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Using a Rolling Vector Error Correction Model to Model Static and Dynamic Causal Relations between Electricity Spot Price and Related Fundamental Factors: The Case of Greek Electricity Market

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ABSTRACT

The purpose of this study is to investigate short and long run relationships between electricity spot prices in Greece, Brent oil, natural gas, lignite fuel cost and carbon allowances using daily data from 2007 to 2014. Static and dynamic Johansen test are applied in order to identify long run relations and also to assess the evolution over time in the level of cointegration. Additionally we test for Granger Causality in a Vector error correction model and embrace impulse response and variance decomposition techniques to model the dynamic response of electricity prices in excitation of another variable. Overall our results suggest an important long run relation between spot electricity prices in Greece, natural gas price and carbon allowances, while in the short run electricity prices are not affected by any of the other variables, results that are of practical importance for the market regulator as well as the wholesale market participants.

Keywords: Vector Error Correction, Electricity Markets, Fuel Markets
JEL Classifications: C4, C5, C8

1. INTRODUCTION

In this paper we examine the long-run relations and short-run dynamics between the wholesale electricity prices and prices for three other fossil fuels - lignite, natural gas and Brent Oil – as well as EUA futures contract prices, using daily data of the Greek Electricity Market (GEM) and Intercontinental Exchange (ICE) over 2007–2014. More specifically, this work attempts to address the following issues:

a. The existence of a (unique) long-run relation between spot electricity prices and the costs associated with the above fuels and the EUA cost, and the nature of that relationship, if it exists,
b. The short-run dynamics of the above mentioned relationships, and more specifically the detection of causal relations and their direction between spot or System Marginal Price (SMP) and fuel and EUA costs,
c. The detection of responses of SMP to various exogenous shocks occurred in one of the fuel or the EUA markets,
d. The impact of the shocks in each fuel market on the dynamic evolution of the SMP.

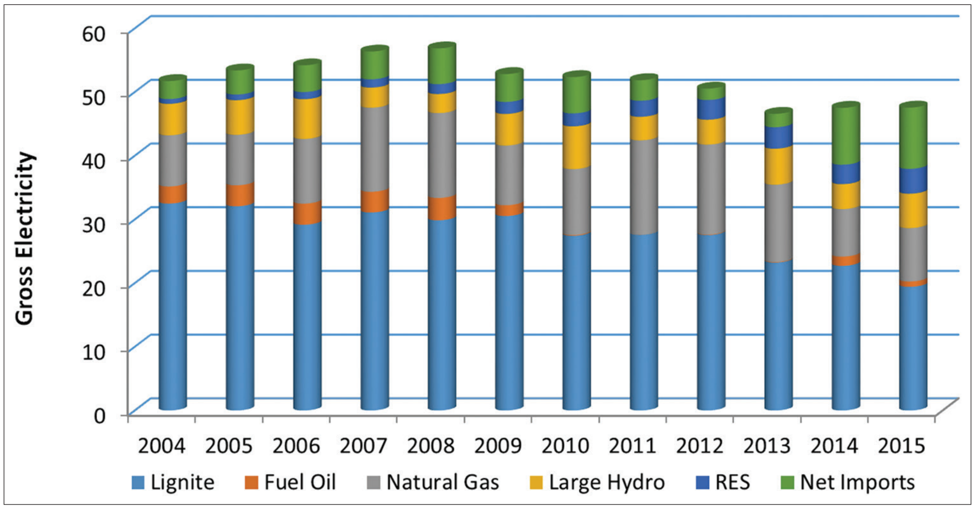
Shedding light on these issues is extremely useful for the following reasons. In the GEM both lignite and natural gas play an important role in the electricity generation mix. As it is described in section 4, Table 1 and Figure 1, the share of lignite and Natural gas, over the period 2004–2014, follow a different direction: Lignite share decreases from 0.66 of the total generation production mix, without accounting for imports, in 2004 to 0.52 in 2015, while the share for natural gas increases from 0.16 to 0.22 in the same period, as can be seen in Figure 2.

Table 1: Fuel-mix generation 2004-2015 in the Greek Interconnected System

	2004 (TWh)	2005 (TWh)	2006 (TWh)	2007 (TWh)	2008 (TWh)	2009 (TWh)	2010 (TWh)	2011 (TWh)	2012 (TWh)	2013 (TWh)	2014 (TWh)	2015 (TWh)
Lignite	32.5	32.1	29.8	31.1	29.9	30.5	27.4	27.6	27.6	23.2	22.7	19.4
Fuel oil	2.69	3.30	3.31	3.26	3.51	1.69	0.11	0.01	0.08	0.08	1.46	0.84
Natural gas	8.1	7.9	10.2	13.2	13.3	9.4	10.4	14.9	14.1	12.2	7.5	8.4
Large hydro	4.93	5.42	6.22	3.14	2.97	4.96	6.70	3.68	3.89	5.64	3.91	5.39
RES	0.757	0.894	1.13	1.31	1.57	1.88	2.04	2.53	3.11	3.38	3.06	3.91
Total local generation	48.9	49.6	50	52	51.3	48.5	46.6	48.6	48.8	44.4	37.3	37.0
Net imports	2.82	3.78	4.20	4.35	5.61	4.37	5.70	3.23	1.78	2.10	8.92	9.61
Grand total	51.7	53.4	54.2	56.4	56.9	52.8	52.4	51.9	50.4	46.5	45.9	46.7

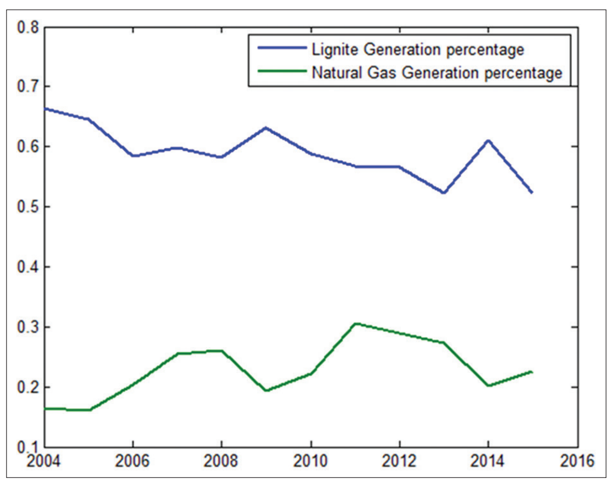
Source: ADMIE S.A

Figure 1: Time evolution of generation mix (in TWh) in GEM, 2004-2015



Therefore, changes in lignite and natural gas prices are expected to have a direct and significant effect on the cost of generating electricity and consequently on its wholesale price. Brent Oil is expected to have and indirect effect on the formation of SMP through mainly changes in market sentiments since its share on the generation mixture is almost negligible resulting in insignificant also direct effect on the electricity generation cost. Another reason is that fuel prices, due to the fact that they can be considered as substitutes on the demand-side of the energy market, fuel prices may also affect electricity prices. The "paradigm shift" from "cost-based" pricing to "market-based" pricing as a result of the liberalization and restructuring of the electricity sector (unbundling of generation, transmission and distribution operations), may have contributed to the changes in the dynamics of wholesale electricity prices. According to the conventional cost-based approach of pricing, SMP should reflect a mark-up over marginal costs. Instead, under the market-based pricing approach, SMP should reflect fuel costs in the long run. From a policy perspective, an in depth understanding of the long run dynamics of interdependence between the aforementioned "assets," is very important, for example, in designing "fair" tax mechanisms in these markets (Yucel and Guo, 1994). Finally, but equally important, is the detection of the degree of integration of GEM and its various energy sources substitutability. The existence of long and short-run relations among SMP and fuel and EUA costs is examined by using cointegration and vector error correction model (VECM) to capture the direction of causality among them.

Figure 2: The evolution of the shares of Lignite's and Natural Gas from 2004 to 2005



In summary, the spot electricity price is a function of fuel prices and CO_2 allowances (EUA).

For electric utilities and National Regulators, a good understanding of the wholesale electricity price is very crucial, given that this price is the underline asset in futures and options markets that in turn serve several purposes for these energy players, as price discovery, trading, valuation and hedging.

Continental Europe electricity markets are dominated by a very large amount of fossil-fuel electricity generation, so fundamental power system economics suggest that a strong interaction between spot price and its related fuel and CO_2 allowances market prices must exist. A natural assumption resulted from the above is that lignite (in Greece) or hard coal in general is at the margin, which means that crude oil (in our study Brent Oil) is not expected to have an effect in shaping SMP directly, since only a small share of European Power plants is Oil-fired.

Taking into consideration the above mentioned a priori economic relationships, the most natural to follow modelling approach seems to be a simultaneous equations model (SEM), highly parameterized and "full" of necessary assumptions regarding price setting mechanism and market "architecture." The model specifications therefore might be complicated and possibly wrong, resulting in misleading outputs.

Another reason for not adopting a SEM approach is that this type of model is not capable in capturing the dynamic relations between the input fuels and EUA, because in SEM lagged values of variables are considered to be exogenous. Thus, in this work we have adopted a VECM in order to determine interactions between the variables considered and capture long-run economic interdependences and short-rum dynamics from time series.

At the best of our knowledge the co-movement or level of integration between fossil fuel prices and electricity prices in Greece and an in depth understanding of possible different dynamics occurring in these markets has not been investigated. The purpose of this study is mainly to analyze the aforementioned level of integration in order to capture possible different long run or short run dynamics caused by a different level of deregulation of the fossil fuels and electricity markets in Greece. A cointegration relationship plays a crucial role since it provides arbitraging opportunities among the various commodities, an extremely important "variable" for the pricing of derivatives consisting of couple of commodities and options based on spreads.

The remainder of this work is organized as follows. In section 2 we provide a brief review of the most relevant to this work literature. In section 3 the background theory is presented, i.e., a short description on structural vector autoregression (VAR), Granger Causality, impulse response (IR) and finally on the VECM. The Greek Electricity market, the data set used and all necessary tests performed on the data (stationarity, Johansen Cointegration tests), are described in section 4. The estimation of the VECM model is given in section 5 and finally section 6 summarizes and outlines a number of policy implications.

