021, electricity prices in Spain have undergone record increases. In the month of August 2021, the average price of electricity was 105.94€/MWh, 192.7% higher than the average price in August 2020 (Lopez de Benito, 2021). According to the Central Bank of Spain (2021), 50% of this increase is due to the high prices in the European natural gas market. In this context, the objective of this paper is to analyse quantitatively this relation.

The structure of following sections is organised in a logical and progressive way. Sections 2 provides an insight on the electricity and natural gas wholesale markets and price formation. Section 3 comprises a literature review of papers that have previously studied the cointegrating relation or volatility spill-over between electricity and natural gas in Spain. Section 4 presents the data and the relevant descriptive statistics. Section 5 introduces the two methodological approaches used, the Vector Error-Correction Model (VECM) and the Multivariate Generalised Autoregressive Conditional Heteroskedastic (MGARCH) Model with its different extensions. Section 6 provides the results of those models. Section 7 finalises with the conclusions of both analyses. After the conclusions and the bibliography, two relevant appendices are included, addressing the electricity and natural gas supply chain in Spain, respectively, that could be reviewed by the reader before the following section.

2. Wholesale market structure and price formation

The present section addresses how the electricity and natural gas markets are structured and how that contributes to the formation of prices in Spain. As mentioned in the Appendices, a key difference between both markets is the nature of the products themselves, since electricity cannot be stored while natural gas can. This implies that electricity is consumed right after its generation, a feature that makes the electricity market to have different submarkets, what does not happen in the natural gas market.

2.1. Electricity market

The supply chain of electricity can be divided into four different stages: generation, transmission, distribution, and consumption. Appendix 1 addresses them one by one while including the state of the Spanish electricity market in each regard. All stages play a relevant role in the price formation of electricity hence the overview shall pinpoint some of the driving factors of electricity prices in Spain.

There are two different markets where electricity is transacted, the wholesale and the retail market. In the latter, final consumers buy electricity from retailers, who have bought electricity in the wholesale market for the purpose of reselling it to those end consumers. Exceptionally, some large consumers from the industrial sector buy electricity directly from the wholesale market. The wholesale market is an organised market, while there is also significant amount of electricity transacted outside the trading platform, by means of bilateral agreements.

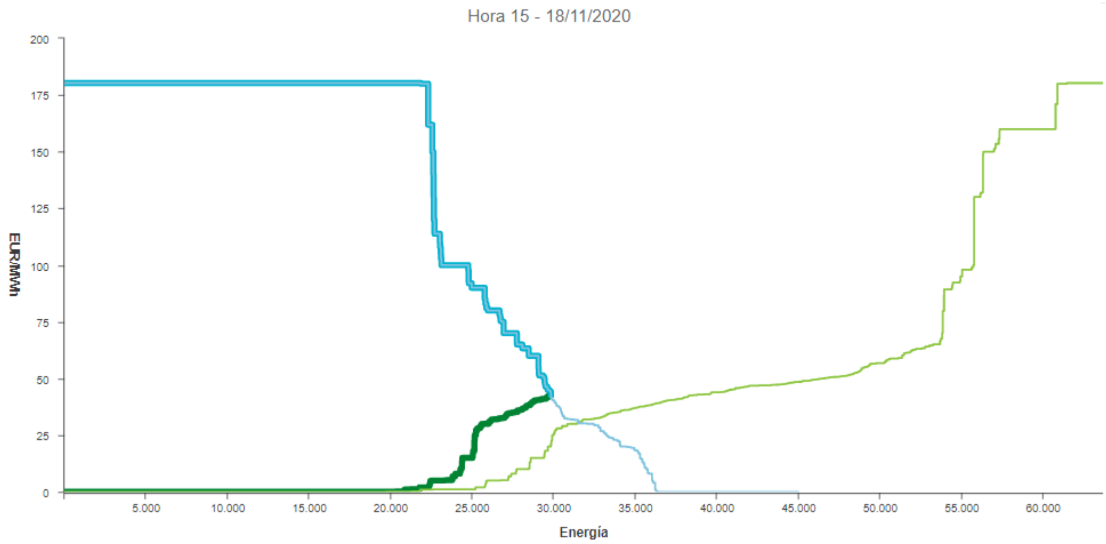
In the wholesale market there are different products as well as different submarkets (Espinosa & Ciarreta, 2004, p.4-5). On the one hand, products are differentiated on the basis of delivery time, also known as maturity. There is a generalist division: short-term and long-term products. Short-term products are those to be delivered in the day or within days from the transaction conclusion. They are also known as spot products. They can be intraday products, to be delivered in the same day of the purchase, day-ahead products, to be delivered in the following day of the purchase, and some other products with a few more days maturity. The market operator in this organised market is the *Operador del Mercado Ibérico de Energía – Polo Español* (OMIE). Following conventional terminology, we will refer to day-ahead prices as spot prices, that are the object of analysis in this paper. Regarding long-term products, there are traded under forward or futures contracts, to be delivered within a month or more, including annually. The organised market trading platform is different for these products and also the market operator, *Operador del Mercado Ibérico de Energía – Polo Portugués* (OMIP)[1].

On the other hand, and, focusing on spot products, there are 24 day-ahead submarkets, one for each hour of the day, in which the volumes of electricity traded are to be generated and delivered in the following day at the corresponding hour. Therefore, the market operator matches the supply and demand of electricity for each hour. There are also 6 intraday submarkets, in which volumes are to be delivered in the same day. They are usually resorted by agents to adjust last moment market fluctuations.

The wholesale market itself is the “pool” where suppliers and retailers make bids to buy and sell volumes of electricity. It is an auction system. With that, the market operator OMIE conforms the supply and demand curves, to reach a market clearing price. The supply and demand curves of the electricity market have some particularities. In Figure 1 the curves for 18th November 2020 at 15:00 can be observed:

[1] For further information visit https://www.omip.pt/es

Figure 1. Agregared curves of Offer and Demand in the electricity wholesale market



Source: OMIE, 2020.
Note: the green ascending curves represent supply bids, and the blue descending curve represents demand bids. The horizontal axis is cumulative amount of electricity, in MWh, and the vertical axis is the price, €/MWh.

As it can be observed, the curves are stepwise. The green curve represents the supply, and the different steps correspond to the manifold technologies used for electricity generation, in accordance, generally, to their marginal cost of production. This is known as the merit order. Therefore, the initial flat part of the curve corresponds to the electricity produced by renewable technologies, where the marginal cost of production is cero. Then, the following step corresponds to nuclear energy, then coal technology, then natural gas combined cycled plants, and finally oil power plants (Posner & Tayari, 2020).

However, these steps are not that clearly identified for two reasons. First, the exact marginal costs of production in each power plant varies in accordance to the specific circumstances of each plant, and second, some suppliers might bid their offer to a higher price for strategic reasons, although this is rather the exception to the merit order rule. If a coal-run power plant is not interested in providing any supply because the aggregated costs of keeping it working outweigh the profit obtained in the transaction, it would bid to a higher price. At the same time, if a nuclear plant is interested in selling their electricity no matter the price since switching off and on the plant has disproportionately high costs, it may bid its electricity at an even lower price, just for the sake of channelling it.

It is also worth noting that there are two green lines, one of which only reaches the equilibrium point. That one is the complex bids curve and the other one is the simple bids curve. While the simple bids consist just of bids where suppliers offer a volume at a specific price, the complex bids include some conditions or restrictions, and only if the market clearing price is higher than the one included in the bid is the supplier willing to produce the electricity. Those conditions could be related to the volume of electricity to be supplied. Complex bids are a particular element from the Spanish electricity system, while in other European countries there are only simple bids.

On the other hand, we find the blue curve, that corresponds to the supply curve. There is an initial long horizontal part, corresponding to bids made by retailers to the highest price possible to make sure they are able to obtain the amount of electricity they need to supply their respective clients and meet their contractual arrangements. The rest of the steps do not correspond to any kind of merit order but simply to other bids made for lower prices.

The equilibrium point is the market clearing price. In Spain, no matter the source of the electricity supplied in the pool, its selling price is the market clearing price. Therefore, for example, while electricity originated from renewables is offered at a zero price, it is then transacted at whatever the market clearing price is. And it happens like that for the rest of the electricity generation technologies. Unless there is a significant production of electricity from renewables and a very low demand at the same time, the market clearing price can hardly be 0. In that case, the market clearing price would be reached in another step of the merit order corresponding to another technology. This is named as the marginal technology.

A particularity of the Spanish electricity pool that has recently changed from 6th July 2021 onwards[2], was that there was a minimum and maximum cap for the electricity prices, the minimum being 0€ and the maximum being 180,3€. Consequently, negative prices were not allowed in Spain, as opposed to other European countries. The new limits for the day-ahead market are -500€ and 3.000€, respectively. In any case, the record of prices resorted for the present analysis do not reach July 2021 and therefore there are no negative prices.

These prices need to be differentiated from those paid by consumers, since in the retail prices there is an important percentage of the price that is regulated, including taxes, tariffs for the transmission system and even compensation of former deficits generated by the system. Nevertheless, this is out of the scope of this analysis and we focus on the interrelation of the supply and demand in the wholesale market.

2.2. Natural gas market

The natural gas supply chain follows a similar logic to that of electricity, and it is also addressed in Appendix 2. As mentioned, the capital difference is that natural gas can be stored, its consumption is not simultaneous to its production. Also, the speed at which it is transported is slower. Appendix 2 includes a description of the upstream, midstream, and downstream parts of the natural gas supply chain. As it is explained, upstream encompasses the "generation", midstream includes transmission, and downstream refers to distribution and consumption, but these tags are more loyal to the terminology used in the usual traffic of the natural gas market.

Natural gas wholesale markets are articulated in the so-called trading hubs (Alvarez Pelegry, 2017). There are two kinds of hubs, the physical and the virtual hubs. The Sabine Pass in the United States, for instance, is a pipeline interconnection where the largest amounts of natural gas are transacted, and it gave rise to the formation of the Henry Hub, as a trading node for the volumes passing through that interconnection point. Since it is a specific point, it is a physical hub.

On the other hand, in the United Kingdom there is not a concrete point like in the United States, but rather all the network is considered as a single common space where the exact location of the volumes is not relevant, but just the fact that they are within the network system. Then, the National Balancing Point (NBP) is the hub that centralises the

[2] As stated in the Resolution of the CNMC from 6 May 2021

trading of natural gas within the network at the same time, and this is a virtual hub. In the case of Spain, there is a virtual hub.

The main difference between the Spanish hub, known as the Iberian hub, and the above-mentioned hubs is their liquidity. To measure the liquidity of a hub the traditional measurement is the churn rate, that considers the amount of natural gas traded within the hub with respect to the overall amount of natural gas traded in the country. In Table 1 we provide the churn rates of the major natural gas hubs in Europe:

Table 1. Churn rates in different European hubs in 2019

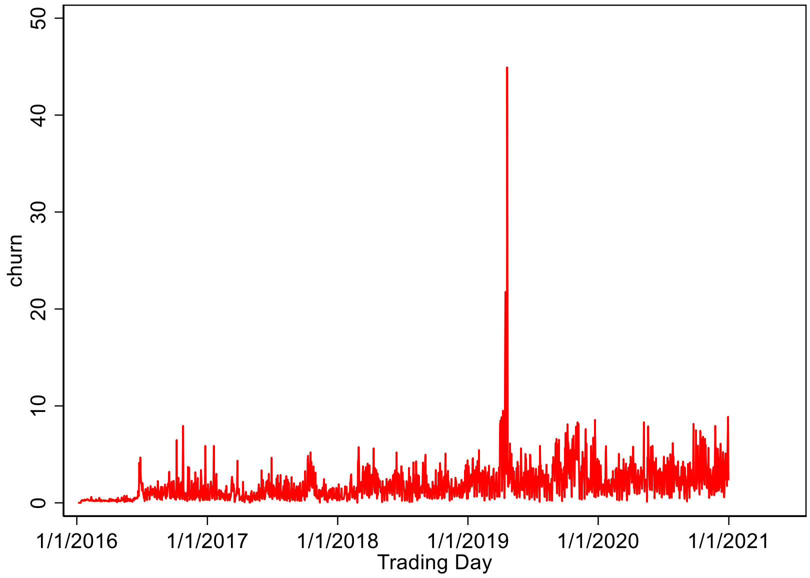
	Traded Gas Hubs Churn Rates				
Hub	**2008**	**2011**	**2017**	**2018**	**2019**
TTF	3.3	13.9	54.3	70.9	97.1
NBP	14.4	19.8	23.9	17.0	14.3
VTP	2.4	2.2	5.3	6.9	9.0
NCG	0.4	1.8	3.4	3.8	4.3
GPL	0.4	0.8	2.6	2.8	2.9
TRF	0.4	1.0	1.6	1.7	2.0
ZEE+ZTP	5.1	4.1	2.9	3.3	1.9
PSV	0.2	0.2	1.2	1.4	1.8
VOB	n/a	n/a	1.1	0.9	1.0
PVB	n/a	n/a	0.2	0.3	0.3

Source: Heather, 2020, p.5.
Note: Colours represent degrees if hub maturity: unmature (red), maturing (orange), mature (green**).**

We can observe how over time, the Title Transfer Facility (TTF), the Dutch hub, has surpassed the NBP in terms of liquidity. The Iberian hub is known as *Punto Virtual de Balance* (PVB, in Spanish) and as we can observe, its churn rate is almost insignificant, meaning that almost all trades happen outside the organised market. It is considered that a hub starts to be liquid after having a churn rate of 10 (Heather, 2020, p.5). Parallelly, as mentioned in Appendix 2, Spain has constituted the first liquified natural gas (LNG) hub in the world, the *Tanque Virtual de Balance* (TVB), although its liquidity has not yet been analysed and its outside the scope of this paper. In Figure 2 we can see an evolution of the churn rate of Spain computed with data reported by the *Comisión Nacional de Mercados y Competencia* (CNMC)[3] for the time period considered in the present analysis. Its average value is 1.9, that can be explained by the significant increase of liquidity of the past two years.

