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Spillover Volatility Between Fuel Mix and Electricity Prices

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Υπεβλήθη για την εκπλήρωση μέρους των

απαιτήσεων για την απόκτηση του

Μεταπτυχιακού τίτλου **«Διαχείριση Ενέργειας & Περιβάλλοντος»**

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Ευχαριστίες

Πρώτα απ’ όλα, θέλω να ευχαριστήσω τον επιβλέποντα της διπλωματικής εργασίας μου, Επίκουρο Καθηγητή, Δρ. Δημήτρη Ψυχογυιό, για την πολύτιμη βοήθεια, την καθοδήγηση και τις πολύτιμες υποδείξεις του κατά τη διάρκεια της δουλειάς μου. Ευχαριστώ όλους που στάθηκαν δίπλα μου με την ηθική υποστήριξή τους. Ευχαριστώ τον Άγγελο, ο οποίος είναι Μεταπτυχιακός φοιτητής του University College London στο Λονδίνο της Μ. Βρετανίας, για τα πολύτιμα σχόλιά του σχετικά με την παρουσίαση της εργασίας μου. Επίσης, ευχαριστώ την Μαρία για την κατανόησή της και την στήριξή της, ιδιαίτερα κατά τη διάρκεια των τελευταίων μηνών της προσπάθειάς μου. Πάνω απ’ όλα, είμαι ευγνώμων στους γονείς μου, Θεόδωρο Κακούρη και Μαρία Χαλιαμπάκα για την ολόψυχη αγάπη και υποστήριξή τους όλα αυτά τα χρόνια. Αφιερώνω αυτή την εργασία στην μητέρα μου και στον πατέρα μου, καθώς και στους ανθρώπους που θα είναι πάντα δίπλα μου.

Κωνσταντίνος Κακούρης

Contents

Abstract

Regulators were the only institution who set the electricity prices, including costs of transmission, distribution and generation. Nowadays, this has changed. Electricity prices are determined by the fundamental economic rule of supply and demand. The forthcoming work examines a potential relationship between electricity price and fuel mix. I use the Nordic System's electricity prices and generation. I conclude that hydropower and nuclear power plays a vital role in the futures energy mix and in the stability of electricity prices. A spillover effect is detected between electricity prices and fuel mix, but a need for further research is recommended.

Chapter 1: Introduction

The last decades, energy markets have been liberalized starting from the fuel markets and continued with electricity markets in mid – ninety's. But first, it should be a distinction between energy markets, to facilitate research and decision making. There are three groups of energy markets, the first is the fuel market (oil, gas, coal etc.), the second is the electricity market and the third is emissions and insurances for sudden outages.

Nowadays, electricity is exchanged in competitive markets, like the other commodities, abandoning the regulated market structure. Nevertheless, electricity has some characteristics that other commodities don't. It's a non-storable product and the demand must be covered immediately. Hence, electricity is characterized as a "flow commodity" with limited storage and transportation. In addition, there are some other features, like temperature and weather conditions, season and day duration, unpredictable outages and grid congestion which accelerate the randomness in the calculation of the electricity prices. Thus, these features are responsible for its high volatility and making difficult the price forecast. In other words, we don't know in which extend volatility is spanned. Into this framework, electricity needs must meet four elements: cover, safety, efficiency and reasonable prices.

Concerning electricity prices, they can be categorized as follows: price of high demand, price of low demand, price of different periods (seasons), price of weekends, working days and vacations, and price of business activities. Taking into account the natural features of electricity and the aforementioned categories of electricity prices, we understand that, in order to calculate the precise future price of electricity is more than complex. As a consequence, the factors, affecting the price volatility in electricity, are difficult to observe. The unobserved components can be characterized as "Unspanned Stochastic Volatility" components. These components have no information about assessments in future changes, which play a vital role in decision making of investors, and more specifically electricity generators, as well as they provide explanations about volatility risk and hedging. R^2 (R – squared) can be consider as a measure of unexplained volatility and as an estimation of the amount of explained volatility. For instance, a very low price of R – squared, means that there is a big amount of unexplained volatility (Collin – Dufresne and Goldstein, 2002).

Taking, all the above, into consideration, researchers decided to make models and develop methodologies in order to deal with these problems. Certainly, these models should include parameters such as time period, price variances and trends. More precisely, they preferred to develop GARCH, ARCH, ARIMA, Demand Elasticity, Levelized Cost of Electricity (LCOE) and Weighted Average Cost of Capital (WACC) models. In general, the dominate opinion in literature suggests that, the electricity price must be examined seasonal (seasonality) and has the trend to return in its mean price (mean reversion) by the "Invisible hand of the market", as Adam Smith stated.

From the fuel mix point of view, it's largely known that the electricity production needs other forms of energy to be produced[1], such as conventional energy (fossil fuels), renewable energy (solar, wind, tidal, hydropower etc.) and nuclear energy. Naturally, factors like political instability in regions with enormous fossil resources – natural inventories, the misbelief of the Russian policy in the

[1] See Figure 1.1, p. 6 in this work

distribution of the natural gas and the expansion of the renewable energy, especially wind electricity generation, are likely the most significant components to keep energy markets highly volatile. A dominate theory suggests that, there is an appropriate fuel mix which can hedge the volatility risk in electricity prices. Nevertheless, is worth mentioned that nuclear energy and hydropower play crucial role hedging and stabilizing the volatility risk in electricity prices. Further to the fuel cost, there is another parameter which indirect affects electricity prices. The CO_2 prices provide the electricity prices with more uncertainty and less stability. Generally speaking, when choosing energy fuels, it is essential to take into account economic, social and environmental consequences as Köne and Büke (2007) pointed out.

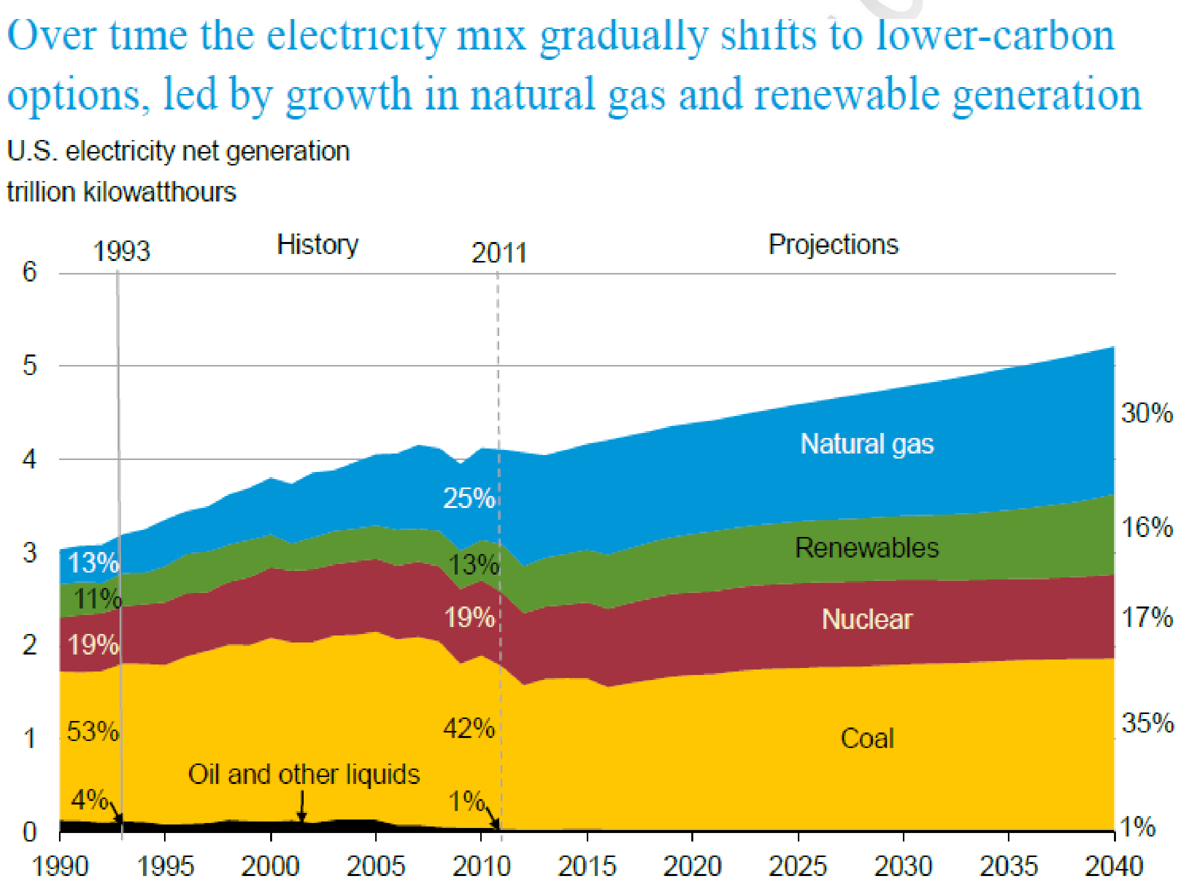
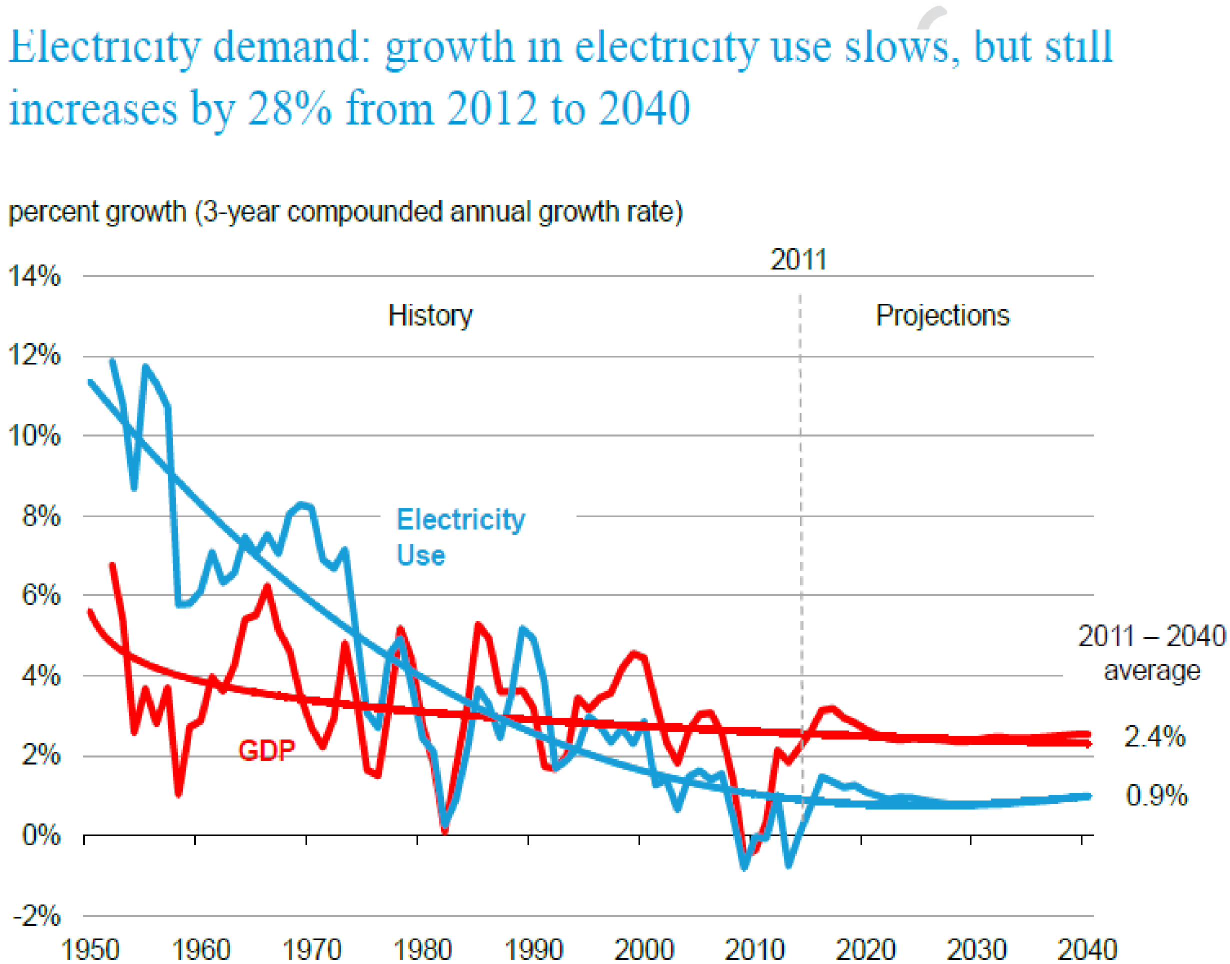


Figure 1.1 – Some Historical data and Projections for the fuel mix in the U.S.