2. BRIEF REVIEW OF RELEVANT LITERATURE

Fundamental or VAR-structural models, try to capture the basic physical and economic relationship present in the generation and trading of electricity. Johnsen (2001) presented a supply-demand model for the Norwegian power market. He used hydro inflow, snow and temperature data to model the dynamics of spot price. Vahvilainen and Pyykkonen (2005) constructed a model to capture the dynamics of hydrological inflow and snow-pack formation that impact hydro electricity generation. The successful model captured the observed fundamentally driven market price movements.

Fundamental models suffer from two major "drawbacks" (Weron, 2006): (a) Data availability and (b) the unavoidable incorporation of stochastic fluctuations of the fundamental variables. For the first, depending on the market and the role of the player, information on plant generation, costs, load profile and transmission constraints may be, more or less, available to build such a model. For the second challenge, the specific assumptions made regarding physical and financial relationships in the market, have a crucial impact on the forecasting of spot prices, given the significant sensitivity of the model's behavior on the assumptions. So, there exists a significant modeling risk in the application of the VAR approach.

Regarding the relationship between natural gas and crude oil, Panagiotidis and Rutlledge (2006) have found evidence of a long-run equilibrium between UK gas prices and Brent oil time series, over the period 1996-2003. They have demonstrated robust cointegrating relationship between the assets, despite the opening of the UK-Europe gas Interconnector. Using an ECM, Bachmeier and Griffin (2006) evaluated the degree of market integration among crude oil, coal and natural gas market. Villar and Joutz (2006), using data from period 1989-2005, claimed to have captured a cointegration relationship between oil and natural gas, although there were periods of decoupling between the two markets. Brown and Yücel (2007) found that short run deviations from the estimated long run relationship could be explained by weather influence, natural gas storage, seasonality and production. The impact of seasonal fluctuations, weather shocks and storage fluctuations on the short run dynamic adjustment of prices has been investigated by Hartley et al. (2008).

In the work of Serletis and Herbert (1999), the price co-movement of natural gas (Henry Hub and Transco Zone 6), fuel oil (New York Harbor) and electricity prices in Pennsylvania Jersey and Maryland is explored. The authors find that natural gas and fuel oil prices are nonstationary, but the spot electricity price, is stationary. Therefore they built a bivariate cointegration only between the two gas markets prices and the fuel oil prices, because a bivariate cointegration for the electricity market, due to its stationarity, would be spurious.

A cointegration between electricity and natural gas futures daily prices was found by Emery and Liu (2002) and they noted that there are no differences in the sensitivity of electricity prices to changes in natural gas prices in the regions of California Oregon Border and Palo Verde.

Based on monthly spot prices on crude oil, natural gas and electricity and using cointegration analysis, Asche et al. (2006) noted differences in the relationship between the prices, depending on the time period. More specifically, they find the UK market as integrated in the period January 1995-June 1998 i.e., during the deregulation period and before the physical Link of gas market to the European market. Due to this degree of market integration they considered that the three markets behave like a single (energy) commodity. They also state that after the Interconnector became fully operational (July 1998-December 2002), the decoupling of prices took place.

In this work we aim to identify the driving factors of electricity prices as well as relationships between the fuel inputs into the power generation mixture and the wholesale power price, in the case of the Greek Electricity Market. Ewing et al. (2002) have used daily historical data to evidence the evolution of oil and gas companies' stock prices, via bivariate models. Significant diffusion between the volatility of gas and oil sector has been evidenced. Polemis et al. (2007) identified the connection between electricity prices in Greece and industrial energy demand, using cointegration methods. Henriques and Sadorsky (2008) investigated the relation between energy prices, stock prices and interest rates. Applying a VAR model, they observed that tech and oil stocks Granger-cause the prices of alternate energy companies. Mohammadi (2009) investigated the relation of electricity prices and the prices of assets that compose the generation mixture. Long-term dependence of electricity prices and coal prices has been observed, while natural gas and crude oil prices have no significant effect on the evolution of electricity prices. Choi and Hammoudeh (2010) analyzed the connection between stock market and commodities markets. Event-driven behavior has been analyzed and volatility of Brent and WTI crude have been proved more sensitive to geopolitical instabilities, while copper to financial crises. Standard and Poor's 500 is sensitive on both occasions. He et al. (2014) have studied the macroeconomic influence of coal price adjustment on the electric power industry of China. As observed, increased electricity prices cause decreased total output and tend to make economic development factors less stationary. Causal relation between coal and electricity prices is identified, with decreasing intensity as coal prices increase. Hondroyiannis et al. (2002) and Payne (2010) developed a survey of the causal connection between economic growth and energy consumption, based on international results. The results yield a highly model-dependent outcome. Timeframe, variable selection, national framework and econometric parameters, all may be factors that shape the varying results. Bencivenga et al. (2010) examined the cointegrating relations between fossil fuels and electricity prices both in the EU and US. Their study aimed to capture variation in the dynamics of the markets caused by deregulation policies applied during the time period of 2001-2009. Their findings include major short-term effects on dynamics and possible significance of regulation to the long term equilibrium. Ferkingstand et al. (2011) identified nonstationarity in oil prices, coal prices and EUR/USD exchange rate. Causal dependence has been observed between gas and electricity prices. The work has contrasting results with the US study, showing only positive innovation shock responses (i.e., of natural gas to coal). Moutinho et al. (2011), using data between 2002 and 2005 of the Spanish Electricity Market, analyzed the relation of commodities prices and spot electricity market prices. Cointegration methods like VAR and vector error correction yield that electricity prices are mainly driven by the evolution of natural gas. Kirat and Ahamada (2011), examined the prices of electricity derivatives and alike instruments in Germany and France and observed constraints in contracts pricing, compelling producers to include carbon prices in their cost functions during the 2 years of the European Emissions Trading Scheme (EU ETS), underlining the significance of carbon prices in the development of electricity markets. Polemis and Dagoumas (2013), using vector error correction, analyzed the Greek Electricity Market and extracted causal relations between energy prices and economic growth indicators. The behavior of electricity prices after a shock has been observed using dynamic IR analysis. Environmental and energy policies are discussed to integrate Greece within the European framework. Brooks and West (2013), studying the energy production of the 27 countries of the EU (including the UK) for the time period of 2009-2012, examined the integration between coal, natural gas, EUA emissions and crude oil. Their DCC GARCH model observed no satisfactory levels of market integration during the volatile period of the study. Frydenberg et al. (2014), using daily historical data from 2006 to 2012, examine the relation of electricity futures prices and fuel sources. Their study in the UK, Germany and Nordic markets identifies cointegration between UK electricity, coal and gas and between electricity in Nordic countries and coal. Madaleno et al. (2014), using vector error correction, examined the relationship in the returns of carbon, electricity and fuel sources using data from the French and German markets. Special attention has been given on the impact of emissions trading, identifying that the significance of carbon depends on the fuel mix of the country studied. Madaleno et al. (2015), using data from 1996 to 2013, investigated the cointegration of electricity, gas, oil and coal, including panel data for both industrial and household sector. The findings of the VECM show that the electricity prices are cointegrated with the fuel prices. Industry sector was observed to be robust in terms of long-term equilibrium and household sector was robust both in short-term and long-term equilibrium. Mensah et al. (2014) examined the role of global crude oil on both gross domestic product and exchange rate of Ghana for the time period of 1980 to 2013. Their VECM developed by Johansen's technique reveals positive causality between the GDP and the electricity prices and no relation with the exchange rate volatility.

3. BACKGROUND THEORY

3.1. A VAR Model

For the sake of completeness of this work we present the VAR model (VAR), although we only employ a VECM. This approach allows economic interpretation to shocks, which influence endogenous variables of interest. A typical VAR model, where the exogenous (or deterministic) component and the endogenous variables are modeled as follows:

$$y_t = c + Bx_t + \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t = c + Bx_t + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + \varepsilon_t \quad (1)$$

Where y_t a k vector of endogenous variables, xt an m vector of exogenous variables, A's are k×k coefficient matrices, B a k×m matrix of coefficient for xt, c a k×1 intercept vector of constants, εt a vector of innovations that may be contemporaneously correlated but uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables. Furthermore, εt = (ε1,t,…,εk,t) is a k dimensional vector of reduced-form errors with the properties $E\left(\varepsilon_t\right)=0, E\left(\varepsilon_t,\varepsilon_s^{'}\right)=\Sigma_\varepsilon$ and $E\left(\varepsilon_t,\varepsilon_s^{'}\right)=0$ for $s \neq t$ where Σε is an invertible k×k variance-covariance matrix. The number of lags p will be determined via Akaike Information Criterion (AIC) and SIC criteria as described below.

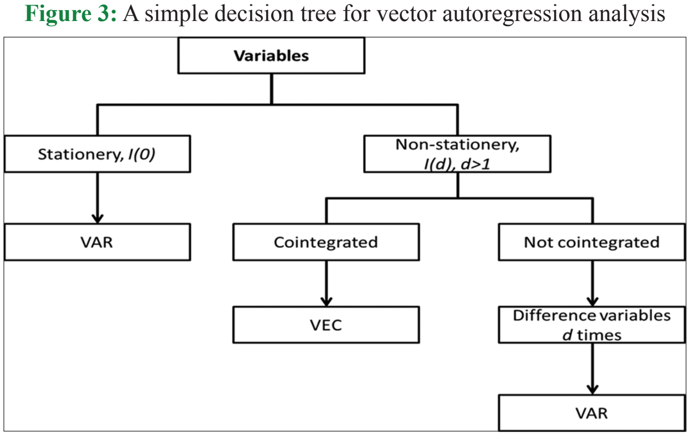
As an example let k = 2, m = 3, p = 2, so the bi-variable VAR(2) model with 3-exogenous variable is written as

$$\underbrace{\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix}}_{y_t} = \underbrace{\begin{bmatrix} c_1 \\ c_2 \end{bmatrix}}_{c} + \underbrace{\begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \end{bmatrix}}_{B} \underbrace{\begin{bmatrix} x_{1,t} \\ x_{2,t} \\ x_{3,t} \end{bmatrix}}_{x_t} + \underbrace{\begin{bmatrix} a_{11,1} & a_{12,1} \\ a_{21,1} & a_{22,1} \end{bmatrix}}_{A_1} \underbrace{\begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix}}_{y_{t-1}} + \underbrace{\begin{bmatrix} a_{11,2} & a_{12,2} \\ a_{21,2} & a_{22,2} \end{bmatrix}}_{A_2} \underbrace{\begin{bmatrix} y_{1,t-2} \\ y_{2,t-2} \end{bmatrix}}_{y_{t-2}} + \underbrace{\begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}}_{\varepsilon_t} \tag{2}$$

The above model is a typical tool of econometrics is VAR model (Hamilton, 1994) is and multivariate time series analysis. The endogenous variables y_t and the exogenous variables xt are the observed random variables depending on (time) t=1, 2,… The main concept in VAR(p) model (p is number of lags) is that yt depend linearly on their k lagged values, as well as the current value of the x_t.