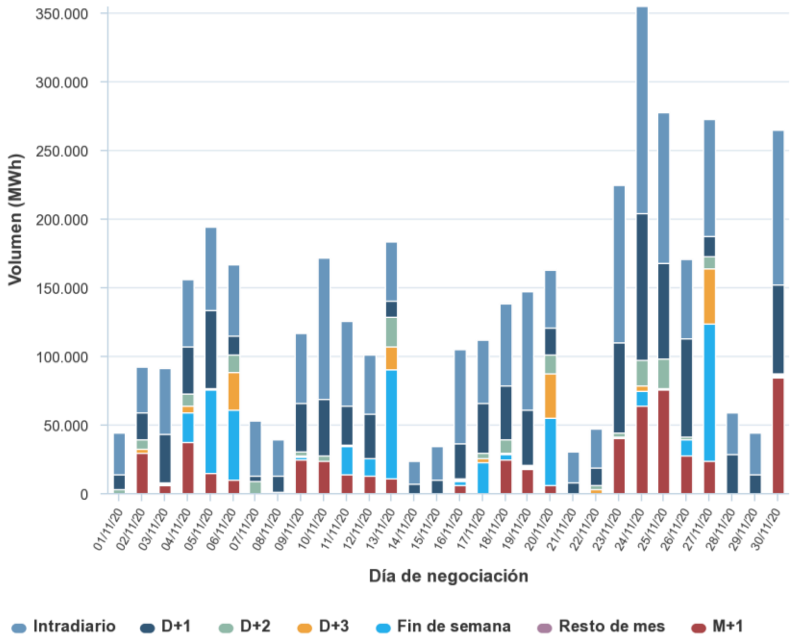
[3] Accessible at https://www.cnmc.es/estadistica/estadisticas-de-gas-natural-1

Figure 2. Evolution of the churn rate of the PVB, Period Jan 2016 – Jun 2021



The traded natural gas products resemble to those in the electricity market, in terms of being taxonomized in accordance with their delivery time. Different products are used by buyers and sellers with different purposes. While volumes transacted in longer term contracts and with higher maturity are directed to cover future demand needs about which there is small doubt that will exist at the delivery time, spot volumes are used to adjust the overall supply, including all other products, to the latest information about the eventually existing demand. In Figure 3, we include the volumes transacted in November 2020, as an example:

Figure 3. Natural gas daily traded volumes by kind of product, Nov. 2020



Source: *Mercado Ibérico del Gas* (MIBGAS), 2020.

Note: the legend includes intraday, day-ahead, two days-ahead, three-days ahead, for the weekend, longer than for the weekend but shorter than in a month, and in a month forward contracts, in that order.

In the case of the natural gas market the supply and demand curves do not have any particularities. However, the fact that the price of natural gas is determined by the interrelation of supply and demand has not always been the general rule. This system of price setting mechanism is known as gas-to-gas competition, and its largely in place in North America and Europe. Before, and still in other world regions, there was a system of oil indexed prices, given that the development of the natural gas market started as a substitute for oil.

Unlike the electricity market, in the natural gas wholesale market the market clearing price is not determined for each hour of the day but for the whole day, that is, there are not different submarkets. This is due to the fact that natural gas does not depend on peak and off-peak hours for its price estimation since it can be stored, as explained.

3. Relationship between the electricity and natural gas markets.

The relation between the electricity and natural gas prices constitutes the main object of analysis of this paper. The amount of natural gas devoted to electricity generation is highly significant in Spain, as it can be observed in Figure 15 of the Downstream section of Appendix 2. At the same time, natural gas has been the most common marginal technology setting the market clearing price of electricity. For these reasons, it would seem reasonable that an increase of the price of natural gas would lead to an increase in the prices of electricity. It however seems harder to draw the same logic the other way round. On contrast, due to the increasing penetration of renewables in the electricity source matrix, natural gas might no longer have such an impact on electricity prices, as pointed out by the Gas Managing Director of the CNMC, Rocio Prieto (2018).

This kind of relationship has been studied in several papers. First, Furió & Chuliá (2012) studied the causal and volatility linkages among the Spanish electricity prices, the Brent crude oil prices, and the natural gas prices in the Belgium hub, the Zeebrugge. The choice of the Belgium hub is justified by its significant higher liquidity that might lead to its use as benchmark hub for the setting of natural gas prices in Spain. The product analysed is the 1 month-ahead forward. The results show that there is not short term statistically significant relationship between the Spanish electricity prices and the Brent or the Zeebrugge prices.

Concerning long term relationships, they provide evidence that electricity prices adjust to past disequilibria by moving toward the trend values of natural gas and oil prices. This does not happen the other way round though. As also studied by Emery & Liu (2002), this makes sense since natural gas is an important resource for electricity generation, but electricity is only one of the uses for natural gas. We have nevertheless observed that it is a use with a significant weight in natural gas consumption in Spain. Finally, regarding the volatility linkages, the paper concludes that there is a strong transmission from the Zeebrugge to Spanish electricity prices.

In Furió & Población (2018), they study the relation between Spanish electricity prices and NBP natural gas prices by means of weekly average observations. The selected product is forward contracts with different maturities, from monthly to annually. The reason for this choice lies on the fact that "forward markets play a crucial role (…) to manage the risk derived from the volatility of spot prices". They resort to a factor model assuming a common long-term trend for both commodities, and it shows that the spark spread only reflects short-term effects. Therefore, the analysis goes a step beyond correlation and cointegration, suggesting that there are share long-term dynamics between both energy products.

Furió, Chuliá & Uribe (2019) carried out later a more comprehensive analysis in which they include prices for 17 commodities markets of electricity, natural gas, coal, oil and carbon. One of the electricity markets considered was the Spanish, while for natural gas markets, the British, Belgian, Dutch, American and the German hubs were included. They use forward contracts daily data, focusing on the study of volatility spill-over among all the 17 markets. The method used is a variance decomposition technique after the application of a VAR model. The results regarding the Spanish electricity market show that around the 86% of the volatility transmission it receives is mainly coming from its own lagged prices, while each of the German, French, Dutch and Italian electricity markets transmit to it between a 1 and 2 % of the volatility, respectively. None of the natural gas markets considered transmits more than a 0.5% of volatility to the Spanish electricity market. At the same time, the volatility spill-over transmitted from the Spanish electricity market to other commodities markets is around 10%, among the lowest figures in the study.

The aforementioned reports are, to our knowledge, the main pieces of work analysing quantitatively the linkages and the volatility spill-over from the natural gas market to the Spanish electricity market. However, there are no studies using the Spanish natural has market as benchmark, presumably due to its low liquidity, as it has been shown.

4. Data and descriptive statistics

The data used for the analysis is of public access. The electricity prices are reported by OMIE[4] and the natural gas prices by MIBGAS[5]. In the case of gas prices, they are reported in a daily form, while the electricity prices are reported in an hourly form. Therefore, the electricity prices have been converted into daily prices by computing the arithmetic mean of all hours in each day. The literature generally resorts to the simple arithmetic mean rather than to the weighted mean since the difference is not usually significative, as in Furió & Chuliá (2013).[6]

Among the different products of the market, the ones currently analysed are the spot products, that is, day-ahead products. Spot prices are usually not the most traded products, as shown. However, the spot product by nature would capture more significantly the short-term market fluctuations, reflected in the form of changing volatility, ultimately allowing a better observation of any volatility spil-over that may exist between the electricity and natural gas markets. This approach is shared by Furió & Población (2018, p. 174).

The data sample ranges from the January 5, 2016, to June 30, 2021[7]. This sums up to a total amount of 1.995 observations. They only include prices for the Spanish market, despite of being reported by the respective Iberian market operator and both Spanish and Portuguese electricity and natural gas markets being coupled. The reason is that despite

[4] Accessible at https://www.omie.es/es/file-access-list

[5] Accessible at https://www.mibgas.es/es/file-access

[6] In the present case, the weighted mean was also computed and, in effect, not any mentionable difference came up, so these results are not included in the main document (available upon request)

[7] Excluding natural gas prices data for 10 days in January 2016 that were not reported and for another 3 days in different years in which there were no actual volumes transacted in spot products

this, each electricity market constitutes a different bidding zone, and each natural gas market constitutes a different balancing zone. At the same time, such coupling leads the Spanish and Portuguese electricity prices to be practically the same every day[8], while slightly more significant differences can be observed in natural gas prices[9]. Both electricity and natural gas prices are reported in euros per megawatt hour (€/MWh).

In Figure 4 it can be observed that both prices follow similar patterns. Prices tend to peak at the beginning of each year and decrease afterwards. Furthermore, electricity prices are generally higher than natural gas prices, what is a logical condition for the gas-to-power operation. At the same time, volatility dynamics appear to be more significant in electricity process.

Figure 4. Evolution of electricity and natural gas prices in Spain, Period Jan. 2016 - Jun. 2021

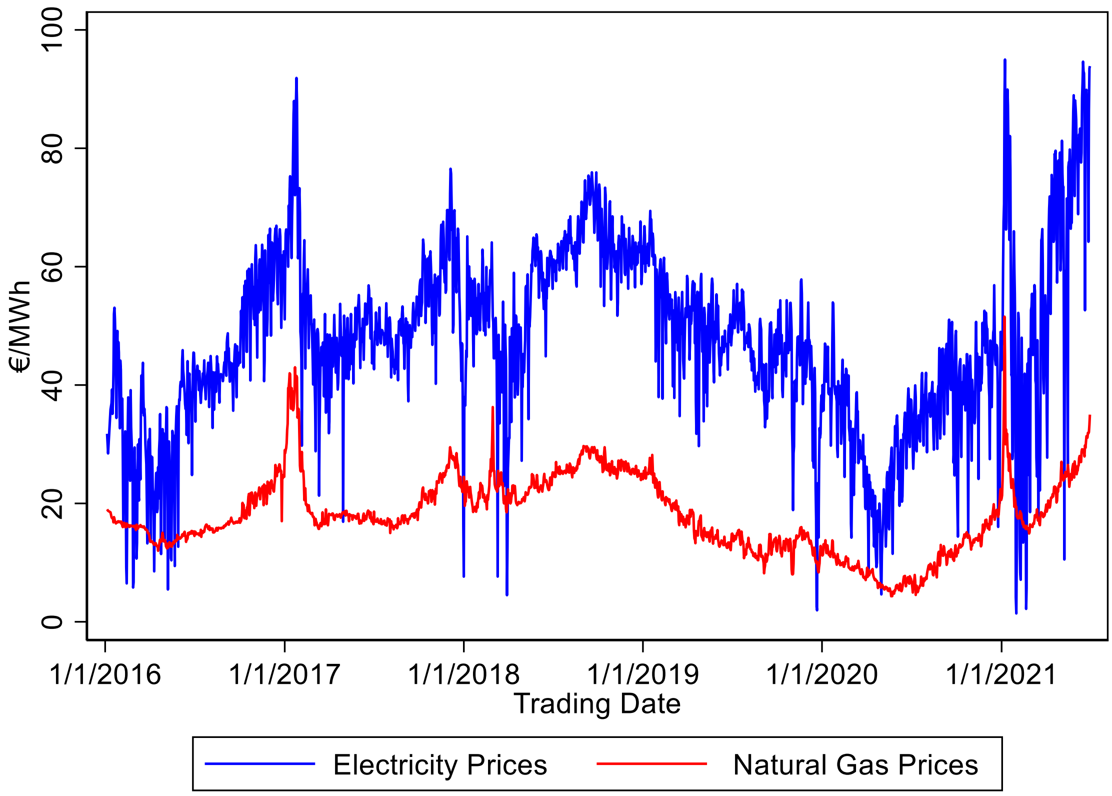


Table 2 includes the main descriptive statistics of electricity and natural gas prices. It confirms some of the initial observations: prices of electricity are higher than natural gas process and they also have a higher volatility. Regarding the skewness, in both prices the value is within -0.5 and 0.5, the closest to 0 the more symmetrical, so we can state that the series are fairly symmetrical. Since the value is negative in electricity prices, it means that the left tail of the distribution is slightly longer than the right tale. It happens the other way round in the case of natural gas prices. For kurtosis, the standard normal distribution is 3, so in these cases we have an excess of kurtosis, and since they are both positive, they can be considered heavy-tailed distributions (Suny Polytechnic Institute, 2012). The

[8] See https://www.omie.es/es/spot-hoy

[9] See https://www.mibgas.es/es

Jarque-Bera results determine that the null hypothesis is rejected, that is, it is rejected that the sample follows a normal distribution. It can be concluded that both samples do not follow a strict normal distribution.

