NORGES HANDELSHØYSKOLE

Bergen, Spring 2012

Clean Spark Spread

Correlation, integration and long-run relationships between electricity, natural gas and CO_2 allowances prices. An empirical study on the markets in Germany, the Netherlands and the United Kingdom.

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Economic Analysis & Financial Economics

NORGES HANDELSHØYSKOLE

Abstract

In this master thesis we study and explore the relationship between the clean spark spread commodities; electricity, natural gas and CO_2 allowances prices in Germany, the Netherlands and the U.K. The time period for the analysis is based on the establishment of the EU Emissions Trading Scheme in 2005 and the following phases. In the statistical analysis we made several observations that are important for various market participants exposed to the markets. The analysis has also emphasized the importance of using several statistical techniques to explore a causal relationship. The statistical frameworks used in the analysis are correlation, co-integration, error-correction model and Granger causality.

In the short-run perspective we found that prices of the same commodity at different hubs were strongly correlated in returns, while cross-commodity (spark spread) return correlations were rather weak. However, in a long-run perspective we found well-defined links between electricity and natural gas prices.

Preface

The thesis completes our Masters of Science in Economics and Business Administration at the Norwegian School of Economics (NHH), Bergen. Christoffer Horni Noreng has chosen Financial Economics as his Master Degree Major, while Even Nilsen Enggrav has chosen Economic Analysis.

The authors alone initiated the topic of this thesis. The topic is also a result of lasting interest of the abovementioned markets. However, since both authors are lucky to have job experiences in these markets it is also a result of various dialogues with prior colleges.

Working with the thesis has been inspiring, both in terms of what we learned about the topic and the statistical concepts used in the analysis. In addition, we acknowledge that the statistical toolbox that we now possess, together with our enhanced understanding of the topic, will be of great relevance to our future career position.

We would like to thank our advisor Jonas Andersson for his feedback and advice during the process of writing the thesis, but also for his contribution to our understanding of various statistical concepts. We also want to thank all those who read through the thesis and have given beneficial feedback. At last we would like to thank former colleges at Vardar, SEB Merchant Banking, Bergen Energi and Statnett for valuable inputs during our years at NHH. The academic learning from NHH combined with practical experience from the mentioned companies has been incredible rewarding.

Bergen, June 2012

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1. Introduction

During the recent 5-10 years there has been game changing developments in the European energy markets. One of the most important inputs in the European energy mix is natural gas and one of the main uses of natural gas is production of electricity. Additionally, EU authorities launched the EU emission-trading scheme (ETS) aiming for price discovery on $C0_2$ emissions. The relationship between these commodities has considerable impact on stakeholders in the market.

On the physical side, the EU energy markets have become progressively concentrated, by new cross-country grids and pipelines which has allowed both electricity and natural gas to flow with less constraints, presumed to cause tighter price linkages between different trading hubs. The physical markets in Western Europe countries are also experiencing a period of large investments in renewable energy and infrastructure. Change in the supply structure will have implications on price development and infrastructure decisions.

At least in Western Europe, exchanges for electricity trading have been more mature than their natural gas counterparties. This implies that in many areas we have transparent and consistent electricity price series that could be analysed thoroughly. Contrary, for decades natural gas deals have been settled on a bilateral basis, often pegged to the price of oil, but during the recent years this has been changing. Movements towards transparent trading hubs, more or less physically linked, will continue. One of the main drivers for the need of liquid and transparent natural gas hubs is the EU legislation and the large spread in crude oil and natural gas prices. Therefore, natural gas price series from recent years, based on the different European trading hubs, have become much more interesting when analysing the relationship between electricity prices and *actual* cost of natural gas. Among others, we believe that hub based natural gas prices will be representing the cost of natural gas in analysis of the European energy markets in the future. On April 5th 2012, journalist Karel Beckman published an article in European energy review with the headline:

"It´s finally coming: the great European natural gas market transformation"

Beckman says *"the old market structure, based on bilateral long-run contracts between a limited number of big suppliers and buyers, will be replaced by (presumably) thriving wholesale markets where sellers and buyers meet on trading hubs to make short-term deals."*

Consequently, our goal is to contribute to the field of analysing connections between European electricity prices, natural gas prices and CO_2 allowance prices in the context of transparent natural gas series and the establishment and phases of EU Emission Trading Scheme (EU ETS)

The key questions that we would like to explore could be summarized as follows:

Does analysing European electricity, natural gas and CO_2 allowances prices, by short-term and long-term statistical concepts, show evidence of market integration between the same commodity in different areas, and are there forces linking the prices in a way that make the (clean) spark spread stable? If so, is it possible to identify "leading markets" by describing the dynamics of the price connections? In addition, what do estimated statistical relationships say about the marginal effect, of price changes, to a natural gas-fired power plant?

With this background we are first motivated to explore short-term relationships by and analysing return, volatility and correlation developments between the variables in the spot and front markets, during the 7 years gone since the EU ETS was established.

Second, we will study long-run relationships between the prices of electricity, natural gas and CO_2, and carefully disclose the dynamics of these relationships. The understanding of these relationships is of great relevance to many markets players that are exposed to the difference between the electricity price and the natural gas price, known as the spark spread.

The analysis is conducted with historical data on electricity and natural gas prices from the Netherlands, Germany and the UK. In addition, we will include a time series representing the price of CO_2 emission to natural gas fired power producer, and seek to understand its relation with both electricity and natural gas prices.

1.1 Framework

1.1.1 Theoretical framework

Market participants in energy markets are often not outright exposed to commodity prices, but rather to the difference of two or more commodity prices involved in the production or transformation process. Therefore one should believe that there is a positive correlation between such commodities.

The correlations between financial quantities are notoriously unstable but correlations are regularly used in almost all multivariate financial problems. An alternative statistical measure to correlation is co-integration (Wilmott, 2009). The advantage of using co-integration is that it captures dynamic relationships between the variables, which could not be captured by correlation analysis of returns.

Part 1 will use correlations extensively to capture short-term relationships, while Part 2 will describe long-run relationship by co-integration, error-correction model and Granger causality.

1.1.2 Limitations of framework

The analysis will only use price variables in the analysis. Both electricity and natural gas are commodities that are dependent on the capacity in the transportation network, both internal and cross-border. Electricity is transported through power lines and high-voltage direct-current (HVDC) power cables. Natural gas is transported by through pipelines or LNG (Liquefied Natural gas). The delivery capacity of commodities is an important price determinant for electricity and natural gas markets, particularly when you consider the low storage capacity for electricity. Throughout the analysis, we will not use capacity constraints as a direct variable, but as part of our interpretation.

Natural gas storage facilities are a well-know price driver in the natural gas market. Storage sites across the European gas network are often filled up during the summer to meet the increasing demand in the winter months. It is out of the scope for this thesis to measure the price effect from changes in storage level in the gas network. We will limit our analysis to the measure the correlation and integration of the commodity prices.

Some argue that the natural gas market in Europe is as much shaped by political forces as by economical factors, especially considering the position of Russia and Gazprom[1]. This thesis will not consider political risk and security of supply associated with the natural gas market.

Being able to generate power strategically, only when it is profitable, is a significant source of value. The flexibility of a natural gas-fired plant is often measured in ramping time, the amount of time a plant requires to ramp up and down production. However it is out of the scope for this thesis to investigate the hourly flexibility of natural gas-fired plants, but flexibility is an important source for profitability regarding a natural gas-fired plant.

1.2 Spark spread

The *spark spread* is the basic marginal production profit relationship between output of electricity and input of natural gas, modelling the production profitability for a natural gas-fired power plant across time. The spark spread is defined as the difference between the electricity price per MWh and the cost of generating that MWh (Hsu, 2001), as shown in equation (1):

1. $$spark\ spread = electricity\ price - (heat\ rate * natural\ gas\ price)$$

Heat rate = Natural gas input/Electricity output

The heat rate of a natural gas-fired power plant is the number of British thermal units (Btus) needed to generate one-kilowatt hour of electricity (CME Group, 2012). It is also possible to view the spark spread by means of the efficiency factor for converting natural gas to electricity. If the power plant uses 2 MWh of natural gas to convert to 1 MWh of electricity the plant has an efficiency factor of 50 per cent.

2. $$spark\ spread = P_{EL} - \left(\frac{P_{Nat\ Gas}}{Fuel\ efficiency\ (\%)}\right)$$

P_{EL} = Price of Electricity (EUR/MWh)

$P_{Natural\ gas}$ = Cost of natural gas (EUR/MWh)

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[1] Gazprom is the largest extractor of natural gas in the world and the largest company in Russia

Fuel efficiency = Standard efficiency Factor for the for natural gas conversion = 49.13 per cent

The efficiency of converting natural gas to electricity is in the range of 20 to 60 per cent. In the UK and Germany is common market methodology to use a standard fuel efficiency factor of 49.13 per cent for the natural gas conversion in the spark spread (ICIS, 2012). In our spark spread analysis we will use that standard efficiency factor as benchmark, unless alternative fuel efficiency is noted. Depending on the plant efficiency, the amount of fuel required to produce 1 MWh of electricity varies. A new Combined Cycle Natural gas Turbine (CCGT) with 58 per cent efficiency (on lower heating value) requires 1.7 MWh of natural gas, whereas an older unit with 50 per cent efficiency requires 2 MWh of natural gas (Los, de Jong, & van Dijken, 2009).

The spark spread does not take into account additional charges such as non-fuel operational costs for a natural gas-fired plant.

1.3 Clean spark spread

In Europe we can expand the simple formula for spark spread to involve the price of CO_2 emissions, called the clean spark spread. The EU Emission Trading Scheme (EU-ETS) makes it mandatory for all heat plants or installations in excess of 20 MW to compensate for the CO_2 pollution. Each participant is given a fixed number of allowances from EU. The National Allocation Plans (NAPs) set out the total quantity of greenhouse natural gas emission allowances that Member States grant to their companies in the first (2005-2007) and second (2008-2012) trading periods (European Commission, 2010). For the last trading period, from 2013, the allocation of allowances will be determined on an EU level rather than on a national level. The allowances (EUA) can be traded among the participants and the price created in this market reflects the price of CO_2 emission in Europe. A heat power generator must therefore consider if the given number of EUA should be used to create electricity or sell EUA on the market for CO_2 as opportunity revenue. The UK has also proposed an additional tax on carbon emission. The so-called carbon price support was set at 11.5 Euro per metric ton for 2014 (Airlie, 2012).

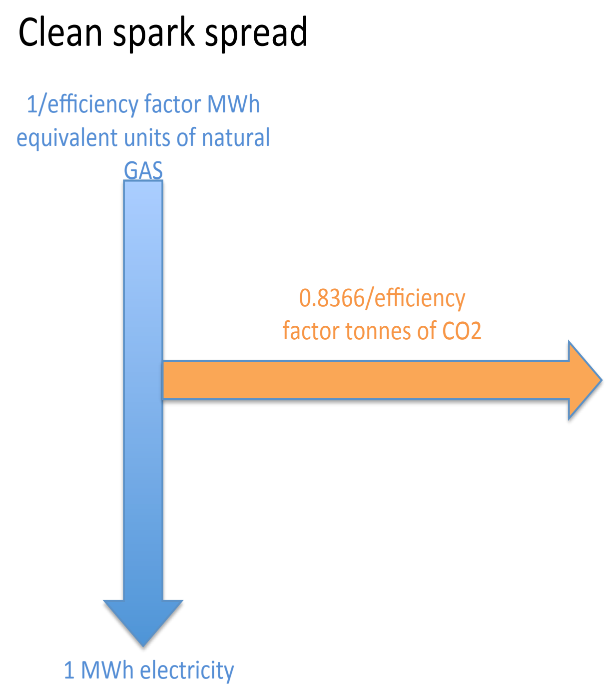
3. $$clean\ spark\ spread = P_{EL} - P_{CO_2} - \left(\frac{P_{Nat\ Gas}}{Fuel\ efficiency\ (\%)}\right)$$

P_{EL} = Price of Electricity (EUR/MWh)

P_{CO2} =EUA (EUR/t CO_2) * 0.411 (t CO_2/MWh) = P_{CO2} (EUR/MWh) for a natural gas plant

$P_{Nat\ gas}$ = Cost of Natural gas (EUR/MWh). [For the UK the natural gas price (Pence/Therm) is converted to EUR/MWh]

Figure 1: Clean spark spread



In our analysis we make the following assumption regarding the emission factor for a natural gas-fired plant as shown in figure 1. The assumption is in line with estimates about emission factor from other sources, such as the ICIS[2] carbon market methodology and the report "Emission Cuts Realities – Electricity Generation" (Lang, 2010). Each individual natural gas-fired plant has distinctive emission factors, even with the same technology. After each calendar year, installations must surrender a number of allowances equivalent to their verified CO_2 emissions in that year. In our general market analysis we use an "average-best" assumption about the emission factor, based on fuel efficiency level. The ICIS methodology

[2] ICIS is a market intelligence provider for the global chemical, energy and fertilizer industries

assumes an emission factor of 0.411 tonne CO_2 per MWh produced electricity for a natural gas-fired plant with 49.13 per cent efficiency. For comparison the average emission factor, using brown coal as input, is 1.200 t CO_2 per MWh (produced electricity).

The emission factor implies a constant relationship between the emission factor and fuel efficiency:

0.411 t CO_2/ 49.13 per cent fuel efficiency = 0.8366

We use the implied relationship to determine the emission factor for other fuel efficiency levels as shown in appendix. The emission factor indicates 0.1195 t CO_2 less emission for every 10 per cent increase in efficiency.

Figure 2: Carbon cost with different fuel efficiency

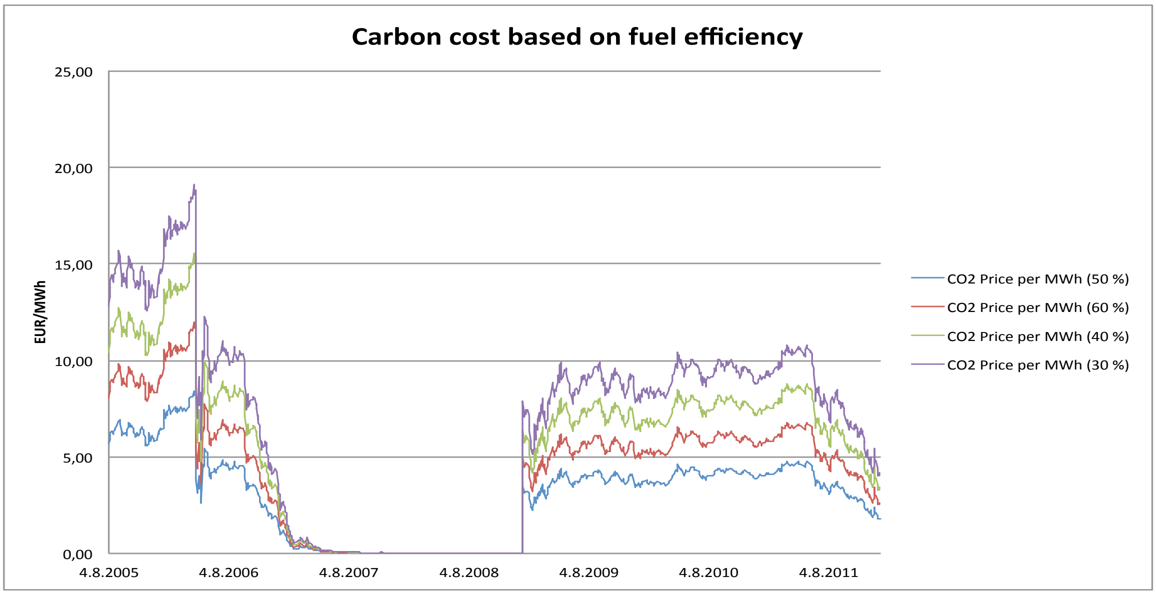


Figure 2 shows the historical carbon-cost per produced electricity (MWh) for natural gas-fired plants among different fuel efficiencies. The highest carbon cost spread (difference between high (60 per cent) and low (30 per cent) fuel efficiency) in our sample was 10.7 EUR/MWh observed on April 18 2006.

1.4 Electricity production by source

This section presents the sources used for electricity production in the three countries covered. It will be considered as background information that will help us to compare and interpret the results. A logical assumption is that the price correlation between electricity and natural gas will be stronger the more natural gas is used in the production mix of electricity. A strong correlation will likely give a more predictable spark spread relationship.

Table 1: Electricity production by source in the Netherlands, the UK and Germany (IEA 2009)[3]

	The Netherlands		The UK		Germany	
	TWh	%	TWh	%	TWh	%
Coal	27	23 %	106	28 %	257	43 %
Oil	1	1 %	4	1 %	10	2 %
Natural Gas	**69**	**61 %**	**165**	**44 %**	**79**	**13 %**
Biofuels	5	4 %	9	2 %	26	4 %
Waste	3	3 %	3	1 %	10	2 %
Nuclear	4	4 %	69	18 %	135	23 %
Hydro	0	0 %	9	2 %	25	4 %
Wind	5	4 %	9	2 %	39	7 %
Other	0	0 %	0	0 %	13	2 %
Total	**114**	**100 %**	**376**	**100 %**	**592**	**100 %**

We observe considerable national differences in the electricity production by source. In terms of percentage points, the Netherlands is the country with the largest dependence on natural gas, and is by far the most important source of electricity production. In 2009, 61 per cent of domestic electricity production stemmed from natural gas.

Thirteen per cent of the electricity production in Germany was generated by the use of natural gas in 2009. This makes Germany less dependent of natural gas compared to the two other countries. However, the domestic electricity production stemming from natural gas was almost 79 TWh, which makes Germany a larger total consumer of natural gas, for electricity production, than the Netherlands. Hence, Germany is a very important player on the European natural gas market.

Moreover, Germany will realize changes in its energy mix during the coming years, mainly due to two factors. First, after the disasters at Fukushima, Germany has decided to phase out all its nuclear power production by 2022 (Dempsey & Ewing, 2011). Second, the German

[3] International Energy Agency. (IEA statistic by country)

subsidies to coal fired production is at risk since EU is aiming to cancel them (Talt, 2010). Consequently, the German energy mix will change considerably and it is a lot of uncertainty regarding the importance of natural gas in the German energy mix.

In the UK, natural gas is generating 44 per cent of the electricity production, which is the single largest source. The UK also has the largest size of electricity production from natural gas in terms of TWh, twice as much as Germany. Considering the comparatively low electricity interconnection capacity between the UK and Europe and the liquefied natural gas (LNG) market in the UK, we should expect to find a stronger correlation between electricity and natural gas prices in the UK.