The same order of integration in all variables is assumed. In the case that all variables are stationary, i.e., I(0), we are dealing with the standard case of a VAR model, instead if all variables are non-stationary, I(d) (d = order of differentiation), d >1, we consider two options. First, in case that the variables are not cointegrated, we must differentiate all variables d times so we can have a VAR. Second, if they are cointegrated, we can adopt a VECM in our analysis (Figure 3).

Figure 3: A simple decision tree for vector autoregression analysis



3.2. Granger Causality

One of the main uses of VAR models is forecasting. The structure of the VAR model provides information about a variables' forecasting ability for other variables. The following intuitive notion of a variable's forecasting ability is due to Granger (1969). If a variable, or group of variables y_1 is found to be helpful for predicting another variable, or group of variables y_2 then y_1 is said to Granger-cause y_2; otherwise it is said to fail to Granger-cause y_2. Formally, y_1 fails to Granger-cause y_2 if for all s>0 the MSE of a forecast of $y_{2,t+s}$ based on (y_2,t, $y_{2,t-1}$,…) is the same as the MSE of a forecast of $y_{2,t+s}$ based on (y_2,t, $y_{2,t-1}$,…) and (y_1,t, $y_{1,t-1}$,…). Note that the notion of Granger causality only implies forecasting ability.

In a bivariate VAR(p) model for yt = $(y_{1t}, y_{2t})'$, y_2 fails to Granger-cause y_1 if all of the p VAR coefficient matrices A_1,…Ap are lower triangular. That is, all of the coefficients on lagged values of y_2 are zero in the equation for y_1. The p linear coefficient restrictions implied by Granger non-causality may be tested using the Wald statistic. Notice that if y_2 fails to Granger-cause y_1 and y_1 fails to Granger-cause y_2, then the VAR coefficient matrices A_1,… A_p are diagonal.

3.3. IR and Variance Decompositions (VD)

As in the univariate case, a VAR(p) process can be represented in the form of a vector moving average process.

$$y_t = c+\varepsilon_t+\Psi_1\,\varepsilon_{t-1}+\Psi_2\,\varepsilon_{t-2}+ \tag{3}$$

Where the k × k moving average matrices Ψs are determined recursively using (6.1.3).

The elements of coefficient matrices Ψs mean effects of ε_{t-s} shocks on yt. That is, the I,jth element, Ψ_{ij}^{s}, of the matrix Ψs is interpreted as the IR

$$\frac{\partial y_{i,t+s}}{\partial \mathring{a}_{j,t}} = \frac{\partial y_{i,t}}{\partial \mathring{a}_{j,t-s}} = \Psi_{ij}^{s} \qquad i,j=1,\ldots,T \tag{4}$$

Sets of coefficients $\Psi_{ij}(s)=\Psi_{ij}^{s},\ i,j=1,\ldots,T$ are called the IR functions (IRF).

It is possible to decompose the *h*-step-ahead forecast error variance into the proportions due to each shock $\varepsilon_{j,t}$.

The forecast VD determines the proportion of the variation y_{jt} due to the shock ε_{jt} versus shocks of other variables ε_{it} for i≠j.

3.4. VECM

Engle et al. (1987) formalized the theory of VECM. In the case where the vectors y_t are I(1), they are differenced once in order to achieve stationarity. The K-dimensional VECM(p) (p order or number of lags) can be deduced from the VAR model in (1),

$$\Delta y_t = c + \Pi y_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta y_{t-i} + Bx_t + \varepsilon_{t,} \tag{5}$$

In which Δ is the lag operator ($\Delta y_t = y_t - y_{t-1}$), and Γi is a kxk matrix which connects the changes in yt, for lagged i periods, to current changes in y_t. Long-run Information lost due to differencing (Juselius, 2006) is compensated through the matrix Π, called an error correction term. If α and β are both of dimensions k × r, (rank r is the number of cointegration relationships), then Π = αβ'. The cointegrated vectors i.e., the r linearly independent columns of β, are each reflecting one long-run relationship between the variables. Then β'yt−1 is stationary, i.e., I(0) process. The elements of matrix α are called adjustment coefficients, representing the speed of convergence to the long-run equilibrium.

In the case that r = 0, the matrix Π is absent, so we have a VAR in difference, not a VECM. In case of a full rank, r = n, we do not specify the model as a VECM because the stationary Δyt in (2) is equal to a non-stationary Πy_{t-1} (plus some lagged stationary variables and so on), which is inconsistent (Juselius, 2006).

Considering (1) and (2) we can write

$$Đ=\alpha\beta^{'}=-\left(I-\sum_{i=1}^{p}A_i\right), \tag{6}$$

And,

$$\Gamma_i=-\sum_{j=i+1}^{p}A_j \tag{7}$$

The k × k matrix Π, as we have mentioned in section 3, conveys information about the long-run relations among the endogenous factors. In particular, rank (Π) = r < κ suggests the existence of r cointegrating relations among the κ factors.

If we are primarily interested, for example, in the ECM for electricity prices in order to capture their dynamics relations with fuel costs, then the presence of a cointegrating relation among SMP and fuel prices forms the basis for the structure of VECM. Actually, the ECM model "reflects" the change in SMP as a linear function of its lagged changes, lagged changes in fuel prices and an error-correction term. Therefore the ECM provides information on the causality or interaction of SMP and fuel prices, on the short-run causality via past changes in energy prices as well as long-run causality via adjustments in equilibrium error. In the produced model, significant coefficients indicate the portion of disequilibrium that is corrected in the following period by the error correction.

IRF and VD are powerful tools of VECM for the analysis of the impacts of shocks in fuel costs on the short-run dynamics of SMP. The IRF reveals the persistence of the shock and the way and speed with which the SMP returns to equilibrium (mean reverting behavior). The degree of contribution of each shock in fuel prices to the total variance of SMP forecasts is provided through VD. In our analysis here, we assume symmetric relations between SMP and fuel costs.

4. THE GREEK ELECTRICITY MARKET: A SHORT DESCRIPTION

Greece's liberalized electricity market was established according to the European Directive 96/92/EC and consists of two separate markets/mechanisms: (1) The Wholesale Energy and Ancillary Services Market and (2) The Capacity Assurance Mechanism.

Greece has adopted in 2005 a pure mandatory pool for the wholesale electricity market. Its implementation was carried out in stages or transitional phases (2000-2005, 2005-2010 and 2010–today). The revised market architecture, launched in September 2010, completed in 2011 its first full year of application, has determined the day-ahead (DA) SMP as the wholesale market index reminiscent to S&P or ASE index, as this price determines in great amounts the cash-flows of market's players. This market design encapsulate fully the all the requirement of the grid and market operation code of 2005. The design makes a clear distinction between the DA market and Balancing mechanism. The evolution of Index HHI[1] which measures the degree of openness of a market to competition has been reduced from the value of 10000 in years 2008 and 2009 to 6844 in 2010 and 5764 in 2011, an improvement of the market evolving to a more competitive state. However, GEM is far from being considered a competitive market.

The wholesale electricity market is a day ahead mandatory pool which is subject to inter-zonal transmission constraints, unit technical constraints and reserve requirements. More specifically, based on forecasted demand, generators' offers, suppliers' bids, Power Stations' availabilities, unpriced or must-run production (e.g. Hydro Power mandatory generation, cogeneration and RES outputs), schedules for interconnection as well as a number of Transmission System's and Power Station's technical constraints, an optimization process is followed in order to dispatch the Power Plant with the lower cost, both for energy and ancillary services. In this pool, Market "agents" participating in the Energy component of the DA market submit offers (bids) on a daily basis. The bids are in the form of a 10-step stepwise increasing (decreasing) function of pairs of prices (€/MWh) and quantities (MWh) for each of the 24 h period of the next day. A single pair of price and quantity for each category of reserve energy (primary, secondary and tertiary) is also submitted by Generators. Deadline for offer submission is at 12.00 pm ("gate" closure time).

LAGIE (the Independent Market Operator) is responsible for the solution of the so-called DA (optimization) problem. This problem is formulated as a Security Constrained Unit Commitment problem, and its solution is considered to be the optimum state of the System at which the social welfare is maximized for all 24 h of the next day simultaneously. This is possible through matching the energy to be absorbed with the energy injected into the System, i.e., matching Supply and Demand (according to each unit's separate offers). In the above mentioned optimization problem besides the objective function there is also a number of constraints. These are the Transmission System Constraints the technical constraints of the Generating Units and the requirements for reserves of energy. The DA solution, therefore, determines the way of operation of each unit for each hour (dispatch period) of

1 HHI stands for Herfindahl-Hishman Index. If HHI =10000 the market is a monopoly, if HHI >5000 the market is over-concentrated, H >1800 concentrated, for 1000 < HHI <1800 efficiently competitive and HHI ≤1000 competitive.

the dispatch day as well as the clearing price of the DA market's components (energy and reserves).