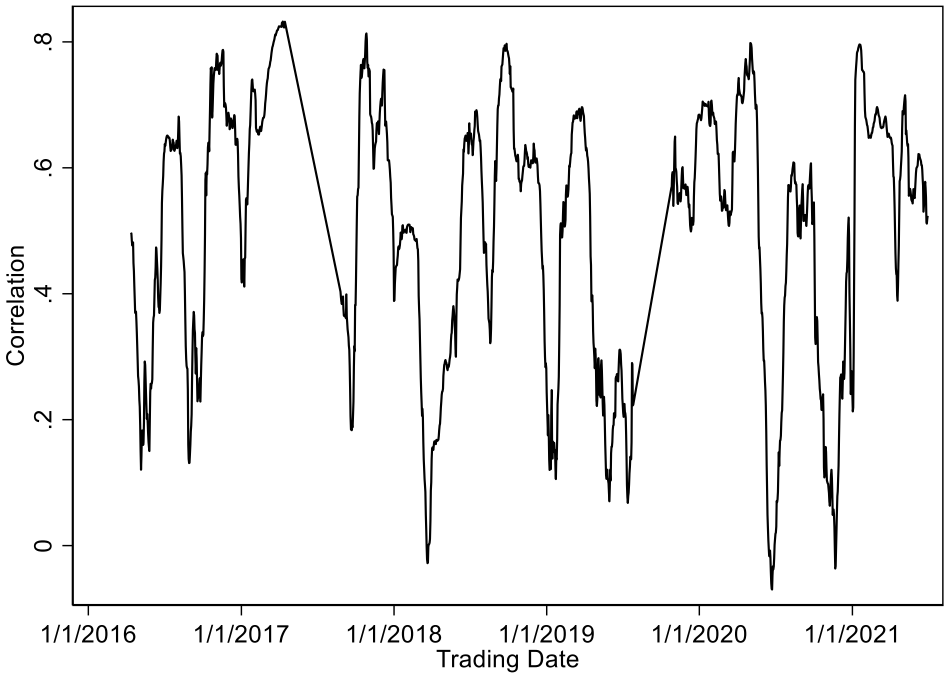
Table 2. Descriptive Statistics of Electricity and Natural Gas Prices

	Electricity	Gas
Mean (€/MWh)	47.38	18.05
Minimum (€/MWh)	1.42	4.32
Maximum (€/MWh)	94.99	51.55
Standard Deviation	15.25	6.47
Volatility (%)	25.72	5.49
Skewness	-0.05	0.44
Kurtosis	3.37	3.66
Jarque-Bera	12.61 ***	101.7 ***
Correlation	0.75	

Note: Jarque-Bera estimates are significant at 1% level of significance

The overall correlation between both samples is high, but given the differences in the fluctuations of each price series presenting a changing correlation throughout time is more accurate. Therefore, in Figure 5, we present a rolling window correlation, with the window being established in 90 days in order to catch the correlation evolution by quarters. The correlation between the electricity and natural gas prices oscillates significantly. At some points in time, it reaches a correlation of 0.8 and in some other it even reaches a negative correlation.

Figure 5. Evolution of Prices Correlation. Period Jan. 2016 – Jun. 2021



Note: Rolling window correlation. Window size of 90 days.

To carry out a subsequent time series analysis, the stationarity of the samples is checked by means of two unit root tests: the Augmented Dickey-Fuller (ADF) and the Phillip-Peron (PP). The results are provided in Table 3. To determine the optimal number of lags considered in the tests they have been used both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Both are resorted because the literature points out that the AIC tends to overestimate the need for lags.

Table 3. Unit root tests analysis

	ADF		PP	
	AIC	**BIC**	**AIC**	**BIC**
Gas	-2.004	-2.555	-3.094**	-2.962**
Electricity	-2.208	-3.007**	-16.424***	-10.899***
Log. Gas	-1.815	-1.972	-2.414	-2.226
Log. Electricity	-2.605*	-3.505***	-21.366***	-17.197***
Return Gas	-5-453***	-11.238***	-47.890***	-47.257***
Return Electricity	-7.377***	-15.133***	-44.896***	-45.262***
Log. Return Gas	-5.747***	-9.196***	-49.684***	-48.578***
Log. Return Electricity	-9.522***	-12.797***	-93.783***	-73.812***

Note: *, ** and *** represent 10%, 5% and 1% level of significance

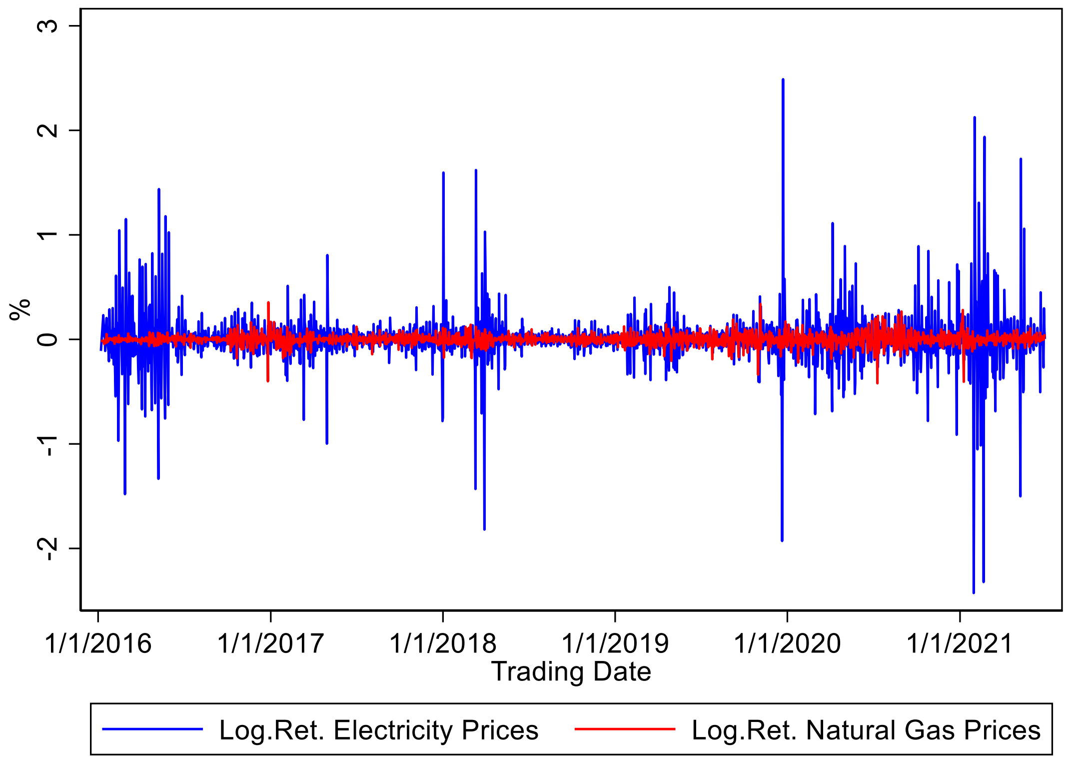
Overall, the results in the level observations look misleading since the ADF and the PP bring opposite results. The ADF generally confirms the existence of a unit root while the PP rejects it at 5% and 1% level of significance. The explanation for this discrepancy, following Ciarreta & Zarraga (2015, p.48), is that both tests have low power against the alternative of a stationary but highly autoregressive process, which reinforces the evidence of stationarity found, especially in this case, in the PP.

Therefore, since there are no negative prices among Spanish electricity and gas prices, we test logarithmic forms. In this latter case, we observe that logarithmic electricity prices are stationary at a 1% or 10% level of significance, depending on the test, while logarithmic natural gas prices still turn out to be non-stationary.

Then, as next step, we test for stationarity in the simple gross price returns, computed as the price of one day divided by the price of the previous day. We observe that the returns price series are stationary at the 1 % level for both electricity and gas prices and in both tests. Finally, we can draw the same conclusion for the logarithmic returns, that have been computed as the difference between the logarithm of one day´s price and the logarithm of the previous day´s price.

We can observe the evolution of the logarithmic returns in Figure 6. This way of displaying the price’s evolution facilitates the visual inspection of volatility clustering. Following conventional methodological choices in financial time series, as well as Furió´s papers, the logarithmic returns are used for the analysis of subsequent econometric models.

Figure 6. Evolution of electricity and natural gas prices logarithmic returns in Spain, Period Jan 2016 – Jun 2021



5. Methodology

The methodology used targets two different elements of analysis. On the one hand, a cointegration study is carried out to determine the level connection between electricity and natural gas prices. On the other hand, a volatility spill-over study is carried out, in order to ascertain how volatility is transmitted from one market to the other, using logarithmic returns of prices.

5.1.Cointegration analysis

Cointegration measures the common patterns or dynamics of the variables. It can be defined, following Engle and Granger as quoted by Harris (1995, p.6), as when "two or more series are linked to form an equilibrium relationship spanning the long-run, then even though the series may contain stochastic trends (i.e., be non-stationary) then will nevertheless move closely together over time and the difference between them will be stable (i.e., stationary)". In other words, when two or more variables are individually non-stationary but a linear combination of them is stationary. The Engle-Granger approach is however reserved by the literature for cointegration analysis in simple equations, able to determine the existence of a single cointegration relationship. Since two variables are considered in the present model, namely electricity and natural gas prices, the cointegration model shall be multivariate rather than univariate.

The cointegration in a multivariate system is carried out by means of the Johansen approach (Abu Hassan Asari et al., 2011), and the data is used in its non-stationary form, thus no transformation or returns are needed at this point. The Johansen and Juselius

Cointegration Test, estimates the cointegration rank, that is, determines the number of cointegrating relations or vectors that exist in the system. It does so by computing two tests: a Trace test and a Maximum Eigenvalue test. The latter tests the null hypothesis of *r* cointegrating relations against the alternative of *r*+1 relations for *r* = 0, 1, 2, …, n-1. Its structure is as follows, where λ represents the Maximum Eigenvalue and T the sample size:

$$LR_{max}\left(\frac{r}{n}+1\right) = -T * \log\left(1-\lambda\right)$$

At the same time, the Trace test checks the existence of *r* cointegrating relations against the existence of *n* cointegrating relations. Its structure is as follows:

$$LR_{tr}\left(\frac{r}{n}\right) = -T * \sum_{1=r+1}^{n} \log\left(1-\lambda\right)$$

With the Johansen and Juselius Cointegration Test the existence of cointegrating relations is determined. The general Johansen approach is focused on the long-term cointegrating relations, a first step to estimating the complete model. In fact, if cointegration is detected with the Johansen approach it means that there exists a long-term equilibrium relationship between them. It is also relevant to study the short-run structure of the system, especially in regard to the short-run adjustment behaviour of the variables. Another complementary layer of analysis that complements the model is the contemporaneous interactions between variables. To analyse the short-term properties of the cointegrated series the Vector Error-Correction Model (VECM) is used which is a Vector Autoregressive Model (VAR) with an equilibrium correction term included. For the present system, the structure of the VECM shall be the following, inspired in the model designed by Furió & Chuliá (2012):

$$\Delta E_t = \delta_1 + \sum_{j=1}^{r} \alpha_{1j}\left(E_{t-1} - \beta_j G_{t-1}\right) + \sum_{j=1}^{p} \theta_{1j}\Delta E_{t-j} + \sum_{j=1}^{p} \gamma_{1j}\Delta G_{t-j} + \varepsilon_{1t}$$

$$\Delta G_t = \delta_2 + \sum_{j=1}^{r} \alpha_{2j}\left(E_{t-1} - \beta_j G_{t-1}\right) + \sum_{j=1}^{p} \theta_{2j}\Delta E_{t-j} + \sum_{j=1}^{p} \gamma_{2j}\Delta G_{t-j} + \varepsilon_{2t}$$

where E_t and G_t represent electricity and natural gas prices respectively at time *t*. The elements α_{ij} for $i = 1, 2$ and $j = 1, 2$ are the (speed of) adjustment parameters to the long-run relationships, with a negative sign, and the elements they multiply within the parenthesis corresponds to the error correction term, thus including the variables´ lagged values, that is, $ECT_{\ t-1} = \left(E_{t-1} - \beta_j G_{t-1}\right)$. The parameters θ_{ij} and γ_{ij} for $i = 1, 2$ and $j = 1, 2, \ldots, p$, are the short-run dynamic coefficients of the model´s adjustment long-run equilibrium, that represent the extent to which the return in one market responds to its own lagged returns and to the lagged return of the other market. Finally, ε_{it} for $i = 1, 2$ are the Gaussian white noise processes.