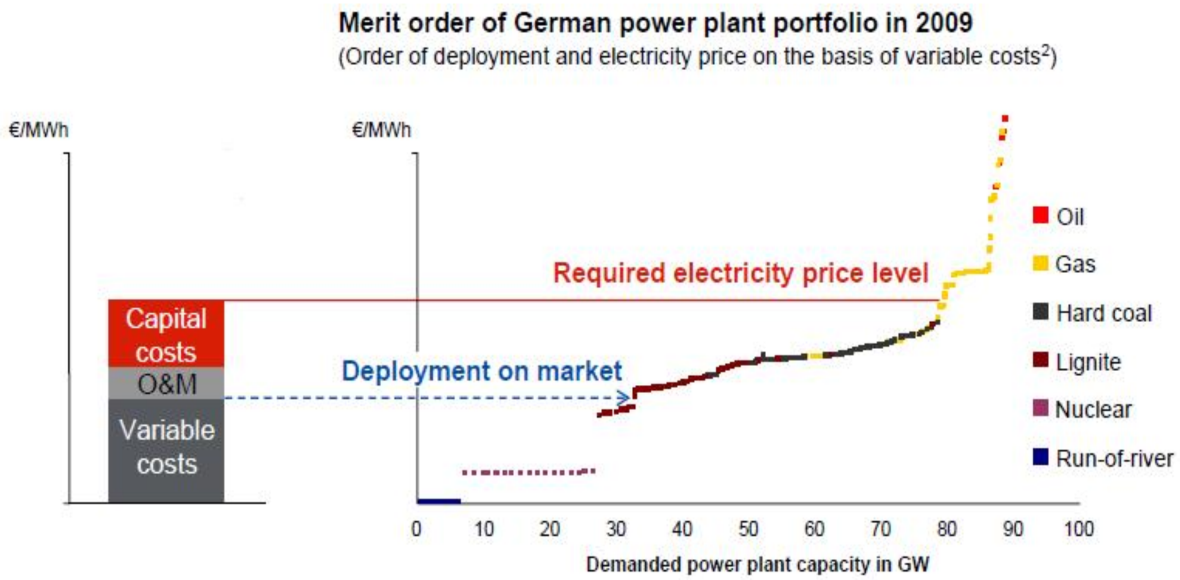
This introduction of the energy mix, and the share of natural gas, gives us an intuition of the natural gas relative dependence on natural gas in each country. Though, to understand how the production sources influence the price of electricity we need to consider the marginal cost of production, which we present by the merit order.

1.5 Merit Order

The merit order shows the supply curve for electricity production and separates the marginal cost of production by the various sources. Figure 3 is an illustration of the merit order in Germany in 2009. The Netherlands, Germany, and the UK all have different proportion of production sources, but natural gas is often the price setter in all three countries because of its flexibility and relative high fuel cost. Figure 3 reveals that natural gas and coal is the price setter if the demand for electricity in Germany is in the range of 60 to 85 GW[4] before oil takes over.

[4] The maximum top-load for Germany in 2009 was 79 GW.

Figure 3: Merit order in Germany (RWE, 2009)



Due to inelastic price elasticity of demand, electricity prices are driven by the merit order structure and seasonal shifts in demand. Fortunately, forecasting the merit order is generally valid for several years (RWE, 2009), which is due to the significant time requirement for planning, permitting, and constructing new generation capacity (as long as there are no systematic shifts in commodity price relations (e.g. hard coal vs. natural gas or renewable sources)). On the other hand, fuel prices and production based on renewables are very volatile, which therefore make short-term dynamics of the merit order to change quickly.

The CO_2 price also influences the marginal cost of different fuels and the merit order. The effect on the merit order depends on the relative emission intensity of the production process and the price relationship between hard coal and natural gas. Given that the price relationships between the fuel commodities stay constant, natural gas have a comparative lower marginal cost due to lower CO_2 emission per produced MWh. Additionally, a modern natural gas-fired power plant has a more flexible production, which means capacity of quick adjustments to meet changing demand of electricity.

Part 1 will explore the short-term dynamics of prices in terms of return, volatility, and correlation. Part 2 of our analysis will focus on the long-run relationships between natural gas, electricity and emission allowances in the merit order.

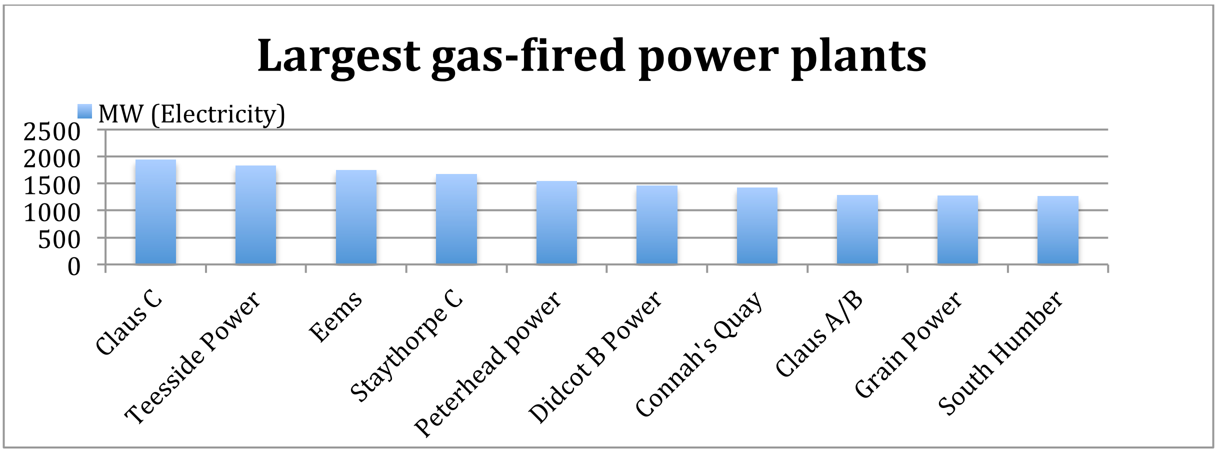
1.6 Natural gas-fired power plants

To further explore the price connection between natural gas and electricity in Germany, the Netherlands and the UK we have collected fundamental data on all major natural gas-fired power plants in the selected countries. The data is collected using different sources, such as power plant information from producers, public data from transmission operators and other sources. To enhance our understanding about the spark spread we need information about the fundamental generation process that is subject for the spark spread. We have collected a data sample that covers 172 natural gas-fired plants with a total installed capacity of 70.6 GW. The data sample includes plants from all three countries and information on age profile, type of plant, location and efficiency[5].

Figure 4 shows the ten largest natural gas-power plants in the three countries. Seven are located in the UK, while the largest plant measured in generation capacity (MW) is the Claus C plant in the Netherlands. None of the ten are located in Germany. The Claus C plant, in the Netherlands, was built by Essent (owned by RWE) in 2012. With its efficiency of 58.5 per cent and 1940 MW installed capacity, it is able to supply power to more than 2 million typical European households.

[5] If we were unable to find data for the efficiency factor regarding a specific natural gas plant, we used an efficiency factor based on age. The reason is that efficiency factor is correlated with age because of developments in technology and deterioration over time. See appendix for the efficiency conversion from age to efficiency factor.

Figure 4: 10 largest natural gas-fired power plants in the UK, DE & NL



The average installed generation capacity for the collected sample is 420 MW per plant. Several analysts predict that existing conventional power plants (both natural gas and coal) will go offline in the coming years (RWE, 2009). There are several reasons for this prediction, but the main two reasons are ageing power plants with low efficiency and stricter CO_2 allocation.

Germany has an older power plant portfolio compared to the UK and the Netherlands. Our data sample shows that the average age of a natural gas-fired plant in Germany is 19 years, while it is 16 and 13 for the Netherlands and the UK respectively. The average generation capacity (installed power) is 259 MW per plant in Germany, while it is 584 MW and 607 MW in the Netherlands and the UK respectively.

The total installed natural gas-fired generation capacity in the Netherlands, Germany and the UK is 72 GW. The total installed natural gas-fired power generation capacity in Europe is 199 GW (2008), which is the largest source in the European energy mix in 2008 (RWE 2009).

The average age of natural gas-fired power plants in Europe is 22 years old. To be able to compare that age in the three countries in a sensible way, we have calculated the capacity adjusted average age:

4. $$Capacity\ adjusted\ average\ age = \sum_i^N \left(age_i \left(\frac{MW_i}{\sum_i^N MW_i} \right) \right)$$

The capacity adjusted average age gives us a better understanding of the plant portfolio for each country. For example if a large proportion of the installed generation capacity is older plants, then the weighted age will penalize this.

The capacity adjusted average age shows that the Netherlands and the UK have a capacity-adjusted average age of 13 years, while in Germany it is 22 years. Hence, Germany has a portfolio consisting of older natural gas-fired plants. An older portfolio implies that the natural gas-fired plants have lower efficiency, lower flexibility (ramping time) and is only profitable when used for peak production. Lower efficiency and slow ramping often indicates lower profit for the existing plants. Since fuel efficiency is even more important than the age, we have calculated the capacity adjusted average fuel efficiency, for the same reasons as we did for the capacity adjusted average age;

5. $Capacity\ adjusted\ average\ fuel\ efficiency = \sum_i^N \left(efficiency_i \left(\frac{MW_i}{\sum_i^N MW_i} \right) \right)$

Figure 5: Capacity adjusted average fuel efficiency for natural gas-fired power plants

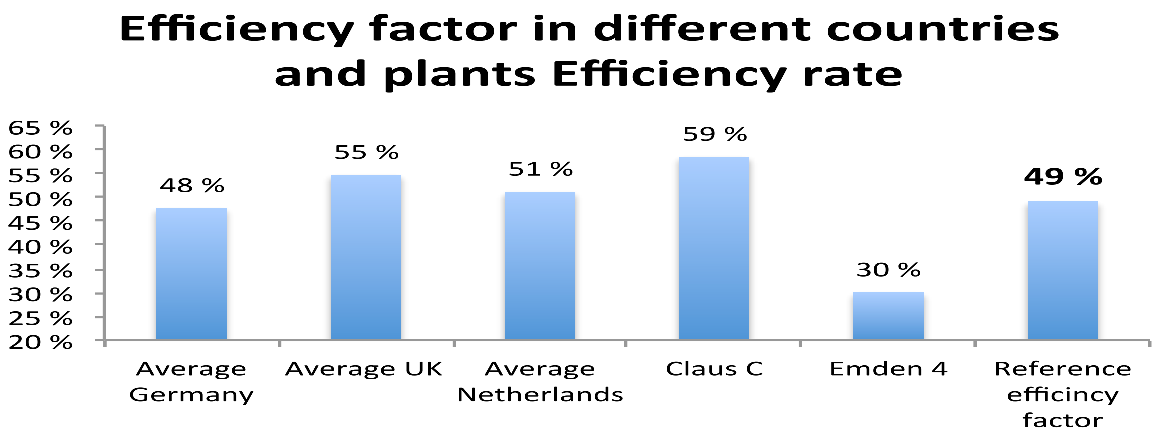


Figure 5 shows that the adjusted average fuel efficiency in the UK is almost 8 percentage-points higher compared to Germany, while the Netherlands is in-between.

1.6.1 New plants and investment costs

The Cambridge Energy Research Associates (CERA) reports that the majority of new power plants in Europe will be natural gas-fired plants. Their estimate is that approximately 60 per cent of new capacity in Europe will be natural gas-fired plants (CERA, 2009). The new plants, like the Claus C power plant, have high efficiency and flexible production capabilities (ramp time), and many new plants have been announced, but several are unlikely to come on grid due to financing difficulties, lack of sufficient price signals and political risk (RWE 2009).

We have collected specific information regarding major planned natural gas-fired plants and a summary of these may be found in the appendix.

The investment cost per installed generation capacity range from €0.62 million to €1.11 million. Some of the planned plants are upgrades of older plants and might be the reason for large variance in investment costs per installed capacity. All of the new planned plants are based on CCGT (combined cycle natural gas turbine technology) with high efficiency.

Currently, there is no information regarding new natural gas-fired plants in Germany. The main reason is the decreasing number of operating hours for natural gas-fired plants due to rising renewable energy production that have primary access to the grid. E.ON, the largest utility company in Germany, is not considering investing into new natural gas-fired capacity in their domestic country, and argues that such investments would not be economically viable in the face of high costs of natural gas procurement as well as Government-backing for subsidised feed-in of renewable power into the German power grid (Gas-to-Power Journal, 2012).

The International Energy Agency (IEA) states in a report from 2010 that, at a 5 per cent discount rate, the *levelised costs*[6] of generating electricity from natural gas-fired power plants vary between 28 and 45 EUR/MWh, but in most cases it is lower than 41 EUR/MWh (IEA, 2010). The cost of carbon emission is not included in the analysis from the IEA. Natural gas cost represents on average nearly 80 per cent of the total cost and up to nearly 90 per cent in some cases over the life span of the plant. Consequently, the predictions made on natural gas prices at the time of investment, are just as important as electricity prices when calculating net present value of a natural gas-fired power plant.

[6] Levelised energy cost (LEC) is the price at which electricity must be generated from a specific source to break even. The IEA calculations use generic assumptions for the main technical and economic parameters as agreed upon in the ad hoc group of experts, e.g., economic lifetime (40 years), average load factor for base-load plants (85 %) and discount rates (5 %) and). Electricity generation costs calculated are busbar costs, at the plant, and do not include transmission and distribution costs.

1.7 Recent development in the European energy market

1.7.1 The integration of the European energy markets

In 1998 the EU took a decision to aim for the establishment of a single, liberalised European energy market. At that time, each member state had its own, strictly national energy market, controlled by state-owned utility companies, and more often than not characterised by heavy subsidies for large energy users (Beckmann, 2010).

As of 2012 the European electricity market is closer to reach its targets compared to the European natural gas market. Our analysis will not describe the physical details of the European market integration process, but market integration is a dynamic element in the price, correlation and co-integration analysis.

1.7.2 European natural gas market transformation

There is an on-going process, after European Union's Third Energy Package, for the transformation of the European natural gas market to an integrated liberalised market. The model is based on natural gas wholesale markets with competitive spot trading across EU.

The natural gas trading platforms that were set up in various areas of Europe have already been seeing a great increase in wholesale spot trading in recent years. In section 2.2 we will give a comprehensive introduction to the various trading platforms for natural gas.

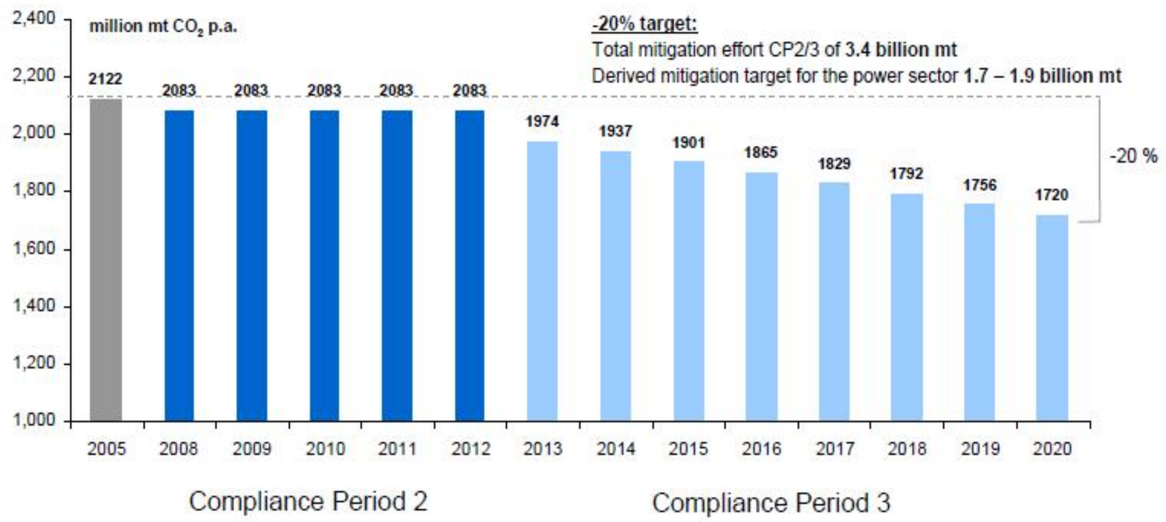
Traditionally, procurements of natural gas have been bilateral oil-linked long-run natural gas contracts, and are still covering the largest share, which have no available transparent and official daily price listed. The hub-based spot prices are often below the oil-linked prices, which were the case in the period between late 2008 and mid 2010, when spot prices in North West Europe at times were close to 50 per cent below oil-linked levels. On the other hand there is no reason, in theory, as well as in practice, why hub-based prices could not exceed oil-linked levels, that is dependent on supply and demand conditions in oil and natural gas markets (Rogers & Stern, 2011).

Several market players, organizations, regulators and studies such as from Oxford Institute for Energy believe the co-existence of oil-linked and hub-based pricing is unsustainable. The key argument is that hub-based pricing is the best price signal of supply and demand conditions in the natural gas market (Rogers & Stern, 2011). Our analysis will only use hub-based prices, because these are more transparent, obtainable and based on the EU´s target model for price discovery of natural gas.

1.7.3 EU Emission trading scheme (ETS)

The EU ETS is a market-based instrument of the EU climate policy with the target to reduce greenhouse emissions at minimal economic costs to set and achieve climate protection targets. It is the first cross-border and, at the same time, the world's largest emissions trading system. The EU ETS is based on the "cap & trade" principle, which means that the amount of greenhouse emissions is capped and the emission allowances are fully fungible and can be traded. This supports the economic incentive to reduce emissions of harmful greenhouse natural gases where it is most efficient (EEX, 2012).