Source: EIA, Annual Energy Outlook 2013

Energy markets will be suffer from extreme volatility for decades because of the continuous changes in policies, globalization, growing energy demand, increasing intensity of climate change, geopolitical strategies and tensions, as well as deregulation of electricity markets (Efimova and Serletis, 2014). It is worth mention here that electricity demand is predicted to rise with lower rates over the next few years. This trend can be confirmed by the graph 1.1 below. Nevertheless, to the best of my knowledge, there is no published paper that examines relationship between the fuel mix volatility and volatility of electricity prices. In this work, I try to contribute to fill this gap.

The rest of the dissertation is organized as follows. In chapter 2, I demonstrate the literature research. In chapter 3, I study and valuate the data and develop a methodology framework in order to come with results. In chapter 4 is presented the results and some recommendations among them and finally, chapter 5 includes some brief conclusions.



Graph 1.1 – The electricity demand seems to hold lower rates of growth especially after 2020 with an average rate of 0.9%. In this graph, a comparison is taking place between the growth of electricity demand and GDP. As a benchmark, it is considering the point after mid – eighty's, where the GDP growth rate overcomes the growth rate of electricity use. This graph corresponds in the U.S..

Source: EIA, Annual Energy Outlook 2013

Chapter 2: Literature Research

2.1 Fuel Mix & Electricity

Diversification of fuel in electricity generation is a common factor to stabilize electricity price's variance. More countries try to find the appropriate proportions of fuels in order to forecast changes in energy prices. Focusing in electricity, parameters, which influence the prices, have been developed in the introduction and in the next section of this work. Nevertheless, it is worth mentioning the impact of limited transportation. Limitations were originated by restricted capacity of the grid and by the losses in the transportation line. These two features makes transportation more expensive and sometimes impossible to take place in plenty areas. As a result, prices begin to behave locally and are dependent by local business activities, weather conditions, climate, energy generation plants etc.

Further to local and national grids, there are international grids. An example, of a developed system of international grid, is the Nordic Power System. It includes Norway, Sweden, Finland, Denmark and Iceland. It works as follows: when the capacity limits are overpassed the spot prices are adjusted in wider region. If contagion takes place in only one country, system operators act in order to hedge and manage the situation. Some statistical results come from this market, point out, that in the warm seasons the price average is less than cold seasons by 22%. Electricity prices are extremely unstable with their variation reaches around 189%. A big part of the variation is explained by spikes which are created by shocks, like announcements about change in temperature (Lucia and Schwartz, 2002). The proportion of explained variance is around 75% in electricity market, where in other markets reaches 95% (Koekebakker and Ollmar, 2005). Even though, demand for electricity follows a standard framework throughout the week. To give more attention in electricity prices internationally, divergence in international framework is due to divergence in commodity prices, in regulation, in technologies and in international trade of electricity.

Following graphs illustrates electricity generation and the fuel mix. Figure 2.1.1 provides information about each country's monthly energy generation and consumption. Generally, energy generation and energy consumption is clearly in the same level except for Denmark which seems to be an export country. Wind power dominates in the generation procedure in Norway, where in Denmark and Finland nuclear power plays a counterpart role. Iceland is supported by hydropower and Sweden invested in both nuclear and wind power for electricity generation. Figure 2.1.2 illustrate the total generation per country in TWh. In the following paragraphs, it's discussed the case of fuel mix in electricity generation in USA and worldwide.

Figure 2.1.3 describes the fuel participation in electricity generation proportionally (in the left side) and quantitative (in the right side) in the United States of America (USA). From the latter figure, some interesting results come to light. Coal slowly has lost its share through the years from natural gas and non – hydroelectric renewables. Nevertheless, coal still plays a central role in the west of US. In other energy forms, renewables are growing, especially, in the State of Texas and Petroleum – fired electricity generation exists as substitute in case with no alternative. The fuel mix is not stable, but fluctuated across months, because it is influenced by cost of fuels, region's transportation capacity and system constraints (US Energy Information Administration, 2013).

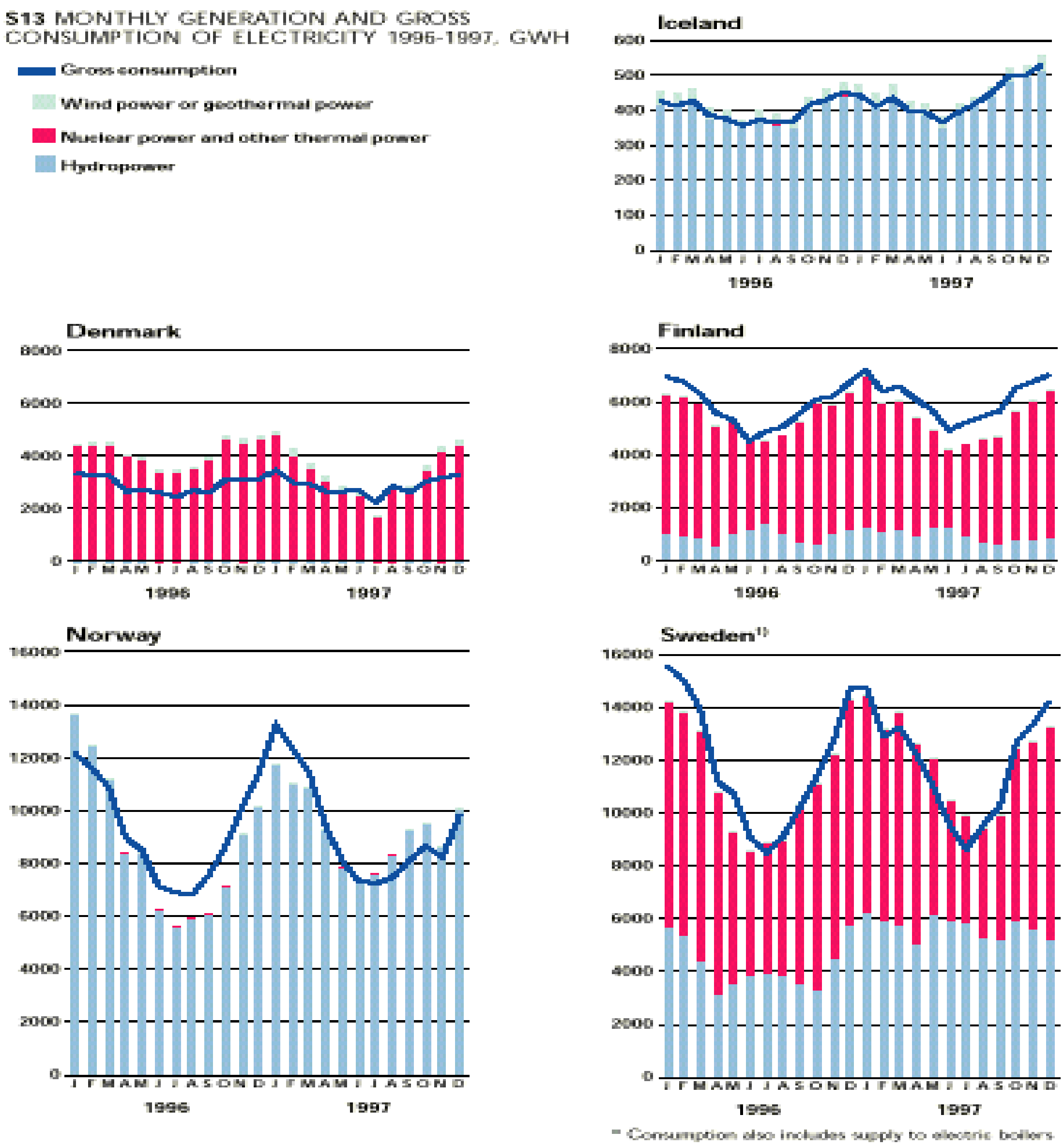


Figure 2.1.1 – Monthly Generation and Consumption of Electricity in Nordic Power System