The ultimate result of the DA solution is the determination of the SMP, (which is actually the hourly clearing price). At this price load representatives buy the absorbed energy for their customers while Generators are paid for their injected energy to the System. The real-time dispatch (RTD) mechanism refers to adjusting the DA schedule taking into consideration data regarding availability and demand as well as security constraints. The dispatch scheduling is used in time period between DA scheduling and RTD where the producers have the right to change their declarations whenever a problem has been occurred regarding the availability of their units. Any deviations from the DA schedule are managed via the imbalances settlement (IS) operation of the market. During the IS stage an ex post imbalance price is produced after the dispatch day which is based on the actual demand, unit availability and RES production. The capacity assurance mechanism is a procedure where each load representative is assigned a capacity adequacy obligation and each producer issues capacity availability tickets for its capacity. Actually this mechanism is facing any adequacies in capacity and is in place for the partial recovery of capital costs. The most expensive unit dispatched determines the uniform pricing in the DA market. In case of congestion problems and as a motive for driving new capacity investment, zonal pricing is a solution, but at the moment this approach has not been activated. Physical delivery transactions are bounded within the pool although market agents may be entering into bilateral financial contracts that are not currently in existence. The offers of the Generators are capped by an upper price level of 150€/MWh.

Table 2 summarizes the time evolution of the net generation capacity for Greece for the period 2007-2014. We observe a gradual decrease in the share of lignite units in the total mixture and an opposite behavior in the share of natural gas units due to constantly increasing number of investments of independent power producers. More specifically, CCGT units during period 2004-2011 have increased their share about 124%. The market was completely dominated by Public Power Corporation (PPC) until 2004. Table 1 and Figure 1 provide information on the market time evolution of generation mix in GEM for the period 2007-2014 and 2004-2015 respectively. The gradual decline of electricity consumption during the financial crisis in Greece, from 2009 onwards has as a result the significantly depressed electricity production from conventional technologies. As it is shown lignite generation remains on average constant to 30 TWh for the period 2004-2009 and then declines gradually to 19.5 TWh in 2015. In 2004 the lignite generation decreased by 2.2% compared to 2013, falling to 22.7 TWh. Natural gas generation shows a constant increase from 2004 to 2008, a slight decrease in years 2009-2010, a significant increase in 2011-2013 and then a gradual decline up to 2015. The generation from gas-fired plants has shown a sharp full of 43% in 2014 compared to 2013.

Figure 4 provides information on the main structural components of the Greek wholesale Electricity Market (taken from RAE's 2010 National Report to the European Commission) (RAE, 2009; 2010).

Table 2: Installed capacity as of 2007-2014 in the interconnected system

Plant type	Net installed capacity (MW) (%) 31.12.2007	Net installed capacity (MW) (%) 31.12.2008	Net installed capacity (MW) 31.12.2009	Net installed capacity (MW) 31.12.2010	Net installed capacity (MW) 31.12.2011	Net installed capacity (MW) 31.12.2012	Net installed capacity (MW) 31.12.2013	Net installed capacity (MW) 31.12.2014
Lignite	4808 (40.50)	4808.10 (38.69)	4808.10 (38.49)	4746 (33.74)	4496 (31.30)	4448 (28.01)	4456 (25.65)	4456 (24.52)
HFO	718 (6.05)	718 (5.78)	718 (5.75)	698 (4.96)	698 (4.86)	698 (4.39)	698 (4.02)	698 (3.84)
CCGT	1962 (16.53)	1962.10 (15.79)	1962.10 (15.71)	3224 (22.92)	3526 (24.55)	3666 (23.08)	4086 (23.52)	4086 (22.48)
Natural gas	487 (4.10)	486.80 (3.92)	486.80 (3.90)	487 (3.46)	487 (3.39)	487 (3.06)	487 (2.8)	487 (2.68)
Large hydro	3017 (25.41)	3016.50 (24.27)	3016.50 (24.15)	3018 (21.46)	3017 (21)	3018 (19)	3018 (17.37)	3173 (17.46)
RES and small	880 (7.41)	993.50 (7.99)	1058.40 (8.47)	1558 (11.08)	2141 (14.90)	3237.5 (20.39)	4295 (24.72)	4940 (27.18)
Cogene-ration								
Large- scale CHP		334 (2.69)	334 (2.67)	334 (2.37)		326 (2.05)	334 (1.92)	334 (1.84)
Other cogene-ration		108 (0.87)	108 (0.86)					
Total	11872	12427	12491.9	14065	14365	15879.2	17374	18174

HFO: Heavy fuel oil, CCGT: Gas Turb. combin. cycle

Figure 4: System marginal price fluctuation versus energy mix for the January of 2012 (Data source ADMIE S.A)

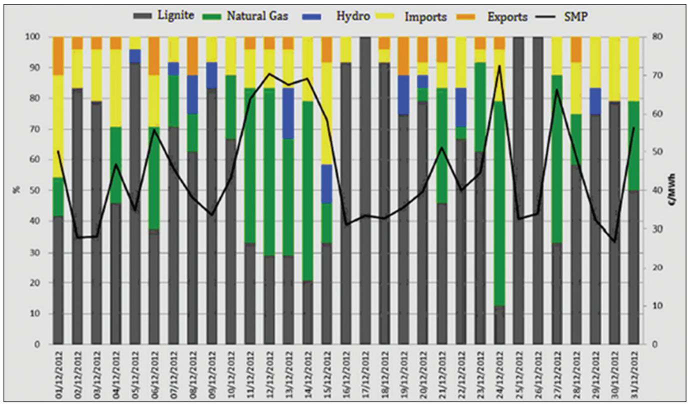


Figure 2 represents the daily generation mix for December 2012 and the daily evolution of SMP for the same period. It is observed that an increased generation by natural gas (and a decreased generation by lignite) stations causes a significant increase on the electricity prices. On the contrary, a decreased generation by natural gas (and an increased generation by lignite or hydraulic systems), causes the SMP to drop. The same behavior is observed for all data, in and out of the examined period of 2004-2014. In the following sections we will see this impact of fundamentals being captured by our VEC model and other similar tools.

4.1. Natural Gas and Lignite in GEM

In this study we used for natural gas, daily prices from the national balancing point (NBP) in UK for a variety of reasons which are explained later (see section 4.3). Although that is not the case, for the sake of completeness in our work we provide a short description of the Natural Gas "Market" in Greece. We should emphasize also that the average monthly dynamics of Natural Gas from NBP strongly resembles the dynamics of the Greek Market in the period of our study (highly correlated).

In Greece there is no indigenous gas production. DEPA is the incumbent and vertically-integrated gas company in Greece owns and operates the National Natural Gas System (NNGS) in Greece. It owns also the 100% of its subsidiary DESFA S.A, the TSO of the NNGS. The share of gas imports in the period 2010-2012 corresponded to about 90% of the total annual imports. The gas market is still organised on the basis of bilateral contracts between suppliers and eligible customers. According to the Greek gas law, eligible natural gas customers were customers with annual natural gas consumption, for two consecutive years, of more than 100 GWh GCV of natural gas. In 2014, law no.4254/2014 has redefined the term Eligible Natural Gas Customers.

All gas-fuelled power plants are considered eligible natural gas customers. No organised wholesale market exists yet. The following "market" mechanisms determine the kind of transactions that exist today: (1) wholesale trading of LNG quantities in-tank, (2) resale of gas between eligible customers and (3) the gas release schedules run by DEPA on a quarterly basis, originated in December 2012.

As set in the relevant Greek legislation, DEPA prepares and submits every year to RAE for approval an annual balancing plan which includes TSO's estimates regarding balancing gas supply sources for the next year. For example, for year 2014 balancing plan, the balancing gas needs were estimated to amount to 3.8% of the total gas consumption, however the year-end data indicated an amount 6.9%, a large deviation due to considerable imbalances occurred at the exit points of the NNGS where gas-fuelled power plants are connected. Every year RAE approves the balancing cost allocation scheme as well as the associated shippers' charges which includes a fixed charge covering the fixed costs of the TSO in providing balancing services and an energy charge which corresponds to the cost of balancing gas procured by the TSO, in accordance with the relevant balancing gas supply contracts, which form the basis of the daily balancing gas price (DBGP), the cash-out price. The methodology of estimating all balancing charges and DBGP (or HTAE in Greek) is available on DESFA's website (http://www.desfa.gr/default.asp?pid=318&1a=2).

DESFA, in order to allow current and potential market participants to gain a better understanding of the price conditions prevailing in the Greek market, publishes on tis internet site, data on daily prices of balancing gas (HTAE).

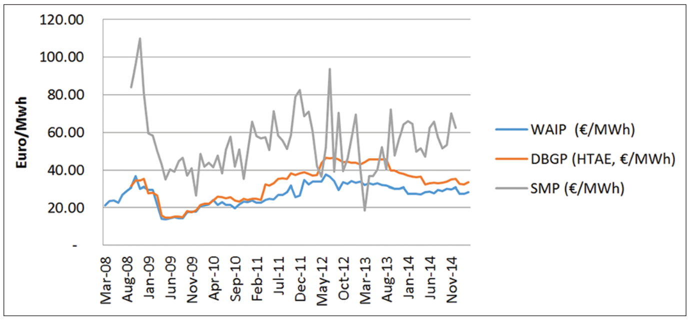
According to the provisions of the Ministerial Decision No Δ1/Γ/400 (Government Gazette Issue B' 33/19.1.2007), entitled «Determination of the procedure applied to collect and process the data required to calculate the weighted average import price (WAIP) of natural gas," the companies importing natural gas in the NNGS are required to submit to RAE, every three months, data about the quantities and prices of imported natural gas.

RAE, within the framework of its competence regarding monitoring of the energy market, following the provisions of par. 1 of article 5 in Law 2773/1999, is publicizing data on the calculated WAIP of natural gas in the NNGS of Greece, on a monthly basis. Publicized data on WAIP prices are the result of calculations performed on the data provided by importers according to the provisions of the aforementioned Ministerial Decision.