Figure 6: EU-ETS emissions allowances until 2020 (RWE, 2009)



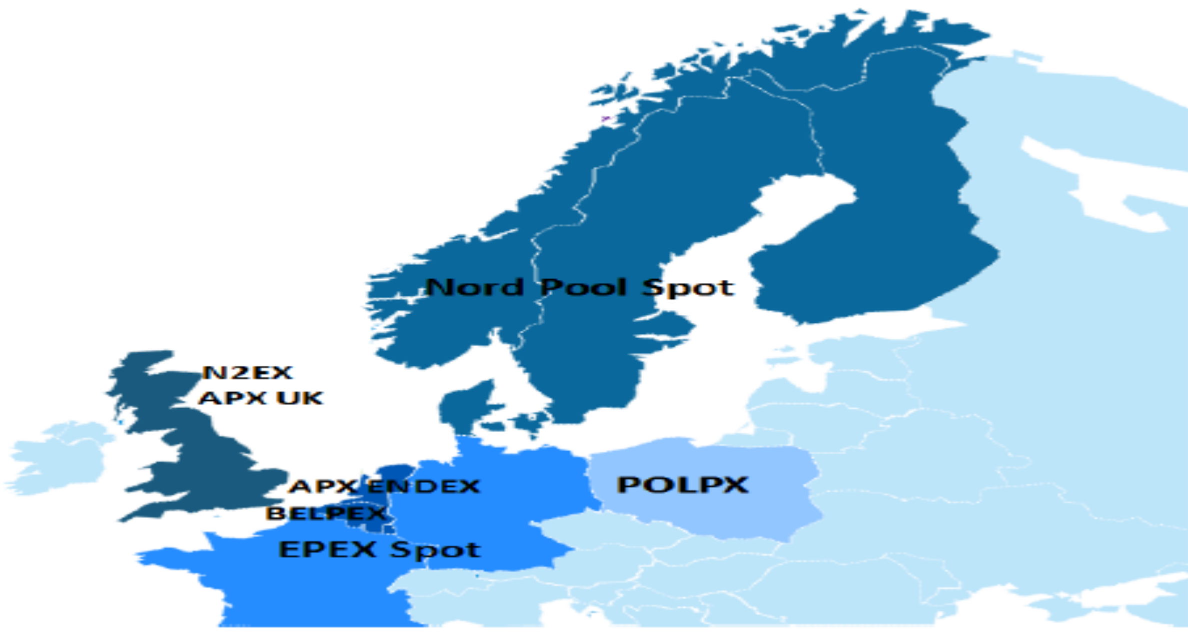
2. Spot markets

To get a better understanding of the underlying data in our analysis we will give a short introduction to the various spot prices that we have covered.

2.1 Electricity spot markets

The spot price for electricity is based on a day-ahead auction for physical delivery the next day and is a two-sided auction model. On the basis of the submitted bids, demand and supply are compared on a daily basis for every hour of the next day.

Figure 7: Electricity Spot market Europe (source: Nord Pool Spot)



The European spot markets for electricity are divided into different regional areas, for example the Nord Pool Spot area for the Nordic region. In Germany and the Netherlands the spot is cleared on the exchanges EPEX Spot and APX, respectively. In the UK there are two exchanges for spot clearing, N2EX and APX-UK. However, the electricity traded in the UK is mainly through bilateral over-the-counter (OTC) contracts, which may weaken the transparency of the listed prices.

Our data contain daily time-weighted average spot prices from EPEX (EEX) Germany, APX Power NL and APX Power the UK. The time-weighted spot price is split into base and peak load. The base load price is the average price for all hours during the day (1 to 24) and the peak load price is the average price for hours with high load (in Germany 9-20 hours, the UK and the Netherlands 8-20 hours).

The reason why we will use the average day spot for electricity is because it makes it easier to compare it with the futures contracts. The financial settlement of a futures contract is based on the average price over a given period, and the marginal account is settled on a day-to-day basis.

2.1.1 Germany/Austria Electricity Spot (EPEX SPOT/Phelix)

Phelix refers to the Physical Electricity Index and is calculated and published as Phelix Base and Phelix Peak.

2.1.2 The Netherlands Electricity Spot (APX Power NL)

The APX Index is determined on a daily basis and we have used the APX-ENDEX time average index for base-load and peak-load. This is consisted with the reporting of the Phelix spot prices.

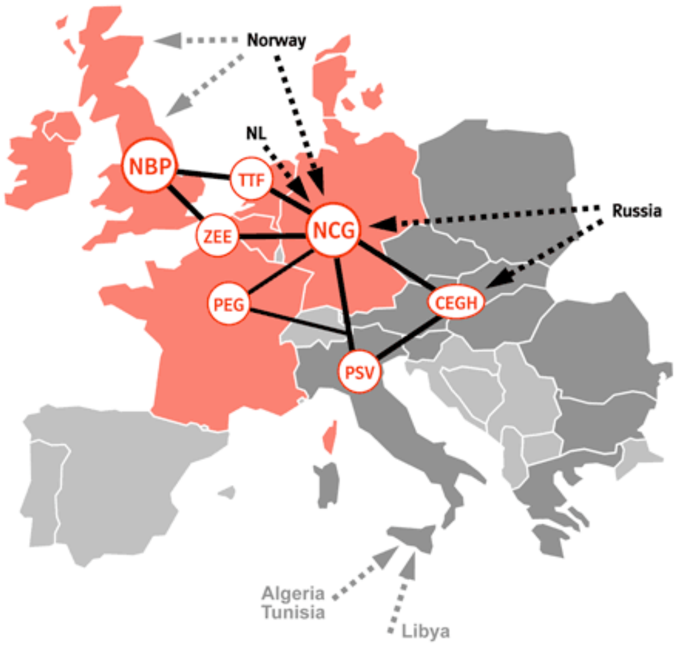
2.1.3 the UK Electricity Spot (APX Power the UK)

APX-ENDEX publishes a range of indices that can be used as a reference price for spot electricity. We have used the time-weighted APX Power UK Spot Base Load Index (and Peak Load) in our analysis as a reference price for spot in the UK.

2.2 Natural gas Spot markets

Natural gas spot trading is located at trading hubs across Europe, and is often located at the intersection of major natural gas pipelines. The hub can also be a virtual trading hub, such as the NCG (NetConnect Germany). We will analyse price data from National Balancing Point (NBP) located in the UK, NetConnect Germany (NCG) and Title Transfer Facility (TTF) located in the Netherlands in our analysis.

Figure 8: European natural gas trading hubs (E.ON Energy Trading, 2011)



In the Netherlands the virtual trading point is TTF (Title Transfer Facility) and is operated by Natural gas Transport Services (GTS), the transmission operator for the pipeline grid. Physical short-term natural gas and natural gas financial futures contracts for TTF are operated by APX-ENDEX.

NetConnect Germany (NCG) is operated by several grid companies[7]. The natural gas spot and forward contracts are operated by EEX (European Energy Exchange). Over the last two years, the German natural gas market has developed significantly and the NCG, Germany's virtual trading point, has seen the highest increase in trading volume of all the European hubs, and is consequently the fastest growing hub in Europe (E.ON Energy Trading, 2011).

[7] Bayernets GmbH, Eni Natural gas Transport Deutschland S.p.A., Open Grid Europe GmbH, GRTgaz Deutschland GmbH, GVS Netz GmbH and Thyssennatural gas GmbH

The National Balance Point (NBP) in the UK is operated by the grid owner National Grid, while the spot and OTC trading is handled by APX-ENDEX. The NBP is the most liquid natural gas-trading hub in Europe and is a virtual trading point.

2.2.1 Germany Natural Gas Spot (NCG)

We will use data on the daily reference price from NCG (NetConnect Germany) spot market reported on EEX. The NCG daily reference price is a volume-weighted index.

2.2.2 The Netherlands Natural Gas Spot (TTF)

We will use the APX TTF Day-Ahead[8] index as our reference price for spot natural gas price in the Netherlands. The APX TTF Day-Ahead index is a volume-weighted average price of all orders that are executed on the day preceding the day of delivery.

2.2.3 The UK Natural Gas Spot (NBP)

The time series to be used as a reference price for the NBP spot price is the volume-weighted APX-ENDEX NBP Day Ahead (Pence per therm).

2.3 $C0_2$ Spot (EEX)

Since 2005 EEX has offered trading of emission allowances on the basis of the EU Emission Trading scheme (EU ETS) among several exchanges.

The EU Allowances (EUA) are traded on the EEX spot and derivatives market on a continuous basis. One EU emission allowance (or EUA) grants the owner of a plant in an EU member state the right to emit one tonne of CO_2 or CO_2 equivalent during the second EU commitment period (2008 to 2012). Contracts in EU ETS have a contract volume of one EUA and are traded in EURO per EUA with two digits after the decimal point.

On the EEX derivatives market a settlement price is established on every trading day for EUA. The settlement price is established after the end of trading on every trading day based on settlement price rules.

[8] APX TTF-Hi All-Day Index (Euro/MWh)

2.4 Volume-weighted vs. time-weighted spot indices

The daily spot prices for natural gas and electricity are volume-weighted and time-weighted, respectively. The rational is linked to the physical attributes of the commodities, e.g. storage capacity. In the electricity market, supply and demand must be matched continuously and spot prices are cleared for every hour. Natural gas is storable, and most natural gas fired power plants has some storage capacity for natural gas that can exploit the flexibility of the plant to adjust the production volume. Therefore, some mismatches between the time of delivery of input factors (natural gas) and the equivalent output factor (electricity) will exist.

Since the electricity price is settled for every hour during delivery day, the time-weighted price is of most relevance, and should therefore be used. Having peak and base load prices enables us to catch price differences that are linked to day and night volumes.

Price settlement of natural gas spot prices are not done at an hourly basis, but during a day, and the volume-weighted price will therefore show the average price for a measurement unit of natural gas delivered. The volume-weighted price is therefore the preferred price representing the average price.

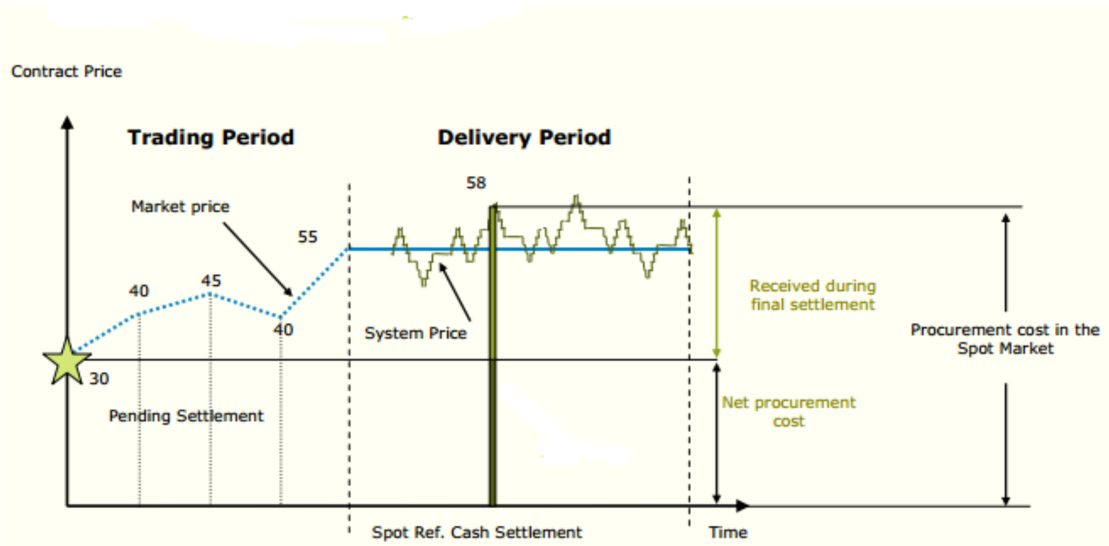
3. Futures Contracts

Futures contracts can be defined as standardised forward contracts traded at commodity exchanges where a clearing-house serves as a central counterparty for all transactions. This eliminates the counterparty risk present in over-the-counter forward contracts (Burger et al 2007). On each trading day a settlement price for the futures contract is determined and gains or losses are immediately realised at a margin account. We only consider one-month futures contracts (front month) in our sample since this is one of the most liquid futures contracts for the chosen commodities (Burger et. al., 2007). We are using futures contracts written on the respective spot prices, except CO_2 as mentioned above. We were not able to find reliable data on the front futures month contracts for electricity in the UK. The ICE exchange operates with futures contract for the UK electricity, but there is no volume traded in this contract.

Futures contracts are commonly used as a risk management tool to get more predictable revenues and costs. For example Statkraft, the largest electricity utility in Norway, states in the 2011 Q4 interim report that they secure 40 per cent of their electricity production in the financial market.

The settlement of futures contracts involves both a daily mark-to-market settlement and a final spot reference cash settlement, after the contract reaches its due date. Mark-to-market settlement covers gains or losses from day-to-day changes in the market price of each contract (NASDAQ OMX, 2011).

Figure 9: Futures contract settlement (NASDAQ OMX, 2011)



This principle for futures contract settlement applies for EEX, APX-ENDEX and ICE. There are minor differences in rules that determine the settlement price at the end of each trading day. The general principle is that the spot price (system price) is the reference price for settlement as shows in figure 8.

3.1.1 Generic time series

Since the variance of futures contracts increases when they approach delivery, known as the Samuelson effect (Samuelson, 1965), we will not attempt to analyse the futures prices directly. Instead we will use generic time-series. Generic time series are artificially constructed so that all prices in the series have approximately the same time to maturity. Since we are using front month generic series, prices shown in January are the futures prices with delivery in February and so on. By using the generic series we are able to analyse the data material without concerns of the Samuelson effect.

4. Data set

The data set consist of daily power and natural gas prices (both spot and one month futures) from APX-ENDEX, ICE and EEX. The data set has approximately 20 000 observations in the period 2005-08-04 to 09-01-2012, and consist of 20 different price variables. One variable covering the whole sample has 1678 observations. All time series are downloaded from Thomson Reuters DataStream, and converted into appropriate and comparable measures. For more information regarding data manipulation and conversion of measurement units see appendix 9.17 and 9.1.8.

The sample period is based on the implementation of the EU-ETS trading scheme. European Union trading scheme commenced operation on 1 January 2005, although national registries were unable to settle transactions for the first few months (Environment Agency UK, 2012). The EUA (EU Allowance for CO_2) began trading on the EEX (European Energy Exchange) 2005-08-04 and is therefore chosen as our sample starting point.

Sub-periods

The sub-periods are first of all chosen to consider the stages of the implementation of EUA trading scheme.

P_1: 2005-08-04 - 2007-01-26 (387 observations)

P_2: 2007-01-29 - 2009-01-15 (514 observations)

P_3: 2009-01-16 - 2012-01-09 (777 observations)

We can clearly see that “there are” three periods; before, under, and after the prices crashed in figure 10. Anyhow, it is also a reflection of the two EU-ETS phases until now;

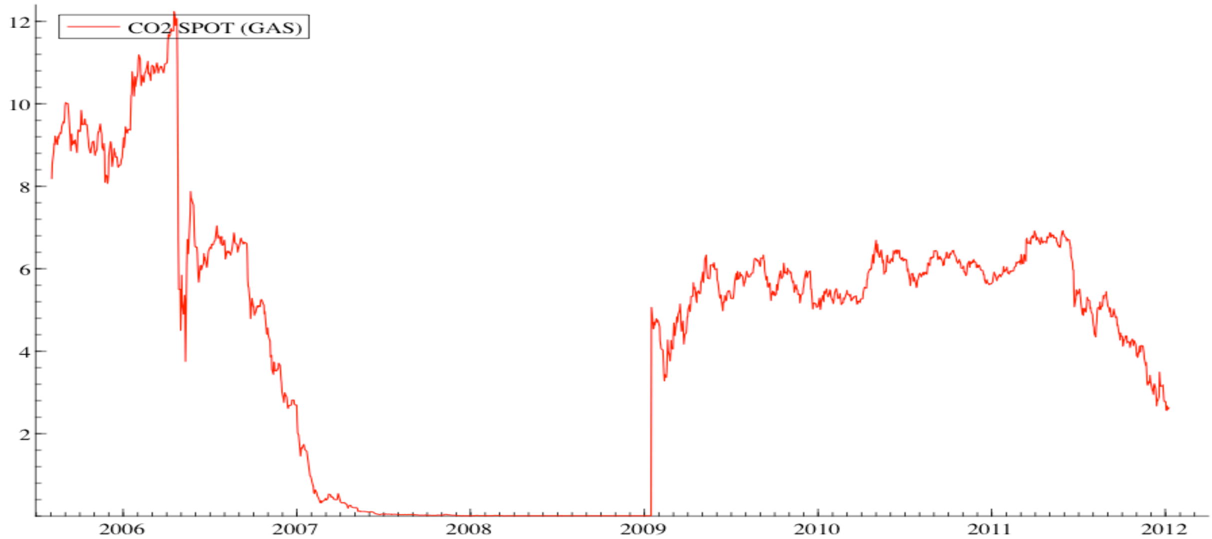
- EU-ETS Phase 1 (2005-2008)
- EU-ETS Phase 2 (2008-2012)

Figure 10 shows how the EUA price collapsed at the end of 2006. Chevallier et.al (2008) point out two main reasons for the collapse:

1) After a price "collapse" on April 2006 due to the publication of the 2005 verified emissions data by the EC, the EUA spot price with maturity December 2007 did asymptotically decreased towards zero because of the impossibility to transfer allowances to the next period.

2) The allocation of allowances did not achieve its objective as some sectors such as power producers were far more constrained than other participants who received an amount of allocation close to their business-as-usual scenario.

Figure 10: CO_2 spot price for an average natural gas-fired plant (EUR/MWh)[9]



[9] The price of CO2 for natural gas is calculated using the benchmark emission intensity factor of 0.411 t CO2/MWh

5. PART 1:

Short-run relationships

In part 1 we aim to explore and analyse return, volatility, and correlation developments in electricity, natural gas, and CO_2 markets during the seven years gone since the EU-ETS first was established.

5.1 Descriptive statistics

We will start the short-run relationship analysis by highlighting the distributional properties of the different variables. These statistics have not been adjusted for seasonal effects. However, as mentioned earlier, the Samuelsson effect has been removed from the front series. In should also be pointed out the properties are for daily observations.