Source: Pontifical Catholic University of Chile

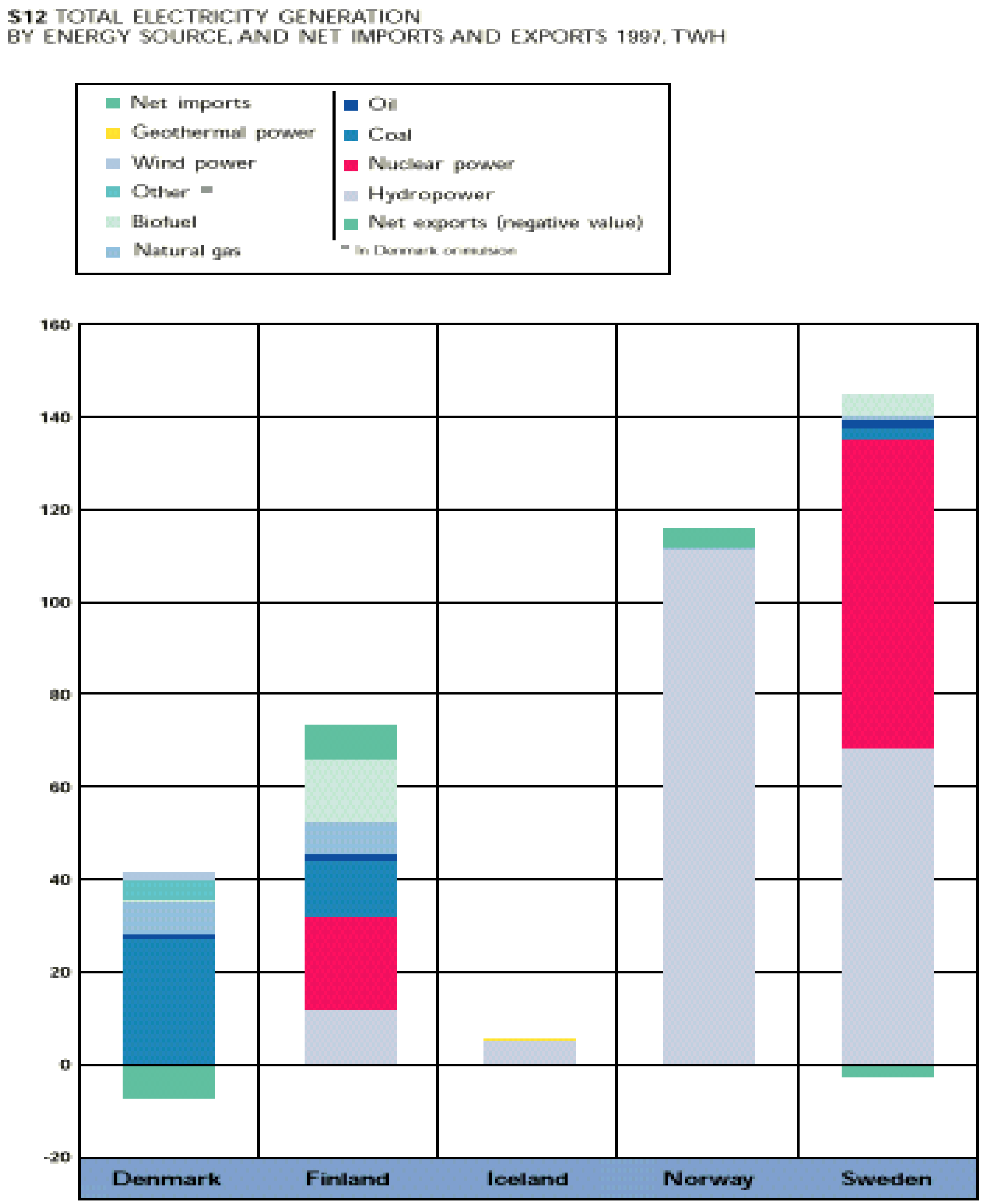


Figure 2.1.2 – Total Electricity Generation and Energy Imports/Exports

Source: Pontifical Catholic University of Chile

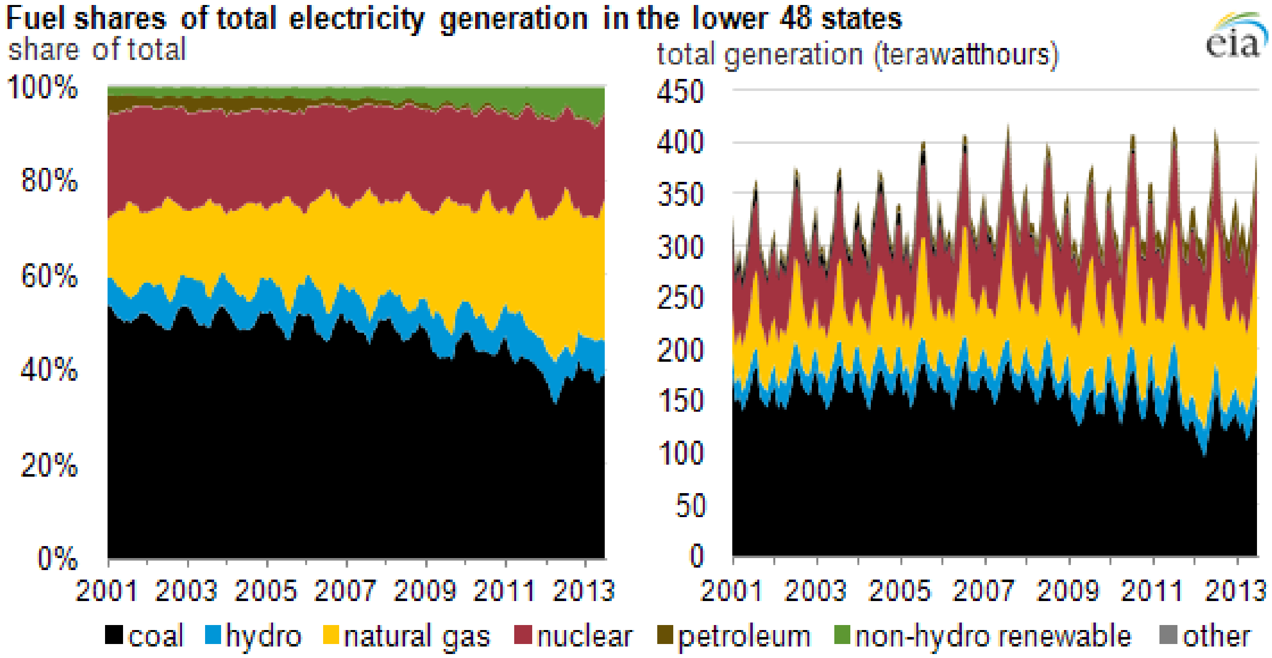


Figure 2.1.3 – Fuel Shares of Total Electricity Generation in the US

Source: U.S. Energy Information Administration

Globally, the main contributors in electricity generation are coal, natural gas and renewables. More precisely, coal holds the 40% of the world electricity generation consumption. It's the most preferable fuel because it is cheap, accessible, abundant, and easily distributed, stored and used. Even though, coal combustion is characterized by a significant drawback, air pollution through Greenhouse Gas Emissions (GHG). Natural gas holds the second place with share of around 20% and has an upward trend. Its emissions include less air pollutants than coal emissions. Its features are that it's more expensive and more volatile. Long – distance transportation and increasing global market demand are the main factors affecting natural gas use. Another energy form is renewable energy. Renewables are sustainable and naturally replenished due to non – creation of air pollution, during the energy generation process, and infinite inventories. Naturally, there are some disadvantages in renewables. Electricity generation takes place locally and it is not characterized as reliable as fossil fuels and nuclear power. Last but not least, nuclear power plays a crucial role, especially in developed economies like Germany and France, where contribute in electricity generation in a big share. Nuclear power is more reliable than renewables and has more clear production than coal and natural gas. Nonetheless, nuclear accidents have led the governments in these countries to turn in alternative choices (Environmental Bureau, Government of Hong Kong, 2014).

2.2 Literature Review

Recent years a lot of literature research has been made in the field of commodities. Nevertheless, the research focuses in storable commodities, where electricity is not. There is no much of research in non – storable commodities, as a consequence plenty methods have been developed in order to forecast and calculate electricity prices.

According to Liu and Shi's study, in 2013, there are three categories of methodology as follows. First of all, is the game theory which includes equilibrium models such as "Nash equilibrium", "Cournot model", "Bertrand model". That method can proceed to strategies and find optimal solutions. Secondly, the methodology is supported by stimulation models, but this method even if it includes the physical characteristics of electricity and operating systems, it has two severe drawbacks. The first considers the complexity of the models for simulation and the second is the high computational cost. Last category includes time series forecasting methods. Briefly, the latter, examine the past behavior of electricity prices in order to forecast future electricity prices. Last but not least, there are two types of model in the last category, the artificial intelligence techniques and statistical models (ex. AR, ARMA, MA, ARIMA etc.).

Through their literature research, they found that in order to predict volatility in electricity prices, GARCH and ARCH models are the most popular ones. They used two models for their empirical analysis. The first is the Generalized Autoregressive Conditional Heteroskedastic (GARCH) model and the second is the Autoregressive Integrated Moving Average (ARIMA) model. These models are largely used to estimate volatility and the mean value of electricity prices. They examined 18960 observations from hourly prices (LMP)[2] in ISO New England[3] from January 1st of 2008 to February 28th 2010. To be clearer, the data from the first two years are used for different models and the remaining data (1416) are used in order to test the accurate prediction of the models. Furthermore, they used the SAS 9.1 software in order to build an ARIMA – GARCH and an ARIMA – GARCH – M model. They investigate the in – of – sample prediction using 10 models. They find more preferable the ARMA – SGARCH – M model and 3 out of ten models are used for the first time, modelling hourly electricity prices. The outcome of their research indicates the road of privatization through the continuous deregulated markets. The last makes more important the accurate prediction of electricity prices. To this extend, Liu and Shi stated that "An accurate hourly ahead price forecasting can help power suppliers to adjust their bidding strategies to achieve the maximal revenue, and meanwhile consumers can derive a plan to minimize their cost and to predict themselves against high prices".

Of course, in order to understand the volatility of electricity prices and the spillover effects with the volatility of fuel mix, first we should examine the characteristics of electricity prices. Geman and Roncoroni (2006) refer some of the characteristics. First of all, prices tend to return in the average value which presents marginal cost and may be constant or periodic. Secondly, there are some random moves around the average trend. These random moves can be explained by imbalances in supply and demand.

[2] Real time location – based marginal prices

[3] ISO New England manages a few electric power markets in the United States. These power markets allow generators to sell their electricity to marketers who sell the electricity to end users then (businesses, households).

In conclusion, spikes[4] are very common, especially in electricity prices. They are created by imbalances in supply and demand which can't be smoothed away through the use of inventories, because electricity is a non – storable product.

The theory of hedging the price through inventories is supported by Lucia and Schwartz (2002). They notice that in storable commodities prices are determined not only by supply and demand mechanism, but also by the level of inventories. As a result, imbalances in supply and demand don't translate, in the same level, in imbalances of electricity prices. Broadly speaking, studies support that inventories is negatively correlated with future spot price volatility.

Geman and Roncoroni (2006) were interested to model electricity spot prices, after the deregulation of energy markets, and they support that the convenience yield is insignificant and there is no reason to exists in the context of electricity, in contrast with the other commodities, because electricity is a non – storable product. Going one step ahead, there is no benefit from holding the commodity because it cannot be stored and there is not a storage cost.

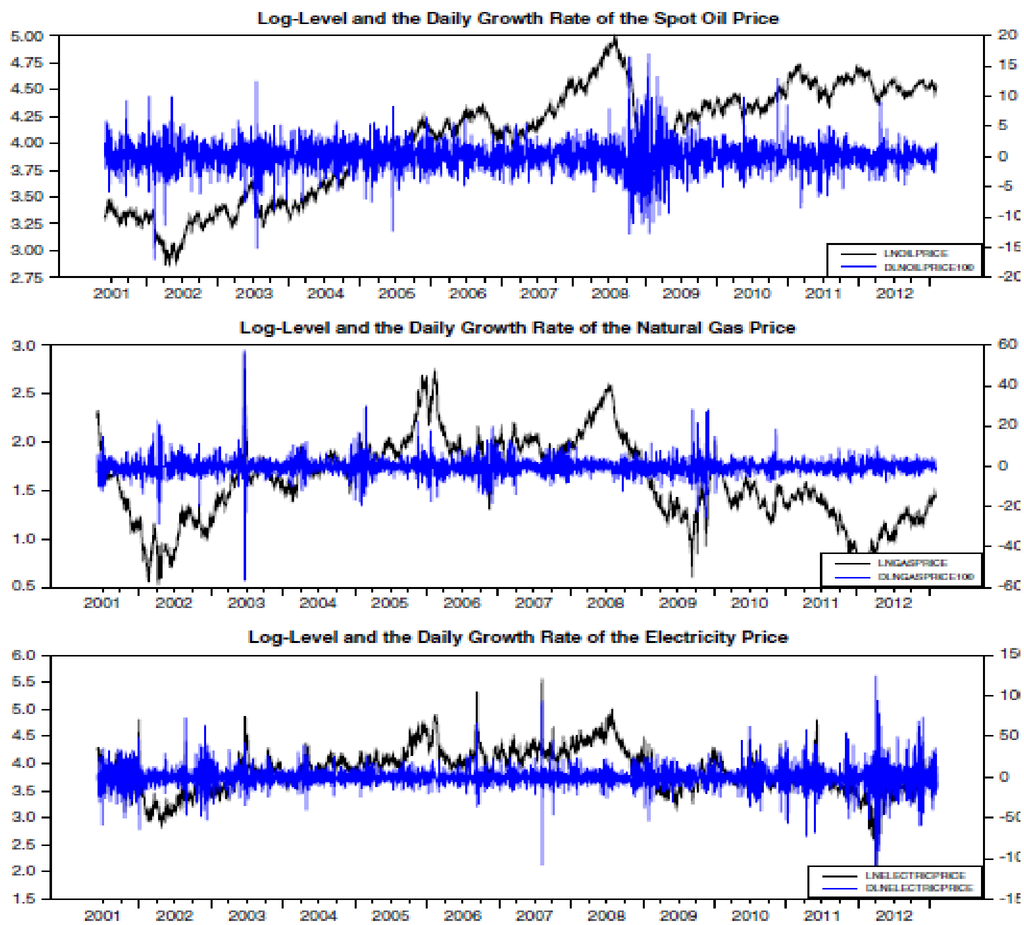
They studied the data from the publication Megawatt – Daily of three major US power markets: COB (California Oregon Border), PJM (Pennsylvania – New Jersey – Maryland) and ECAR (East Center Area Reliability Coordination Agreement). In terms of price behavior, the previous markets represents "low – pressure", "medium – pressure" and "high – pressure" markets, respectively. 750 daily average prices were used. These markets consider representative of the US power markets because are distributed in various locations and use different mix for generation. Furthermore, they introduced some parameters that explain power prices like temperature, fuel mix and types of grid. In conclusion, clearly difference was discovered between the markets in the field of the daily variation extend. Here, it's worth mentioning that where there is hydroelectric power, the spikes, hence, the volatility can be smoothed easily.

Huisman and Mahieu (2003) mainly studied extreme jumps and modelling electricity prices. According to their work, participants in energy markets faces more risk than the participants in other markets, due to the higher daily volatility of energy prices compared to stock prices, which reaches around 29% and 20%, respectively. They noticed that, after spikes, the force with which the price reverts to the long – term price trend is stronger than in normal periods. Moreover, they found that electricity prices are characterized by high volatility, mean – reversion[5], seasonality[6] and frequent extreme jumps in prices. Furthermore, they present that the jumps in electricity prices are not strongly correlated with the existence of normal mean reverting process. They selected data, where are available, from Dutch APX market, German LPX and Telerate UK Power Index. The prices were day – head base load. Spikes frequency was really high. They found that 40%, 20% and 33% of all observations in APX, LPX and the UK, respectively, can be seen like jumps. In contrast, if jumps hold 10% of all observations is considering as a "non – jump" market. In other words, there is more volatility in "jump" markets and less volatility in "non – jump" markets.