The publication of data on WAIP, in combination with the publication of data on daily prices of balancing gas (HTAE) in DESFA's internet site, allows current and future participants in the natural gas market to gain a better understanding of the price conditions prevailing in the Greek market, and therefore to exploit business opportunities and enhance competition to the benefit of consumers of natural gas. Furthermore, the publication of wholesale prices constitutes a necessary prerequisite for the organization, in a later stage, of a wholesale gas market, where the prices will be determined by the supply and demand in real time terms. Figure 5 presents the monthly WAIP against the daily price of balancing gas (DBGP) for the same month, as announced on the internet site of DESFA (March 2008-March 2015), versus the average monthly SMP in Greece.

The installed capacity of electricity generation plants in Greece currently stands as follows (as of August 2015): 3,912 MW lignite-fired plants, 4,906 MW natural gas-fired plants, 1,684 MW

Figure 5: Monthly weighted average import price of natural gas in Greece



oil-fired plants on the islands, 3,018 MW hydro plants, 1,767 MW wind farms in the interconnected grid and 317 MW on the islands, 2,443 MW solar PV parks in the interconnected grid and 136 MW on the islands, 224 MW small hydro, 49 MW biogas - biomass.

In 2014, the Greek PPC commissioned a study[2] to Booz and Co Consultants in order to compare the costs of lignite-fired power generation in the lignite-mining European countries (Germany, Poland, Greece, Turkey, Czech Republic, Romania, Bulgaria, Serbia) in the year 2012, in view of identifying the key cost parameters and the differences among the various lignite systems in Europe. According to the findings, the cost of extraction in Greece (at € 2.12 per ton) is the lowest, comparable to that in Germany. However, if the extremely low calorific value of Greek lignite is taken into consideration (as well as other variable production cost parameters), then lignite-fired power generation in Greece proves to be the costliest in Europe, at 59.9 €/MWh, vs. 53.6 in Germany, 39.0 in the Czech Republic, 38.6 in Poland, 54.2 in Romania, 31.6 in Bulgaria, 40.3 in Serbia, and 52.7 in Turkey.

4.2. Data Sets, Processing and Tests (Basic Strategy to Identify Model)

As we have already mentioned, the purpose of this paper is to investigate the short and long run dynamics between the SMP in the Greek Energy Market (GEM) and the fossil fuel prices, along with the cost of carbon allowances. The SMP data (average of 24 hourly data) has been provided from the official site of the Greek IPTO, ADMIE S.A (www.admie.gr). The dataset covers the period from 2007 to 2014, i.e., containing 2160 data observations corresponding to 7 years. We are focusing our study in this period due to unavailability of data for the rest of the variables (namely carbon allowances and lignite fuel cost). The market was less mature before 2005. We note that the SMP data are ex-ante. Figure 6 shows the dynamics of evolution of SMP. Regular (weekly, quarterly) patterns can be seen, as well as some short-lived spikes and volatility clusters (although not easily distinguished). SMP exhibits also, besides volatility clustering, the typical features of mean reversion and spikes, an tendency of the data to fluctuate around a long-term stable state or equilibrium, as well as extremely high values of short duration (spikes). Figure 7 depicts the log prices of all the time series considered in this work.

For the purposes of this study we consider 3 assets that are the most liquid energy commodities, namely Brent Oil, Natural Gas and European Carbon Allowances (eua). Also for the same reason we will refer to all these as "fuel prices." Daily spot price of Brent Oil in $/bbl was considered. For natural gas we selected 1 month ahead future prices traded at the NBP in UK, expressed in Euro/MWh, obtained from the ICE. Since contracts at NBP Hub are in pence sterling per therm we used the appropriate conversion which is 1 therm per 0.0293 MWh ICIS[3], and the conversion of pence sterling to Euro is according to the daily exchange rate published by the European Central Bank[4]. Since the late 1990s, UK NBP Hub gas market is Europe's longest established wholesale (spot-traded) market in operation. This wholesale gas market is the most liquid one in Europe nowadays, alongside a number of newly established Continental Europe hubs (e.g. Zeebrugge in Belgium and TTF in Netherlands) and gas anywhere in UK within the Natural Gas National Transmission System counts as NBP gas. This Hub brings together buyers and sellers so the trading is greatly simplified. There is a variety of products: Within-day (for same day delivery), DA (for next day delivery), months, quarters, summers (April to September) and winters (October to March), as well as annual contracts.

In order to test whether the price of NBP consists an adequate "representation" of the natural gas in Greece, daily prices were converted to monthly and compared to with the prices provided by DESFA (Figure 8). The prices have similar evolution and follow the same trends over time. Moreover the correlation coefficient between them was found $\rho = 0.8485$, suggesting that the prices strongly co-move, thus no significant loss of information should occur when using prices from NBP to calculate long-term relations. One important note is the two dates pointed out in Figure 8. First, 01.09.2011 is the reference (activation) day for a controversial levy tax on natural gas and the second, 18.12.2012, is the recall day of the same tax. Overall the graph suggests that this tax increased the spread between NBP prices and prices in Greece, and the importance of this date would be further analyzed in next sections, as well as tested for structural breaks after modeling a VECM (Papaioannou et al., 2017).

Daily settlement prices of EUA futures contracts (€/ton) traded on the ICE ECX are used to form a continuous price time series that combines a number of contracts expiring in Phase II and III (2008-2012 and 2013-2020), following the approach of Koch (2014). We mention here that trading of EUA futures contracts started not until April 22, 2005. The price of the 2008 contract constitutes the continuous carbon price time series during Phase I. This series changes to the December 2009 contract in Phase II, up to the last trading day, on which day the series changes again into the next yearly contract. According to Koch (2014) this method

2 https://www.dei.gr/Documents2/INVESTORS/MELETH%20BOOZ/Understanding%20Lignite%20Generation%2https://www.dei.gr/Documents2/INVESTORS/MELETH%20BOOZ/Understanding%20Lignite%20Generation%20Costs%20in%20Europe.pdf0Costs%20in%20Europe.pdf

3 http://www.icis.com/energy/gas/europe/spot-market-methodology/.

4 http://www.ecb.europa.eu/stats/exchange/eurofxref/html/eurofxref-graph-gbp.en.html.

Figure 6: (a and b) System marginal price prices in Euro/MWh (up) and SMP log returns (down)

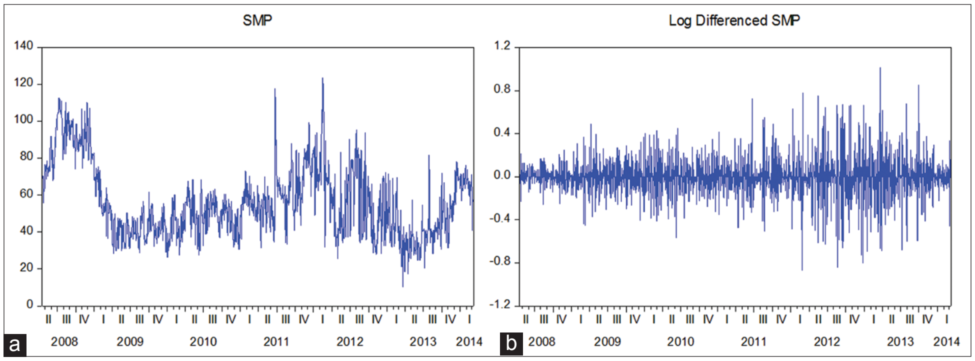
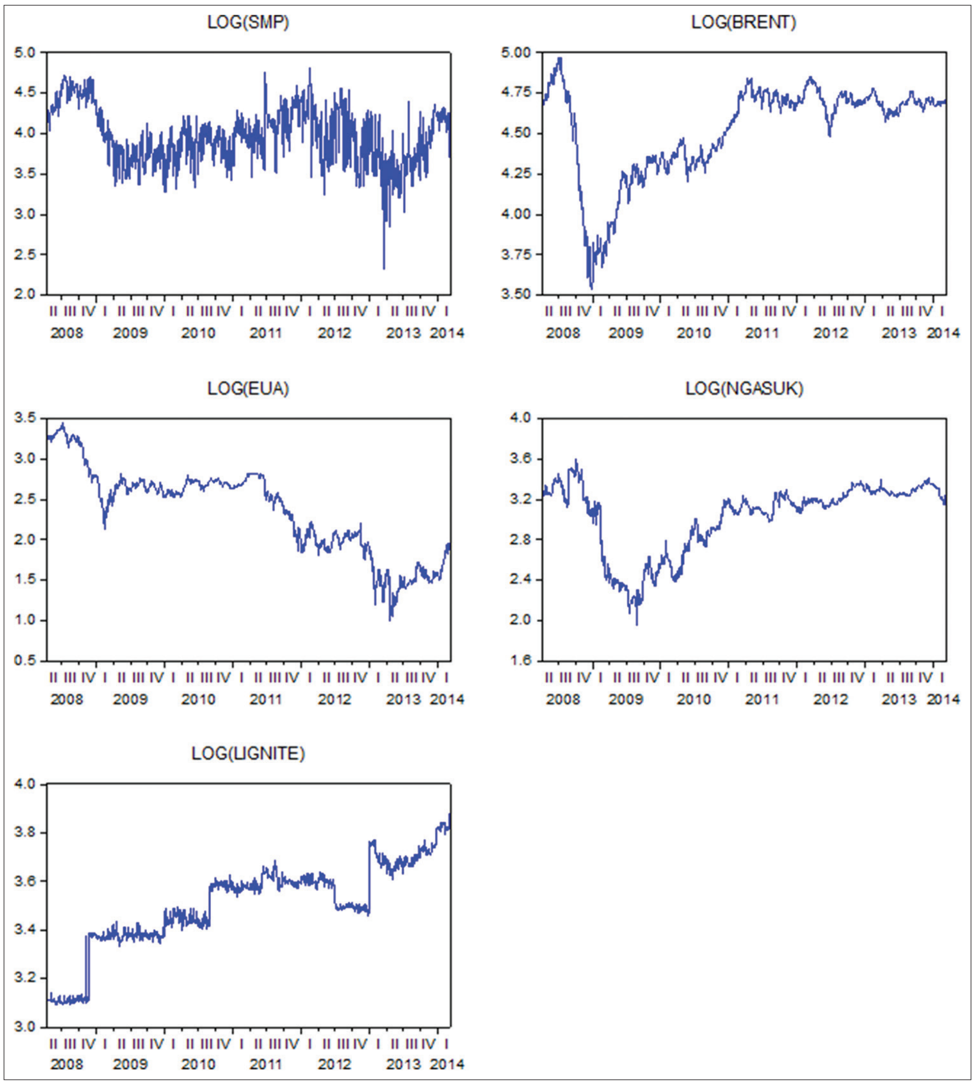