In the VECM there are two possible sources of causation, the long-term adjustment parameters α_{ij} or the short-term cointegrating dynamics parameters θ_{ij} and γ_{ij}. According to Granger (1988), cointegration between two variables is already sufficient to indicate the presence of causality in at least one direction.

5.2. Volatility Spill-over

Volatility spill over is an important indicator of the degree of interconnection of markets. It basically encompasses the idea of a shock originated or affecting one market would be transmitted to another market. The traditional models resorted to capture the volatility of the variance of returns in financial time series have been the Autoregressive Conditional Heteroskedastic (ARCH) Model and its extension, the Generalised ARCH (GARCH). The former was developed by Engel (1982) and the latter by Bolleslev (1986).

The ARCH modelling of the variance resembles more to a Moving Average (MA) model specification given that its conditional variance equation only includes lagged innovations:

$$\sigma_t^2 = w + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2$$

The formulation of the conditional covariance leads to estimations that capture partially the volatility dynamic. It captures volatility only when it is so-called "bursty", that is, when there is a sudden shock and then it stabilises for subsequent realisations. However, by doing this it misses the possible volatility clustering, the fact that a moment of high volatility can be transmitted to following realisations in time. For this reason, the GARCH model includes a "GARCH element", an additional autoregressive structure, that represents the perseverance of a shock occurred in previous realizations. In the present paper different extensions of the GARCH model are resorted, even moving from the univariate to the multivariate use of the model, for the sake of representing the volatility spill over to the greater extent possible as well as with the aim of methodologically testing these different extensions.

The GARCH model, as the ARCH model does, has two main equations in its structure (Andersen *et al*., 2009, pp.201-226; Francq & Zakoian, 2010, pp.273-307; Hafner, 2009). On the one hand, it has the conditional mean equation, giving a sense of how the value of contemporaneous realisations are affected by former realisations. On the other hand, the conditional variance equation, including former innovations and former variances as a function of the contemporaneous variance.

$$y_t = x_t\theta + \varepsilon_t$$

$$\sigma_t^2 = w + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^2$$

The same mean equation applies in the case of the ARCH model, while the different conditional variance mean has been already pointed out. That mean equation also applies to the multivariate GARCH model, since its element represent vectors. The element y_t is a $m \times 1$ vector of dependent variables, x_t is a $k \times 1$ of independent variables, what may also contain lags of y_t. In the conditional variance equation, there is an ARCH element, α_i, and a GARCH element, β_j, the former accounting for the volatility generated by former innovations and the latter for the persistence of previous volatilities. According to the literature, for the model to be stable the sum of α_i and β_j should not be equal or higher than 1, since in that case the persistence of volatility would be indefinite.

However, this specification does not consider possible volatility transmissions between different markets, that is, from the natural gas market to the electricity market or vice versa. Therefore, a conditional covariance equation that would consider the volatility dynamics in other variables is needed. To do so, there is a need to go deeper in the elements of the equation. We model ε_t as a stochastic vector process with dimension $N\, x\, 1$ such that its expected value is 0, $E\varepsilon_t = 0.$ Additionally, we assume it is conditionally heteroskedastic and we model it as follows:

$$\varepsilon_t = H_t^{1/2}\eta_t$$

In this case, η_t is an independent and identically distributed vector error process such that $E\eta_t\eta_t' = I.$ In financial applications, ε_t is usually represented as a vector of log-returns of the assets (Andersen *et al*., 2009, p.203), as we shall do in the present paper. At this point, only $H_t$is left to be defined, and the way in which it is defined would lead to different variants of the MGARCH model. H_t is the conditional covariance matrix of ε_t. Next, some of these extensions are presented.

The first extension is the Constant Conditional Correlation (CCC) MGARCH. It assumes that the conditional correlation along all the sample of the variables is constant, for the sake of simplification. In this case, the conditional correlations are as follows:

$$H_t = D_t^{1/2} R D_t^{1/2}$$

where

$$\mathrm{D}_t = \begin{pmatrix} \sigma_{1,t}^2 & 0 & \cdots & 0 \\ 0 & \sigma_{2,t}^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & \sigma_{m,t}^2 \end{pmatrix}$$

and

$$\mathrm{R} = \begin{pmatrix} 1 & \rho_{12} & \cdots & \rho_{1m} \\ \rho_{12} & 1 & \cdots & \rho_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{1m} & \rho_{2m} & \cdots & 1 \end{pmatrix}$$

D_t is a diagonal matrix of conditional variances and R_t is the matrix of conditional correlations, as observed, time-invariant.

The second extension to be considered is the Dynamic Conditional Correlation (DCC) MGARCH, in which the conditional correlation is expected to change along the sample observations.

$$H_t = D_t^{1/2} R_t D_t^{1/2}$$

where

$$\mathrm{R}_t = \begin{pmatrix} 1 & \rho_{12,t} & \cdots & \rho_{1m,t} \\ \rho_{12,t} & 1 & \cdots & \rho_{2m,t} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{1m,t} & \rho_{2m,t} & \cdots & 1 \end{pmatrix}$$

or

$$\mathrm{R}_t = diag(\mathrm{Q}_t)^{-\frac{1}{2}}\mathrm{Q}_t diag(\mathrm{Q}_t)^{-\frac{1}{2}}$$

considering that

$$\mathrm{Q}_t = (1 - \lambda_1 - \lambda_2)\mathrm{R} + \lambda_1 \tilde{\epsilon}_{t-1}\tilde{\epsilon}'_{t-1} + \lambda_2 \mathrm{Q}_{t-1}$$

In the former equation, Q_t is stationary and R is a weighted average of the unconditional covariance matrix of the standardized residuals and the unconditional mean of Q_t. At the same time, λ_1 and λ_2 are parameters that govern the dynamics of conditional quasicorrelations, where $\lambda_1, \lambda_1 > 0$ and $0 \leq \lambda_1 + \lambda_1 < 1$.

Finally, the third extension is the Varying Conditional Correlation (VCC) MGARCH, in which the conditional correlation is also time-variant, but by dispensing with Q_t, the model becomes more parsimonious. That addition is a follows:

$$\mathrm{R}_t = (1 - \lambda_1 - \lambda_2)\mathrm{R} + \lambda_1 \psi_{t-1} + \lambda_2 \mathrm{R}_{t-1}$$

In this case, ψ stands for a rolling estimator of the correlation matrix, that uses the previous $m + 1$ observations.

All the aforementioned explains the inner differences between the MGARCH models resorted for this analysis. Nevertheless, there is no need to compute the values for all R, R_t, D_t and Q_t. An equally insightful and simpler way of studying the variance and covariances is as follows. The matrix is already laid out in the specific context of the electricity and natural gas prices analysis, that is, as a bivariate MGARCH variance-covariance matrix:

$$H_t = \begin{bmatrix} h_{ee,t} & h_{eg,t} \\ h_{ge,t} & h_{gg,t} \end{bmatrix}$$

where

$$h_{ee,t} = w + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{e,t-1}^2 + \sum_{j=1}^{q} \beta_j \, h_{ee,t-j}$$

$$h_{gg,t} = w + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{g,t-1}^2 + \sum_{j=1}^{q} \beta_j \, h_{gg,t-j}$$

These diagonal elements are modelled as in the univariate GARCH model, while the off-diagonal elements are modelled as non-linear functions of the diagonal terms, that is, not to observe the behaviour of the conditional variances of each variable but also the conditional covariance between them. Therefore, the off-diagonal element shall be modelled as follows:

$$h_{eg,t} = h_{ee,t}^{1/2}\, \rho_{eg,t} h_{gg,t}^{1/2}$$

We should note that this would be the off-diagonal element for the DCC and VCC extensions, since $\rho_{eg,t}$ is time-variant, whereas in the case of the CCC extension it would be ρ_{eg}, that is, time-invariant.

6. Results

Following the same structure as the previous section, first the results regarding the cointegration analysis are displayed and then the results of the volatility spill-over study.

6.1. Cointegration analysis

The first set of results are those of the Johansen and Juselius Cointegration Test. The output table is provided as follows:

Table 4. Johansen cointegration test results

Maximum Rank	Eigenvalues	Trace Statistic	1% critical value	Max Statistic	1% critical value
0	.	30.91	20.04	25.04	18.63
1	0.01261	5.87*	6.65	5.87	6.65
2	0.00297				

Given that this is a bivariate model the maximum possible rank is 2, that would imply a bidirectional relation of cointegration. Looking at the Trace statistics and at the Maximum Eigenvalues, same results are obtained. Considering cointegration of rank 0, the null hypothesis is that there are 0 cointegrating relations and the alternative hypothesis is that there are more than 0 cointegrating relations The Trace and Maximum Eigenvalues surpass the critical values at 1% level of significance and thus the null hypothesis is rejected. Then, considering cointegration of rank 1, the null hypothesis is that there is 1 cointegrating relation and the alternative hypothesis is that there are more than 1 cointegrating relations. Since the statistics here do not surpass the critical values, the null hypothesis claiming the existence of at least one cointegrating relation shall not be rejected at the 1% level of significance.

Once confirmed that there is some cointegrating relation between electricity and natural gas prices, the VECM output can deepen into the intensity of such long-term relations as well as show the short-term cointegrating dynamics. In the following equation, the element representing the long-term dynamic is provided.

$$ECT_{\ t-1} = (1.000E_{t-1} - 1.756G_{t-1} - 15.859)$$

All coefficients are highly statistically significant, what points to a clear long-term shared dynamic. At the same time, the VECM provides coefficients with their respective significances regarding short-term dynamics. To observe the short-term dynamics, we have run different VECM models, with slight changes, with the view to observing additional layers of these short-term dynamics. First, we computed the VECM model with 14 lags, to see their respective significances in the two weeks effects.

Table 5. Results of Vector Error-Correction Model (VECM) – Short-term

Electricity Equation						Natural Gas Equation					
Lags	ΔE_{t-}	ΔG_{t-i}	Lags	ΔE_{t-i}	ΔG_{t-i}	Lags	ΔE_{t-i}	ΔG_{t-i}	Lags	ΔE_{t-}	ΔG_{t-i}
1	-	+	8	-	+	1	-	+	8	+	-
2	-	+	9	-	+	2	-	-	9	-	-
3	-	+	10	-	+	3	-	-	10	-	+
4	-	+	11	-	+	4	-	-	11	-	+
5	-	+	12	-	+	5	+	-	12	+	-
6	-	+	13	-	+	6	+	-	13	-	-
7	+	+	14	+	-	7	-	+	14	-	+

Note: re-marked squares represent they are significant at 10%, 5% or 1% significance level.

In this table we portray the results of the short-term dynamics in a simplified way, although the complete output is included in the Annex. We can observe important asymmetries. In the left-hand side of the table the coefficients for the electricity VECM equation appear. For all previous week lagged values, we observe that all electricity and natural gas lagged prices are significant. In the two weeks previous lagged values, almost all coefficients are significant in the case of electricity prices, and somewhat less in the case of natural gas. Parallelly, all electricity lagged prices affect negatively the contemporaneous expected price, except for the one week and two weeks lag. In contrast, nearly all natural gas lagged prices affect positively.

On the other hand, in the natural gas VECM equation lagged prices tend to be less significant and irregularly positive or negative. In particular, we observe that only 5 electricity lagged prices are significant within the 14 lagged prices. In the case of natural gas lagged prices, 8 of them are significant.

This shows how natural gas lagged prices play a predominant role in contemporaneous electricity prices, while the role of electricity lagged prices in the contemporaneous price of natural gas is much lower. Additionally, in the VECM output table included in the Annex corresponding to this first layer of analysis, we observe the value of the coefficients, and we appreciate that they start with considerably high values, and they steadily diminish as the lags are higher. A graphical representation of the weight of such coefficients is provided in the third layer on analysis.