[4] Spikes are considered to be created by sudden disruptions in the transmission grid, extreme weather conditions and generation outages
[5] The electricity prices are forced to fall back to a normal level after a shock or jump
[6] See subsection 3.1.2 in this work

Efimova and Serletis (2014) suggest that will be a continuous increase in energy prices. To clarify, it is expected that natural gas price will increase by 60%, the electricity price by 7%, and the price of crude oil by 62% until 2035. Their work tries to fill the gap on energy price volatility modelling by using and expanding the univariate GARCH model, trivariate BEKK and DCC model and multivariate GARCH. Univariate GARCH model considers more accurate in prices forecast.

Data was selected by the U.S. Energy Information Administration (EIA). More precisely, oil prices selected from the region of Cushing, Oklahoma[7], natural gas prices from Henry Hub and electricity prices from the six largest wholesale markets[8]. Some additional data was selected by S&P500 index[9] and National Climatic Data Centre (2012). The data was selected refers to oil, natural gas and electricity wholesale daily prices for the period from January 2nd 2001 to April 26th 2013. The graph 2.2.1 illustrates the daily growth rate of oil, natural gas and electricity prices.



Graph 2.2.1 – Daily growth rate of oil, gas and electricity prices

Source: Efimova and Serletis, Energy Economics 43, (2014), 264 - 273

[7] West Texas Intermediate
[8] Nepool Mass Hub, PJM West, Entergy, Mid-Columbia Hub, SP15 EZ & SP15 hubs and ERCOT South hub
[9] Yahoo! Finance

The previous graph describes the Log of the Spot Oil Price, Gas Price and Electricity Price with the blue and the daily growth rate with the black for each component. Using logarithms, we can smooth away the large fluctuations of prices. From their empirical research, they discovered that a 10% increase in the S&P 500 Index is causing a 1.2% increase in oil price and only in oil prices considers significant. Furthermore, electricity price volatility seems to be more abnormal than natural gas price volatility.

According to Efimova and Serletis, crude oil price volatility is of great interest to energy participants and policymakers and sometimes is used as a macroeconomic indicator. As concern the natural gas, studies suggest that in the U.S. 31.2% is used to generate electricity. The other 32.4% and 27.8% is used to residential consumers and industrial sector, respectively. Finally, electricity prices are widely vulnerable in extreme events because of its physical structure and highly inelastic demand. They support that electricity price volatility is the best candidate for GARCH modelling.

They underlying that, there is a significant price spillover effect affecting natural gas and electricity markets, not oil markets. More precisely, an increase in crude oil prices by 10% will give an increase in electricity prices by 0.28% and decrease in natural gas next period's prices by 1.3%. On the other hand, 10% increase in natural gas will increase next period's electricity prices by 1.3% - 1.4% as a consequence. These findings of spillover effect suggest that there is a hierarchy of influence from oil to gas and electricity markets. Generally, correlation between oil – gas and oil – electricity decreases over time of recession and time of slow economic growth. In contrast, correlation between gas – electricity increases the same time. In conclusion, they recommend that in future studies the weak linkage between energy markets must be examined.

Roques, Newbery and Nuttall (2008) examined the correlation between electricity, fuel and CO_2 in liberalized electricity markets. The contribution of this research was the presentation of a new methodology using a two-step simulation approach. The first step was the Monte – Carlo simulations and the second step was the Mean – Variance Portfolio theory in order to diversify the risk of fuel, CO_2 and electricity prices. The latter give, to investors, incentives to invest in liberalized markets. They used three case studies from Britain (2001 – 2005). They found that there is a correlation between electricity, fuel and CO_2. Specifically, the correlation between fuel and electricity prices is affected by plenty factors as follows: the type of fuel used by power plant, fuel contracts, operational strategies of electricity power plants, and the behavior of traders in electricity and fuel markets. For instance, in Britain, the correlation between gas and electricity prices is significantly high and increases through the years – from 40% in 2001 to 90% in 2005.

Mari's (2014) study examines the hedging of electricity price volatility. His research added to the literature that fossil fuels can affect electricity prices through CO_2 emissions. The latter is based in the environmental policies supporting low – carbon technologies, which introduce further uncertainty in energy markets. These uncertainties in correlation with some random movements of carbon credits and fossil fuels price are factors that increase the, already, high volatility in electricity prices. A solution was proposed in order to hedge and control the high variance. Nuclear power is a carbon – free technology, thus, volatility becomes more sustainable and more predictable because it offers a possibility of risk hedging.

Moreover, he added that the cost of generating electricity is sensitive to fossil fuels price. Furthermore, the fuel costs affect electricity generation. For example, coal plants affect electricity generation more than 35%. As a result, fossil fuels market price affects electricity prices. Hence, the variance and the unpredictable prices in fossil fuels make electricity prices highly volatile.

In his paper, an illustration was made, that even if nuclear plants have bigger costs than fossil fuel plants, the outcome of a diversification in electricity generation would be really optimistic. For his empirical analysis, he used LCOE through the WACC method in order to assess generating costs and Mean – Variance approach. Data selection was made from "Annual Energy Outlook 2012", "US Energy Information Administration" and "The Future of Nuclear Power" by Massachusetts Institute of Technology (MIT).

Garcia – Martos, Rodriguez and Sanchez (2011) illustrates that, nowadays, climate policy is more intensive and strict. Thus, CO_2 emissions are considered in generation cost and influence energy markets. They noticed that multivariate GARCH model is difficult to estimate correctly, because of the high number of parameters and constraints. It is suffering from the so – called "Curse of Dimensionality". On the other hand they remind that univariate GARCH model doesn't include all significant features. They used, for the univariate time series, ARIMA and ARMA models and for multivariate time series VARMA models (Vector ARMA). For their research, data was selected by Iberian Peninsula electricity market from 1998 to 2008.

Garcia, Contreras and Akkeren (2005) approach the prediction of electricity prices with a GARCH model, in 2005. They selected data from Spanish and Californian market[10]. A GARCH model gives high quality results with an average forecast errors around 9%. In the same way, Nogales, Contreras, Conejo and Espinola examined time series model to forecast electricity prices. Their outcome presents that there is an average error of approximately 5% in Spanish market and around 3% in Californian market. In addition, Contreras used ARIMA models to predict next – day electricity prices. The average error in Spanish market is 10% and in Californian market is around 5%.

In conclusion, as many studies agree with each other, volatility in prices is explained by the growing demand in electricity and by the fact that electricity is a "flow commodity" and cannot be stored. Of course, there is not only the nature of the electricity which affect its prices but also the raw materials which contribute in electricity generation. As raw materials considers fossil fuels, nuclear energy and renewable energy. Some aforementioned studies find out that the volatility in fuel mix affects the electricity prices. To make it clear, as our generation production supported by fuels, like natural gas, which are volatile from their nature, electricity prices are doomed because of their dependence in such fuels. Certainly, there are some theoretical solutions in this problem. Hydropower and nuclear energy comes to solve the problem of volatility. Electricity from hydro power can be considered as storable commodity. Therefore, electricity price volatility can be smoothed and hedged by "inventories". This issue needs further research in order to examine the structure and operation of a hydroelectric power station, if it is beneficial from the environmental, economic and energy aspect. The same thing should be examined for the nuclear power plants.

Broadly speaking, spillovers are in foreground in economics and finance. Thus, researchers developed a lot of econometric models to calculate and measure spillovers between markets. The most

[10] Hourly electricity prices in both areas, with different periods of selection. September 1st, 1999 to November 30th, 2000 for Spain and January 1st, 2000 to December 31st, 2000 for California

used model is a multivariate GARCH model or BEKK – GARCH model (Aboura and Chevallier, 2014)[11]. Focusing in methodology, finding volatility in fuel mix and its correlation with electricity prices, we can estimate spillover volatility between them. Because the scarcity of literature research in spillover effect between fuel mix and electricity prices, it is recommended the application of the methodology which has been used in other cases, such as spillovers between stock markets and energy markets. General ideas are limited in these factors, which can hedge volatility and lower the spikes. Namely, hydroelectric power should be hold a bigger share in electricity generation and fuel mix with rich transmission networks must be included to stabilize the highly fluctuated prices.

The question which needs further research is separated in two parts. The first part should answer the question, if these factors are the only ones which affecting electricity price volatility and the second part should answer, if these factors are actually the only factors which affect volatility prices. Afterwards, the extension of influence volatility in electricity prices should be examined. In other words, in which proportion each component is responsible for this spillover effect.

[11] Definitions and extended analysis of models is posted in Appendices A & B

Chapter 3: Data & Methodology

3.1 Data

3.1.1 Data Selection

Data selection for the Nordic Electricity System was occurred by different institutions and organizations. Specifically, electricity prices and production were selected by the Nord Pool Spot. Electricity price is represented by system price. The data is daily and includes the dates between 01/01/2012 and 12/19/2014, excluding weekends. To make it clear, the selected data were for each country, as a consequence, Nordic System price and production was estimated after some adjustments and calculations. The data adjustments were made in order to examine the Nordic System as a whole. In the following sections and subsections, electricity price (system price) will be considered as the dependent variable (PRICE___MWH_). To clarify, the word production means that there are four deferent sources for electricity production. First of all, power comes from non – hydroelectric renewables, as wind, tidal, solar, geothermal, biomass (RES__MWH_). Secondly, electricity comes from nuclear power plants (NUCLEAR__MWH_). Thirdly, power comes from fossil fuels, such as, oil, coal, natural gas (FOSSIL__MWH_). Last but not least, power is originated by hydropower plants (HYDRO__MWH_). Finally, as it seems from the symbols of each variable, the data is selected in MWh and the price in €/MWh.

World Bank Database was a vital contributor in the calculation of the data. It provided the shares from each energy source in electricity production process. Oil and Gas prices were provided by US Energy Information Administration – Independent Statistics & Analysis. Oil and Gas price units are converted in €/MWh in order to make the research more reliable and correct[12]. In conclusion, the exchange rate ($ to €) is selected by OANDA Corporation[13].

3.1.2 Seasonality

Seasonality is one of the most critical factors in economics and, more specifically, in economic time series variables, especially in case of commodity prices. The deseasonalization process removes the short – term fluctuations from the data. As a consequence long – term components can be clearly identified and mistakes are avoided. EViews helps to create model with dummy variables in order to find seasonalities between prices at a specific day of the week[14]. The table indicates that Monday is the only day which has a p – value less than 5%, more precisely p – value = 0.0000, which means that Monday is statistically significant. In other words, Monday prices must be deseasonalized. In addition, the diagram below (Graph – 3.1.2.1) illustrates that the deseasonalization process smooth away the prices[15].

[12] The conversion of the Oil and Gas prices is represented in Appendix C
[13] Unfortunately, the exchange rates weren't daily, so I decided to choose weekly exchange rates
[14] The result of such a model is demonstrated in Appendix D, Table – 1
[15] Some additional graphs are represented in Appendix D

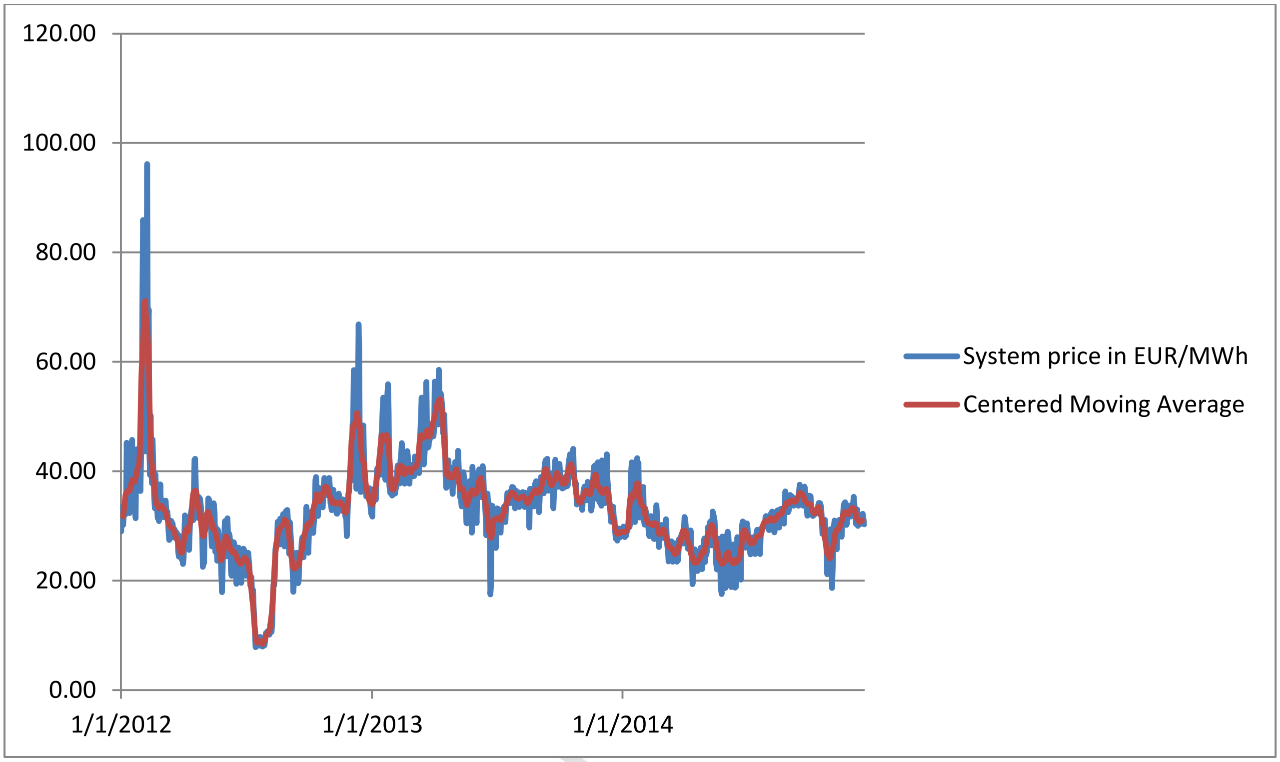
As concerning the deseasonalization process, it is taking place with the help of the Microsoft Excel. First of all, the data was selected for 7 days per week. According to this, the next steps are presented.