Table 2: Full sample return distributions[10]

Full sample (EUR/MWh)	Mean	Volatility	Skewness	Excess Kurtosis	Normality test
NL EL SPOT BASE	0,0 %	18,1 %	0,01	13,69	2510,1 (**)
NL EL SPOT PEAK	0,0 %	21,5 %	-0,01	14,75	2739 (**)
NL EL FRONT MONTH BASE	-0,2 %	2,1 %	0,04	6,56	1004,2 (**)
NL EL FRONT MONTH PEAK	---	---	---	---	---
DE EL SPOT BASE	0,0 %	20,4 %	-0,09	14,73	2727,7 (**)
DE EL SPOT PEAK	0,0 %	23,0 %	0,04	12,11	2171,2 (**)
DE EL FRONT MONTH BASE	-0,1 %	2,4 %	0,54	15,36	2635,7 (**)
DE EL FRONT MONTH PEAK	---	---	---	---	---
UK EL SPOT BASE	0,0 %	17,4 %	0,41	5,76	747,39 (**)
UK EL SPOT PEAK	0,0 %	21,1 %	0,33	4,55	553,73 (**)
NL TTF SPOT	0,0 %	6,4 %	-1,36	84,93	16007 (**)
NL TTF FRONT MONTH	-0,2 %	2,5 %	0,16	4,95	672,33 (**)
DE Spot GAS (Proxy)	0,0 %	5,9 %	-1,65	122,56	23108 (**)
DE Gas Front (Proxy)	-0,1 %	1,8 %	1,99	25,93	2033,9 (**)
UK NBP SPOT	0,0 %	8,8 %	1,41	21,93	2622,6 (**)
UK NBP FRONT MONTH	-0,3 %	3,3 %	0,75	6,82	727,77 (**)
CO2 Spot	-0,1 %	17,6 %	28,87	1047,60	505110 (**)

[10] $Mean = \frac{\sum_i^N x_i}{N} = \mu$, $Vol = \frac{\sum_i^N (x_i - \mu)^2}{N} = \sigma$, $Skew = \frac{\frac{\sum_i^N (x_i-\mu)^3}{N}}{\sigma^3}$, $Excess\ Kurtosis = \frac{\frac{\sum_i^N (x_i-\mu)^4}{N}}{\sigma^4}$

Table 3: Period 1 return distribution

P1 (EUR/MWh)	Mean	Volatility	Skewness	Excess Kurtosis	Normality test
NL EL SPOT BASE	0,0 %	25,1 %	-0,03	4,25	140,33 (**)
NL EL SPOT PEAK	0,1 %	31,6 %	0,04	4,45	149,66 (**)
NL EL FRONT MONTH BASE	-0,2 %	2,6 %	-0,08	4,75	163,08 (**)
NL EL FRONT MONTH PEAK	---	---	---	---	---
DE EL SPOT BASE	0,0 %	27,3 %	-0,11	10,86	473,76 (**)
DE EL SPOT PEAK	0,0 %	31,7 %	0,11	9,36	394,83 (**)
DE EL FRONT MONTH BASE	-0,2 %	3,0 %	-1,04	5,44	90,511 (**)
DE EL FRONT MONTH PEAK	---	---	---	---	---
UK EL SPOT BASE	-0,1 %	20,3 %	1,03	7,37	155,77 (**)
UK EL SPOT PEAK	0,0 %	24,5 %	0,85	5,17	105,74 (**)
NL TTF SPOT	0,0 %	10,4 %	-1,36	51,39	2239,5 (**)
NL TTF FRONT MONTH	-0,5 %	2,0 %	-0,54	4,32	111,81 (**)
DE Spot GAS (Proxy)	0,0 %	10,4 %	-1,36	51,39	2239,5 (**)
DE Gas Front (Proxy)	-0,4 %	2,2 %	1,34	17,40	489,69 (**)
UK NBP SPOT	0,0 %	14,1 %	1,55	11,42	173,17 (**)
UK NBP FRONT MONTH	-0,6 %	4,1 %	1,55	9,69	128,10 (**)
CO2 Spot	-0,5 %	5,0 %	0,70	32,36	1515,9 (**)

Table 4: Period 2 return distribution

P2 (EUR/MWh)	Mean	Volatility	Skewness	Excess Kurtosis	Normality test
NL EL SPOT BASE	0,1 %	19,5 %	-0,14	20,18	1252,6 (**)
NL EL SPOT PEAK	0,1 %	23,4 %	-0,21	18,71	1145,9 (**)
NL EL FRONT MONTH BASE	-0,2 %	2,4 %	-0,08	4,05	168,77 (**)
NL EL FRONT MONTH PEAK	---	---	---	---	---
DE EL SPOT BASE	0,2 %	21,4 %	-0,35	3,72	133,52 (**)
DE EL SPOT PEAK	0,2 %	25,7 %	-0,22	4,28	175,77 (**)
DE EL FRONT MONTH BASE	-0,1 %	2,9 %	1,58	16,46	442,03 (**)
DE EL FRONT MONTH PEAK	---	---	---	---	---
UK EL SPOT BASE	0,2 %	21,1 %	0,02	2,31	73,761 (**)
UK EL SPOT PEAK	0,2 %	25,7 %	0,00	2,02	60,087 (**)
NL TTF SPOT	0,1 %	5,5 %	0,19	3,51	133,31 (**)
NL TTF FRONT MONTH	-0,2 %	3,0 %	0,59	4,86	165,78 (**)
DE Spot GAS (Proxy)	0,1 %	4,4 %	0,38	6,03	266,64 (**)
DE Gas Front (Proxy)					
UK NBP SPOT	0,1 %	6,8 %	0,09	2,65	90,294 (**)
UK NBP FRONT MONTH	-0,2 %	3,4 %	0,42	3,08	94,934 (**)
CO2 Spot	-1,0 %	13,5 %	0,69	14,25	735,03 (**)

Table 5: Period 3 return distribution

P3 (EUR/MWh)	Mean	Volatility	Skewness	Excess Kurtosis	Normality test
NL EL SPOT BASE	-0,1 %	11,9 %	0,53	7,78	512,70 (**)
NL EL SPOT PEAK	-0,1 %	11,8 %	0,49	6,83	436,48 (**)
NL EL FRONT MONTH BASE	-0,1 %	1,5 %	0,82	9,28	533,30 (**)
NL EL FRONT MONTH PEAK	---	---	---	---	---
DE EL SPOT BASE	-0,1 %	15,0 %	0,51	33,79	3124,4 (**)
DE EL SPOT PEAK	-0,1 %	14,2 %	0,61	15,89	1281,5 (**)
DE EL FRONT MONTH BASE	-0,1 %	1,6 %	1,69	16,14	536,03 (**)
DE EL FRONT MONTH PEAK	---	---	---	---	---
UK EL SPOT BASE	-0,1 %	12,4 %	0,08	3,62	209,58 (**)
UK EL SPOT PEAK	-0,1 %	15,1 %	0,13	3,51	198,33 (**)
NL TTF SPOT	0,0 %	3,9 %	-0,56	5,94	337,02 (**)
NL TTF FRONT MONTH	-0,1 %	2,4 %	-0,28	3,38	175,57 (**)
DE Spot GAS (Proxy)	0 %	2,77 %	1,40	15,95	742,12 (**)
DE Gas Front (Proxy)	-0,1 %	0,7 %	6,07	97,80	739,16 (**)
UK NBP SPOT	0,0 %	6,2 %	-0,39	19,36	1717,8 (**)
UK NBP FRONT MONTH	-0,1 %	2,8 %	-0,02	2,60	129,11 (**)
CO2 Spot	0,7 %	23,2 %	27,34	754,30	579530 (**)

5.1.1 Mean return

In tables 3 to 6 we found a tendency, in the sign of the average return, among the commodities in the different sub-samples; either most of the series exhibit a positive average return or a negative average return. This is an indication that during a given time interval, these commodities will drift in the same direction, and possible some connecting forces co-exist. For example a negative drift can be explained by factor such as lower demand after the financial crisis and/or lower average production cost due to the fact of increased share of wind and photovoltaic production in Germany.

5.1.2 Volatility

Tables 3 to 6 show that the spot electricity has an immense volatility, where the daily volatility of the spot electricity returns are about 20 per cent. Peak-load are slightly higher than base-load volatility returns. The volatility is not pure uncertainty, but a reflection of the fundamental factors of the electricity market that changes rapidly from day to day. Adjusted for "known-unknowns" like planned operational maintenance, planned capacity and various seasonal effects, the volatility would be somewhat lower.

We observe that the volatility of the front futures prices (both natural gas & electricity) is considerably lower compared to the spot prices. The front futures price is the expected average price for spot delivery the next month without capacity congestion, unexpected outages and other unexpected conditions. A change in the front futures price is therefore a change in the excepted average spot price for the next month. Consequently the volatility is lower in the futures market and a direct comparison of spot and futures volatility is invalid.

As we observed with the average returns there is a clear tendency that almost all series have their highest volatility in the first period and the lowest in the last. This is an additional signal of price linkage between returns of the different series. We could therefore form a hypothesis testifying that at times where there is "turmoil" in the natural gas markets with high volatility, we would similarly observe high volatility in the electricity market and vice versa. Similar hypothesis could be made between for example the electricity markets in the Netherlands and Germany.

The reason of reduced volatility may be fundamental factors such as increased capacity, lower demand and increased market integration that lowers price spikes. A second explanation is that market players have become more mature.

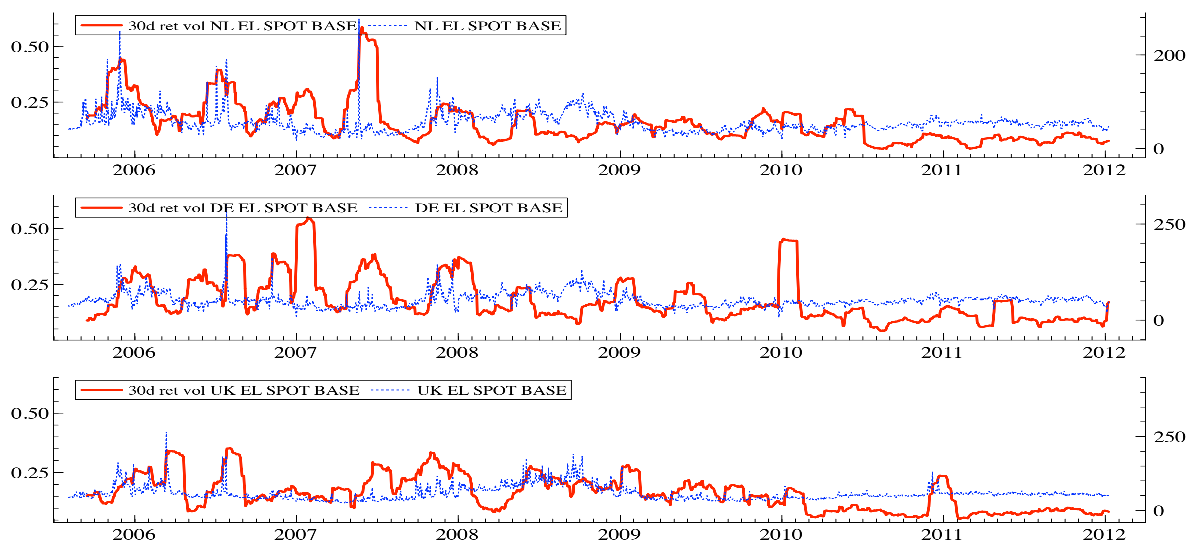
5.1.2.1 Impact of CO_2 prices and its volatility

If we then look at the connection between the volatilities of electricity and natural gas returns and their relation to the CO_2 volatility in the three periods, we see no connection of high volatility in CO_2 prices would cause higher volatility in the two energy prices. In period 1 we see that CO_2 volatility is at its lowest, at the same time as natural gas and electricity prices have their lowest volatility. In period 3 we see opposite results; high volatility in CO_2 returns and lower in natural gas and electricity returns. It should be mentioned that we do not infer causality in this observation, but we limit our self to highlight these observations. In addition we note that CO_2 return skewness is very high in period 3, which means that the estimate of the standard deviation (volatility) will overestimate the actual risk (Bodie, Kane, & Marcus, 2009).

5.1.2.2 Rolling volatility

To get a better understanding of how the volatility has developed during the sample, we have constructed series for a 30-day rolling volatility.

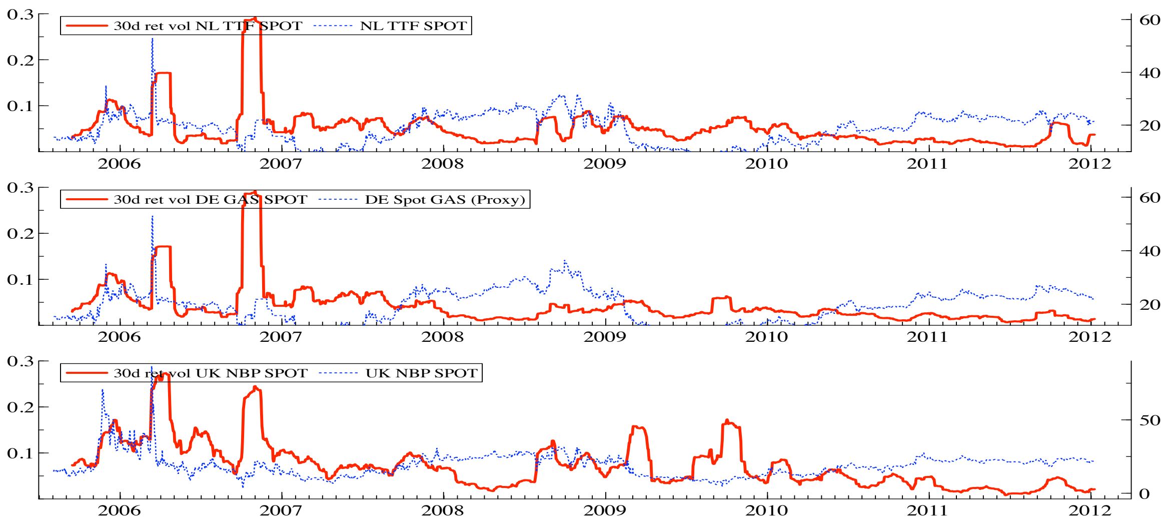
Figure 11: 30 day rolling volatility EL Spot



The red lines in figure 11 show the development in the 30-day rolling volatility for the spot electricity returns in the Netherlands, Germany, and the U.K. For all three countries it seems like the lower average volatility in the last period is mostly due to less seasonal fluctuations in the volatility, resulting in a more stable volatility. This is supporting our argument in section 5.1.2 where we stated that the average lower volatility in period 3 is most likely due to reduced capacity constraints that increase the well-functioning of the markets.

Visually, it also seems like there is a very strong connection between the volatility in the three electricity markets, which was expected. However, it is difficult to tell from these plots whether the connection is stronger in the last part of the sample, but this will be described in more detail in section 6.2.2. A spike on a single day will also effect the 30-day rolling volatility for exactly 30 days. For example following the sharp increase in the electricity in Germany on July 2, 2006 and the subsequently increase in relative volatility. On July 2, 2006, the daily average base-load price for electricity changed from 100 EUR/MWh the previous day to 301 EUR/MWh the next day.

Figure 12: 30 day rolling volatility NATURAL GAS Spot



In figure 12 we plot the similar series for the spot natural gas markets in the same three countries, and in contrast to the electricity markets it seems like the higher volatility in the first period is due to specific events, rather than stronger seasonal fluctuations. However, turmoil in any of the markets has a tendency to be present in the two others at the same time, even though there are clear exceptions, as in the UK in 2009.

If we plotted the same series for the front markets we would have found similar results as in the spot, but with lower volatility in general.

5.2 Correlations

After the visual discussion in section 5.1 about the relationships between the various series, a natural next step is to investigate connections by statistical measures, where we start by estimating correlation in returns. These measures would answer questions regarding the short-run relationship between the commodities.

Our expectation was that the increased transparency of prices would lead to tighter integration, and therefore strong correlation in later parts of our samples. Except from calculating regular correlations between two time series in a given time interval, we will strengthen the analysis of short-run relationships by performing a 100 days rolling correlation in return analysis. This analysis will give support to the importance of performing long-run relationship analysis, and whether seasonalties are an important part that should be accounted for in those relationships.

Thereafter, we will investigate the discussed relationships in volatility further, by calculating correlations between 30-day rolling volatilities.

5.2.1 Correlation returns

5.2.1.1 Correlation returns full sample

The return correlations for the full sample are listed in table 7. Naturally we find the highest correlations between spot base load and peak load prices, which range between 94 per cent and 99 per cent. The fact that these correlations are high is not by itself interesting at all, but seen together, it indicate less difference between peak load and base load price, on average, in U.K. than in Germany and the Netherlands.

Table 6: Correlation returns full sample

Correlation return Full	NL TTF Spot	NL TTF FRONT MONTH	NL EL SPOT BASE	NL EL SPOT PEAK	NL EL FRONT MONTH BASE	UK NBP SPOT	UK NBP FRONT MONTH	UK EL SPOT BASE	UK EL SPOT PEAK	DE EL SPOT BASE	DE EL SPOT PEAK	DE EL FRONT MONTH BASE	CO2 SPOT (GAS)	DE SPOT GAS	DE GAS FRONT
NL TTF Spot	1														
NL TTF FRONT	4 %	1													
NL EL SPOT BASE	7 %	-1 %	1												
NL EL SPOT PEAK	6 %	-3 %	95 %	1											
NL EL FRONT BASE	4 %	35 %	1 %	1 %	1										
UK NBP SPOT	8 %	31 %	3 %	2 %	12 %	1									
UK NBP FRONT	2 %	72 %	-3 %	-5 %	31 %	39 %	1								
UK EL SPOT BASE	-1 %	8 %	12 %	12 %	1 %	23 %	14 %	1							
UK EL SPOT PEAK	-2 %	6 %	12 %	12 %	0 %	21 %	13 %	99 %	1						
DE EL SPOT BASE	4 %	-2 %	47 %	45 %	-2 %	0 %	-1 %	11 %	11 %	1					
DE EL SPOT PEAK	4 %	-3 %	46 %	47 %	-3 %	1 %	-3 %	13 %	13 %	94 %	1				
DE EL FRONT	5 %	32 %	3 %	3 %	72 %	14 %	31 %	1 %	1 %	5 %	6 %	1			
CO2 SPOT (GAS)	2 %	0 %	-3 %	-3 %	5 %	1 %	1 %	-2 %	-2 %	-4 %	-5 %	3 %	1		
DE SPOT GAS	77 %	23 %	4 %	3 %	10 %	12 %	20 %	-1 %	-1 %	1 %	1 %	11 %	-1 %	1	
DE GAS FRONT	6 %	63 %	-3 %	-4 %	21 %	23 %	51 %	6 %	5 %	-1 %	1 %	22 %	5 %	7 %	1

If we instead look at the correlations between the spot prices of natural gas and electricity in the separate countries, we would at least expect to find positive correlation, and that the magnitude some how could be described by the relative dependence on natural gas in the electricity generation mix. As expected the correlations are positive, but the magnitude are more remarkable. From table 1 (Electricity production by source), we know that the Netherlands has the greatest dependency on natural gas (61 per cent), followed by U.K. (44 per cent), and Germany (13 per cent). For Germany we observe a correlation of 1 per cent. Practically, there is no correlation in returns between German natural gas and electricity in the spot markets. However, in the front market there is a correlation coefficient of 22 per cent, which might be an indication that there is a connection on a semi-long term (futures for delivery during a month). The front series also exhibit less noise (short-term price spikes) and therefore we also see a stronger connection in the semi-long term. Generally we cannot compare the spot and front correlation coefficients direct, but we can state that the connection is stronger in the front market.