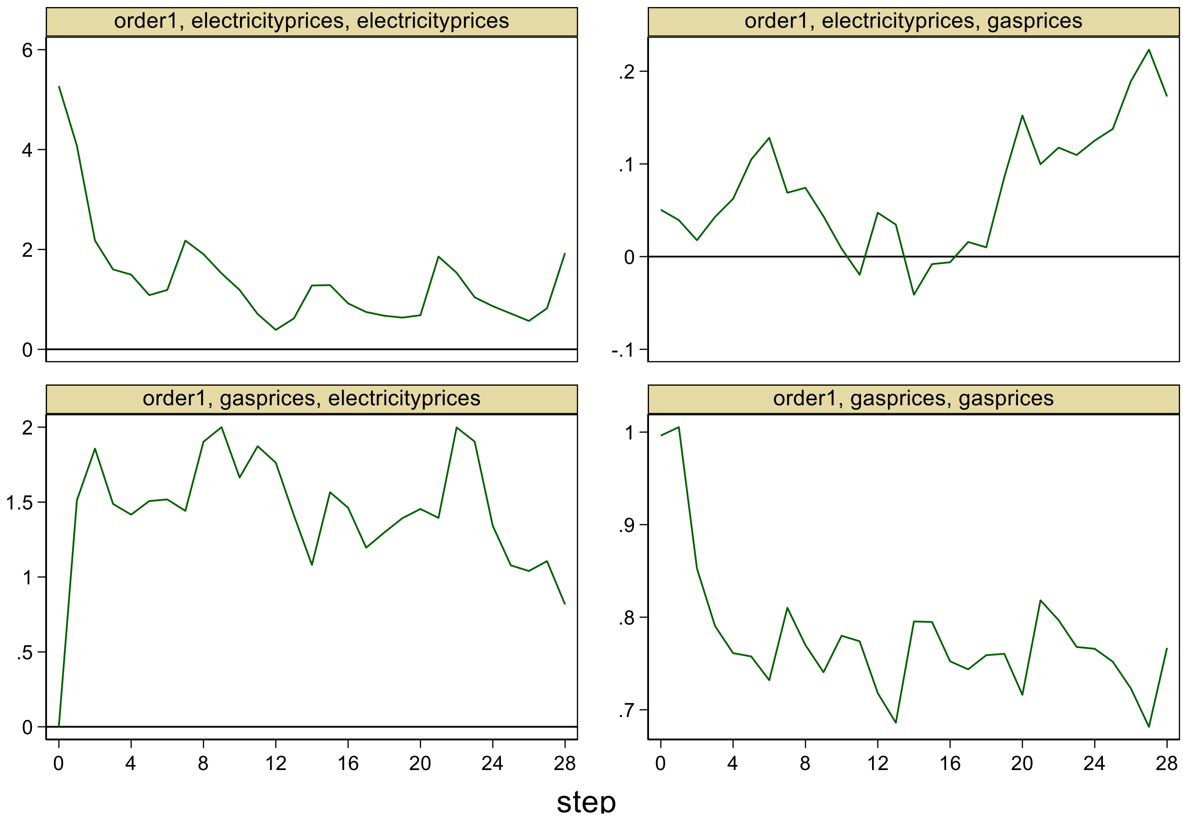
In a second layer of analysis, we have included several dummy variables, including additional data relevant to the market state and definitely to the price formation. First, we included a dummy variable standing for the relative weight of electricity generation on the overall natural gas consumption, data introduced in Figure 15 of the Downstream section of Appendix 2. In this case the dummy variable has a value of 1 when the share of natural gas devoted to electricity consumption with respect to the total gas consumption is above the sample average, and 0 otherwise. The results show that in the long-term dynamics the coefficient is not only highly significant with a p-value of 0.000, but also its value is 13.5789, meaning that it has a huge impact in the long-run cointegrating dynamic of both electricity and natural gas prices. Conversely, in the short-run dynamics no lags appear as significative for either of the VECM equations, so its short-run impact on the variables in barely inexistent.

Second, we also analyse separately the influence of the churn rate in the Iberian gas hub to see how it does impact on the cointegrating relation. The dummy variable in this case receives a value of 1 when it has a value over the sample average, provided in Section 2.2. The long-term results show that it is also very significant with a p-value of 0.005 and a coefficient of 10.7629, meaning that it has also a great impact on the long-run shared dynamics of both electricity and natural gas prices. As it happened in the case of the previous dummy variable, in the short-run equation elements it turns out significant for nearly all lags. Therefore, we can also conclude that the liquidity of the natural gas market does influence on the long run its shared dynamics with electricity prices.

However, when we include in the same VECM both dummy variables, the one for natural gas devoted to electricity generation as a share of overall natural gas consumption and the churn rate one, the latter turns out not statistically significant, while the former stays equally significant.

The third and final layer of this VECM analysis consists of impulse response functions. In the first analysis we observed that there were manifold significant lags with different signs, but another important element to ascertain the actual degree of influence of those lags is the value of the coefficients. Therefore, to depict them in a simplistic way, at this point we plot the impulse response function. Rather than limiting the analysis to two weeks, we extent it to four weeks, to observe also the month effect. The output underlying these impulse response functions is included in the second part of the Annex.

Figure 7. Impulse response functions of the VECM coefficients



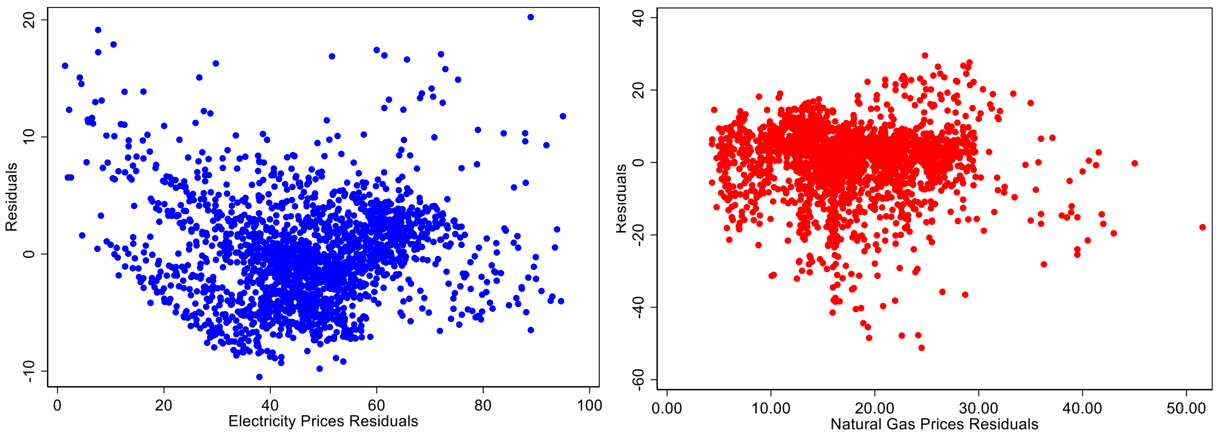
In each of the graphics, the first variable appearing in the title stands for the impulse and the second variable for response. We observe that the monthly impulse response functions are quite similar in the case of electricity-electricity and gas-gas, that is, own lags influence in a similar way each variable. However, the degrees of influence are different, much higher in the case of electricity, as appreciated in the scales of the graphs. Therefore, we can conclude that electricity is much more influenced by its own lags than natural gas.

Then we also observe the impact of natural gas prices on electricity prices and vice versa. Natural gas has a positive impact on electricity prices, but the other way round there are some negative inputs. Moreover, the scale of the graphic is ten times bigger in the case gas-electricity, meaning that the influence of natural gas on electricity is exponentially higher than electricity on natural gas, a conclusion also obtained in the first layer of analysis.

6.2. Volatility Spill-over analysis

The first element to consider before applying a GARCH model is the heteroskedasticity of the data since, by definition, that would be what would let us appreciate the volatility spill-over from one market to another. Heteroskedasticity refers to the variance of the disturbance terms, assuming that it is not constant. Most econometric models assume, in contrast, that the data is presented with a constant variance of the disturbance terms, that is, homoscedastic. Even if this step does not strictly correspond to the methodological development of the MGARCH model, we study this as a condition *sine qua non* for its successful functioning. This can be done by simply observing the variance of the error terms:

Figure 8. Spread of Electricity and Natural Gas prices residuals



From the visual examination, there is no doubt that the variance of the error terms is not constant. For further rigorousness, we apply the Breusch-Pagan test. Its null hypothesis is that the variance of the errors is constant, and it is rejected under a 0.05 p-value.

Table 6. Breusch-Pagan test results

	Chi^2	P-value
Electricity Prices	75.45	0.00
Gas Prices	89.03	0.00
Returns of Electricity Prices	171.05	0.00
Returns of Gas Prices	6.54	0.01

According to the results of the test both electricity and natural gas prices are highly heteroskedastic. We also include the logarithmic returns of the prices since we will use the data with this transformation for the application of the model. The returns also appear to be heteroskedastic.

The fact that there is unequal variance in the errors overtime implies that there is volatility in the time series. And this is what the ARCH element represents, that is, the volatility spikes in the series. A common test to look for an ARCH process in the sample data is the Lagrange Multiplier test. The results in this case for the logarithmic returns is as follows:

Table 7. Lagrange Multiplier test results

	Chi^2	df	P-value
Returns of Electricity Prices	428.995	21	0.0000
Returns of Gas Prices	226.064	21	0.0000

In both electricity and natural gas prices logarithmic returns the p-value is clearly under 0.05, so the null hypothesis that there are no ARCH effects in rejected and we accept the alternative hypothesis that there are ARCH disturbances, in other words, volatility.

At this point, we have examined all the prerequisites for the MGARCH model to be suitable for our time series analysis. In the following output table, we can observe the results of the different MGARCH models run with different conditional correlations:

Table 8. MGARCH Models results

	CCC (I)	CCC (II)	CCC (III)	DCC	VCC
$\boldsymbol{\omega_{ee}}$	0.00048 ***	0.00048***	0.00007**	0.00009***	0.00009***
$\boldsymbol{\omega_{gg}}$	0.00006***	0.00006***	0.000001**	0.000002**	0.000002**
$\boldsymbol{\alpha_e}$	0.34282***	0.34809***	0.14878***	0.1097***	0.1075***
$\boldsymbol{\alpha_g}$	0.2233***	0.2211***	0.0934***	0.0933***	0.0944***
$\boldsymbol{\beta_e}$	0.7177***	0.71453***	0.87081***	0.8906***	0.8932***
$\boldsymbol{\beta_g}$	0.8121***	0.8169***	0.9078***	0.9142***	0.9141***
$\boldsymbol{\lambda_1}$				0.0301***	0.1424***
$\boldsymbol{\lambda_2}$				0.9416***	0.00000002
Log-Lik.	4860.132	4844.722	6198.929	6300.9	6303.604
Corr. ($\boldsymbol{\rho}$)	0.0467*	0.0477*	-0.277***	-0.3471***	-0.3316***

Note: CCC (I), (II) and (III) represent normal, asymmetric and two stages versions, respectively. DCC and VCC are only provided in the two-stage version.
*, ** and *** represent 10%, 5% and 1% level of significance.

The model CCC model has been computed in three different ways, normal, including all 21 lags of both variables in both electricity and natural gas mean and variance equations; asymmetric, not including the lags of electricity in the equations of natural gas; and the two-stage version, running the model on the residuals of the variables. In the case of the DCC and VCC only the two-stage approach has been provided because other ways of calculation were not able to reach convergence of the model.

There are four main aspects to be considered from the output table: significance of the coefficients, log-likelihoods, conditional correlations, and stability of the models.

First, all coefficients of ARCH and GARCH elements are highly significant in all models, implying an existing transmission of volatility between both markets. The ARCH element in the electricity variance equation is always higher than in the natural gas equation, and therefore the GARCH element has a higher value in the natural gas equation than in the electricity equation. This is consistent with the results obtained in the cointegration analysis. The ARCH element captures the effect of the past disturbance in the contemporaneous price variance, and such disturbance is modelled partially as the result of the variance-covariance matrix of both electricity and natural gas prices, as shown in previous equations.

The fact that the ARCH element has a higher coefficient in the electricity equation implies that electricity prices are influenced by the variance of natural gas prices. At the same time, in the case of natural gas the value of the ARCH element has a lower coefficient, implying a lower influence by the electricity price variance, that is, volatility.

Regarding the GARCH element, it captures the effect of previous variance of the variable on its own contemporaneous variance, allowing for the appreciation of volatility clustering. The fact that the GARCH element coefficient is higher in the natural gas conditional variance equation means that natural gas is more affected by its own former volatility than electricity does, leading to higher volatility clustering. Therefore, the key conclusion than can be derived from these values is that the transmission of volatility is higher from the natural gas market to the electricity market than vice versa.

Second, the log-likelihoods serve as measurements of the effectiveness or reliability of the model. The closest the log-likelihood is to 0, the higher assessing or predicting effectiveness the model has. We can clearly observe two different groups of values, one around a log-likelihood of 4850 and another around a log-likelihood of 6200. The former, corresponding to the CCC, are as well consistent with previous results. When the electricity lags are removed from the equations of natural gas the model gains robustness and therefore the log-likelihood improves. In contrast, the latter shows that with the two-stage approach there is a loss of robustness since the log-likelihood gets worse. A not expected outcome is that the DCC and VCC log-likelihoods are worse than that of the CCC´s. It was reasonable to expect that with a time-varying conditional correlation, which it has been observed in the rolling window correlation analysis carried out in the descriptive statistics section, the effectiveness of the model would be improved. Nevertheless, the values show otherwise.