- *Centered Moving Average (CMA)*. CMA was calculated by the average of the average from the first seven days and the average from the next day and by 7 days from the first seven days of the sample. For instance, the first average is calculated by the values of electricity prices from Sunday 1/1/2012 to Saturday 7/1/2012 and the second average is calculated from Monday 2/1/2012 to Sunday 8/1/2012. Using these two averages and find their average gives the result of the CMA. This process continues further in the next weeks.
- *Ratio*. The ration is calculated by the system price divided by the CMA.
- *Unadjusted Factor*. The unadjusted factor is the average of the ration value from each day separately, and is repeated every week.
- *Sum of Unadjusted and Sum of Adjusted Factors*. The adjusted factor's sum takes the number of 7 because there are 7 days per week. The unadjusted factor's sum takes the number of the sum of the unadjusted factors every week. The latter is equal to 6.993158.
- *The Adjusted Factor*. The adjusted factors are calculated by the corresponding unadjusted factor multiplied with the following fraction $\frac{Sum\ Adjusted}{Sum\ Unadjusted}$.
- *Deseasonalized Price*. Deseasonalized prices are the scope of this extended process. The deseasonalized price is originated by the system price divided by the adjusted factor for each day separately. These prices are significant because there are not any short term fluctuations anymore.

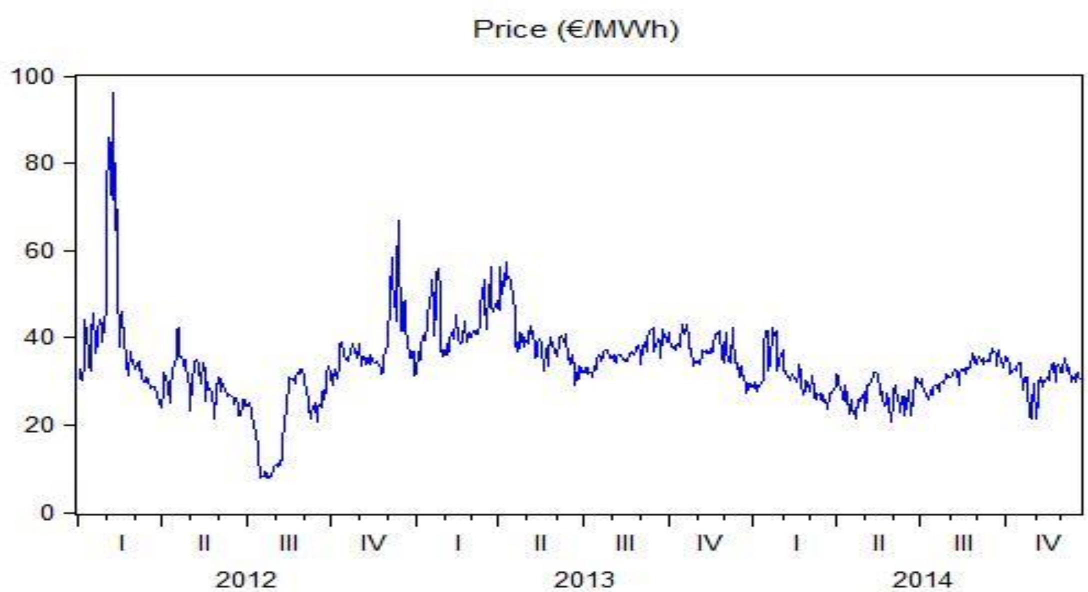
The final decision about the prices is taking after the combination of the above process and the regression with the dummy variables in EViews. The results indicates that Monday's electricity prices are the only ones which considering statistically significant. More precisely, the p – value is less than 5%. As a result, the only prices that should be changed are the Monday's prices. Sundays and Saturdays are not included in the following analysis and the other day's prices remained as it was.

3.1.3 Electricity Prices

As concern electricity prices it seems that the first half of 2012 there is a downward trend and afterwards the trend begins to upward. It is worth mentioned 2 phases. The first is taking place in the middle of the first quarter of the year 2012, where suddenly the price is rocketed from around 41 to 96 euros per MWh. This sudden abnormality has duration of a week and after this sudden fluctuation the prices reach the average value. The second sudden trend is taking place in the summer of 2012, especially in July where the price reaches its minimum value of the whole sample, approximately 7.92 €/MWh in July 23rd. The aforementioned trends are illustrated by the following graph (Graph – 3.1.3.1). Although, after these two extreme abnormalities in the first half of 2012, the diagram reveals more slightly and smoothly moves in electricity prices variance. They can be separated in two phases too. The first phase is considering from the middle fourth quarter of the 2012 until the middle of 2013. In this period, there are some sharp and sudden outbursts of the price, moving the price from, approximately,



Graph 3.1.2.1 – Graph for System Price and Centered Moving Average



Graph 3.1.3.1 – Daily Electricity Prices (except weekends) in Nordic System from 2012 – 2014

30 euros per MWh to 65 euros per MWh. The second phase continues with smooth fluctuations from 20 to 40 euros per MWh, taking into account the period from the middle of 2013 until today.

3.2 Methodology

After the data analysis in subsection 3.1, subsection 3.2 examines and analyses the methodology behind the outcomes of this research work. The methodology, which I preferred to accomplish this research, is the GARCH model and Principal Component Analysis (PCA). From both models, some interesting results come to forefront[16]. The GARCH model[17], more precisely GARCH (1, 1), is very common and more preferable from the researchers to use, in order to explain volatilities in different subjects. As a consequence, I decided to use the aforementioned models in order to find the factors that can explain electricity price volatility.

3.2.1 GARCH (1, 1) Model

The GARCH (1, 1) model is originated by the GARCH (p, q) model, where p is the ARCH terms and the q is the GARCH terms. The general form of a GARCH equation is represented in Appendix B, equation (2). If we consider the fraction (2) and try to put values in p and q term then we can have the desirable model. For GARCH (1, 1) model the following values is determined and the GARCH equation takes the form of equation (3) below:

$$p = q = 1, GARCH(p, q) \rightarrow GARCH(1, 1)$$

$$\sigma_t^2 = a_0 + a_1 u_{t-1}^2 + \gamma_1 \sigma_{t-1}^2 \quad (3)$$

In contrast, if p and q were taken bigger values then the estimation would be difficult and more mistakes were might be occurred. In the next table (Table – 3.2.1.1) is represented the GARCH (1, 1) model.

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[16] The results will be discussed in section 4

[17] The GARCH model is presented in Appendix B

Table 3.2.1.1 – GARCH (1, 1) outcomes

Dependent Variable: PRICE____MWH_
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/21/15 Time: 15:59
Sample: 1/02/2012 12/19/2014
Included observations: 775
Convergence achieved after 48 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(6) + C(7)*RESID(-1)^2 + C(8)*GARCH(-1) + C(9)
*OIL_PRICES____MWH_ + C(10)*GAS_PRICES____MWH_

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	20.78639	0.932904	22.28139	0.0000
HYDRO__MWH_	5.70E-05	3.18E-06	17.88933	0.0000
FOSSIL__MWH_	0.000188	8.65E-06	21.71380	0.0000
RES__MWH_	-2.96E-05	9.73E-06	-3.039629	0.0024
NUCLEAR__MWH_	-0.000156	1.06E-05	-14.72540	0.0000
Variance Equation				
C	20.91070	3.866048	5.408804	0.0000
RESID(-1)^2	0.570621	0.093590	6.097040	0.0000
GARCH(-1)	0.358414	0.060422	5.931874	0.0000
OIL_PRICES____MWH_	-0.121197	0.016404	-7.388176	0.0000
GAS_PRICES____MWH_	-0.264251	0.165258	-1.599015	0.1098

R-squared	0.290674	Mean dependent var	33.90574
Adjusted R-squared	0.286989	S.D. dependent var	8.977161
S.E. of regression	7.580314	Akaike info criterion	5.990033
Sum squared resid	44245.09	Schwarz criterion	6.050070
Log likelihood	-2311.138	Hannan-Quinn criter.	6.013131
Durbin-Watson stat	0.178477		

According to Table – 3.2.1.1, I conclude in the following estimations:

$$\boldsymbol{Mean\ Equation}^{18}$$

$$Y_t = b_0 + b_1X_{1t} + b_2X_{2t} + b_3X_{3t} + b_4X_{4t} + u_t \quad (4)$$

(4)→PRICE___M_=20.78639 + 5.70E-05HYDRO__MWH_ + 0.000188FOSSIL__MWH_ - 2.96E-05RES__MWH_ - 0.000156NUCLEAR__MWH_ (5)

[18] Mean Equation values are taking from the first part of the Table – 3.2.1.1

$$\boldsymbol{Variance\ Equation}$$[19]

$$\sigma_t^2 = a_0 + a_1 u_{t-1}^2 + \gamma_1 \sigma_{t-1}^2 + \delta_1 X_5 + \delta_2 X_6 \quad (6)$$

(6) →GARCH = 20.91070 + 0.570621RESID (-1) ^2 + 0.358414GARCH (-1) - 0.121197OIL_PRICES___MWH_- 0.264251GAS_PRICES___MWH_ (7)

Equations (5) and (7) are the estimations of the GARCH (1, 1) model. The variables in mean equation are defined in subsection 3.1.1. On the other hand, the variables in variance equation are defined as follows:

Where, OIL_PRICES___MWH_: price of oil, calculated in $€/MWh$
GAS_PRICES___MWH_: price of natural gas, calculated in $€/MWh$
GARCH (-1): GARCH term or previous days volatility of electricity prices
RESID (-1) ^2: ARCH term or previous period square residuals
GARCH: Variance of the residuals derived from equation (5)[20] or volatility of electricity price

The P – value of all variables is considered less than 5%. As a result, all the variables, except GAS_PRICES___MWH_, are considered as statistically significant. Furthermore, it is important to mention that OIL_PRICES___MWH_ and GAS_PRICES___MWH_ are considered as exogenous variables or predetermined variables. The results will be discussed further in the next chapter.