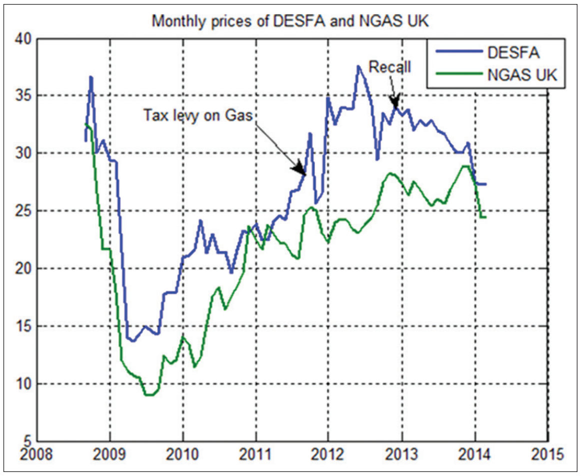
Figure 7: Log levels of prices of system marginal price, input fuels and EUA



of constructing the continuous EUA series is unlikely to introduce a bias because the used futures contracts are not redeemable in Phase I. This choice in forming the EUA series is further enhanced by the fact that EUA are required only once a year, for the reason of compliance, so holding spot EUAs does not offer any advantage in comparison with holding a corresponding futures position (Daskalakis et al., 2009). Also, Koch (2014) concludes that the EUA futures prices for Phase II can be considered as the reliable "real" price signal for investors. We have used EUA data, Phase II, obtained from ICE ECX market because this is the leading exchange (Mizrach and Otsubo, 2011).

We have to mention here that for the purposes of this paper, we consider EUA into the group of "fuel prices" or "Energy commodity" assets, although there are arguments about this like the work of Kanamura (2010) who argue that EUA is not a real commodity asset as those considered in the financial theory.

Figure 8: Monthly prices of national balancing point UK and natural gas in Greece



Finally indigenous lignite price, which is fuel cost for a Greek typical lignite-fired power plant, was considered. As we can be seen in Figure 5 lignite, which is in abundance in Greece, consists a large portion of the production allocation portfolio.

The logarithmic prices of all the variables can be seen in Figure 7. All the graphs (except the indigenous lignite) present a significant drop in late 2008, close to the collapse of the Lehman brothers. This is can be attributed to the financialization of the energy commodities (Koch, 2014).

A summarized description of the data used can be seen in Table 3.

4.3. Testing for Stationarity

In order to construct a VEC model we need to test for non-stationarity in the time series and confirm that they are integrated of order 1. Economic and financial time series, due to the fact that they depend on exogenous factors, exhibit a non-stationary behavior (Brock and de Lima, 1995; Pagan, 1987). However, it has been found that electricity market data are more stationary than all financial series, reported so far in empirical analyses (Strozzi et al., 2002; Bunn, 2004; Weron, 2006). Augmented Dickey Fuller (ADF) test with intercept has been performed on (logarithmic) levels, for testing the null hypothesis that the variables have unit roots i.e., are nonstationary. Table 4 lists the results.

The P-value rejects the null hypothesis of unit root for the SMP, therefore we can conclude that the series is stationary around a non-zero mean (since we tested including an intercept). This comes as contrast to other works (Theodorou and Karyambas, 2008; Petrella and Sapio, 2012). Papaioannou et al. (1995), have applied a nonlinear tool for stationarity detection in financial and electricity markets. It should be mentioned that the ADF test is very sensitive to the model selected. Testing for unit roots without trend or intercept failed to reject the null hypothesis at all significance levels, suggesting that the SMP is non-stationary. The results for the other time series cannot reject the unit root test in levels, and all series are stationary in first differences. We can confirm that Brent, ngasUK, eua and lignite are all I(1) and SMP is either I(0) or I(1). Since in this paper our purpose is to model a VEC, SMP does not need explicitly to be non-stationary since the other variables are I(1), but we proceed with caution to the ordering of the variables. As suggested in the work of Lutkenpohl and Kratzig (2004) any stationary variables should be placed in the upper r-dimensional subvector of yt where r=rank of cointegration, which must be at least as great as the number of I(0) variables in the system.

Table 5 shows the critical values for the various models and the various confidence intervals of the ADF test.

4.4. Static and Rolling Johansen Cointegration Test

Johansen cointegration test is applied to estimate the number parameters of the cointegrated variables. Firstly, the test is conducted multiple times, for increasing number of model variables and each time the statistical likelihood is calculated via numerous methods (AIC, Schwartz, log likelihood). Through this process, we identify number of cointegrated variables. Then, the test is applied once again, this time for the optimal number of cointegrated variables and the parameters of the coefficient matrices α and β are estimated with the least squares algorithm. Multiplying the α and β matrices, we can calculate the Π matrix of reduced rank. With matrixes α and β respresenting:

$$a \in R^{k\times r},\ \beta \in R^{k\times r},\ \Pi = \alpha\beta^{T} \in R^{k\times k} \tag{8}$$

Where k is the original dimension of the system and r is the number of cointegrated equations. Matrix α is the residual matrix and matrix β is the matrix of the r largest eigenvectors.

Before applying the Johansen cointegration test the optimal of the autoregressive order must be selected. The optimal lag is selected by finding the optimal lag for an unrestricted VAR fitted in the data, as suggested by the AIC, Schwarz Criterion (SC) and Hannan-Quinn Criterion (HQ). SC and HQ seem to fit better in systems with more than 2 variables, due to their ability to estimate the order in large samples and that the consistency property applies for integrated processes also (Paulsen, 1984; Tsay, 1984).

AIC suggests order of 4 lags while, SC and HQ suggest 2 lags (Table 6). We proceed by testing for cointegration for both lag orders by applying the Johansen test. It should be noted that since we estimated the optimal Lag of order p, for unrestricted VAR in levels, we will use Lag of order p-1 when estimating the VECM since it is in differences. The tests for both lags result in one cointegration relation in the system. The test assess the null hypothesis of cointegration at every rank r, with r = 0 meaning that there is no cointegration and r = k, where k is the number of endogenous variables, suggesting that every linear combination of the variables is stationary, thus the system is stationary at levels (Lutkenpohl and Kratzig, 2004). According to Table 7 there is evidence of cointegration in SMP at 1%-level. We remind here that a probability value above 0.05 indicate a failure to reject the null of r number of significant cointegration vectors. In our case, since P = 0.000 we reject the null for non and accept H1: r≥1, i.e., that there exist at least one significant vector cointegrated with SMP.

Table 3: List of data set and name of variables used in modeling

Name of data TS	Description	Length of time series	Units of measure	Source	Period covered
smp ex-ante or smp	Ex-ante SMP (GEM pool)	2160	€/MWh	IPTO data base	2007-2014
brent	Brent crude OIL price	2160	\$/bbl	ICE (Inter. exchange, Bloomberg 2004-2014)	2007-2014
lignprice	Lignite unit variable cost	2160	€/MWh	IPTO data base	2007-2014
natgas_UK	Nat gas price NBP	2676	€/MWh	ICE	2007-2014
eua_co2	CO2 emissions tax	2160	€/tCO2	EEX	2007-2014

Table 4: ADF test for stationarity

Variables	Log levels		First log difference	
	Intercept	P value	Intercept	P value
smp	−4.83 (7)***	0.00	−25.54 (6)***	0.00
brent	−1.43 (0)	0.56	−47.17 (0)***	0.00
natgasUK	−1.67 (0)	0.44	−46.42 (0)***	0.00
eua_CO2	−1.59 (2)	0.48	−35.06 (1)***	0.00
lignprice	−1.66 (2)	0.44	−41.60 (1)***	0.00

*Numbers in parenthesis give the optimal lag length, based on SIC, max number of lags=25. ***Denotes rejection of the null hypothesis in the 1% confidence interval, ADF: Augmented Dickey Fuller

Table 5: Asymptotic critical values for the unit root test (ADF test)

Critical values	1%	5%	10%
None	−2.560	−1.940	−1.616
Constant	−3.431	−2.862	−2.567
Constant+trend	−3.960	−3.410	−3.127

ADF: Augmented Dickey Fuller

4.5. Rolling Johansen Test

The Johansen test as presented previously performs static analysis in the dataset. In order to assess the evolution over time in the level of cointegration between the variables we elect to perform the Johansen test with a rolling window. Fratzscher (2001) showed that static analysis even in many subperiods is still problematic in representing correct the evolution of the integration, thus we select a rolling window analysis. However, before proceeding we should emphasize the possible problems related with the rolling window analysis. One potential problem is the size of the rolling window, which we set at 1000 observations following the work of Elving (2011). Lucey et al. (2008) used a rolling window of 500 observations and concluded that the sample was small regarding the complexity of the system. Another potential problem is the selection of the lag length for each event window. While we could test for the optimal lag length at each window before performing Johansen test, we don't expect significant differences and since our goal is to investigate the various trends in the evolution of integration and not the precise number of cointegrating relations in each window, we selected a constant lag as suggested by Table 6.