Third, the correlations obtained in the results are at odds in the different models approaches. In the normal and asymmetric CCC a positive correlation is computed but in all two stage approaches it appears as negative. Both previous results and intuition point to the direction of a positive correlation, so at this point the validity of the results obtained by the two-stage approaches might be questioned. Regarding $\boldsymbol{\lambda}_1$ and $\boldsymbol{\lambda}_2$, the first represents how much the conditional correlation depends on shocks and the second one represents the extent to which the correlation depends on its own lags. The DCC model shows that the correlation of the contemporaneous prices depends significantly on previous correlations.

Finally, we can assess the stability of the model. As previous indicated, for the model to be stable the sum of α_i and β_i should not be equal or higher than 1. If that would happen, it would mean that previous variances affect future variances indefinitely, that is, their effect would not banish along time, what is not possible (unless we refer to structural breaks, what is outside the scope of this analysis). We can observe that in all approaches of the models the sum of α_i and β_i is slightly higher, what undoubtedly points to the instability of the models and to question the reliability of the results, so further research in this sense should be needed, in order to find the best model.

7. Conclusions

The present Master Thesis has studied the relation between electricity and natural spot prices in Spain from January 2016 to June 2021 by means of a cointegration and a volatility spill-over analysis.

On the one hand, the cointegration analysis reveals that there is a cointegrating relationship between electricity and natural gas prices that derives into common long-term and short-term dynamics. The analysis has shown that the short-term causal relation is stronger from natural gas to electricity than from electricity to natural gas prices. This is consistent with the characteristics of the electricity and gas markets. Natural gas is used to produce electricity but not otherwise. However, it does exist a slighter causal relation from electricity to natural gas since electricity generation has been one of the main sources of natural gas consumption in the last years. An increase in natural gas prices leads to an increase in electricity prices given that the market clearing price is set at a higher step of the supply curve. This relation is clear and has been quantitatively shown. However, the other way round, the link is much lighter but existent, possibly because both price series are affected by a common third market or force.

Additionally, we have observed that this cointegrating relationship depends to a great extent on the peak or off-peak season. Not necessarily aligned with weather circumstances but rather with the demand context, the higher the relative weight of electricity generation has in the natural gas consumption matrix, the higher the stronger the cointegrating relation is. In other words, in the periods in which natural gas has been more resorted for electricity generation, the causal relations between both prices have shown to be higher.

At the same time, we also assessed the relevance of the Iberian natural gas hub liquidity. Given that one of the reasons for not having used the Iberian natural gas market as object of analysis previously in the literature was its lack of liquidity, it was reasonable to consider if the cointegrating relation increased with the higher liquidity of the market in the last years. Eventually, the analysis has revealed that this element was as well significant.

On the other hand, the volatility spill-over analysis has been less successful, mainly because the results cannot be considered as conclusive given the instability of the models. In any case, it can be resorted to some extent as a possible orientation of the volatility transmission between both markets, which are also consistent with the observations made in the cointegration analysis. The results show that the volatility of electricity is influenced by its own lagged volatility and by natural gas lagged prices volatility in a significant way. In contrast, this relation is weaker the other way round, since we find a lower effect of natural gas price volatility coming from lagged electricity volatility.

Being aware of this relation between electricity and natural gas prices is of utmost relevance for financial hedging and investment decisions. These results are consistent with previous results in the literature, ascertaining a strong connection between natural gas prices and electricity in Spain. Future lines of research could continue the study of the relevance of the liquidity of the Iberian natural gas hub, yet to be developed to significant proportions. The evolution of the Spanish energy mix will also play an important role. An even higher penetration of renewable energies may imply a lower role of natural gas, although there is less clear if natural gas has secured its backup technology role in such context.

Finally, MGACH models with its CCC, DCC and VCC extensions have turned out to be ineffective in this analysis, what also is a significant contribution to the existing literature. Future analysis might find interesting to consider the BEKK extension, as used by Furió & Chuliá (2012) or the variance decomposition technique in the way applied by Furió, Chuliá & Uribe (2019).

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Appendix 1. Electricity life cycle

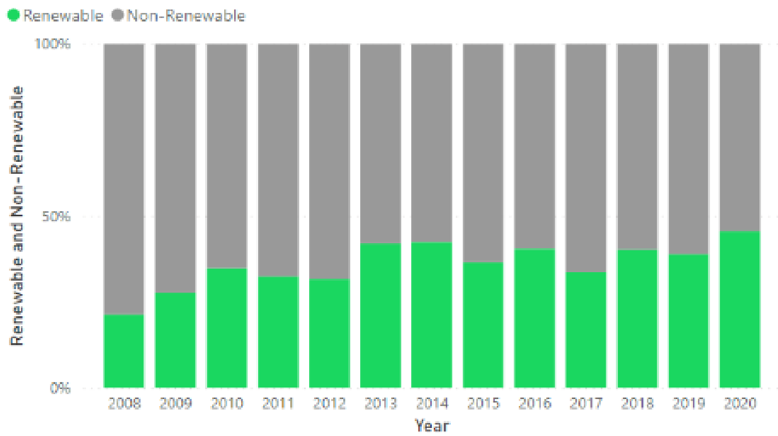
A1.1. Generation and Mix

The generation of electricity is carried out from manifold energy resources and with different technologies, usually in power plants. The composition of the matrix of these resources evolves along time for market reasons, political reasons, etcetera. For instance, if a country depends excessively in a single resource, it shall eventually seek for a diversification of its electricity mix. It is also relevant whether such resources are imported or not. In the case of Spain, there was an overdependency on oil for electricity production in 1973, accounting for 33% of all national generation (Costa Campi, 2016). In that year, the oil crisis shocked oil western importers and the security of supply of a key asset such as electricity was put at risk.

From that moment forth, Spain took measures with the view to further diversifying its electricity generation mix[11]. Already by 1985 only 7% of electricity generation came from oil. That generation was mainly replaced by nuclear energy, shifting from an 8% in 1973 to a 22% in 1985, and by coal, shifting from a 20% in 1973 to a 45% in 1985 (López Milla, 1999, p.45).

In the last years the goal of the Spanish regulatory authorities has not been to diversify to a greater extent the electricity generation but rather to substitute fossil fuels by renewable energies in the electricity generation mix, in line with the decarbonisation objectives set regionally (European Union Green Deal and Decarbonisation Package) and worldwide (Paris Agreement).

Figure 9. Evolution of renewable of non-renewable generation in Spain

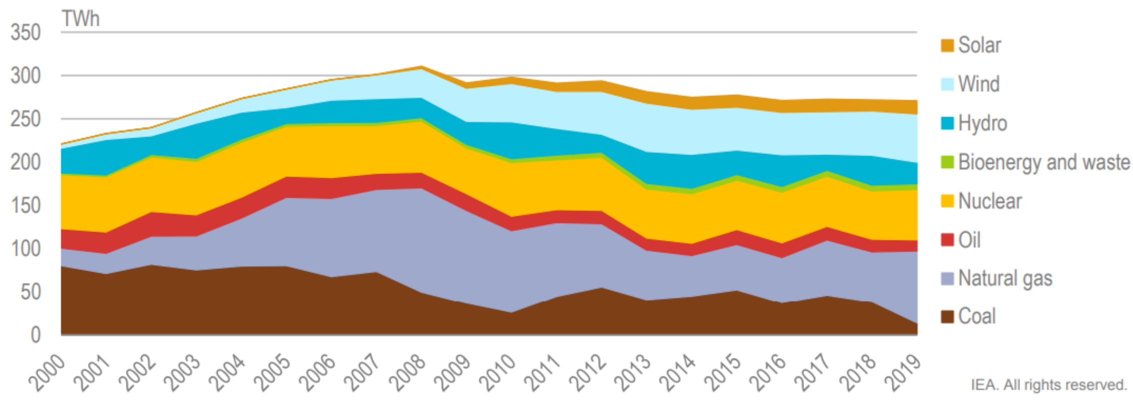


Note: Self-made from The Spanish Electricity System reports of 2017 (p.24) and 2020 (p.28) from *Red Eléctrica de España*

We can observe a significant switch from 2008 to 2020, considering that in twelve years the relative generation of electricity from renewable sources has more than doubled. For this reason, the International Energy Agency (2021, p.107-108) ranked Spain as 13th country in the world in terms of renewable electricity generation. In the Figure 10 we observe the evolution of the Spanish electricity mix by different sources.

[11] Adopting the subsequent National Energy Plans in 1975, 1978 and 1983

Figure 10. Evolution of electricity supply by source in Spain, Period 2000-2019



Source: International Energy Agency, 2021, p. 107.

The evolution of the electricity mix is characterised by some trends. In the last two decades the amount of electricity produced from nuclear energy has been very regular, with almost no changes from year to year. In the case of hydro resources, it has followed a more irregular evolution, increasing and decreasing conditionally to other resources. Oil has steadily decreased, and coal has had a considerable reduction. In the case of natural gas, there was a considerable boost in the half of the first decade and it remained as the source with a highest share until 2013. Then, the amount of electricity produced with natural gas continued steady until another increase happened in 2019, accounting in this year for almost one third of the generation. Overall, we can also observe that the peak of electricity generation was reached in 2008, with the production of 311 TWh and steadily descending up to 271 TWh in 2019 (considering the net import of 6.9 TWh).

A1.2. Transmission and distribution

The transmission system is the part of the supply chain that connects physically by means of pipelines the geographical points of electricity generation and of electricity consumption when long distances are in between. Given that the significant distance and magnitude of the high voltage networks require a strong investment, there are little economic incentives to carry them out, even though they are necessary for the construction of an electricity system. It entails a social dilemma since there are not individual incentives for such investment, but there are strong collective incentives. It is therefore treated as a natural monopoly, it is usually not liberalised and it is highly regulated.

When electricity is generated, it is done so in a high level of voltage. At that level is also carried in the transmission system. The reason that is due to the characteristics of this energy product, there are significant losses of electricity while it is transported, and by doing so in a high voltage those loses are minimised (Bell, 2010).

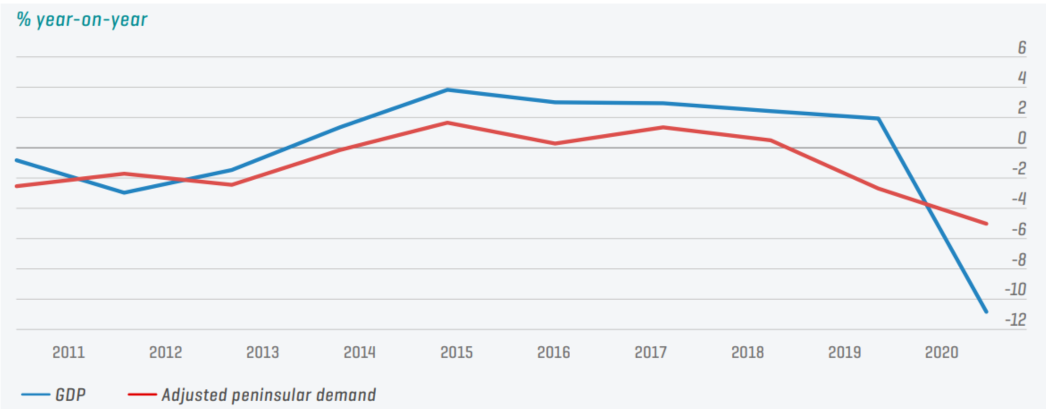
In the case of the Spanish electricity transmission system, it is operated by its only agent *Red Eléctrica Española*, constituted in 1985. It owns all of the transmission grid and manages it under homogenous criteria. It also deals with electricity flows from external system and guarantees third party access to the grid (*Red Eléctrica de España*, n.d.). At the European Union level several rules have been developed, known as grid codes, that try to harmonies the connection and operational rules of the different electricity transmission systems in Member States with the aim of getting to a European electricity integrated market (ACER, n.d.). The ultimate goal is to have better connected markets so that electricity can be transported more easily from one country to another, with the commercial implications that that may have, and also for security of supply reasons. In the case of Spain, the transmission system is coupled with the Portuguese one, and therefore electricity transactions can happen as if it was as single market. This project received the name of *Mercado Ibérico de la Electricidad* (MIBEL)[12]. However, such connections are significantly poorer with France, mainly for geographical reasons.

After the electricity is moved to the consumption point, its level of voltage is transformed from high to low in order to access distribution lines. Such lines are in charge of getting the electricity to end consumers. The electricity distribution is also regulated but it is not a natural monopoly like transmission, and there are different companies that take part in the distribution system (González Ruiz & Descalzo Benito, 2020). As it is explained in the following section, retailers are those who operate in this part of the supply chain.