3.2.2 PCA

Principal Component Analysis (PCA) is a very useful tool when you want to reduce the number of the variables and make linear combinations of the data. Every linear combination is accorded to a principal component. The first principal component (F1) is the linear combination that has maximum variance, so it accounts for as much variation in the data as possible. The second principal component (F2) is the linear combination that accounts for as much of the remaining variation as possible, with the constraint that the correlation between the first and second component is 0. The number of principal component is diversified by research to research due to different data. As a result, the n[th] principal component (Fn) must be uncorrelated with all the previously defined components. In conclusion, all principal components are uncorrelated with one another. Naturally, the extraction and use of the right factors are determined after the application of some criteria. According to Hair, Andersen, Tatham and Black there are several criteria:

[19] Variance Equation values are taking from the second part of the Table – 3.2.1.1
[20] A graph of the residuals is demonstrated in Appendix D

- *Kaiser's criteria or Eigenvalue criterion*. The only factors considered significant are these with eigenvalues greater to 1 (eigenvalue > 1)
- *Scree test criterion*. Scree plot has one axis to the left where the eigenvalues are placed. The right axis represents the cumulative variability and the horizontal axis indicates the 7 principal components. The shape of the curve is used to evaluate the point where the break is occurred. The point below this break indicates the number of factors to be taken, but excluding the break itself.
- *The cumulative percent of variance criterion*. Even if there is no predetermined fixed threshold, the measure is up to the research topic and different sciences.

Further to these criteria, successive differences between the eigenvalues should be examined. The aforementioned criteria are noted in table 3.2.2.1 below.

Table 3.2.2.1 – Criteria

Table a – Scree Plot

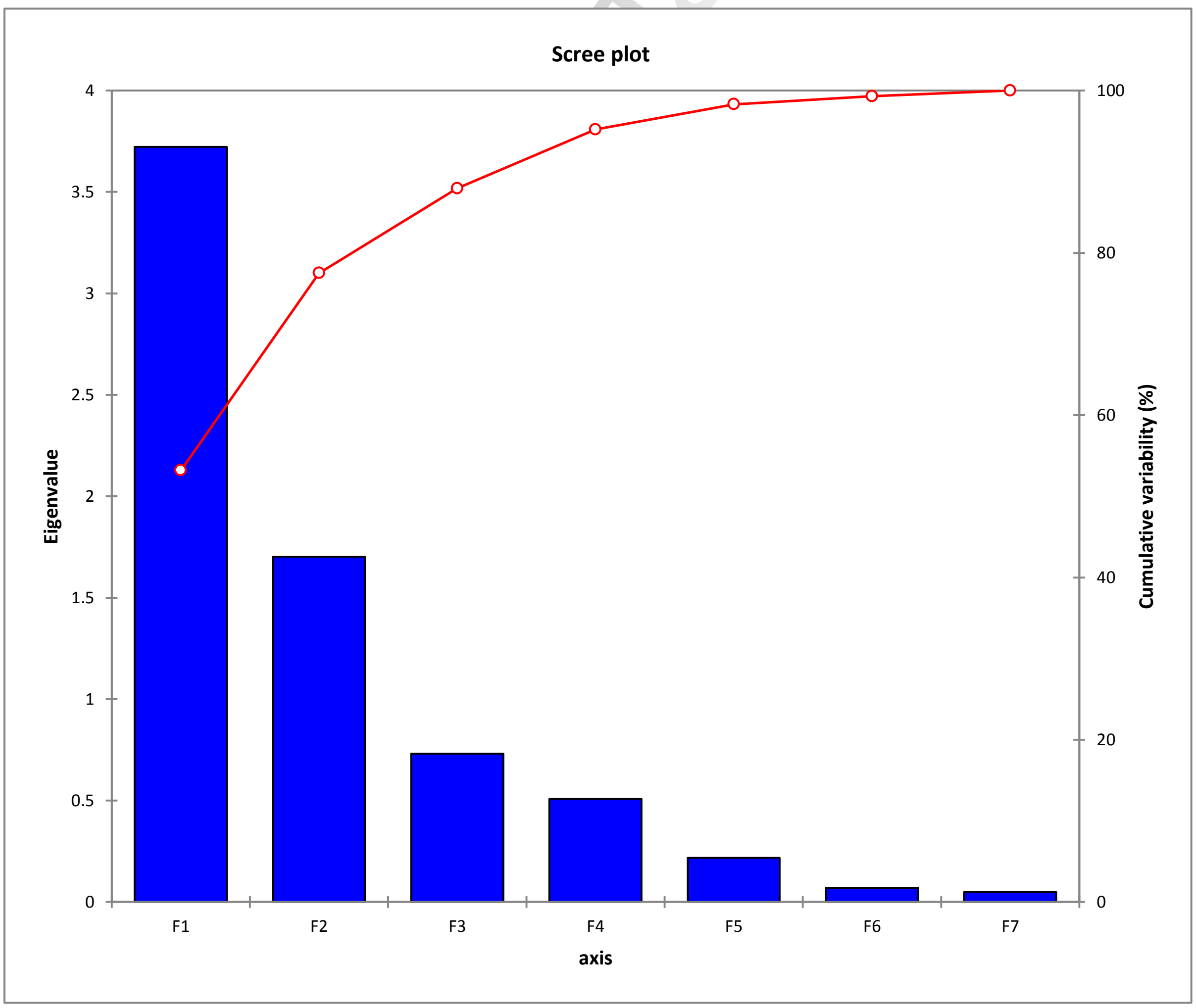


Table b – Eigenvalue

	F1	F2	F3	F4	F5	F6	F7
Eigenvalue	3.723	1.702	0.732	0.508	0.217	0.070	0.050
Variability (%)	53.180	24.311	10.454	7.250	3.098	0.997	0.709
Cumulative %	53.180	77.491	87.946	95.196	98.294	99.291	100.000

Taking into account all of these criteria, resulting a total of 2 factors out of 7 which are significant to use in the following analysis. More specifically, eigenvalues of component 1 and 2 is more than 1 (F1 = 3.723 > 1, F2 = 1.702 > 1), so they are considered significant. From the Cumulative percentage, the first two factors are explaining around 77.5% of the total data's variation. Finally from the Scree plot, the break point seems to be the F4, as a result the data should be analyzed with 3 components. The first three components have a cumulative percentage of 87.946% which is more preferable than 77.5%, but the third factor (F3) is insignificant. In conclusion, for the purpose of this research, the first two factors (F1 and F2) will be used for further analysis as 80% is considered as acceptable number of the percentage, which describes the data well. In this manner, the variables are decreasing from 7 to 2, which were the first purpose of a PC analysis. The successive differences are illustrates more the results from the Scree plot. A sharp drop from one eigenvalue to the next may serve as another indicator of how many eigenvalues to consider. The result of first differences are 2.021, 0.970, 0.224, 0.291, 0.147 and 0.020, for F2 –F1, F3 – F2, F3 – F4, F4 – F5, F5 – F6 and F6 – F7, respectively. The next table (Table – 3.2.2.2) notes the coefficients of the factors (F1 and F2).

Table 3.2.2.2 – Coefficients of F1 and F2 factors

Eigenvectors		
	F1	F2
Price (€/MWh)	0.310	-0.091
FOSSIL (MWh)	0.473	-0.205
HYDRO (MWh)	0.478	-0.007
NUCLEAR (MWh)	0.491	0.058
RES (MWh)	0.456	0.290
Oil Prices (€/MWh)	0.049	-0.641
Gas Prices (€/MWh)	-0.002	0.671

PC analysis indicates that now we have two new components that include the same information with the initial 7 variables. The calculation of each new factor is as equation (8) and (9). Furthermore, the correlation between these two factors should be zero.

For the first component:

$$F1 = 0.310PRICE + 0.473FOSSIL + 0.478HYDRO + 0.491NUCLEAR + 0.456RES + 0.049OIL_{PRICES} - 0.002GAS_{PRICES} \quad (8)$$

And for the second component:

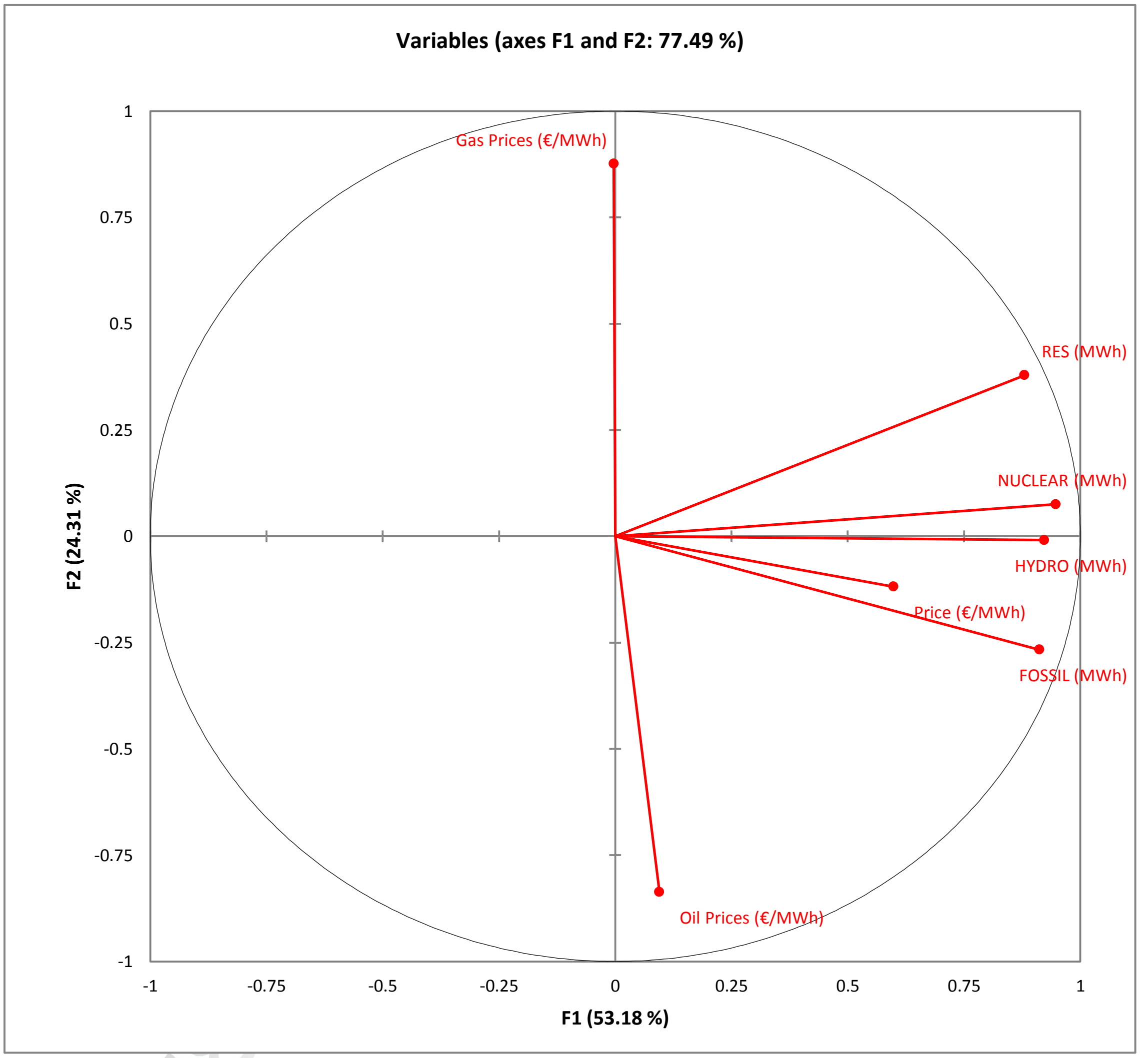
$$F2 = -0.091PRICE - 0.205FOSSIL - 0.007HYDRO + 0.058NUCLEAR + 0.290RES - 0.641OIL_{PRICES} + 0.671GAS_{PRICES} \quad (9)$$

Hence, PC analysis introduces new combination of the variables. Nevertheless, in order to interpret the components, the calculation of the correlation between each component and each variable is necessary. The correlations between the principal components and the original variables are represented in the Table 3.2.2.3 below.

Table 3.2.2.3 – Correlations between the principal components and the original variables

Factor loadings or Correlation between Variables and Factors		
	F1	F2
Price (€/MWh)	0.599	-0.119
FOSSIL (MWh)	0.912	-0.267
HYDRO (MWh)	0.923	-0.009
NUCLEAR (MWh)	0.948	0.075
RES (MWh)	0.880	0.379
Oil Prices (€/MWh)	0.095	-0.837
Gas Prices (€/MWh)	-0.003	0.876

From this table, we are looking for these variables which are most strongly correlated with each component. In other words, we want to find which number is large in magnitude or far from zero in either negative or positive direction. Thus, the numbers considering significant will be more than 0.5. The correlations in blue are the most significant ones; they are above of 0.5 in absolute values. The first principle component is strongly correlated with five out of seven variables (Price, Fossil, Hydro, Nuclear and Renewables or Res). This means that these five variables vary together, when one increases the others increases too. Furthermore, if the first principle component increases then the five variables which are strongly correlated with this component increases too. It is worth mentioning that nuclear, hydro and fossil are strongly correlated with F1. The latter means that the F1 is mainly a measure of nuclear, hydro and fossil. Moreover, if there is an increase in production from nuclear power, then an increase will be observed in the production from fossil fuels, hydropower and renewables, but also the price will be increased further. The results from the Table – 3.2.2.3 can be confirmed by the graph (Graph – 3.2.2.1).