Our methodology is as follows: Johansen cointegration test is performed in the first 1000 observations (window size), then the window moves one observation ahead while dropping the oldest observation, thus maintaining a constant number of 1000 observations. Johansen test is then performed in the new subset and the process is repeated until the end of the sample and the results are analyzed by visual inspection. The trace statistics for every null hypothesis are scaled, i.e., divided by the 95% critical value of the test, and plotted in time. When the scaled statistic is ≥1 indicates rejection of the null hypothesis, while when ≤1 the test fails to reject the null hypothesis. The nature of the test suggests that every subsequent series to be lower than the previous, thus the first test, which tests the null H0: r = 0, i.e., the number of cointegrating vectors is zero, will be at the top, followed by the statistic of the H0: r≤1 etc. The logic behind this is the following: If the test fails to reject cointegration of r = 0 (no cointegration), it is highly unlikely that any of the subsequent tests will fail reject their respective null hypothesis. For simplicity purposes and in order to present the results more clearly, Figure 9 shows the evolution of the trace statistic produced from the Johansen test for the null H0: r = 0, i.e., no cointegration.

Since the trace statistic is constantly over 1 the null of no cointegration is rejected at all times, meaning that smp, fuel prices and carbon allowances always had some level of integration. This level of integration is volatile before 2012 and becomes less volatile after. If we interpret the level of the trace statistic above 1 as a measure for the integration between the variables, our findings suggest that the level of integration peaked in the middle of 2011, followed by downward trend in the latter half of 2011 afterwards, and remained steady in the period after 2012. This behavior and the overall volatility of the integration level during 2011 may be attributed to the regulatory market reform, which was a controversial decision by the ministry of finance to impose a new tax levy on natural gas from 01.09.2011 and onwards. The asymmetric impact on gas fired production vs lignite production, combined with shrinkage in hydro production resulted in a substantial increase in the electricity spot price (RAE, 2012; 2013). The tax ceased after 18.12.2012, but it may be responsible for the downward trend on the integration between smp and fuel prices in the end of 2011.

5. MODEL ESTIMATION

VECM (VEC or VECM) are used to perform VAR on nonstationary data, where long-run relationships between the variables are present. The VEC has the cointegration relations built into the specification so that it restricts the long-run behavior of the endogenous variables to converge to their cointegrating relationships while allowing for short-run adjustment dynamics. The cointegration term is known as the error correction term since the deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments. After determining the number of cointegration equations from the static Johansen

Table 6: Lag length criteria

Lag	LogL	AIC	SC	HQ
0	−7.372.598	0.689832	0.703016	0.694655
1	21721.73	−2.015.960	−2.008.050	−2.013.067
2	21852.25	−2.025.767	−20.11265*	−20.20462*
3	21898.17	−2.027.711	−2.006.618	−2.019.995
4	21929.33	−20.28283*	−2.000.598	−2.018.156
5	21950.99	−2.027.973	−1.993.696	−2.015.434
6	21962.44	−2.026.714	−1.985.846	−2.011.764
7	21988.82	−2.026.842	−1.979.382	−2.009.480
8	22016.78	−2.027.117	−1.973.065	−2.007.344

Table 7: Johansen cointegration test

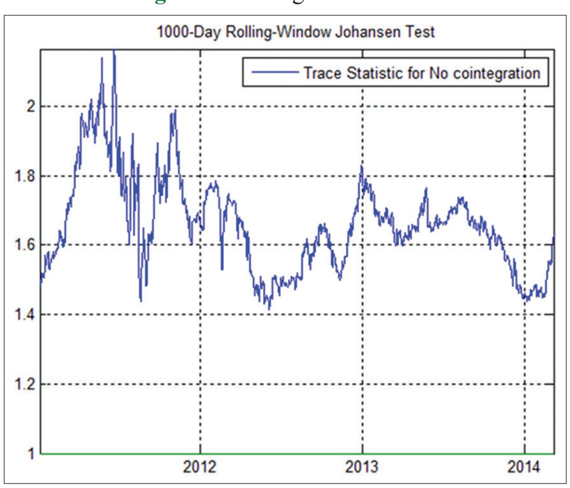
Unrestricted cointegration rank test (trace)				
Hypothesized Number of CE (s)	Eigenvalue	Trace Statistic	0.05 Critical value	P**
None *	0.048084	153.8959	69.81889	0.0000
At most 1	0.011576	47.60146	47.85613	0.0528
At most 2	0.005781	22.48672	29.79707	0.2722
At most 3	0.004280	9.981041	15.49471	0.2822
At most 4	0.000338	0.729686	3.841466	0.3930

Trace test indicates 1 cointegrating eqn (s) at the 0.05 level, *denotes rejection of the hypothesis at the 0.05 level, **MacKinnon-Haug-Michelis (1999) P values

Unrestricted cointegration rank test (maximum eigenvalue)				
Hypothesized Number of CE (s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical value	P**
None *	0.048084	106.2945	33.87687	0.0000
At most 1	0.011576	25.11475	27.58434	0.1003
At most 2	0.005781	12.50568	21.13162	0.4986
At most 3	0.004280	9.251356	14.26460	0.2658
At most 4	0.000338	0.729686	3.841466	0.3930

Max-eigenvalue test indicates 1 cointegrating eqn (s) at the 0.05 level, *denotes rejection of the hypothesis at the 0.05 level, **MacKinnon-Haug-Michelis (1999) P values

Figure 9: Rolling Johansen test



test in the whole sample, we construct a VECM (1), based on the minimum SC. Since our data has clearly non-zero mean value as can been seen in Figure 7, we build a VEC with intercept (constant). The trace test and the maximum eigenvalue test suggest 1 cointegrated relation. The VECM in this study is as follows (due to space limitations we only present the equation for the smp):

$$\Delta smp=a_1\ (c+smp_{t-1}-\beta_2 brent_{t-1}-\beta_3 eua_{t-1}-\beta_4 ngasUK_{t-1}-\beta_5 lignite_{t-1}) \quad (9)+\Phi_{1,1}\Delta smpt-1+\Phi_{1,2}\Delta brent_{t-1}+\Phi_{1,3}\Delta eua_{t-1}+\Phi_{1,4}\Delta ngasUK_{t-1}+\Phi_{1,5}\Delta lignite_{t-1}+\varepsilon_{1,t}$$

Where Δ is the difference operator ($\Delta y_t = y_t\text{-}y_{t-1}$), ($c+smp_{t-1}\text{-}\beta_2 brent_{t-1}\text{-}\beta_3 eua_{t-1})\text{-}\beta_4 ngasUK_{t-1}\text{-}\beta_5 lignite_{t-1}$) is the error correction term driving the long run dynamics and Φi,j the coefficients on the lagged differences, which drive the short run dynamics, a is a (5 × 1) matrix with elements the speeds of adjustment and β a (5 × 1) matrix of cointegrating vectors, with β1 = 1. Finally, ε_t is a (5 × 1) vector of errors. The estimated parameters can be seen in Tables A1 and A2 in the appendix.

6. RESULTS ESTIMATION

6.1. Short Run Dynamics

The parameters estimated from the VECM (1) fitted to the data are shown in Table A2 in appendix A. By studying the t-parameters of the coefficients a lot of parameters have low absolute values, suggesting that they can be omitted from our model. In order to better understand the short run linkages between electricity and fuels prices returns, we apply pairwise Granger causality test. As seen in Table 8 the test fails to reject the null hypothesis of the coefficients being zero in all confidence levels when the SMP is the dependent variable, suggesting no short run relationship between electricity prices returns in Greece and fuel prices returns. Furio and Chulia (2012) found similar results in the short run dynamics between electricity and fossil fuel prices in Spain. The rest of the results suggest two one-directional relations “flowing” from ngasUK to Brent and domestic lignite respectively, and one from Brent oil to eua.

6.2. Long Run Dynamics

As earlier stated, a cointegration relation suggests a long-run equilibrium between non-stationary variables. The estimated cointegration relation for our model can be seen in Table A1 in the appendix. By applying a Wald test to the estimated coefficients we are able to test their significance. Results are shown in Table 9. The coefficient of the equation a1 as well as the cointegrating vectors for the eua and the natgasUK, β_3 and β_4 respectively, reject the null hypothesis of no significance at 1% significance level. Regarding the Brent oil and lignite their corresponding cointegrating vectors fail to reject the null hypothesis at any level, suggesting that there is no significant long run relationship between these two fuel prices and the electricity prices. Overall our findings suggest that the smp tends to adjust to past disequilibria by ‘following’ the trend values of eua and natgasUK.

6.3. Chow Breakpoint Test

Rolling Johansen test in section 4.2 showed that the level of integration presented a sharp decrease in the second half of 2011. In order to better test our assumption that the regulatory reform, which imposed a levy tax on natural gas, we apply Chow breakpoint test. The test strongly rejected the null hypothesis of no breaks at the specific date, with a p-value of 0.000, confirming our intuition that the levy tax on the natural gas did indeed ‘disturbed’ the long-run equilibrium between smp and fuel prices.

6.4. IR and VD

The above tests aid in identifying qualitatively the Granger Causality relations between the model parameters. However, the extent to which an endogenous variable contributes to the evolution of the asset of interest cannot be determined. Therefore we conduct the analysis of the dynamic interactions among the variables in the post-sample period through IRF and VD.

Forecast error IR of one standard deviation are used in this study. While this test doesn't take in consideration the correlation between the residuals and must be used cautionary, the residuals from the estimated VECM(1) present unsignificant correlations (with the exception of eua-Brent), as seen in Table 10 so we proceed by analyzing the IR.

The Figure 10 show permanent effects on smp of the various shocks. Most significant results are the substantial positive effect of the ngasUK and eua shocks to smp price, which converge to a constant after about 40 days.

VD is applied to the group of endogenous variables of the model in order to identify the contribution of each variable to the development of the variance of electricity prices. While IR explores the dynamics of the model, showing how typical shocks affect the variable through time and examining its evolution, VD highlights the shocks that are most significant in this evolution.