Next, and contradicting our expectation, we find a correlation coefficient in the Netherlands of only 7 per cent between spot natural gas and electricity returns. Again, there is a much stronger correlation between front natural gas and electricity returns (35 per cent), again indicating a relationship on a longer term. In the U.K., the correlation between the spot natural gas and electricity returns is 23 per cent, which is distinctive from the two other countries.

If we look at cross-country correlations we see that there are tighter connection between returns in Germany and the Netherlands than any of the two and the U.K. in the spot markets. Between Germany and the Netherlands the correlations are 47 per cent and 77 per cent for electricity and natural gas respectively. Note that the high correlation in natural gas is partly artificial due to the use of a proxy natural gas series in Germany for the first period. Between the UK and the two other countries the correlation is close to 10 per cent in both natural gas and electricity spot markets.

The last correlations are between the various natural gas and electricity series and the CO_2 series. We note that these are practically zero but due to the collapse in the second period these measures only give meaning in the first and last period.

5.2.1.2 Correlation returns sub-periods

In the sub-periods[11] we see that for the first and second time period there are almost perfect correlations between base and peak load spot electricity returns, while there is a small drop to 87 per cent in both the Dutch and German markets in the third period.

Concerning the changes in correlations between natural gas and electricity within the countries, there are no clear trends shared by the three countries. While there are slight increases in in the correlations between spot natural gas and electricity in Germany and the Netherlands, it is a steep decline in the U.K. In the first time period the correlation was 38 per cent in the U.K. dropping to 16 per cent and 8 per cent in the following two periods. For the similar front correlation the picture is also mixed, and it is difficult to see a connection between the developments in the front and spot markets return correlations. We observe a movement towards stronger correlation in the Netherlands and weaker in Germany.

Then, in the cross-country correlations we find in the spot electricity market a fairly stable correlation with a small increase between the Netherlands-U.K. and Germany-U.K, but still much weaker than between the Netherlands-Germany. In the connection between the last two countries we observe that the front electricity correlation has increased from 56 per cent in the first period to 87 per cent in the last. This must be seen in connection with tighter integration between these countries due more efficient use of cross-border capacity as described earlier.

The cross-boarder connection in natural gas returns shows what we commented above. In the first period the correlation is of course 100 per cent between spot natural gas returns in

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[11] Tables of results can be found in the appendix.

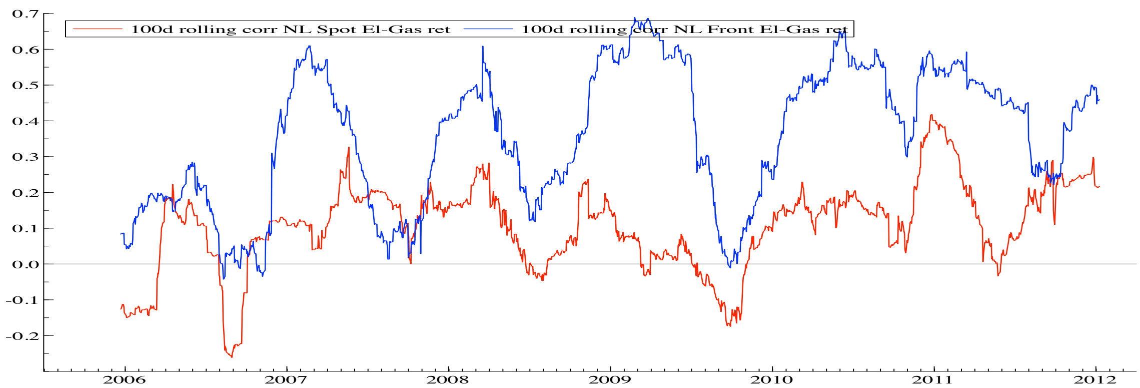
Germany in the Netherlands, but now as the correlation only is 5 per cent in the last, it seems like using Dutch natural gas prices as a proxy for German prices is no longer perfect when comparing returns. The correlation between the spot natural gas returns in the Netherlands and the U.K. are stable and low, while for the German-U.K. connection the correlation has increased from 8per cent in the first to 30 per cent in the last period. Considering the front natural gas connection the natural gas market picture become quite confusing, so it is difficult to see any connection by the correlation changes in the spot and front market.

Since we found it challenging to discover clear and lasting trends in the correlation developments between electricity and natural gas, we would like to examine this further. Hence, in the next section we will plot and analyse a 100 days rolling correlation between returns.

5.2.2 100 days rolling correlation in returns

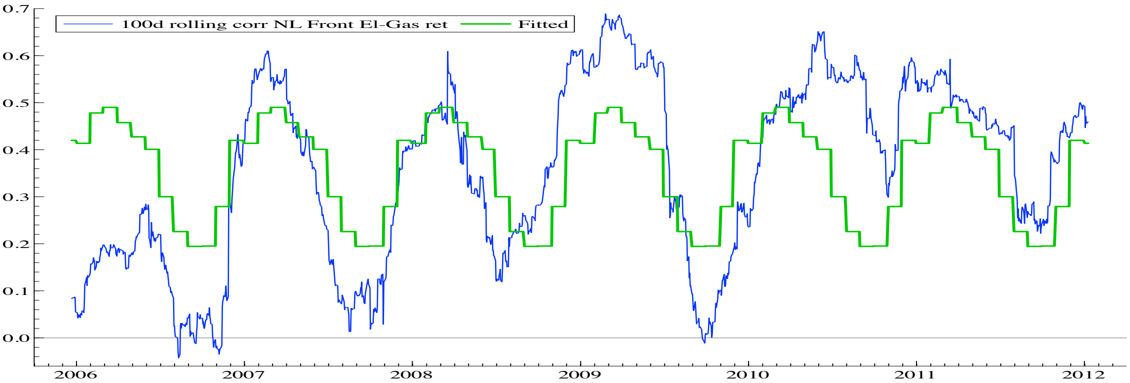
Analysing the connection between natural gas and electricity is of special interest since we want to have a detailed understanding of the spark spread. Therefore the following figure shows a 100 days rolling correlation in returns between electricity and natural gas in both spot and front markets in the Netherlands. Similar plots on the British and German variables are found in the appendix.

Figure 13: 100 days rolling correlation in returns



This plot reveals something interesting. Especially in the front market there are strong seasonality in this correlation. We interpret this as during winter months, natural gas is much more often the marginal production source on the merit order since demand is higher. To see this more clearly, we have plotted the fitted values of a regression with the blue series above as the left-hand-side variables, and only dummies on the right, one for each month.

Figure 14: 100 days rolling correlation in returns with dummies



Blue line: $z_t = corr(\{r_{t-100}^{el}, \dots, r_t^{el}\}, \{r_{t-100}^{gas}, \dots, r_t^{gas}\})$

Green line: $\hat{z}_t = \alpha + \beta_1 Jan_t + \beta_2 Feb_t + \cdots + \beta_{11} Nov_t + \varepsilon_t$

As we see, only regressing on dummies gives a fairly good fit indicating strong seasonal effects. Natural gas storage facilities also play a crucial role in balancing supply and demand, and there are substantial seasonal effects. In table 7 we have listed the value of the dummy coefficients and added the constant value. Thus, the table shows the average 100 days rolling correlations for each month. The largest value is the March dummy coefficient. That implies that the highest correlation between front electricity and gas is from December to March. Similarly, the lowest correlation is from June to September. During summer month excess production is injected into storage and in the winter months the storage natural gas is withdrawn to supply any excess load (Alexander, 1999).

Table 7: Results of regression in figure 14

Constant + Dummy			
Jan	42 %	Jul	30 %
Feb	48 %	Aug	22 %
Mar	49 %	Sep	19 %
Apr	46 %	Oct	19 %
May	43 %	Nov	28 %
Jun	40 %	Des	42 %

If seen together with the similar figures in the appendix for the two other countries, there is again no clear trend in how the correlations between natural gas and electricity changes, depending on the three sup-periods we have chosen.

5.2.3 Summary of return correlations

To sum up our results of correlation in returns we found that base and peak-load returns are strongly correlated, because the two series are interrelating. The two spark spread commodities are only weakly correlated in spot returns. However, it is somehow better in the front markets, where it also is a strong seasonal correlation component. Cross-boarder correlation in electricity returns is only present between Germany and the Netherlands, while for natural gas the picture is very mixed.

5.2.4 Correlation in volatility

We have now described the short-run connection in returns thoroughly, and before we end the short-run relationship section, we find it valuable to see these connections in volatility terms. In table 8 we have listed correlations between all (el: base load) spot series 30 days rolling volatility. By doing this we intend to discover possible effects of cross market/country turmoil properties, that might suggest common influencing parameters not captured by return connections alone. If the correlation is high we have an argument that the prices are connected even though return connections are low.

In the electricity market alone the correlation coefficients are rather low in period 1 ranging between 4 and 31 per cent. However, we find a clear shift towards higher correlation ranging between 47 and 61 per cent in period 3. Compared to correlation in returns, this indicates that there actually are some common behaviour or similar forces affecting British, German and Dutch spot electricity prices. For example, it may be similar seasonal fluctuations in demand, but also an evidence of tighter market integration.

In the analysis of correlation in natural gas returns we found some confusing results, not revealing any clear statement of strong connection, opposed to what was expected. After the results in table 8 we can at least say that the natural gas markets are connected to some extent. With correlations between 64 and 87 per cent we are confident to argue that we at least found some evidence of what we expected.

Table 8: Volatility correlation

Correlation Full	30d ret vol CO2 SPOT	30d ret vol NL EL SPOT BASE	30d ret vol DE EL SPOT BASE	30d ret vol UK EL SPOT BASE	30d ret vol NL TTF SPOT	30d ret vol DE GAS SPOT	30d ret vol UK NBP SPOT
30d ret vol CO2 SPOT	100 %						
30d ret vol NL EL SPOT BASE	11 %	100 %					
30d ret vol DE EL SPOT BASE	28 %	66 %	100 %				
30d ret vol UK EL SPOT BASE	13 %	40 %	43 %	100 %			
30d ret vol NL TTF SPOT	-3 %	28 %	24 %	29 %	100 %		
30d ret vol DE GAS SPOT	-2 %	32 %	26 %	27 %	96 %	100 %	
30d ret vol UK NBP SPOT	-5 %	38 %	28 %	47 %	76 %	76 %	100 %
Period 1							
30d ret vol CO2 SPOT	100 %						
30d ret vol NL EL SPOT BASE	-6 %	100 %					
30d ret vol DE EL SPOT BASE	30 %	31 %	100 %				
30d ret vol UK EL SPOT BASE	-49 %	11 %	4 %	100 %			
30d ret vol NL TTF SPOT	-21 %	-16 %	-10 %	3 %	100 %		
30d ret vol DE GAS SPOT	-21 %	-16 %	-10 %	3 %	100 %	100 %	
30d ret vol UK NBP SPOT	-13 %	-13 %	-13 %	36 %	80 %	80 %	100 %
Period 2							
30d ret vol CO2 SPOT	100 %						
30d ret vol NL EL SPOT BASE	-40 %	100 %					
30d ret vol DE EL SPOT BASE	-7 %	71 %	100 %				
30d ret vol UK EL SPOT BASE	-78 %	46 %	17 %	100 %			
30d ret vol NL TTF SPOT	-40 %	6 %	-4 %	26 %	100 %		
30d ret vol DE GAS SPOT	-44 %	-10 %	-6 %	29 %	64 %	100 %	
30d ret vol UK NBP SPOT	-51 %	-8 %	-29 %	37 %	87 %	76 %	100 %
Period 3							
30d ret vol CO2 SPOT	100 %						
30d ret vol NL EL SPOT BASE	24 %	100 %					
30d ret vol DE EL SPOT BASE	9 %	61 %	100 %				
30d ret vol UK EL SPOT BASE	13 %	49 %	47 %	100 %			
30d ret vol NL TTF SPOT	23 %	60 %	36 %	55 %	100 %		
30d ret vol DE GAS SPOT	22 %	45 %	27 %	56 %	75 %	100 %	
30d ret vol UK NBP SPOT	29 %	38 %	20 %	49 %	70 %	76 %	100 %

Concerning the correlation coefficients between natural gas and electricity volatility, the spark spread variables, we observe that there has been a movement toward stronger connection in the last period. In period 1 the volatility correlation was negative in the Netherlands (-0.16) and Germany (-0.10), while it was positive in the UK (0.36). We observe almost the same picture in period 2 with a small positive correlation in the Netherlands (0.06), negative in Germany (-0.06) and almost unchanged in the UK (0.37). In the last period the picture changes completely, with a strong positive volatility correlation in the Netherlands (0.60), Germany (0.27) and the UK (0.49). Overall the correlation in volatility has been relative stable and strong in the UK in all three periods, but rather unstable in the two other countries. It seems that in the UK, the natural gas volatility is, and has been, one of the key drivers for the uncertainty in the spot electricity price. For the two other countries natural gas volatility only play that role in the last period.

Last, the correlation in volatility against CO_2 is showing similar movements as correlation between natural gas-electricity volatility. In the first period, the correlation is negative for all spot volatilities except the German that is 30 per cent. In period 3 all are positive, indicating that CO_2 quotas are influencing natural gas and electricity markets, or that the CO_2 price partly in determined by forces of natural gas and electricity. Surprisingly, the lowest correlation is found for the German spot electricity volatility, moving the opposite way compared to period 1. We have not reached a meaningful explanation of this. On average we find that natural gas are more linked to CO_2 than electricity in terms of correlation in rolling volatility. The last finding will be analysed further in the section 7.6 about Granger causality.

5.3 Part 1 summary

In part 1 we started by presenting the first and second movement of the return distribution of the various time series. The first indication of a connection between the commodities was clear trends in the sign of mean returns in different time intervals. Later in part 1 we analysed correlation in returns and found strong correlation between variables of the same commodity. At the same time it was difficult to use these measures to establish clear arguments of tighter connection, on a daily basis, between electricity, natural gas, and CO_2 prices with respect to the three time intervals we have chosen. However, by the analysis of the mean returns and their relations we have stressed the importance to investigate long-run relationships, which will be our focus in part 2. We also discovered that there were strong seasonalties in the relationship between electricity and natural gas, which suggests that these properties must be accounted for in part 2.

Furthermore, we analysed the second movement, volatility, of the distributions deeply. Here it seemed clear that if it was high volatility in the electricity market in one country, the same would be true in the two other countries, and visa versa. The same connections were found in the natural gas markets. When we looked at this connection between natural gas and electricity prices, high volatility in one market was not clearly shared by the other market. Nevertheless, in the last period we found a correction, were the correlation in 30 days rolling volatility between natural gas and electricity were strong and positive. Last, we saw this in relation with volatility in the CO_2 price and found that in general there was stronger correlation between volatility in electricity and gas markets and volatility in the CO_2 price in the last period, compared to the firsts. An intuitive explanation of that may be the recent macro economical turmoil, which affects all price series.

So, considering the difficulties of discover evidence of tighter market integration by analysing returns we believe that the volatility analysis revealed that there are some shared forces affecting prices of physically linked commodities, such as natural gas, electricity and CO_2 allowances.

By the analysis of part 1 we have established a motivation to explore the long-run relationships between these commodities and as we not have approached any attempt to infer causality between them. Causality between the commodities will be an important section of the long-run relationship analysis of part 2.

6. Part 2:

Long-run relationships

As we move to study long-run relationships between the prices of electricity, natural gas and CO_2, and disclose the dynamics of these relationships, we would highlight that the understanding of these relationships is of great relevance to many markets players that are exposed to the difference between the electricity price, natural gas price and CO_2. The difference in price between the commodities is known as the clean spark spread.

To further explore the spark spread relationships we clarified in part 1 we need to look beyond the short-terms dynamics of return, volatility, and correlations. We need to analyse the variables on level form, which can give valuable information on long-run dynamics between energy commodities. If we observe mean-reversion in the relationship between electricity and natural gas, we can argue that the spark spread is "tied together" by long-run forces.

The analysis of part 2 is based on regression analysis of time-series variables. To get valid results with time-series we need to stress the concept of stationary variables and avoiding spurious regression. The next sections will give a short introduction to these concepts, but before that we will give a brief presentation of the variables on level form.

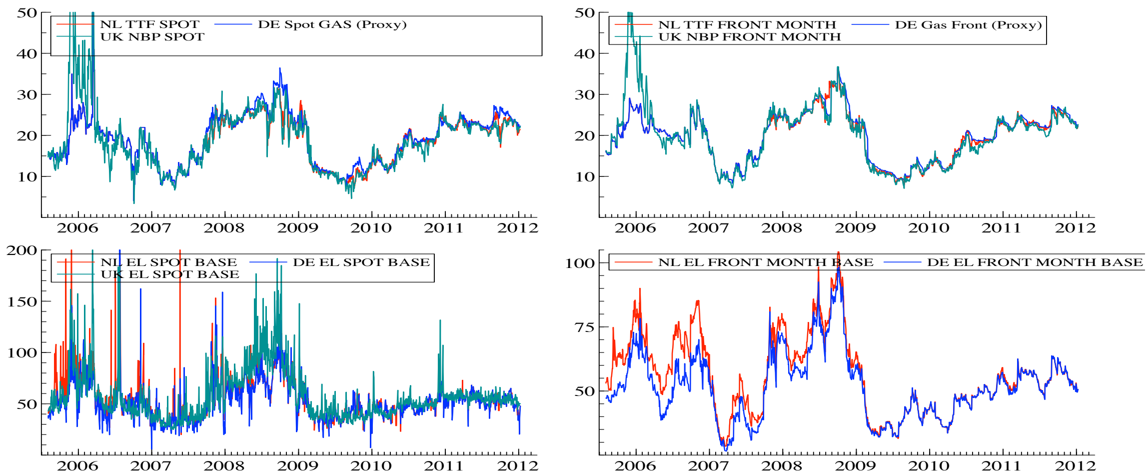
6.1 Descriptive statistics

Table 9: Full sample summary

Full sample (EUR/MWh)	Mean	Minimum	Maximum
NL EL SPOT BASE	56	17	277
NL EL SPOT PEAK	71	16	523
NL EL FRONT MONTH BASE	56	28	104
NL EL FRONT MONTH PEAK	---	---	---
DE EL SPOT BASE	53	6	302
DE EL SPOT PEAK	65	7	544
DE EL FRONT MONTH BASE	52	27	98
DE EL FRONT MONTH PEAK	---	---	---
UK EL SPOT BASE	58	25	266
UK EL SPOT PEAK	66	27	345
NL TTF SPOT	19	4	53
NL TTF FRONT MONTH	20	8	36
DE Spot GAS (Proxy)	19	4	53
DE Gas Front (Proxy)	20	8	36
UK NBP SPOT	19	3	87
UK NBP FRONT MONTH	20	7	58
CO2 Spot	4	0	12

The mean spot base electricity price was highest in the UK with an average 57.64 EUR/MWh over the full sample period. The mean spot peak electricity price was highest in the Netherlands. The average natural gas spot price was slightly higher in Germany for the full sample with 19.29 EUR/MWh. Overall the natural gas prices are on average very similar across markets, both spot and futures prices. This is an indication that the natural gas prices in Europe are converging.