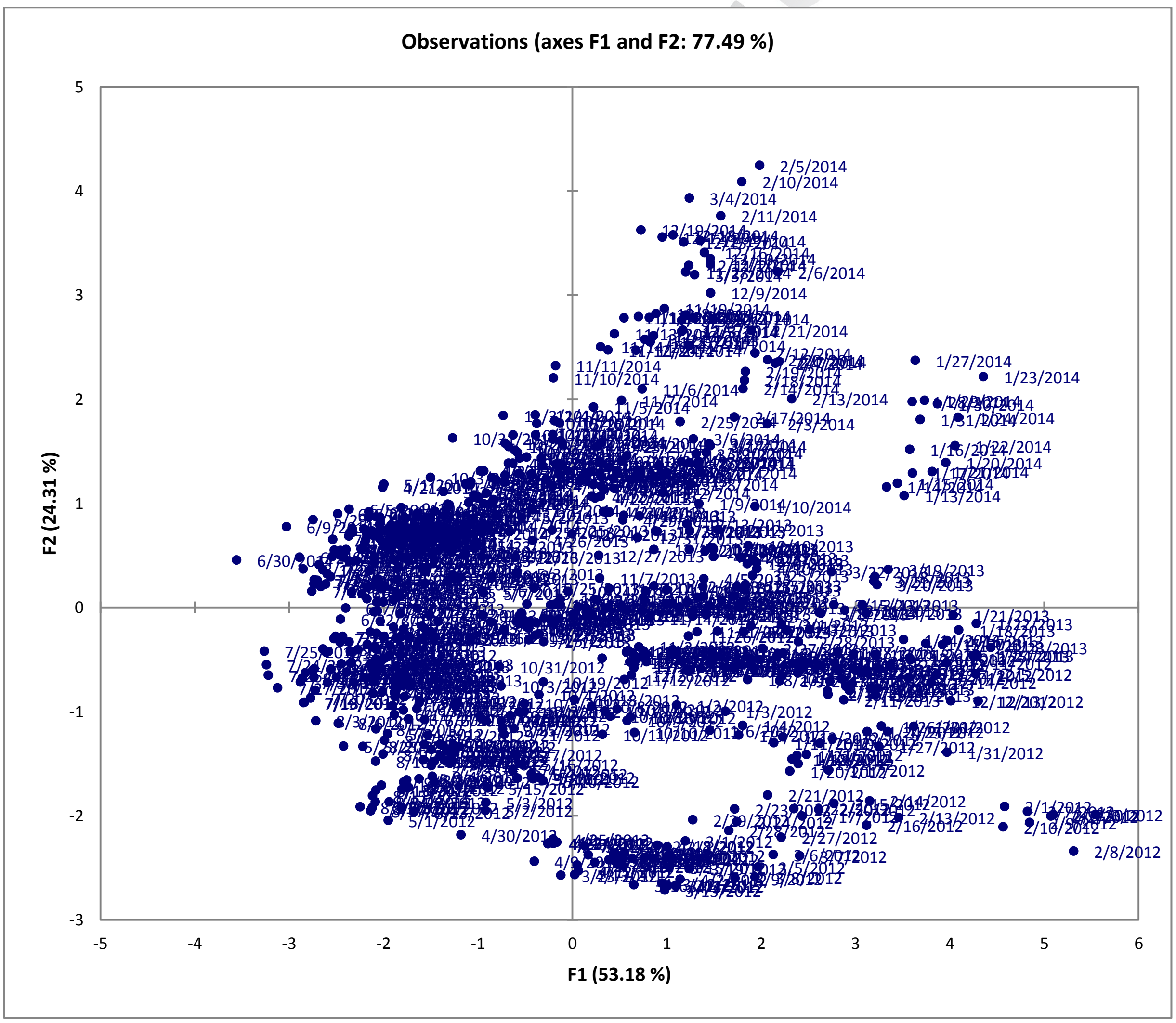


Graph 3.2.2.1 – Correlation between the variables and the first and second principal component

As can be seen, for the F1 component Oil and Gas prices are almost zero, which means zero correlation between these 2 variables and the F1. On the other hand, principal component 2 is strongly correlated with oil and gas prices and is not correlated with the other five variables. More specifically, gas price is positively correlated (0.876) and oil price is negatively correlated (-0.837) with the F2. This means that, when F2 increases then gas prices increases and oil prices decreases. This component suggests that if there is an increase in gas prices the oil prices will be decreased. The latter seem quite reasonable, because these two products considers as substitutes with each other.

Finally, in order to complete the component analysis is needed a scatter plot of the components scores (Scatter plot – 3.2.2.1). Each of these dots represent one day of the week. Taking into account the place of each dot in the scatter plot, we understand the followings:

- The dots, where are close to the right line of the graph, have very high values of first principal component. As a result, we expect these days to have high values for price, nuclear, fossil, res and hydro. In contrast, if we are looking for the dots near to the left line, we should expect that these days the 5 variables will have low values. To sum up, the price (electricity price) these days will be high.
- The dots where are exactly down of the top line have high values of the second principal component. So, we should expect that these days would have high values in gas prices and low values in oil prices. On the other hand, if we look the dots near above the down line, we should expect low values in gas prices and high values in oil prices.



Scatter plot 3.2.2.1 – Results for F1 and F2

Taking into account the PC analysis and GARCH (1, 1) model a clearer picture of the result is revealed. To summarize the result from this section, first I will discuss the results from GARCH (1, 1) model and secondly I will try to combine these two model's outcomes[21].

From GARCH (1, 1) model has been extracted that natural gas prices has no effect in price variation or price volatility. This outcome comes from the p – value which is more than 0.05; more precisely the p – value = 0.1098 > 0.05, which means that it is not statistically significant. Thus, from the PC analysis, F2 component is strongly correlated with oil prices. Hence, on the one hand, an increase in gas prices causes a decrease in oil prices and leaving the electricity prices untouched. On the other hand, increase in oil prices gives a decrease in gas prices and a slightly decrease in electricity prices. As a consequence, gas prices can affect oil prices but not the electricity prices. In contrast, oil prices can affect gas prices and electricity prices. This spillover effect comes to an agreement with Efimova and Serletis (2014) study which they found a spillover effect, proposing that there is an influence from oil to gas and electricity markets.

[21] PCA and GARCH

Chapter 4: Results

To summarize the aforementioned analysis a demonstration of the result and results of other similar studies was made. I found that the variance of electricity prices reaches 80.5%[22] from 01/01/2012 to 12/19/2014, in the Nordic System. On the other hand, Lucia and Schwartz in 2002 discovered that electricity price variation reaches approximately 189%. The outcomes from these two different works come into agreement in terms of high variation, but the volatility of electricity prices in the last three years seems to be lower than the volatility in previous years. This outcome is not certain because the data and methodology which each research used are different and the sample is not the same. So it is wise to recommend a further research in that field.

There is a popular opinion that supports the higher share of nuclear and hydropower in the fuel mix in order to produce electricity. These two sources are considered very significant for the stabilization and for the spikes control. They smoothed away these frequent abnormalities in electricity prices. The aforementioned consequences, from hydropower and nuclear power, have been originated by the natural characteristics of each technology.

Hydropower considers as a storable product. Geman and Roncoroni (2006) and Lucia and Schwartz (2002) supports the theory of inventories[23], and believes that the electricity prices can be controlled and hedged by inventories. In my research, electricity from hydro power is statistically significant, which means that can affect electricity prices. As a result, theoretically speaking, the number of percentage of electricity, comes from hydropower, should be increased with a positive impact in electricity prices. The nature of electricity as a non – storable product becomes lower and more insignificant.

As concerning nuclear power, Mari's (2014) study indicates that CO_2 emissions affect electricity prices through the extended use of fossil fuels. Solution to this problem seems to be the nuclear power because is a carbon – free technology. Furthermore, the substitution of fossil fuels becomes mandatory because of the following mechanism. Fossil fuels prices affect electricity prices, but fossil fuels prices are volatile from their nature. The result is that electricity prices become volatile too. As a consequence, nuclear power seems to be a valuable solution in order to stop this dead – end. According to the analysis of previous chapter, nuclear power significantly affects electricity prices. Taking all the above into consideration, it is discovered that production from fossil fuels affects electricity prices by both factors; the emissions and fossil fuels volatility prices.

To this extend, I agree with Mari's work and idea[24] and I suggest that production from hydropower and nuclear power plants should hold a bigger share in future. These two forms of energy, can transform electricity from non – storable product to a storable product and from "pollutant" to a free – carbon product. The last two introduce new ideas fighting price's extreme variance. Garcia – Martos, Rodriguez and Sanchez (2011), supports this theory of CO_2 emissions. They believe that because

[22] The variance was estimated by squared standard deviation of electricity prices
[23] Inventories can hedge the risk of volatility
[24] Diversification in electricity generation is very optimistic

climate policy has become stricter, the emissions add more operational costs in the industries and that costs jumps to the energy market, making it more vulnerable and more unstable.

Finally, Efimova and Serletis (2014) found that an increase in oil prices has a consequence of an increase in electricity prices. On the other hand, an increase in gas prices introduces an increase in electricity prices too˙ but the impact is a little more than the impact from oil prices. An interesting result come out from Roques, Newbry and Nuttall (2008) research, where they support that the correlation between electricity prices and gas prices reach the level of 90% in 2005, in Britain. In current work, the results are quite different. There is no statistically significant correlation between electricity price variation and natural gas prices. Furthermore, the latter is confirmed by the GARCH (1, 1) model, which indicates that, gas prices do not affect volatility in electricity prices. On the other hand, decreasing oil prices increases the variation of electricity prices.

Chapter 5: Conclusions and Suggestions

To estimate the variance in commodity's prices, researchers prefer to use GARCH models. Because there is not much literature in this specific topic, I decided to choose the same model in order to explain volatility of electricity prices. Although, electricity price volatility is inevitable because of its nature and from the fuel vulnerable prices, in which electricity production depends. The inevitable volatility can be hedged and fought by more electricity production from hydro power and nuclear power and by suitable fuel mix with rich transmission networks.

Furthermore, in this paragraph can be make some suggestions, according to the results in this dissertation and in my way of thought. First of all, the share of hydropower should be increased in order to stabilize the electricity prices, through the storability. Secondly, the share of nuclear power in electricity generation should be increase too. It can be control and affect positively the electricity prices through the carbon – free technology criterion. Last but not least, the share of fossil fuels, considering the volatility of their prices and the greenhouse gas emissions, should be minimized.

In conclusion, there is a lot of room to extend the investigation of this topic and I think that further research is essential in order to come with more reliable results. In this extend, I propose more research in this field. There is poor data selection and literature, related to this topic. That may drive us to the wrong way. The more rich the data and literature are, the more reliable the results are, and as a consequence, the likelihood of wrong conclusions is minimized. Thus, further research may be wise to be occurred, in the near future, in order to find and cross the existing results and the future results. That will lead to more trustful, reliable and valuable results and suggestions. Finally, the significance of the aforementioned is revealed in policy making. Having in mind the right results, only then suitable policies can be made by policy makers and other interested parties concerning energy and fuel mix.

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Appendices

Appendix A

The **mechanism of supply and demand** sets price as follows:

- ✓ Generators offer bids for certain amount of power at a certain price
- ✓ These bids are ranked in terms of their price
- ✓ Bids are taken in this order until the demand is satisfied
- ✓ The last accepted bid sets the market price

Source: “Factoring the Elasticity of Demand in Electricity Prices” by Kirschen, Strbac, Cumperayot, Mendes (2000)

Spike prices are created by some disorders, disruptions, as well as from congestion in the grid. Spike prices are a result of the inelastic demand. This situation leads the prices to higher level. In other words, spikes are characterized with high speed of mean reversion (jumps) and do not leads to sustainable higher price levels, thus, they lead to extreme variance as a consequence.