A1.3. Consumption

It has long been studied the relationship between the amount of electricity consumption and degree of development in a country, that is, the higher the development the higher the amount of electricity consumed (Wolde-Rufael, 2006). In the Figure 11 the parallel tendency between these two elements can be observed, using gross domestic product (GDP) as a proxy for economic development:

Figure 11. Evolution of annual variation of electricity demand and Gross Domestic Product (GDP)



Source: *Red Eléctrica de España*, 2020, p.10

The consumption of electricity is typically divided in that carried out by the industrial sector and that carried out by households. In the Figure 12, we can observe how energy is consumed by sectors:

[12] For further information visit https://www.mibel.com/es/home_es/

Figure 12. Electricity consumption mix by sector in Spain in 2020

Source: *Red Eléctrica de España*, 2020, p.14

This static image corresponds to the consumption mix in year 2020. As opposed to the generation side, observing how this mix has evolved overtime is less relevant. Only to have a reference, the share of these consumption sectors has remained similar along the years (*Red Eléctrica de España*, 2020, p.15). In regard to the geographical spread of the consumption, the three autonomous communities with the higher consumption are Barcelona, Andalucía and Madrid, with 43.991 GWh, 39.067 GWh and 26.899 GWh, respectively (*Red Eléctrica de España*, 2020, p.18).

Appendix 2: Natural gas life cycle

A2.1. Upstream

The upstream part of the natural gas supply chain does not properly refer to its generation since natural gas is not generated but extracted. This phase englobes the exploration for underground natural gas deposits, the drilling to access the deposits and the extraction of the gas. Depending on how the natural gas is kept underground different technologies are used for its extraction (Energy Information Administration, 2019). If it is conventional gas means that it is found in an underground space, a proper deposit. If it is unconventional gas means that the gas is impregned in a specific mineral and therefore water has to be bombed with high pressure against the minerals to release the gas. In fact, this way of obtaining gas, also known as shale gas or fracking, has caused one of the mayor changes in the world natural gas market, since the United States, greatest developer of the technique, has made the most of it to the point of switching from net importer to net exporter of natural gas in a matter of a decade.

In the case of Spain, the extraction of natural gas is almost inexistant. It amounts to 0.1 bcm, accounting for less 0.3% of total natural has supply in the country (International Energy Agency, 2021, p.161). Given that all the rest is imported, it is addressed in the midstream section.

A2.2. Midstream

The midstream phase includes the processing of the gas after its extraction, to obtain "pipeline quality gas", and its transportation. The latter is a key element of the supply chain regarding the price formation. Large amounts of natural gas can be transported by either pipelines or vessels across the sea.

In the first case, pipelines operate right as the transmission system in the electricity sector. They are organised by MIBGAS. In addition, the transmission system operator is Enagás. Although lagging behind the degree of integration in the European system of electricity, the natural gas system is also integrated to some extent. The European Union Agency for the Cooperation of Energy Regulators (ACER) monitors the implementation of common network codes to harmonise at European level different scopes of the transmission system: capacity allocation, congestion management, balancing regimes, and system tariffs[13].

It is worth noting that the transmission tariffs affect the entry and exit point of natural gas in the transmission system, that entry from LNG facilities is discounted, and that transmission from or to storages is exempted, in Spain. Spain is actually one of the European countries with the highest storage capacity. Since the 50% of the tariff is applied in the entry point, and the other 50% in the exit point, the wholesale market price already bears part of the tariff, while the other part is only reflected in retail prices.

In the second case, we speak about liquified natural gas (LNG). If natural gas is cooled down extremely it is comprised and it reaches the liquid state, being able to occupy 600 times less space than in its gas state. By doing this, transporting this energy product overseas becomes profitable, and the market boundaries are not delimited by the pipeline network reach. The development of LNG has advanced steps towards a global market of

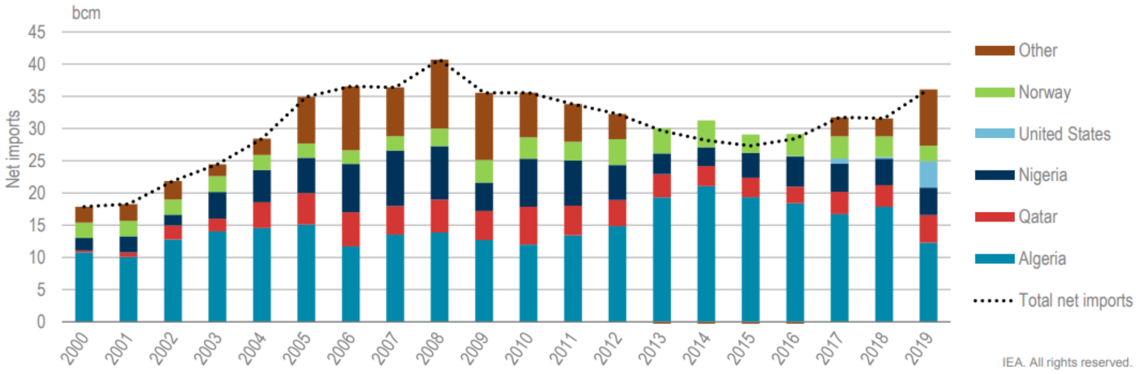
[13] For further information visit https://www.acer.europa.eu/gas/network-codes

natural gas, and for its consideration as a *commodity*. In fact, this, together with the shale revolution in the United States is what has enabled it to become as an energy power.

In the Spanish context LNG is highly relevant, as Spain is the largest or one of the largest LNG importing countries in Europe, counting with 7 LNG importing terminals. This has been materialised at policy level, since from year 2020, Spain operates with a *Tanque Virtual de Balance* (TVB, in Spanish) what consists of having a single common pool for all the imported LNG, that can thus be transacted no matter in what terminal it is received. Given the weight of LNG in the Spanish natural gas supply, this influx conditions natural gas prices overall. For example, although Spain usually has higher natural gas prices that other European countries, in 2020 they were lower due to a massive influx of LNG.

In the latest report of the International Energy Agency, we can observe how the natural gas imports by country of origin have evolve in the last two decades:

Figure 13. Spain´s natural gas net imports, Period 2000-2019



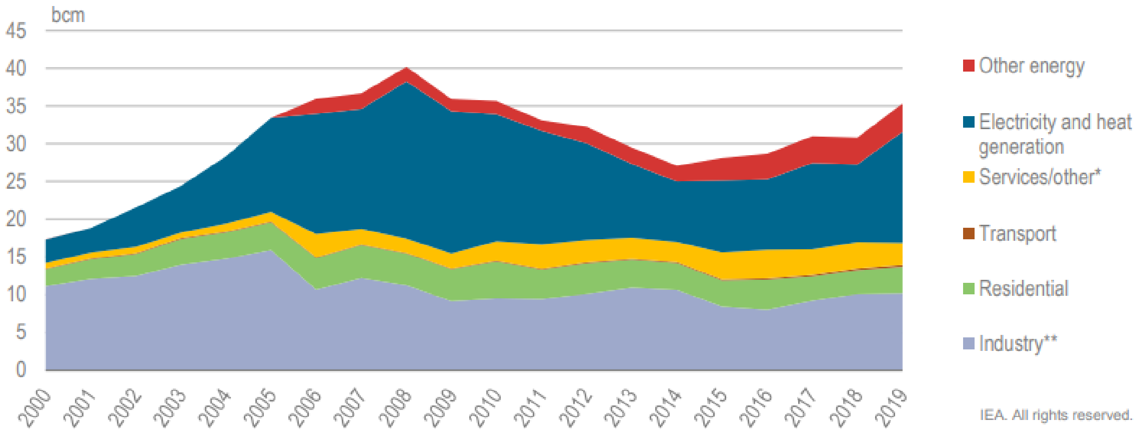
Source: International Energy Agency, 2021, p.164.

We can appreciate that the main natural gas supplier has been Algeria, by means of pipeline connection. The supply from Norway is also connected through pipeline while United States, Qatar and Nigeria transport is through LNG vessels. Under the tag of "Other", Russia would be the main exporter. In the last year considered, the net imports amounted to 36.1 bcm, not comparable with the amount extracted nationally.

A2.3. Downstream

The distribution pipelines of natural gas have a smaller diameter than those used for the transmission and the pressure of gas is also lower. In Figure 14 the evolution of natural gas consumption by sector is provided:

Figure 14. Natural gas consumption in Spain by sector, Period 2000-2019

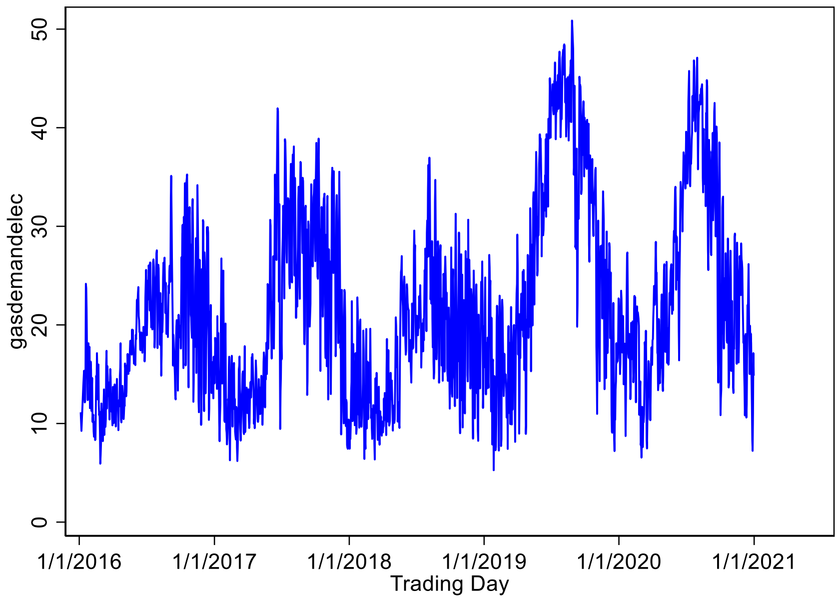


Source: International Energy Agency, 2021, p.163.

The graph shows how natural gas consumption has increased since the beginning of the century, and that the amount increased was mainly destinated for electricity and heat generation. For that reason, in the first decade natural gas appeared as a key new source for power generation. By the end of the decade, the relative weight of natural gas used for electricity generation was reduced, partly as a consequence of the penetration of renewables in the electricity mix, as explained in the previous appendix. However, that relevance has recovered to some degree in the last years. For that reason, it is worth analysing the impact of the natural gas market on the electricity market, and its evolution, what constituted the main objective of this paper.

In particular, it is worth including how the relative weight of electricity generation on the overall natural gas consumption has evolved overtime, that is, the percentage of natural gas devoted to electricity production with respect to total natural gas consumption. From open access data reported by the CNMC[14], we have obtained Figure 15.

Figure 15. Evolution of natural gas consumption for electricity generation, Period Jan. 2016 – Jun. 2021



[14] Accesible at https://www.cnmc.es/estadistica/estadisticas-de-gas-natural-1

The main findings from Figure 15 are that the higher or lower natural gas consumption for electricity generation as a share of overall natural gas consumption does not necessarily evolve in complete accordance with seasonality. We do not observe a clear match between summer period-lowest relative consumption and winter period-higher relative consumption. The same computation has been made in absolute terms and the correlation with the data in relative terms is of 0.9173. Therefore, we can conclude that some other factors influence in this, such as market conditions, natural gas supply arrangements, and the circumstance of other electricity generating technologies. In any case, the average share is of around 20%.