Table 8: Granger causality results

Dependent variable					
	Δsmp	Δbrent	Δeua	ΔngasUK	Δlignite
Δsmp_{t-1}	-	0.2741	0.5454	0.6232	0.2793
$\Delta brent_{t-1}$	0.8684	-	0.0171**	0.1085	0.3196
Δeua_{t-1}	0.7196	0.1816	-	0.3177	0.8527
$\Delta ngasUK_{t-1}$	0.3703	0.0084***	0.5370	-	0.0757*
$\Delta lignite_{t-1}$	0.6106	0.6984	0.4545	0.3947	-

***, **, *Denotes rejection of the null hypothesis on the 1%, 5% and 10% confidence interval respectively

Table 9: Wald test for the error correction term

	Δsmp	
	Coefficient	P value
a_1	−0.140071	0.0000***
β_2	0.037607	0.6876
β_3	−0.316053	0.0002***
β_4	−0.541192	0.0000***
β_5	0.096060	0.2905

Table 10: Residuals correlation matrix

	log (smp)	log (brent)	log (eua)	log (ngasUK)
log (smp)	1.00	−0.01	0.02	0.01
log (brent)	−0.01	1.00	0.21	0.08
log (eua)	0.02	0.21	1.00	0.11
log (ngasUK)	0.01	0.08	0.11	1.00

In this case we examine the endogenous variables of each group and seek the major drivers of their volatility.

As Table 11 ngasUK and, in a lesser extent, eua, explain a significant amount of the variance of the smp in a 90-day period, while Brent oil and lignite have no significant contribution in the variance of electricity prices. These findings confirm the long-run relations from the estimated VECM and underline the importance of ngasUK and eua prices in the formation of electricity prices in Greece.

7. CONCLUSIONS

In this study we analyzed the long-run and short-run relationships between electricity prices in Greece and price levels of various fuels, namely Brent oil, natural gas, carbon allowances, as well as the fuel cost price of a Greek typical lignite-fired plant. Using the method established by Johansen one cointegrating relation was found between the endogenous variables. Due to the static nature of the Johansen test, we applied a rolling window methodology in order to assess the evolution over time in the level of integration. Our findings suggest higher levels of integration in 2011, followed by lower and less volatile integration afterwards.

After constructing the corresponding VECM we investigated via Granger Causality the short-run dynamics and found that the electricity prices in Greece present no significant short-run relationship, suggesting a low degree of integration between the GEM and the energy commodities markets Papaioannou et al. (2017). On the other hand a significant long-run relationship was found suggesting that the electricity prices tend to adjust to past disequilibria of the eua and the natural gas prices, while long-run relationships with Brent oil and lignite were found statistically insignificant.

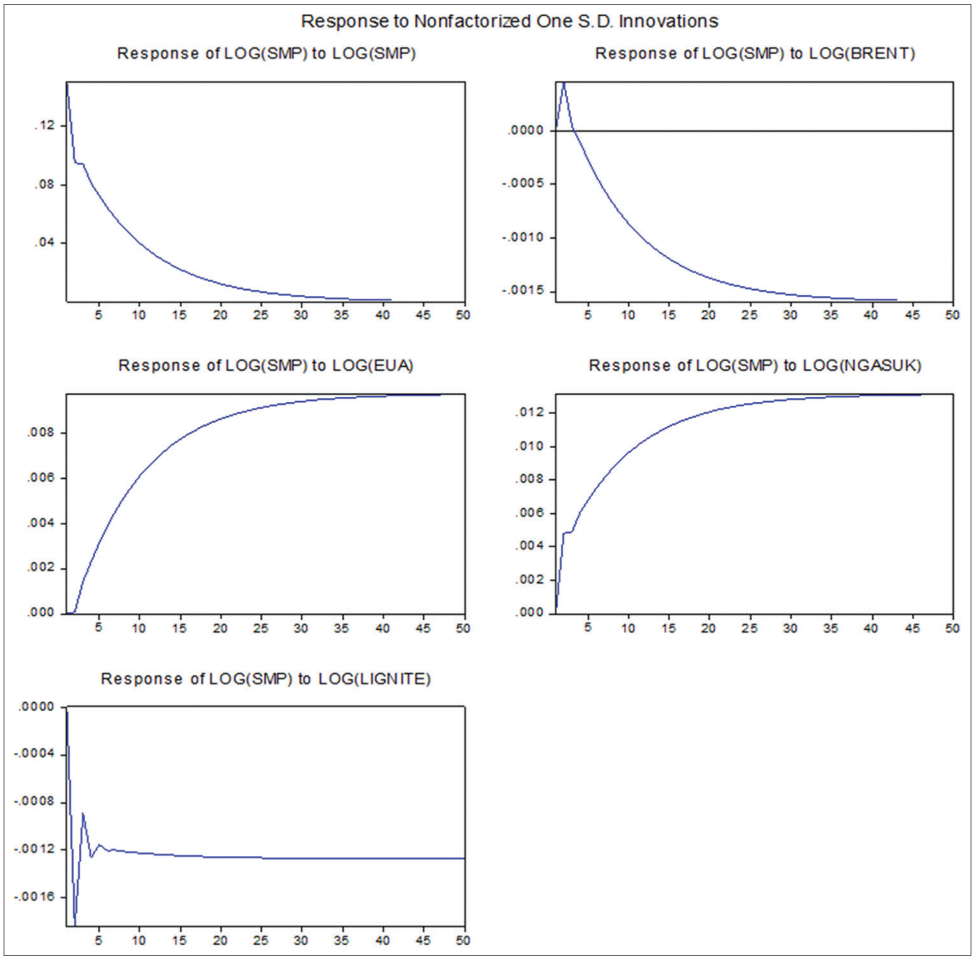
Furthermore we are interested in observing the response of an endogenous variable to an excitation of another. This response, in a practical application like our case, will be a strong indicator of the expected behavior of the said variable in a scenario of an unexpected shock to another variable by one standard deviation, namely the response of smp to shock in fuel prices. This allows the researcher to perform simulations on various real-life scenarios and observe the dynamics and weaknesses in order to design the necessary adjustments or regulations prior to a crisis. For this purpose we performed IR and VD analysis. By using IR of one standard deviation we found that shocks in the fuel prices have a lasting effect on the electricity prices, with the ones of natural gas and eua being the most significant. VD also showed that a significant portion of the electricity price variance is explained by the natural gas variance, with eua accounting for smaller portion.

Overall our results suggested that the Greek electricity market is not highly integrated with the fuel markets. Brent oil has insignificant relations with the electricity prices, which was expected since it consists an extremely small portion of the

Table 11: Variance decomposition

Period	S.E.	LOG (SMP)	LOG (BRENT)	LOG (EUA)	LOG (NGASUK)	) LOG (LIGNITE)
90	0.309072	76.27105	0.190668	9.257142	14.13187	0.149265

Figure 10: Impulse responses of smp to one S.D. innovations from the other endogenous variables



generation mix and very rarely sets the price via the merit order principle. Lignite also present nonsignificant short and long run relationships, even though it consists a much larger portion of the mix and sets frequently the price via the merit order. This can be attributed to the fact that lignite is in abundance in Greece and while its price increases in Greece, the fuel cost of the lignite-fired plants remain significantly lower than the one of the gas-fired ones.

EUA and natural gas on the other hand, present a significant long-run relationship with the electricity prices suggesting that electricity prices in Greece tend to adjust to the trends of these two assets, while the day to day dynamics are insignificant. IR analysis showed that a shock to eua or natural gas has a permanent positive effect on the electricity prices which converges to a constant about 30 days after its occurrence.

Overall our results suggest a small degree of integration between the Greek electricity market and the most liquid energy commodities traded in Europe, possibly due to its deregulation being still an ongoing process.

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APPENDIX A

Table A1: Estimated parameters of the error correction term

Cointegrating Eq:	LOG (SMP(-1))	LOG (BRENT(-1))	LOG (EUA(-1))	LOG (NGASUK(-1))	LOG (LIGNITE(-1))	C
CointEq1	1.000000	0.037607	−0.316053	−0.541192	0.096060	−2.092.470
		(0.10305)	(0.06945)	(0.08597)	(0.21190)	
		[0.36493]	[−4.55054]	[−6.29512]	[0.45332]	

Standard errors in () and t-statistics in [ ]

Table A2: Estimated parameters of the VECM

Error correction:	D (LOG (SMP))	D (LOG (BRENT))	D (LOG (EUA))	D (LOG (NGASUK))	D (LOG (LIGNITE))
CointEq1	−0.140071	0.000801	0.003196	−0.000931	0.003248
	(0.01264)	(0.00154)	(0.00241)	(0.00209)	(0.00145)
	[−11.0809]	[0.52111]	[1.32842]	[−0.44554]	[2.23525]
D (LOG (SMP(−1)))	−0.226265	−0.002796	0.002419	0.001708	0.002615
	(0.02102)	(0.00256)	(0.00400)	(0.00348)	(0.00242)
	[−10.7621]	[−1.09370]	[0.60463]	[0.49134]	[1.08185]
D (LOG (BRENT(−1)))	0.030008	−0.026034	−0.082231	−0.048061	−0.020724
	(0.18111)	(0.02203)	(0.03447)	(0.02995)	(0.02082)
	[0.16568]	[−1.18196]	[−2.38554]	[−1.60490]	[−0.99533]
D (LOG (EUA(−1)))	−0.041656	0.018851	0.049192	0.019170	0.002477
	(0.11603)	(0.01411)	(0.02208)	(0.01919)	(0.01334)
	[−0.35901]	[1.33589]	[2.22748]	[0.99917]	[0.18567]
D (LOG (NGASUK(−1)))	0.117805	0.042176	−0.015451	0.000148	0.026850
	(0.13150)	(0.01599)	(0.02503)	(0.02174)	(0.01512)
	[0.89583]	[2.63711]	[−0.61733]	[0.00679]	[1.77600]
D (LOG (LIGNITE(−1)))	−0.092838	−0.008593	−0.025954	0.025660	−0.232013
	(0.18234)	(0.02218)	(0.03470)	(0.03015)	(0.02096)
	[−0.50916]	[−0.38749]	[−0.74786]	[0.85111]	[−11.0683]
C	−0.000174	2.21E-05	−0.000558	−2.84E-06	0.000440
	(0.00324)	(0.00039)	(0.00062)	(0.00054)	(0.00037)
	[−0.05370]	[0.05601]	[−0.90494]	[−0.00531]	[1.18246]

Standard errors in ( ) and t-statistics in [ ]