Levelized Cost of Electricity (LCOE) is the minimum selling price of the electricity produced by generators. It’s a marginal price covering all expenses (taxes, interests, debt etc.). LCOE considers as the price where the present value (PV) of the revenues is equal with the present value of expenses during the plant’s life – time. The LCOE represents the break even selling price.

Appendix B

ARCH & GARCH model

ARCH model is described from the following equation:

$$\sigma_t^2 = a_o + a_1 u_{t-1}^2 + a_2 u_{t-2}^2 + \cdots + a_p u_{t-p}^2 \quad (1)$$

Where, σ_τ^2: *variation of disruption term*
u_t : *disruption term*
a_0: *constant coefficient*
u_{t-1}^2: *squared price of disruption term of previous period*

It is denoted as follows: **ARCH (p)**.

GARCH model is a Generalized ARCH model and it has the following formation:

$$\sigma_t^2 = a_0 + a_1 u_{t-1}^2 + \cdots + a_p u_{t-p}^2 + \gamma_1 \sigma_{t-1}^2 + \cdots + \gamma_q \sigma_{t-q}^2 \quad (2)$$

Where, γ: *weighted coefficient*
It is denotes: **GARCH (p, q)**.

ARIMA model

An **ARMA (p, q)** model when is applicable in an integrated d order series is called Autoregressive Integrated Moving Average or **ARIMA (p, d, q)**. An ARIMA process can take 3 different forms:

- ✓ Difference equation form
- ✓ Inverted form
- ✓ Random shock form

Source: Introduction in Econometrics, Volume B, G.K. Christou, 2008

Appendix C

1btu = 2.9307107 x 10^{-7} MWh
1boe = 1.6282 MWh
After the conversion of Btu and boe to MWh, I used the exchange rate to convert $ to €

Appendix D

Table 1 – Examine possibly seasonality

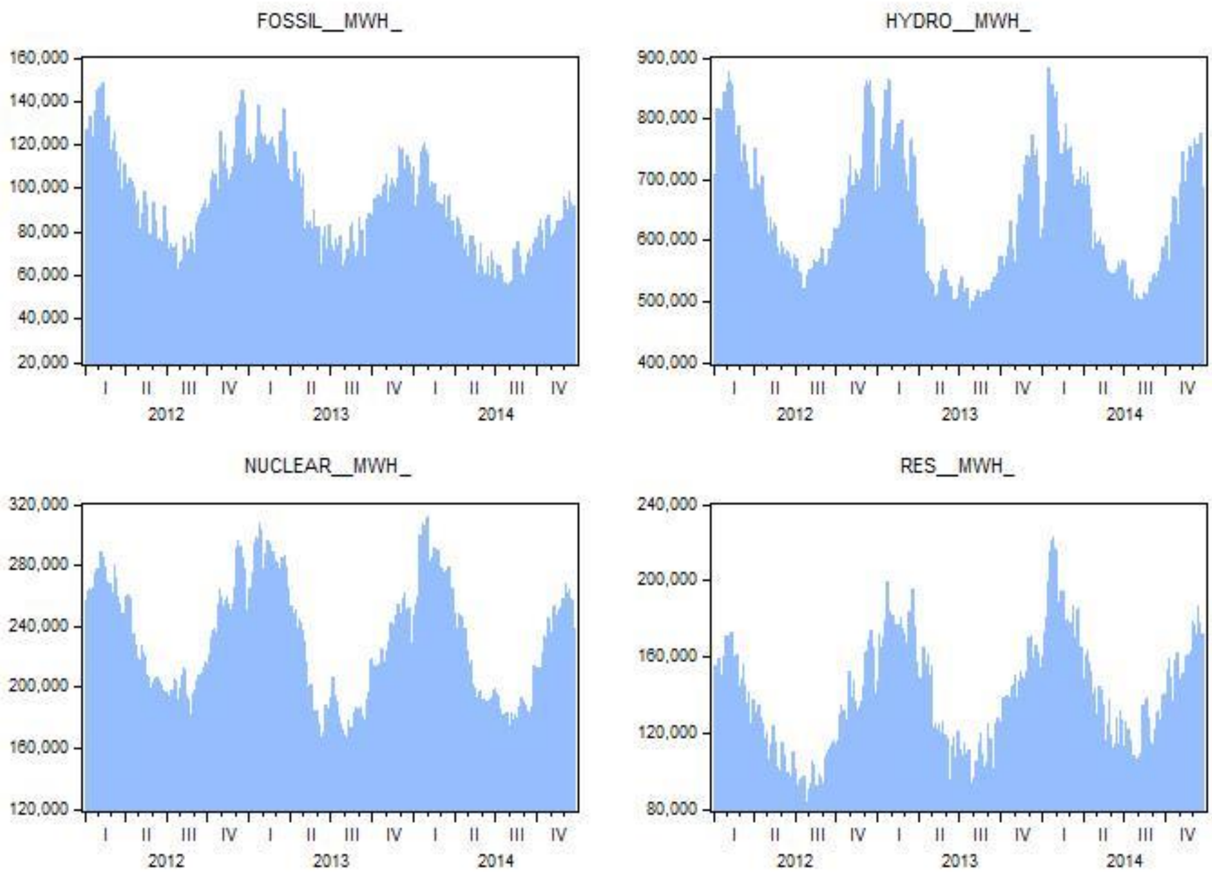
Dependent Variable: PRICE_IN_EUR_MWH
Method: Least Squares
Date: 12/22/14 Time: 13:21
Sample: 1/02/2012 12/19/2014
Included observations: 775

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	33.68032	0.723904	46.52594	0.0000
TUESDAY	0.535484	1.023755	0.523059	0.6011
WEDNESDAY	0.938839	1.023755	0.917054	0.3594
THURSDAY	0.555355	1.023755	0.542468	0.5877
FRIDAY	-0.167032	1.023755	-0.163156	0.8704

R-squared	0.002005	Mean dependent var	34.05285
Adjusted R-squared	-0.003180	S.D. dependent var	8.998241
S.E. of regression	9.012535	Akaike info criterion	7.241541
Sum squared resid	62543.86	Schwarz criterion	7.271559
Log likelihood	-2801.097	Hannan-Quinn criter.	7.253090
F-statistic	0.386705	Durbin-Watson stat	0.129970
Prob(F-statistic)	0.818236		

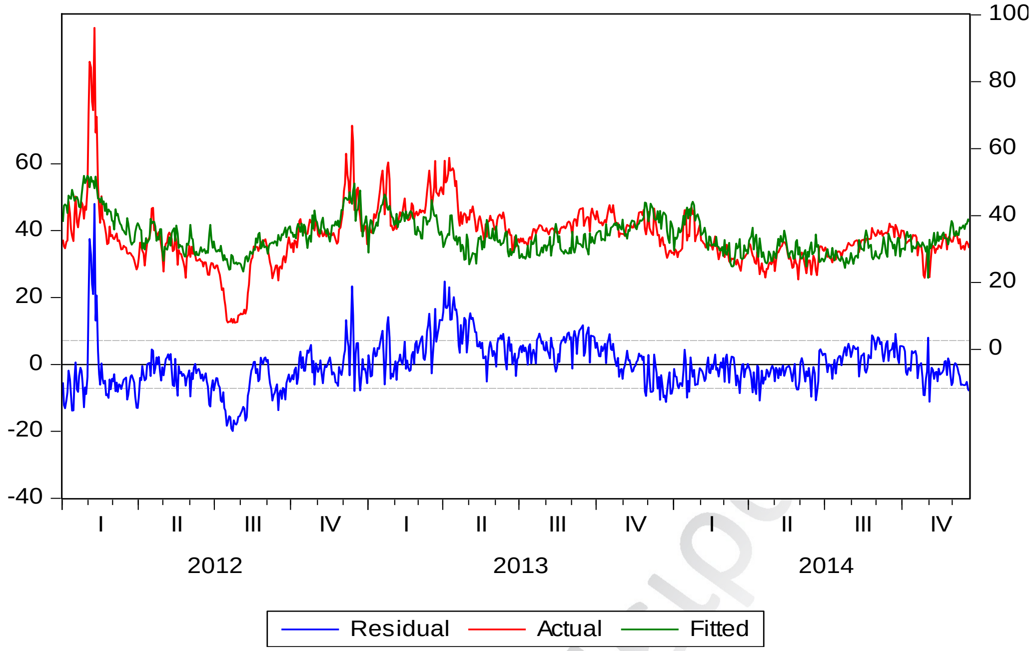
As has been analyzed in the chapter 3, here we can see that Monday denoted as C in the above table, and takes a p – value = 0.0000 < 0.05, means that it is statistically significant variable. I denoted Monday with C, because C is the constant term. I did not use five dummy variables (MONDAY, THUESDAY, WEDNESDAY, THURSDAY, FRIDAY) but I used four dummy variables (TUESDAY, WEDNESDAY, THURSDAY, FRIDAY) in order to avoid dummy variable trap[25].

[25] Explanation of Dummy Variable Trap is beyond this research. See Christou (2004), p. 165.



Graph 1 – Electricity production in MWh for each energy source in Nordic System

The above graph illustrates the electricity production from four different forms of energy. The most popular seems to be the hydropower, after the nuclear power and renewables and fossil fuels are following. They seem to have similar behavior through the months, regardless their contribution in electricity generation.



Graph 2 – Residuals from Mean Equation (5)

The "graph 2" is giving a clear image about the residuals. There is a short period with high volatility from the beginning of February 2012 until the end of this month. Furthermore, there is a prolonged period of not so high volatility and an existence of a prolonged period from the middle of 2013 until today, with low volatility. Residuals with high volatility are followed by residuals with high volatility and residuals with low volatility are followed by residuals with low volatility. In other words, residuals are heteroskedastic, thus, a GARCH model seems to be appropriate to represent them.

Table 2 – Correlation matrix between the variables

Correlation matrix (Pearson (n))							
Variables	**Price (€/MWh)**	**FOSSIL (MWh)**	**HYDRO (MWh)**	**NUCLEAR (MWh)**	**RES (MWh)**	**Oil Prices (€/MWh)**	**Gas Prices (€/MWh)**
Price (€/MWh)	**1**	**0.553**	**0.445**	**0.382**	**0.393**	**0.072**	-0.056
FOSSIL (MWh)	**0.553**	**1**	**0.776**	**0.814**	**0.724**	**0.282**	**-0.245**
HYDRO (MWh)	**0.445**	**0.776**	**1**	**0.912**	**0.758**	0.070	-0.051
NUCLEAR (MWh)	**0.382**	**0.814**	**0.912**	**1**	**0.866**	0.066	0.058
RES (MWh)	**0.393**	**0.724**	**0.758**	**0.866**	**1**	**-0.194**	**0.325**
Oil Prices (€/MWh)	**0.072**	**0.282**	0.070	0.066	**-0.194**	**1**	**-0.496**
Gas Prices (€/MWh)	-0.056	**-0.245**	-0.051	0.058	**0.325**	**-0.496**	**1**
**Values in bold are different from 0 with a significance level alpha=0.05*							

From the table 2, the electricity price seems to correlate significantly with the electricity generation from fossil fuels, hydropower, nuclear power, res and oil prices. Gas prices are not significantly correlated with electricity prices in significance level of 5%.

Table 3 – Statistics from the data

Summary statistics							
Variable	**Observations**	**Obs. with missing data**	**Obs. without missing data**	**Minimum**	**Maximum**	**Mean**	**Std. deviation**
Price (€/MWh)	775	0	775	7.920	96.150	33.906	8.977
FOSSIL (MWh)	775	0	775	35591.568	148645.284	88583.716	21897.515
HYDRO (MWh)	775	0	775	436577.623	882035.427	627757.137	103359.702
NUCLEAR (MWh)	775	0	775	150151.539	311750.256	227555.183	38088.019
RES (MWh)	775	0	775	81514.335	223171.351	133508.112	28880.398
Oil Prices (€/MWh)	775	0	775	76.199	159.149	132.263	12.132
Gas Prices (€/MWh)	775	0	775	4.730	20.459	9.379	2.096

In table 3, some interesting statistics are revealed. Minimum and Maximum corresponds in the minimum and maximum price of each variable. I would like to insist in electricity price and take a more careful glance. With the mean value equals to 33.906, the maximum price seems to take outliers. This is a mark that extreme volatility exists in electricity prices.