Annex: VECM outputs

Vector error-correction model (Corresponding to first layer of analysis)

	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
L._ce1	-.09	.017	-5.31	0	-.123	-.056	***
LD.electricityprices	-.145	.027	-5.45	0	-.197	-.093	***
L2D.electricitypri~s	-.336	.027	-12.68	0	-.388	-.284	***
L3D.electricitypri~s	-.204	.027	-7.47	0	-.257	-.15	***
L4D.electricitypri~s	-.193	.027	-7.06	0	-.247	-.139	***
L5D.electricitypri~s	-.24	.027	-8.76	0	-.294	-.187	***
L6D.electricitypri~s	-.145	.028	-5.22	0	-.2	-.091	***
L7D.electricitypri~s	.072	.028	2.58	.01	.017	.126	***
L8D.electricitypri~s	-.063	.028	-2.26	.024	-.117	-.008	**
L9D.electricitypri~s	-.034	.027	-1.25	.211	-.087	.019	
L10D.electricitypr~s	-.076	.026	-2.90	.004	-.128	-.025	***
L11D.electricitypr~s	-.101	.026	-3.93	0	-.151	-.051	***
L12D.electricitypr~s	-.087	.025	-3.49	0	-.136	-.038	***
L13D.electricitypr~s	-.066	.023	-2.86	.004	-.112	-.021	***
L14D.electricitypr~s	.084	.022	3.87	0	.042	.127	***
LD.gasprices	1.508	.125	12.09	0	1.263	1.752	***
L2D.gasprices	.589	.129	4.56	0	.336	.842	***
L3D.gasprices	.425	.131	3.25	.001	.169	.681	***
L4D.gasprices	.5	.131	3.82	0	.243	.757	***
L5D.gasprices	.442	.132	3.35	.001	.183	.7	***
L6D.gasprices	.506	.132	3.83	0	.248	.765	***
L7D.gasprices	.23	.132	1.74	.082	-.029	.489	*
L8D.gasprices	.423	.133	3.19	.001	.163	.683	***
L9D.gasprices	.411	.132	3.12	.002	.153	.67	***
L10D.gasprices	.051	.131	0.39	.699	-.207	.308	
L11D.gasprices	.407	.131	3.12	.002	.151	.663	***
L12D.gasprices	.126	.13	0.97	.332	-.129	.381	
L13D.gasprices	.145	.128	1.13	.259	-.107	.396	
L14D.gasprices	-.231	.128	-1.80	.072	-.482	.02	*
Constant	.001	.122	0.00	.996	-.238	.24	
L._ce1	.004	.003	1.35	.176	-.002	.01	
LD.electricityprices	-.006	.005	-1.26	.208	-.016	.003	
L2D.electricitypri~s	-.008	.005	-1.70	.088	-.018	.001	*
L3D.electricitypri~s	-.001	.005	-0.15	.884	-.011	.009	
L4D.electricitypri~s	-.003	.005	-0.58	.56	-.013	.007	
L5D.electricitypri~s	.006	.005	1.22	.223	-.004	.016	
L6D.electricitypri~s	.008	.005	1.55	.121	-.002	.018	
L7D.electricitypri~s	-.009	.005	-1.82	.068	-.019	.001	*
L8D.electricitypri~s	.002	.005	0.45	.651	-.008	.012	
L9D.electricitypri~s	-.01	.005	-2.03	.042	-.02	0	**
L10D.electricitypr~s	-.007	.005	-1.50	.134	-.017	.002	
L11D.electricitypr~s	-.012	.005	-2.47	.013	-.021	-.002	**
L12D.electricitypr~s	.005	.005	1.09	.275	-.004	.014	
L13D.electricitypr~s	-.003	.004	-0.75	.45	-.012	.005	
L14D.electricitypr~s	-.013	.004	-3.35	.001	-.021	-.006	***
LD.gasprices	.017	.023	0.73	.465	-.028	.062	
L2D.gasprices	-.141	.024	-5.92	0	-.188	-.094	***
L3D.gasprices	-.045	.024	-1.85	.064	-.092	.003	*
L4D.gasprices	-.046	.024	-1.88	.06	-.093	.002	*
L5D.gasprices	-.017	.024	-0.69	.489	-.065	.031	

L6D.gasprices	-.065	.024	-2.67	.008	-.113	-.017	***
L7D.gasprices	.079	.024	3.24	.001	.031	.127	***
L8D.gasprices	-.042	.024	-1.73	.084	-.09	.006	*
L9D.gasprices	-.016	.024	-0.66	.507	-.064	.032	
L10D.gasprices	.034	.024	1.42	.156	-.013	.082	
L11D.gasprices	.003	.024	0.11	.912	-.045	.05	
L12D.gasprices	-.039	.024	-1.61	.106	-.086	.008	
L13D.gasprices	-.054	.024	-2.29	.022	-.101	-.008	**
L14D.gasprices	.111	.024	4.70	0	.065	.157	***
Constant	.013	.023	0.57	.569	-.031	.057	

Mean dependent var	-0.032	SD dependent var	0.216
Number of obs	1980.000	Akaike crit. (AIC)	.

**** p<.01, ** p<.05, * p<.1*

Vector error-correction model (Corresponding to third layer of analysis)

	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
L._ce1	-.066	.018	-3.68	0	-.101	-.031	***
LD.electricitypric	-.176	.028	-6.32	0	-.231	-.121	***
L2D.electricitypri	-.352	.028	-12.59	0	-.407	-.298	***
L3D.electricitypri	-.223	.029	-7.71	0	-.28	-.167	***
L4D.electricitypri	-.206	.029	-7.04	0	-.263	-.149	***
L5D.electricitypri	-.24	.029	-8.14	0	-.297	-.182	***
L6D.electricitypri	-.16	.03	-5.36	0	-.218	-.101	***
L7D.electricitypri	.011	.03	0.35	.725	-.048	.069	
L8D.electricitypri	-.085	.03	-2.83	.005	-.143	-.026	***
L9D.electricitypri	-.05	.03	-1.66	.096	-.108	.009	*
L10D.electricitypr	-.088	.03	-2.96	.003	-.147	-.03	***
L11D.electricitypr	-.136	.03	-4.53	0	-.194	-.077	***
L12D.electricitypr	-.127	.03	-4.23	0	-.186	-.068	***
L13D.electricitypr	-.112	.03	-3.74	0	-.17	-.053	***
L14D.electricitypr	-.031	.03	-1.02	.306	-.089	.028	
L15D.electricitypr	-.035	.03	-1.16	.248	-.093	.024	
L16D.electricitypr	-.078	.03	-2.64	.008	-.136	-.02	***
L17D.electricitypr	-.057	.029	-1.95	.051	-.114	0	*
L18D.electricitypr	-.046	.029	-1.58	.114	-.102	.011	
L19D.electricitypr	-.025	.029	-0.89	.375	-.082	.031	
L20D.electricitypr	-.053	.029	-1.85	.064	-.109	.003	*
L21D.electricitypr	.116	.028	4.10	0	.06	.171	***
L22D.electricitypr	-.03	.028	-1.04	.297	-.085	.026	
L23D.electricitypr	-.014	.028	-0.50	.616	-.068	.041	
L24D.electricitypr	-.03	.027	-1.12	.261	-.083	.022	
L25D.electricitypr	-.048	.026	-1.83	.067	-.099	.003	*
L26D.electricitypr	-.046	.025	-1.84	.066	-.096	.003	*
L27D.electricitypr	-.04	.023	-1.69	.092	-.085	.006	*
L28D.electricitypr	.065	.022	2.95	.003	.022	.109	***
LD.gasprices	1.391	.124	11.18	0	1.147	1.635	***
L2D.gasprices	.572	.128	4.46	0	.321	.824	***
L3D.gasprices	.447	.13	3.44	.001	.192	.702	***
L4D.gasprices	.492	.13	3.77	0	.236	.748	***
L5D.gasprices	.475	.131	3.62	0	.218	.732	***
L6D.gasprices	.477	.131	3.63	0	.22	.735	***
L7D.gasprices	.348	.132	2.64	.008	.089	.606	***
L8D.gasprices	.422	.132	3.19	.001	.163	.681	***
L9D.gasprices	.367	.132	2.78	.006	.108	.627	***

L10D.gasprices	.125	.133	0.94	.346	-.135	.385	
L11D.gasprices	.468	.133	3.52	0	.208	.728	***
L12D.gasprices	.189	.133	1.42	.155	-.071	.45	
L13D.gasprices	.14	.133	1.05	.292	-.121	.401	
L14D.gasprices	-.051	.133	-0.38	.702	-.312	.21	
L15D.gasprices	.181	.133	1.35	.176	-.081	.442	
L16D.gasprices	-.207	.133	-1.55	.121	-.468	.055	
L17D.gasprices	.002	.133	0.01	.988	-.258	.262	
L18D.gasprices	.028	.133	0.21	.835	-.233	.288	
L19D.gasprices	.052	.133	0.39	.693	-.208	.313	
L20D.gasprices	.163	.133	1.23	.219	-.097	.423	
L21D.gasprices	.173	.132	1.31	.191	-.086	.432	
L22D.gasprices	.227	.132	1.72	.086	-.032	.487	*
L23D.gasprices	.052	.132	0.39	.693	-.206	.31	
L24D.gasprices	-.147	.131	-1.12	.261	-.403	.109	
L25D.gasprices	-.273	.13	-2.11	.035	-.528	-.019	**
L26D.gasprices	-.171	.129	-1.32	.186	-.424	.082	
L27D.gasprices	-.003	.127	-0.02	.982	-.252	.246	
L28D.gasprices	-.273	.127	-2.15	.032	-.522	-.024	**
Constant	.002	.12	0.01	.989	-.233	.237	
L._ce1	.007	.003	1.98	.047	0	.013	**
LD.electricitypric	-.009	.005	-1.69	.09	-.019	.001	*
L2D.electricitypri	-.01	.005	-1.86	.063	-.02	.001	*
L3D.electricitypri	-.003	.005	-0.59	.556	-.014	.008	
L4D.electricitypri	-.004	.006	-0.69	.49	-.015	.007	
L5D.electricitypri	.003	.006	0.62	.536	-.007	.014	
L6D.electricitypri	.002	.006	0.39	.693	-.009	.013	
L7D.electricitypri	-.011	.006	-1.98	.048	-.022	0	**
L8D.electricitypri	0	.006	0.06	.955	-.011	.011	
L9D.electricitypri	-.011	.006	-1.96	.05	-.022	0	**
L10D.electricitypr	-.013	.006	-2.29	.022	-.024	-.002	**
L11D.electricitypr	-.015	.006	-2.71	.007	-.026	-.004	***
L12D.electricitypr	-.002	.006	-0.33	.74	-.013	.009	
L13D.electricitypr	-.014	.006	-2.53	.011	-.025	-.003	**
L14D.electricitypr	-.019	.006	-3.39	.001	-.03	-.008	***
L15D.electricitypr	-.006	.006	-1.15	.251	-.018	.005	
L16D.electricitypr	-.011	.006	-1.89	.059	-.022	0	*
L17D.electricitypr	-.002	.006	-0.33	.744	-.013	.009	
L18D.electricitypr	-.009	.005	-1.60	.109	-.019	.002	
L19D.electricitypr	.003	.005	0.55	.582	-.008	.014	
L20D.electricitypr	.008	.005	1.49	.136	-.003	.019	
L21D.electricitypr	-.004	.005	-0.83	.409	-.015	.006	
L22D.electricitypr	.004	.005	0.69	.49	-.007	.014	
L23D.electricitypr	-.002	.005	-0.39	.699	-.012	.008	
L24D.electricitypr	.003	.005	0.55	.579	-.007	.013	
L25D.electricitypr	.002	.005	0.49	.626	-.007	.012	
L26D.electricitypr	.003	.005	0.53	.599	-.007	.012	
L27D.electricitypr	.003	.004	0.78	.432	-.005	.012	
L28D.electricitypr	.002	.004	0.49	.627	-.006	.01	
LD.gasprices	.022	.024	0.94	.346	-.024	.068	
L2D.gasprices	-.137	.024	-5.65	0	-.185	-.09	***
L3D.gasprices	-.041	.025	-1.67	.095	-.089	.007	*
L4D.gasprices	-.043	.025	-1.76	.079	-.092	.005	*
L5D.gasprices	-.014	.025	-0.58	.561	-.063	.034	
L6D.gasprices	-.044	.025	-1.77	.076	-.093	.005	*
L7D.gasprices	.067	.025	2.68	.007	.018	.116	***
L8D.gasprices	-.038	.025	-1.50	.133	-.087	.011	

L9D.gasprices	-.006	.025	-0.25	.804	-.055	.043	
L10D.gasprices	.048	.025	1.90	.057	-.001	.097	*
L11D.gasprices	.009	.025	0.36	.716	-.04	.058	
L12D.gasprices	-.025	.025	-0.98	.327	-.074	.025	
L13D.gasprices	-.023	.025	-0.93	.353	-.073	.026	
L14D.gasprices	.103	.025	4.11	0	.054	.153	***
L15D.gasprices	.026	.025	1.03	.303	-.023	.075	
L16D.gasprices	-.002	.025	-0.08	.936	-.051	.047	
L17D.gasprices	.009	.025	0.34	.734	-.041	.058	
L18D.gasprices	.03	.025	1.20	.23	-.019	.079	
L19D.gasprices	.025	.025	0.99	.324	-.024	.074	
L20D.gasprices	-.04	.025	-1.58	.115	-.089	.01	
L21D.gasprices	.074	.025	2.94	.003	.025	.123	***
L22D.gasprices	-.006	.025	-0.24	.812	-.055	.043	
L23D.gasprices	-.005	.025	-0.21	.837	-.054	.044	
L24D.gasprices	-.013	.025	-0.51	.611	-.061	.036	
L25D.gasprices	-.026	.025	-1.04	.297	-.074	.023	
L26D.gasprices	-.034	.024	-1.39	.165	-.082	.014	
L27D.gasprices	-.048	.024	-2.01	.044	-.096	-.001	**
L28D.gasprices	.025	.024	1.05	.293	-.022	.072	
Constant	.017	.023	0.75	.456	-.028	.061	

Mean dependent var	-0.032	SD dependent var	0.216
Number of obs	1966.000	Akaike crit. (AIC)	.

**** p<.01, ** p<.05, * p<.1*