Figure 15: Price developments of natural gas and electricity



The average CO_2 price for a typical natural gas-fired power plant was 4.7 EUR per MWh produced electricity[12]. The CO_2 price is strongly affected by the period with close to zero prices. For all three countries we observe that the mean front natural gas price is greater than the mean spot natural gas price, while for the electricity markets it is the opposite.

In the daily return series we rarely found correlation coefficients greater than 50 per cent, which suggested that the short-run relationship often were weak. As table 10 shows, in level prices the correlation is most often above 50 per cent, except the CO_2 variable. That takes us into the next section of analysis of long-run relationships in level series, by performing various regressions between the variables.

[12] A combined cycle natural gas turbine (CCGT) plant with 49.13 per cent efficiency

Table 10: Correlation in level prices (full sample)

Correlation (level) Full	NL TTF Spot	NL TTF FRONT MONTH	NL EL SPOT BASE	NL EL SPOT PEAK	NL EL FRONT MONTH BASE	UK NBP SPOT	UK NBP NBP FRONT MONTH	UK EL SPOT BASE	UK EL SPOT PEAK	DE EL SPOT BASE	DE EL SPOT PEAK	DE EL FRONT MONTH BASE	CO2 SPOT (GAS)	DE SPOT GAS	DE GAS FRONT
NL TTF Spot	1														
NL TTF FRONT	89 %	1													
NL EL SPOT BASE	60 %	62 %	1												
NL EL SPOT PEAK	47 %	50 %	97 %	1											
NL EL FRONT BASE	71 %	86 %	68 %	60 %	1										
UK NBP SPOT	82 %	73 %	63 %	53 %	60 %	1									
UK NBP FRONT	79 %	89 %	68 %	59 %	81 %	86 %	1								
UK EL SPOT BASE	70 %	69 %	68 %	58 %	67 %	75 %	70 %	1							
UK EL SPOT PEAK	65 %	64 %	66 %	58 %	64 %	71 %	67 %	99 %	1						
DE EL SPOT BASE	62 %	63 %	81 %	72 %	65 %	62 %	65 %	71 %	69 %	1					
DE EL SPOT PEAK	52 %	53 %	77 %	72 %	59 %	55 %	58 %	64 %	64 %	97 %	1				
DE EL FRONT	78 %	91 %	68 %	57 %	96 %	65 %	82 %	73 %	70 %	69 %	62 %	1			
CO2 SPOT (GAS)	-7 %	-11 %	-1 %	0 %	-19 %	9 %	6 %	-12 %	-14 %	-5 %	-7 %	-17 %	1		
DE SPOT GAS	97 %	92 %	60 %	47 %	84 %	79 %	80 %	72 %	67 %	64 %	53 %	83 %	-13 %	1	
DE GAS FRONT	89 %	98 %	62 %	49 %	90 %	72 %	88 %	69 %	64 %	63 %	53 %	89 %	-12 %	92 %	1

In level form we make an unexpected observation. The correlation between the spark-spread variables is stronger in Germany than the Netherlands. In the spot market the correlation is 60 per cent in the Netherlands, 64 per cent in Germany and 75 per cent in the UK. The correlation is stronger in the front prices than the spot prices. The front spark spread correlation is 86 per cent in the Netherlands and 89 per cent in Germany.

6.2 Stationary time series

When performing regression analysis it is crucial to know whether the variables involved are stationary or not. A stationary time-series has a finite mean, finite variance and the autocorrelations are time-independent (Enders, 2010). Further on, Granger and Newbold (1974) presented the term “spurious regression” that is a problem of regressions with non-stationary variables. They showed that spurious regressions can generate artificial high R-squared and t-statistics, even though the variables were independent, hence causing statistical inference to be invalid. Since then it has become common practice to test whether the series are stationary by investigate the characteristic roots lie within the unit circle.

6.2.1 Characteristic roots and the unit circle

The expression characteristic roots in time series regression is used to describe the stability of an autoregressive process of a variable, and are the homogenous solutions to the process. Stability requires that all characteristic roots lie within the unit circle, otherwise, if the any of the characteristic roots are equal to unity, it is called a unit root process (Enders, 2010). Hence, stability, stationary and none unit roots are equivalent concepts to describe the properties of a variable.

6.2.2 The integrated order of a variable

During our analysis we will describe variables according to integrating order I(*d*). Integrated order means how many unit roots the sequence contains. If the variable is stationary, we say that it is integrated of order zero I (0). If It contains a single unit root, it is integrated of order one I (1), and the first difference of the variable is stationary.

6.2.3 Augmented Dickey Fuller Test

To test whether a series is stationary, we practically test if the series contains any unit roots. Dickey and Fuller (1979) considered three different equations to test for unit roots. The three equations are based on possible assumptions that the researcher has about the true data-generating-process. The three possible assumptions are:

- A pure random walk (RW)
- A RW plus a drift, or
- A RW plus a drift and a time trend

To control for autocorrelation in the error term the equations were extended to higher order autoregressive processes. In addition, any seasonality should be adjusted for when possible.

6.2.3.1 Assumption about the data-generating-process

After a visual study of our time-series we assume that natural gas, electricity, and CO_2 do not have a linear time trend, meaning that time in itself do not have a significant effect on the price developments. However, since we are working with energy commodities that often exhibit seasonality in demand, and the fact that both electricity and natural gas has its storage limitations, seasonality is expected to be part of the process. We also found support for that in part 1. Thus, we should account for deterministic seasonal effects.

Our assumptions suggest to test whether the differenced series is a RW plus a drift, while we account for seasonal effects:

H_0: $\boldsymbol{\gamma = 0}$, unit root or drift, non-stationary

$$\Delta \boldsymbol{y_t} = \boldsymbol{a_0} + \sum_{i=1}^{11} D_i + \boldsymbol{\gamma y_{t-1}} + \sum_{i=1}^{p} \boldsymbol{\beta}_i \Delta \boldsymbol{y_{t-i}} + \boldsymbol{\varepsilon_t} \text{ (Random walk plus drift)}$$

We have used monthly dummy variables, D_i, with value one in period i, and zero otherwise. Arbitrarily, we would capture seasonal effects by using quarterly or weekly dummies instead, but since we have used monthly futures contracts in our analysis, monthly dummies seem natural.

The incorporation of seasonal dummies will not change the limiting distribution of the coefficient of the $\boldsymbol{y_{t-1}}$ variable, $\boldsymbol{\gamma}$ (Dickey, Bell, & Miller, 1986). We can therefore use the regular critical values used in augmented Dickey Fuller tests for unit roots. Hence, the equation contains an intercept, so we have to use the Dickey Fuller τ_μ statistic.

If the series contain a unit root we should also check if it is only a single unit root, that is the differenced series is stationary. In that case we do not include the drift term:

H_0: $\gamma = \boldsymbol{0}$ unit root, non-stationary

$$\Delta \boldsymbol{y_t} = \boldsymbol{\gamma y_{t-1}} + \sum_{i=1}^{p} \boldsymbol{\beta}_i \Delta \boldsymbol{y_{t-i}} + \boldsymbol{\varepsilon_t}$$

In this case we use the Dickey Fuller τ statistic since we neither include an intercept nor a time trend.

The t-statistics returned from the tests is compared to the critical values from table A in the book “Applied Econometric Time Series” (Enders, 2010).

For both models we have minimized Akaike information criteria when we have selected the number of differenced lags. The differenced lags are used to capture systematics in the $\{\varepsilon_t\}$-series. We performed the test for the three sub-periods and the full sample.

Critical values for Augmented Dickey-Fuller tests of unit root

5 per cent significant level (*), 1 per cent significant level (**)

Dickey Fuller τ_μ statistic: -2.86 (*) and -3.43 (**)

Dickey Fuller τ statistic: -1.95 (*) and -2.58 (**)

(Statistics for sample size ∞)

6.2.3.2 Augmented Dickey-Fuller Results (full sample)

The following table shows the Dickey-Fuller results with t-statistics.

Table 11: Full sample Augmented Dickey-Fuller results

Full sample	Integrated order	Level t-statistic	Selected-lags (AIC)	Model	Differenced t-statistic	Selected-lags (AIC)	Model
NL TTF SPOT	I(0) stationary	-2.96(*)	9	constant	----	----	----
NL TTF FRONT	I(1) unit root	-2,05	4	constant	-13.52 (**)	10	non-constant
NL EL SPOT BASE	I(0) stationary	-5.18 (**)	10	constant	----	----	----
NL EL SPOT PEAK	I(0) stationary	-5.94 (**)	10	constant	----	----	----
NL EL FRONT MONTH BASE	I(1) unit root	-2,27	3	constant	-27.37 (**)	2	non-constant
UK NBP SPOT	I(0) stationary	-3.64 (**)	10	constant	----	----	----
UK NBP FRONT MONTH	I(1) unit root	-2,8	10	constant	-12.94 (**)	9	non-constant
UK EL SPOT BASE	I(0) stationary	-3.94 (**)	10	constant	----	----	----
UK EL SPOT PEAK	I(0) stationary	-4.33 (**)	10	constant	----	----	----
DE Spot GAS	I(1) unit root	-2,61	9	constant	-17.53 (**)	8	non-constant
DE Gas Front	I(1) unit root	-2,04	0	constant	-12.11 (**)	0	non-constant
DE EL SPOT BASE	I(0) stationary	-5.44 (**)	10	constant	----	----	----
DE EL SPOT PEAK	I(0) stationary	-6.35 (**)	10	constant	----	----	----
DE EL FRONT MONTH BASE	I(1) unit root	-2,66	4	constant	-30.39 (**)	1	non-constant
CO2 SPOT (GAS)	I(1) unit root	-1,71	6	constant	-16.33 (**)	5	non-constant

Note that DE Spot gas is stationary on a 10 per cent level. This will be used later in Part 2.

An interesting observation is that all spot series (both natural gas and electricity) are stationary, except DE Spot Natural gas and CO_2 Spot. That gives us confidence to analyse most spot relationships with regression analysis without worrying about spurious regression. A possible rationalisation of the spot series to be stationary, and not the futures series, is that deviation from the average spot price is often a short-term spike. The spot series is therefore quickly corrected back to the finite statistical properties of the series (adjusted for seasonality), which are the fundamental properties of a stationary time series. We also observe that all first-differenced time series are stationary for the full sample.

6.2.3.3 Augmented Dickey-Fuller Results (sub-samples)

Table 29 (in appendix) shows the augmented Dickey-Fuller results for sub-periods. Based on the results for full sample we assume that all variables that are non-stationary have stationary differenced series, thus only test for level series are conducted.

For the spot series the results are generally distinctive between natural gas and electricity in the sub-periods. In the Netherlands both electricity spot series are stationary for all samples, while the spot natural gas price is only stationary for the full sample and the first period. This may be interpreted as stronger *mean-reversion* properties in the spot electricity market than in the natural gas market. Generally, the findings in the UK and German spot markets are similar, with some exceptions.

For the front series we find unit roots in all series, both natural gas and electricity and within every period. It seems like the mean-reversion effect that was present in the spot price of electricity is not strong enough to conclude that the front price developments are statistically stationary. The CO_2 price for the last period is stationary in level terms.

6.3 Co-integration

Due to spurious regression there were for a long time a general wisdom to difference all non-stationary variables used in regression, thereby throwing away useful information about the variables level. Often non-stationary variables follow the same or linked stochastic trends, as are common with commodities and indicated in the section covering short-term relationships. In a multivariate case differencing the variables will result in loss of information relevant to describe the long-run relationship, so that the appropriate way to threat non-stationary variables is therefore not that straightforward. Clive Granger introduced the concept of co-integration when recognizing the possibility that a linear combination of non-stationary variables can be stationary (Granger C. , 1981).

The Augmented Dickey-Fuller results showed that all futures series were non-stationary. Instead of rejecting long-run analysis of these series now, we will analyse them by the concept of co-integration. In relation to commodities such as natural gas, electricity and CO_2, theory of co-integration is especially relevant, and is capturing the concepts of market arbitrage and the law of one price. In the short run there might be sustainable deviations from a long-run mean but eventually the prices will return to the long run relationship. This might be the price of natural gas in the UK, the Netherlands and Germany, or the price difference between natural gas and electricity known as spark spread. The long-run relationship should be valid, as long as it exists a physical and fundamental connection between the commodities.

Engle and Granger (Engle & Granger, 1987) developed estimation procedures and tests for co-integration, first introduced by Granger, arguing that deviations from the long-run equilibrium between integrated variables only have meaning if these *equilibrium errors* follow a stationary process. In economic terms this means that a deviation from equilibrium not is a contradiction of a plausible economic relationship between two variables as long as the deviation is corrected in the long run.

6.3.1 Co-integration defined

If two variables are co-integrated there exist a long-run equilibrium that could be described by the following formal expressions:

Two vectors: $\beta = (\beta_1, \beta_2, \dots, \beta_n)$ and $x_t = (x_{1t}, x_{2t}, \dots., x_{nt})'$ are used to describe the long-run equilibrium between a set of variables non-stationary variables x_i integrated of same order such that:

$$\beta x_t = \beta_1 x_{1t} + \beta_1 x_{1t} + \cdots + \beta_n x_{nt} = 0$$

When the equation holds the variables are in a long-run equilibrium, but short-run deviations are allowed in the concept of co-integration.

$$\beta x_t = e_t$$

The equilibrium errors $\{e_t\}$ captures short run deviation from the long-run equilibrium but will only have meaning if it cannot drift too far apart. Therefore, the requirement for variables x_i to be co-integrated is that the equilibrium errors are stationary.

$$e_t \sim I(0)$$

(Enders, 2010)

In general there are two distinctive procedures to test for co-integration; the Engle-Granger Methodology and the Johansen methodology. The Johansen methodology may have an advantage to Engle-Granger methodology that it uses maximum likelihood estimators to circumvent the troubles caused by the two-step estimators of the Engle-Granger methodology. This is one of the weaknesses of the Engle-Granger methodology. The first step is to generate the residual series $\{\hat{\boldsymbol{e}}_{\boldsymbol{t}}\}$, and the second step uses the *generated* errors to estimate the regression $\Delta\hat{\boldsymbol{e}}_{\boldsymbol{t}} = \boldsymbol{a}_{\boldsymbol{1}}\hat{\boldsymbol{e}}_{\boldsymbol{t-1}} + \cdots$. The problem occurs if the researcher has misspecifications in the first regression that is carried to the second through the stored residuals. Nevertheless, the Engle-Granger methodology is commonly used because it is easily implemented. In the case of a two-variable co-integration relationship, the methodology is applicable in using the residuals from either[13] of the two following regressions:

I. $\boldsymbol{y}_{\boldsymbol{t}} = \boldsymbol{\beta}_{\boldsymbol{10}} + \boldsymbol{\beta}_{\boldsymbol{11}}\boldsymbol{z}_{\boldsymbol{t}} + \boldsymbol{e}_{\boldsymbol{1t}}$
II. $\boldsymbol{z}_{\boldsymbol{t}} = \boldsymbol{\beta}_{\boldsymbol{20}} + \boldsymbol{\beta}_{\boldsymbol{21}}\boldsymbol{y}_{\boldsymbol{t}} + \boldsymbol{e}_{\boldsymbol{2t}}$

In the following tests for co-integration, between variables of integrated order 1, we have adopted the Engle-Granger methodology, where we deployed the following steps:

1. Estimate the long run relationship: $\boldsymbol{y}_{\boldsymbol{t}} = \boldsymbol{\beta}_{\boldsymbol{0}} + \sum_{i=1}^{11}\gamma_i D_i + \boldsymbol{\beta}_{\boldsymbol{1}}\boldsymbol{z}_{\boldsymbol{t}} + \boldsymbol{e}_{\boldsymbol{t}}$, and store the residual sequence $\{\hat{\boldsymbol{e}}_{\boldsymbol{t}}\}$

Note that we have included monthly dummy variables D_i to allow for deterministic seasonal properties in the series, as we did with stationary tests earlier.

If the variables are co-integrated the residuals $\{\hat{\boldsymbol{e}}_{\boldsymbol{t}}\}$ will be stationary, and the OLS estimators $\boldsymbol{\beta}_{\boldsymbol{0}}$ and $\boldsymbol{\beta}_{\boldsymbol{1}}$ are "super-consistent" since they converge faster to the true coefficients than in OLS models using stationary variables (Stock, 1987).

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[13] "As the sample size grows infinitely large, asymptotic theory indicates that the test for a unit root in the $\{\boldsymbol{e}_{\boldsymbol{1t}}\}$ sequence becomes equivalent to the test for a unit root in the $\{\boldsymbol{e}_{\boldsymbol{2t}}\}$ sequence" (Enders, 2010) p 385.

2. Test if $\{\hat{e}_t\}$ is stationary

Since $\{\hat{e}_t\}$ are residuals from another regression we have to use different critical values than for ordinary augmented Dickey-Fuller tests. Tables for these tests are found in most applied books for time series regressions such as Enders (2010).

H_0: $a_1 = 0$, $\{\hat{e}_t\}$ not a white noise, no co-integration

$$\Delta\hat{e}_t = a_1\hat{e}_{t-1} + \sum_{i=1}^{p} a_{i+1}\Delta\hat{e}_{t-i} + \varepsilon_t$$

The intercept term is unnecessary since the sequence is a residual series from an OLS regression, and we have minimized Akaike information criteria when we have selected the number of distributed lags.

If we are able to reject H_0 we can conclude that the variables are co-integrated.

Critical values for the Engle-Granger co-integration test with two variables[14]

5 per cent significant level: -3.350 (*)
1 per cent significant level: -3.921 (**)

(Enders, 2010)

[14] Critical values if sample size is 500

6.3.2 Co-integration test

6.3.2.2 Cross-commodity electricity and natural gas

When we adjust for seasonal effects we observe that *all our tested* relationships are co-integrated. This gives us confidence to analysis the long-run relationship, without having spurious regression.

Table 12: Co-integration tests

Relationship error term	Period	Selected lags (AIC)	ADF test statistic for error term	Conclusion	
NL EL FRONT MONTH BASE - NL TTF FRONT MONTH	Full sample	5	-3.62 (*)	CI (1,1)	Co-integration
	Period 1	0	-5.80 (**)	CI (1,1)	Co-integration
	Period 2	0	-4.35 (**)	CI (1,1)	Co-integration
	Period 3	2	-4.36 (**)	CI (1,1)	Co-integration
DE EL FRONT MONTH BASE - DE Gas Front	Full sample	5	-4.65 (**)	CI (1,1)	Co-integration
	Period 1	0	-7.85 (**)	CI (1,1)	Co-integration
	Period 2	1	-4.66 (**)	CI (1,1)	Co-integration
	Period 3	5	-4.05 (**)	CI (1,1)	Co-integration

We observe that the spark-spread relationship cannot deviate too much from a long-run relationship. The price should always drift back to an equilibrium level independent of sub-periods.

6.3.2.3 Cross-country electricity, cross-country natural gas

We would also want to test for co-integration between the same commodities for the front market in different national regions.

In the front electricity markets we have mixed results depending on the chosen time interval. For the whole sample we were not able to reject the null of no co-integration between the front natural gas price in the Netherlands and in Germany. We got the same result for the first time interval. In the last two periods we find evidence against the null; we have statistical evidence to state that the front market for electricity in Germany and the Netherlands are co-integrated.

Table 13: Co-integration test

Relationship error term	Period	Selected lags (AIC)	ADF test statistic for error term	Conclusion	
NL EL FRONT MONTH BASE - DE EL FRONT MONTH BASE	Full sample	9	-2,86	CI(1,0)	No Co-integration
	Period 1	0	-7.79 (**)	CI(1,1)	Co-integration
	Period 2	3	-5.17 (**)	CI(1,1)	Co-integration
	Period 3	0	-9.46 (**)	CI(1,1)	Co-integration
NL TTF FRONT MONTH - DE Gas Front	Period 3	4	-3.93 (**)	CI(1,1)	Co-integration
UK NBP FRONT MONTH - DE Gas Front	Period 3	8	-6.52 (**)	CI(1,1)	Co-integration
UK NBP FRONT MONTH - NL TTF FRONT MONTH	Full sample	8	-3.63 (*)	CI(1,1)	Co-integration
	Period 1	5	-2,4	CI(1,0)	No Co-integration
	Period 2	6	-5.05 (**)	CI(1,1)	Co-integration
	Period 3	5	-5.22 (**)	CI(1,1)	Co-integration

6.3.3 Co-integration summary

We have found co-integrating relationships between most of the non-stationary variables we want to analyse, at least in some of the periods. Based on these results, we are able to estimate valid long-run relationships between most non-stationary variables and between variables that are stationary.

6.4 Long-run equilibrium

We will start by estimating the long-run equilibrium between the spark spread commodities. Thereafter, we will analyse the equilibrium between the same commodities in two markets to evaluate how well the markets are integrated with each other. Throughout this section we will directly incorporate monthly seasonalties in the estimated regression models.

6.4.1 Asymptotic *t*-distribution for co-integrated relationships

The analysis in section 6.4.2, long-run relationships between electricity and natural gas prices, and section 6.4.3 for the cross-country commodity price relationships, presents results of the beta coefficients in the co-integrating vector. Inferences on regression coefficients are regularly done by *t*- and F-tests. However, one should do that with caution, and as Walter Enders points out, on page 376 – 377, the coefficients in the co-integrated vector have an asymptotic *t*-distribution (Enders, 2010) only if certain restrictive requirements are satisfied. Nevertheless, the coefficients are still super-consistent but the standard errors are not. Consequently, simple inference on the beta coefficient is not appropriate unless the co-integrating relationship could be described as follows:

$y_t = \alpha + \beta_1 z_t + \varepsilon_{1t}$

$\Delta z_t = \varepsilon_{2t}$,
and $E\varepsilon_{1t}\varepsilon_{2t} = 0$

The point is that both residuals are uncorrelated white noise disturbances.

6.4.2 Cross-commodity electricity and natural gas (spark spread)

In a theoretical framework we would expect the beta coefficient to be equal to 2, if we assume:

1) Natural gas is the only input used to generate electricity
2) The average plant efficiency is equal to 50 per cent
3) No price for carbon emission
4) Perfect competition in the electricity market

If the natural gas price is equal to 20 EUR/MWh then the price of electricity should be equal to 40 EUR/MWh if it is perfect competition, and if the natural gas price is equal to 25 EUR/MWh the price of electricity should be equal to 50 EUR/MWh. In this theoretical framework the beta coefficient in the long-run relationship should be equal to 2.

The estimated beta coefficient can be explained by many factors such as the price of supplementary production sources for electricity, shift in demand for the commodities, imperfect competition, and the actual average efficiency factor in each country.

The relationship between electricity and natural gas prices also depends on the aggregate mix of generators polices (reserve, off-peak, peak power) and fuels used by the power companies in the service area (Emery & Liu, 2001).

Given our understanding of the different markets we should expect beta values to be close to 2, particularly in the UK and the Netherland, since the capacity adjusted average efficiency factor presented in section 1.5 was approximately 50 per cent in these countries. We find it most reasonable to model the relationship as a linear function.

Estimated model for long-run relationship:

$$\boldsymbol{F_{t,El} = \alpha + \sum_{i=1}^{11} \gamma_i D_i + \beta F_{t,gas} + \varepsilon_{1t}}$$

Table 14: Long-run relationship

Y-X	Period	beta (s.e.)	R^2
NL EL FRONT MONTH BASE - NL TTF FRONT MONTH	Full sample	2.09 (0.03)	76.40 %
	P1	2.36 (0.09)	78.78 %
	P2	2.35 (0.04)	91.76 %
	P3	1.35 (0.02)	92.49 %
DE EL FRONT MONTH BASE - DE Gas Front	Full sample	1.88 (0.02)	81.75 %
	P1	1.76 (0.06)	86.56 %
	P2	2.31 (0.04)	91.69 %
	P3	1.33 (0.02)	80.87 %
NL EL SPOT BASE - NL TTF SPOT	Full sample	2.17 (0.07)	40.44 %
	Period 1	2.26 (0.28)	38.95 %
DE EL SPOT BASE-DE GAS SPOT	Period 1	2.27 (0.27)	36.18 %
UK EL SPOT BASE - UK NBP SPOT	Full sample	2.43 (0.05)	59.31 %
	Period 1	1.96 (0.08)	74.17 %

These relationships involve the variables that give the spark spread, and changes in the coefficients across time may indicate changes in the properties of the respective spark spreads. As mention in the introduction the spark spread is the basic marginal production profit for a gas-fired plant. The slope coefficient *beta* is the marginal effect of a change in natural gas price on the change in electricity price. In regression analysis the marginal effect of the independent variable on the dependent variable is constant (Wooldridge, 2009).

As expected all beta coefficients are positive, an increase in natural gas price as a positive marginal effect on electricity price. Beta values close to unity would imply that the estimated relationship gives on average a marginal loss in the estimated period, modelling a benchmark natural gas-fired plant (ignoring the intercept term). If the beta is 2, then the marginal profit effect for the benchmark natural gas-fired plant is break even, excluding operational cost.

If the beta is 1.33, as observed in the last period in German front market, it implies that if the price of natural gas increases by 1 EUR/MWh, the prices of electricity will on average increase by 1.33 EUR/MWh in the period, ceteris paribus. Translated into the marginal benefit to the producers; the marginal income from electricity sales will on average increase by 1.33 EUR/MWh, while marginal cost increases by 2 EUR/MWh[15], imposing a marginal loss of 0.67 EUR/MWh. The translated interpretation of the coefficients will be that in the last period the producers was, on average, unable to pass the increased cost of natural gas procurement to the price paid by the electricity buyers.

A beta greater than 2 indicate a positive marginal effect to the producer is the natural gas price increases, so one might argue that the expected beta should be close or equal to 2 in the long-run in pure electricity and natural gas environment.

For the long-run relationship we observe that the *beta* for the front spark spread has changed considerably in the last period. The beta coefficient changes from 2.09 (1.88) to 1.35 (1.33) for the Netherlands (Germany). One could argue that the reason for the drop in the beta-coefficient is due to the presence of a positive CO_2 price, but we also observe a positive CO_2 price in period 1. Other reasons are falling demand after the financial crises and increased supply from renewable generation, which has resulted in a negative electricity price trend. The price of natural gas has actually increased in the period.

[15] A natural gas-fired plant with 50 per cent efficiency will have an increased marginal cost of 2 EUR/MWh if the natural gas price increases by 1 EUR/MWh. (1 EUR/MWh / 50%) = 2 EUR/MWh

6.4.3 Long-run spark spread profitability dynamics

The estimated full sample long-run beta-coefficient is within the range 2.09 to 1.88. As mention the estimated beta coefficient can be explained by many factors such as the price of supplementary production sources for electricity, shift in demand for the commodities, imperfect competition, price of carbon emission and the actual gas-plant portfolio efficiency factor in each country.

We explained in section 6.4.2 that in the long run gas-fired producers must be compensated in the electricity market for an increase in the natural gas price to be profitable. A marginal effect less than 2 means that a benchmark gas-fired plant is not able to push the entire cost of natural gas procurements on to the electricity price, when the procurement cost is increasing. In the last period we observe a beta-coefficient equal to 1.33 in Germany. A beta-coefficient equal to 1.33 implies a marginal reduction in the spark spread of 0.67 EUR/MWh when the cost of natural-gas procurements increases by 1 EUR/MWh [16]. The analysis reflects initially a base-load plant, but the result also shows the importance (value) of flexible production to be able to earn profit in the market. As mentioned in section 6.4.2, the estimated long-run relationship is not a representation of a pure gas-electricity relationship. Both commodities are affected by other factors and have several uses.

Given the knowledge of co-integration and our best estimate for the long-run relationship we should expect the low beta-coefficient in the last period to return to a sustainable level for gas-fired plant. Considering the importance of natural gas as production source, especially in the UK and the Netherlands, we expect the beta coefficient level to increase in the long run from the level observed in the last period. There are several ways the marginal-effect could change, for example an increase in the average fuel efficiency and/or lower natural gas prices. Another scenario is if the marginal effect stays at 1.33 and the natural gas is unchanged, the consequence is a large-scale low-efficient plant phase-out. The plant phase-out will force the inefficient excess natural gas capacity out of the market. In the next section we will explain why old inefficient gas-fired plants, especially in Germany, are likely to be replaced.

[16] The observed average clean spark spread profit in the period, for a benchmarked gas-fired plant, was 5.34 EUR/MWh

6.4.4 Inefficient gas-fired plant phase out

As we earlier assumed, the fuel efficiency factor is highly correlated with operating hours, which implies that high efficiency yields more profitable operating hours and is therefore more profitable on average. During a given period the gas-fired plant must run a minimum of profitable operating hours yield required return on investments, and this is again based on the fuel efficiency of the plant in relation to the commodities prices. We will therefore analyse the average profitability in relation to fuel efficiency further.

Germany

One reason for the low beta-coefficient for the last period in Germany is the large-scale installation of photovoltaic[17] capacity. Since this capacity may only be exploited during sunshine, which again is during peak-hours, the movement is somewhat larger for peak load than base load prices (Böhme, 2011).

If the beta-coefficient returns to a higher level, several of the large German installations will still be in the "danger zone". The reason is their low fuel efficiency. The database of natural gas-fired power plants in Germany shows that 46 out of 90 have efficiency lower than 40 per cent.

Emden 4 (450 MW), a natural gas-fired power plant operated by Statkraft, was put in cold reserve on February 2012 during Q4 2011. They argue that the increase of new renewable energy capacity in 2011, the fall in electricity prices, and high natural gas prices, resulted in low margins for the plant in Germany. Dr. Jürgen Tzschoppe, Senior Vice President, Head of Continental Energy at Statkraft explains the current situation at Emden plant 4: *"Plans to replace the old plant with a new one in the same location have been put on hold. Currently we do not see any market signals in favour of investments into additional generation capacity in Germany. Energy demand has levelled out as a result of the financial crisis. At the same time, we are facing high natural gas costs and low power prices at the spot market, indicating excess capacities across Europe."* (Statkraft, 2012)

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[17] Photovltaic is the generation of electricty by the use of solar.

Overall, if the price signal for the spark spread are consistent, old inefficient natural gas-fired plants of a total 15 600 MW installed capacity needs to be replaced by more efficient sources[18]. The replacement may be more energy efficient buildings, renewable energy capacity or new flexible and efficient fuel power plants. As mention, the total installed capacity of photovoltaic in Germany was 24 800 MW in 2011.

The Netherlands

The database on natural gas-fired plants in the Netherlands shows that only 2 out of 28 natural gas-fired plants have efficiency lower than 40 per cent. Expect for the last period the observed long-run beta-coefficient is over 2. The result implies that a benchmark gas-fired plant will on average be profitable in the sample period. An substantial gas-fired plant phase-out in the Netherlands is very unlikely, given the average efficiency factor and historical prices for clean spark-spread commodities.

The newly built Claus C plant in the Netherlands is a 1940 MW natural gas-fired plant with an efficiency of 58.5 per cent, which is enough capacity to supply power to more than 2 million typical European households. Given the historical development in the clean spark spread, the plant would have been on average profitable in base-load and peak-load hours during the sample years. If the plant secured natural gas procurements and CO_2 allowances in the front market, the plant would be profitable in all base-load operating hours based on our time-series.

The UK

The clean spark spread is on average highest in the UK followed by the Netherlands. In the long-run analysis we have only spot price data, but the beta-coefficient for the full sample is the highest of all countries, equal 2.43. A gas-fired plant with approximate 40 per cent efficiency would be on average profitable during the full sample period.

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[18] Full sample beta-coefficient = 1.88 (Implies a long-run efficiency equal 53% to been on average profitable). Plant with lower efficiency is estimated to be phased out.

The fuel efficiency gas-plant portfolio is also the most efficient in the UK. The database on natural gas-fired plants in the UK shows that 0 out of 53 natural gas-fired plants have efficiency lower than 40 per cent.

6.4.5 Cross-country electricity and natural gas relationship

The hypothesis is that the long-run beta should be equal to 1. The markets should be integrated in Europe if there is enough capacity between the countries. The electricity market is market-coupled (implicit auctions) in central-western Europe (CWE). Market-coupling means that the prices are cleared (merit order books) simultaneous in Germany and the Netherlands, with respect to the cross-border capacity for flow of electricity.

Long-run relationship $\boldsymbol{F_{t,1} = \alpha + \sum_{i=1}^{11} \gamma_i D_i + \beta F_{t,2} + \varepsilon_t}$

Table 15: Long-run relationships

Y-X	Period	beta (s.e.)	R^2
NL EL FRONT MONTH BASE - DE EL FRONT	Period 1	1.30 (0.03)	89.06 %
	Period 2	1.01 (0.05)	98.94 %
	Period 3	1.01 (0.03)	99.53 %
NL TTF FRONT MONTH - DE Gas Front	Period 3	1.00 (0.01)	97.47 %
UK NBP FRONT MONTH - DE Gas Front	Period 3	0.97 (0.01)	96.09 %
UK NBP FRONT MONTH - NL TTF FRONT MONTH	Full sample	1.08 (0.01)	81.75 %
	Period 2	1.02 (0.01)	98.20 %
	Period 3	0.98 (0.03)	80.87 %
NL EL SPOT BASE - DE EL SPOT BASE	Full sample	0.87 (0.02)	65.84 %
	Period 1	0.63 (0.04)	55.75 %
	Period 3	0.91 (0.01)	86.75 %
NL EL SPOT BASE - UK EL SPOT BASE	Full sample	0.57 (0.02)	49.65 %
	Period 1	0.49 (0.04)	45.86 %
	Period 3	0.63 (0.02)	54.60 %
UK EL SPOT BASE - DE EL SPOT BASE	Full sample	0.91 (0.02)	51.04 %
	Period 1	0.51 (0.05)	44.86 %
	Period 3	0.75 (0.03)	50.19 %
NL TTF SPOT -UK NBP SPOT	Full sample	0.61 (0.01)	68.56 %
	Period 1	0.26 (0.02)	65.17 %

As stated above we would expect to find beta coefficients close to unity due to an arbitrage principle in integrated markets.

Futures relations:

For all practical purposes all, except one, of the betas are approximately equal to unity.

The beta between electricity futures in the Netherlands and Germany is 1.3 in the first period, which is an evidence of lack of market integration compared to the last two periods.

As expected the other long-run relationship betas are equal to one, both for natural gas and electricity after 2006.

Spot relations:

Compared to the betas between futures contracts, the betas of the spot relations are far from unity. In the electricity markets the low beta is suggesting interaction constraints forcing differences in prices for the same commodity in different markets. There might be many reasons that can explain these numbers, some mentioned in other parts of the thesis. However, the explanatory power of the regression are all strong, so we are confident that there are strong forces connecting the cross-boarder prices.

As a next step we would like to explore were the “price leader”, if it is one, of the respective markets is located. This analysis will be conducted with the Error-correction model (ERM) and the testing procedure for Granger causality. Thereby we are able to understand interaction between the various markets better, and a better understanding of movements in the spark spread. The error-correction model will give a thorough explanation on how deviations are corrected and the average time to restore equilibrium in the long-run relationships.

6.5 Error Correction Model

We have now estimated long-run equilibriums between stationary variables and variables that are co-integrated, implying that there are long-run dynamics relating the price developments of two variables. However, yet we have not said anything about how deviations are corrected. We will describe this in two ways. First to investigate how *fast* deviations are corrected we will apply the error-correction model and interpret the speed-of-adjustment parameter. Second we will try to discover the *direction* of these dynamics, that is which variable is the causing changes in the other. Testing for Granger causality will answer that.

The concepts of this section are of special relevance in the case of understanding the dynamics behind the spark spread. The long-run equilibrium between electricity and natural gas has its equivalent in a predictable solution to the spark spread. Deviations from the long-run equilibrium will similarly yield deviations from the expected solution to the spark spread. Therefore, specification of “correction processes” to deviations in the long-run equilibrium, will answer questions regarding the developments of the spark spread. Understanding these relationships will enhance risk management for market players. To justify the use of an error-correction model the following theorem is stated in section 6.5.1:

6.5.1 Granger Representation Theorem

If two variables are co-integrated there is a guarantee that an error-correction model exists. Therefore, for any set of non-stationary variables integrated of same order, error-correction and co-integration are equivalent representations.

(Enders, 2010)

The error correction model has the following representation:

$$\Delta \boldsymbol{y_t} = \boldsymbol{\alpha_{10}} + \boldsymbol{\alpha_y}(\boldsymbol{y_{t-1}} - \boldsymbol{\beta_1 z_{t-1}}) + \sum \boldsymbol{\alpha_{11}}(\boldsymbol{i})\Delta \boldsymbol{y_{t-i}} + \sum \boldsymbol{\alpha_{12}}(\boldsymbol{i})\Delta \boldsymbol{z_{t-i}} + \boldsymbol{\varepsilon_{yt}}$$

$$\Delta \boldsymbol{z_t} = \boldsymbol{\alpha_{20}} + \boldsymbol{\alpha_z}(\boldsymbol{y_{t-1}} - \boldsymbol{\beta_1 z_{t-1}}) + \sum \boldsymbol{\alpha_{21}}(\boldsymbol{i})\Delta \boldsymbol{y_{t-i}} + \sum \boldsymbol{\alpha_{22}}(\boldsymbol{i})\Delta \boldsymbol{z_{t-i}} + \boldsymbol{\varepsilon_{zt}}$$

Except that it is augmented by the error-correction terms $\boldsymbol{\alpha_y}(\boldsymbol{y_{t-1}} - \boldsymbol{\beta_1 z_{t-1}})$ and $\boldsymbol{\alpha_z}(\boldsymbol{y_{t-1}} - \boldsymbol{\beta_1 z_{t-1}})$, the model is simply a bivariate VAR in first differences, and $\boldsymbol{\alpha_y}$ and $\boldsymbol{\alpha_z}$ can be interpreted as speed-of-adjustment parameters. A large $\boldsymbol{\alpha}$ means that deviation from equilibrium is quickly corrected, while a $\boldsymbol{\alpha}$ close to zero indicate that deviation never is corrected. Note that if the $\{\boldsymbol{y_t}\}$ and $\{\boldsymbol{z_t}\}$ are co-integrated at least one of the $\boldsymbol{\alpha's}$ must be non-zero. In a case when $\boldsymbol{\alpha_y} = \boldsymbol{0}$, it implies that $\{\boldsymbol{y_t}\}$ does not respond to deviations in the long-run equilibrium, and that all the adjustments to "restore" equilibrium is done in the $\{\boldsymbol{z_t}\}$ – sequence, and $\{\boldsymbol{y_t}\}$ is said to be weakly exogenous (Enders, 2010). Therefore, testing the speed-of-adjustment parameters is also a test of exogeneity (weak), where exogeneity requires that the variable is not responding to contemporaneous values of the other.

Since $\boldsymbol{\beta_1}$ is the parameter from the co-integrating relationship, and is unknown, Engle & Granger (Engle & Granger, 1987) suggested that $(\boldsymbol{y_{t-1}} - \boldsymbol{\beta_1 z_{t-1}})$ could be approximated by the generated $\{\boldsymbol{\hat{e}_t}\}$-sequence from the estimated co-integrated relationship. We will therefore estimate the error-correction model with these stored residuals:

$$\Delta \boldsymbol{y_t} = \boldsymbol{\alpha_{10}} + \boldsymbol{\alpha_y \hat{e}_{t-1}} + \sum \boldsymbol{\alpha_{11}}(\boldsymbol{i})\Delta \boldsymbol{y_{t-i}} + \sum \boldsymbol{\alpha_{12}}(\boldsymbol{i})\Delta \boldsymbol{z_{t-i}} + \boldsymbol{\varepsilon_{yt}}$$

$$\Delta \boldsymbol{z_t} = \boldsymbol{\alpha_{20}} + \boldsymbol{\alpha_z \hat{e}_{t-1}} + \sum \boldsymbol{\alpha_{21}}(\boldsymbol{i})\Delta \boldsymbol{y_{t-i}} + \sum \boldsymbol{\alpha_{22}}(\boldsymbol{i})\Delta \boldsymbol{z_{t-i}} + \boldsymbol{\varepsilon_{zt}}$$

The speed-of-adjustment parameters are of particular interest, and if OLS is an efficient estimation strategy, restrictions on these can be conducted by a simple t-test. Since all variables, including $\{\hat{e}_t\}$, are zero-mean stationary the above statement is true. Nevertheless, we have used heteroskedasiticy and autocorrelation consistent standard errors (HACSE) when we performed the tests on speed-of-adjustment parameters.

The differenced lags in the model is called autoregressive distributed lags of order p and q; ADL (p,q) which is decided using the general-to specific approach starting at lag length 10, which is yielding serially uncorrelated errors.

6.5.2 Error correction model with seasonal adjustments

Our theoretical assumption is that the first difference for all variables is unbiased for seasonal effects. For example the price level for natural gas changes with seasonal effects, but the average return is constant over the year. The suggested approach is that the generated error term sequence from the estimated co-integrated relationship is adjusted for seasonal effects, but the rest of the error correction model is estimated without seasonal adjustment for the first differences variables.

6.5.3 Testing speed-of-adjustment parameters

Critical Values for Error-Correction Model (t-statistics)

5 per cent significant level: -1.960 (*)
1 per cent significant level: -2.576 (**)

H0: $\alpha = 0$

6.5.3.1 Speed-of-adjustment

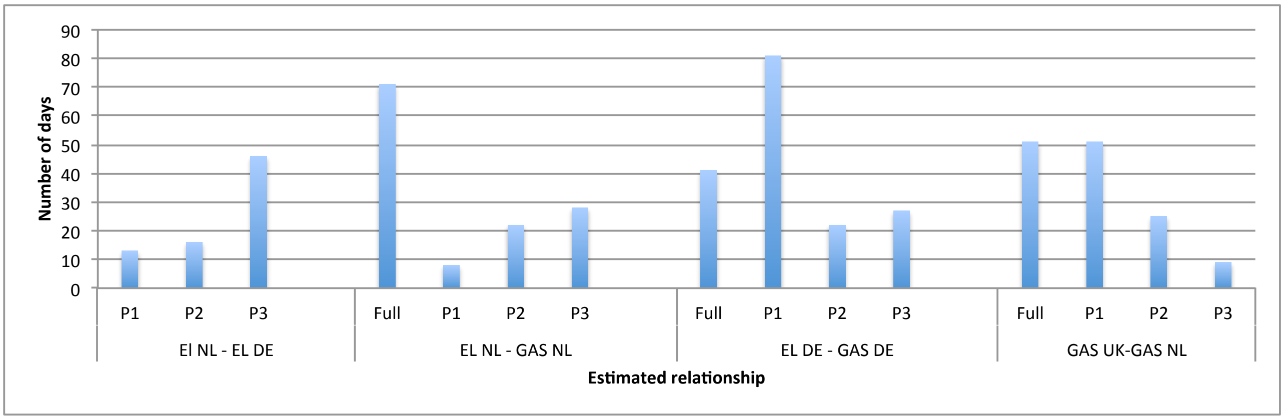
Table 16: Speed-of-adjustment

Relationship	Period	Speed-of-adjustment (t-test)	ADL(p,q) p = Δ Y lag, q = Δ X lag	R^2
NL EL FRONT MONTH BASE - DE EL FRONT MONTH BASE	Period 1	-0.075166 (**)	2,0	6.27 %
	Period 2	-0,0610783	0,1	1.66 %
	Period 3	-0.0216418	1,0	7.80 %
NL EL FRONT MONTH BASE - NL TTF FRONT MONTH	Full sample	-0,014181	2,1	4.42 %
	Period 1	-0.11840(**)	2,0	13.02 %
	Period 2	-0.0452502 (**)	1,0	3.60 %
	Period 3	0.0361798 (**)	1,1	13.67 %
DE EL FRONT MONTH BASE - DE Gas Front	Full sample	-0.0247639 (**)	1,0	1.51 %
	Period 1	-0.0124104 (**)	2,0	8.98 %
	Period 2	-0.0450528 (**)	1,0	3.32 %
	Period 3	-0.0370343 (**)	1,1	6.58 %
UK NBP FRONT MONTH - NL TTF FRONT	Full sample	-0.0196741 (**)	2,0	2.35 %
	Period 1	-0.0197362 ()	0,0	0.31 %
	Period 2	-0.0408053 ()	1,1	3.00 %
	Period 3	-0.115626 (**)	0,0	0.94 %
NL TTF FRONT MONTH - DE Gas Front	Period 3	-0.0195305 ()	1,0	5.09 %
UK NBP FRONT MONTH - DE Gas Front	Period 3	-0.0402304 (*)	1,0	2.47 %

The speed-of-adjustment is relative low (slow adjustment) and differs a lot for various sample and long-run relationship. All estimates are adjusted for monthly seasonal effects. The adjustment back, measured in days, to the estimated long-run relationship can take from 8 to 81 trading days[19]. When interpreting coefficients we always see them as the ceteris paribus effect of a unit change in one variable (independent) on another (dependent). Since we here look at the lagged deviation in a relationship, the coefficient (speed-of-adjustment) tells us if there is 1 EUR/MWh deviation in the relationship (lagged one day), the dependent variable is changes by the coefficients size, ceteris paribus. If that is true we could use the estimate to calculate how many days it takes to correct 1 EUR/MWh deviation in the long-run relationship, by taking the inverse of the speed-of-adjustment value.

[19] Trading days back to long run relationship = 1/ Speed-of-adjustment parameter = 1/ $\boldsymbol{\alpha_y}$

Figure 16: Trading days to adjust (front market)



In the first period the speed-of-adjustment for the spark spread differs a lot between the two countries, 8 and 81 days. Contrary, in the two last periods the speed-of-adjustments are approximately 22 to 28 trading days, respectively in the Netherlands and Germany. The speed-of-adjustment gives us additional knowledge in the complex dynamics of the spark spread.

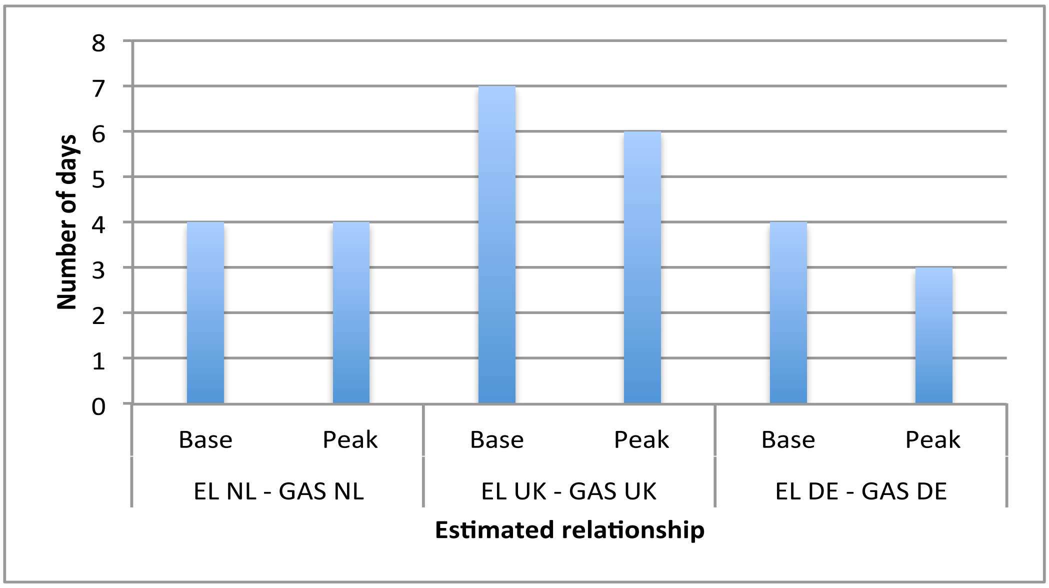
6.5.4 Speed of adjustment spot series

In the spot relationships between electricity and gas we have chosen to calculate both with base load and peak load price series. As we see form table 17 the speed of adjustment parameter are higher than the equivalent front measures. This should not be surprising since the separate series are stationary themselves.

Table 17: Speed of adjustment spot series

Relationship	Period	Speed-of-adjustment (t-test)	ADL(p,q) p = Δ Y lag, q = Δ X lag	R^2
NL EL SPOT BASE – NL TTF SPOT	Full sample	-0.226938 (**)	9,1	23.17 %
NL EL SPOT PEAK – NL TTF SPOT	Full sample	-0.238228 (**)	9,1	25.46 %
UK EL SPOT BASE – UK NBP SPOT GAS	Full sample	-0.138114 (**)	10,4	23.34 %
UK EL SPOT PEAK – UK NBP SPOT GAS	Full sample	-0.168759 (**)	10,3	24.98 %
DE EL SPOT BASE – DE NCG SPOT GAS	Full sample	-0.252935 (**)	10,0	25.83 %
DE EL SPOT PEAK – DE NCG SPOT GAS	Full sample	-0.290520 (**)	3,0	31.01 %

Figure 17: Trading days to adjust (spot)



Translating the results into trading-days to adjust, as shown in figure 17, it takes between 4 and 7 days for the base load relationship to correct 1 EUR/MWh deviation from the long-run equilibrium, while for the base load it takes between 3 and 6 days. The results are intuitive in that spot prices, especially electricity, are more often exhibiting temporary spikes, resulting from impermanent deviations from business-as-usual (e.g. physically). Following the same argument, the peak prices are more affected by the same deviation, since demand is higher during peak hours and the correction is larger back to equilibrium for the same amount of time to correct.

6.6 Granger Causality

As stated earlier we would like to investigate the direction of the dynamics between two variables that are connected, either in a link between two stationary variables, or for two non-stationary variables that are co-integrated. The Granger causality test is a way to test the relationship between two or more variables, and refers to the effects of past values of $\{\boldsymbol{z_t}\}$ on the current value of $\boldsymbol{y_t}$. The most common way to test the causality is to consider whether lags of one variable enter into the equation of another variable.

6.6.1 For stationary variables

If we are working with a bivariate VAR model where both variables are stationary, the test is simply done by an F-test of the joint-significance of the lagged independent variable.

The test procedure could be described as follows:

$\boldsymbol{H_0} = \{\boldsymbol{z_t}\}$ Does not Granger cause $\boldsymbol{y_t}$

Control for past values of y by estimating the autoregressive model for $\boldsymbol{y_t}$ AR(p):

$$\boldsymbol{y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{11}(i) y_{t-i} + \varepsilon_t} \qquad \text{(Restricted model)}$$

The appropriate model could be selected by the general-to-specific approach. As an alternative we will use OxMetrix´s advanced algorithm[20] for model selection. After the software selects the appropriate AR(p) model we enter 10 distributed lags of $\boldsymbol{z_t}$ into the model:

$$\boldsymbol{y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{11}(i) y_{t-i} + \sum_{i=1}^{10} \alpha_{12}(i) z_{t-i} + \varepsilon_t} \qquad \text{(Unrestricted model)}$$

$$\boldsymbol{F - stat = \frac{\frac{(R_{UR}^2 - R_R^{2)}}{r}}{\frac{(1 - R_{UR}^2)}{(T - k - 1)}}}$$

[20] The software is called “Autometric” and is available on OxMetrix´s 6.01 and newer.

UR = Unrestricted model, R =Restricted model, T= observations, r= dropped variables in restricted model (=10), k= total number of variables in unrestricted model.

If F-stat is greater than F-critical from the F-distribution, we reject H_0 and conclude that $\{\boldsymbol{z_t}\}$ Granger cause $\boldsymbol{y_t}$.

Then, we perform the same test procedure in the opposite direction, that is to investigate whether $\{\boldsymbol{y_t}\}$ does not Granger cause $\boldsymbol{z_t}$.

Critical Values:

5 per cent F-test: 1.83 (*)
1 per cent F-test: 2.32 (**)

6.6.2 Granger Causality Spot Series

We want to investigate the Granger Causality for the spot spark spread commodities in all three markets. This analysis is restricted to the full sample because we want to keep the analysis on level form. All the full sample spot prices are stationary time series[21]. The autoregressive model captures some seasonal effects, so the seasonal adjustment (with monthly dummies) has less significant influence for the results. We will therefore *not* take into account seasonal adjustment in this analysis.

Overall the results show that in Germany, the Netherlands and the UK the natural gas price Granger Causes the electricity price, but the electricity price does not Granger Cause the natural gas price on a 5 per cent significance level.

The result is similar with the findings elsewhere in the world; Emery & Liu (2001) confirms that a asymmetric response make sense in the US market, considering that natural gas is an important resource for generating electricity, while generating electricity is only one of many uses for natural gas.

[21] The DE Spot NATURAL GAS full sample time series is stationary on 10 per cent significance level

Table 18: Granger causality test between Electricity and Natural Gas

Relationship	Period	Unrestricted (R^2)	Restricted (R^2)	Granger (F-test)	ADL(p,q), p=Y lag, q= 10 lag	Portmanteau/ DW (Unrestricted) 12 lag
NL EL SPOT BASE - NL TTF SPOT	Full sample	0,639824	0,628904	5,04 (**)	P(1,2,3,5,10)	15,527/2,00237
NL TTF SPOT - NL EL SPOT BASE	Full sample	0,958356	0,957754	2,30 (*)	P(1,2,3,7,8,9,10)	4,2576/1,99971
NL EL SPOT PEAK – NL TTF SPOT	Full sample	0,531972	0,521115	3,83 (**)	p(1,2,3,5,9)	14.169/2.00196
NL TTF SPOT - NL EL SPOT PEAK	Full sample	0,958296	0,957754	2.15 (*)	p(1,2,3,7,8,9,10)	4.4223/1.99965
UK EL SPOT BASE – UK NBP SPOT GAS	Full sample	0,739537	0,730354	5.82 (**)	p(1,2,,4,6,10)	20.649/2.02699
UK NBP SPOT GAS - UK EL SPOT BASE	Full sample	0,918625	0,918108	1,05	p(1,2,3,4,5,6,9)	18.825/1.99114
UK EL SPOT PEAK – UK NBP SPOT GAS	Full sample	0,680702	0,669731	5.67 (**)	P(1,2,4,6,10)	18,221/2,02741
UK NBP SPOT GAS - UK EL SPOT PEAK	Full sample	0,91858	0,918108	0,96	p(1,2,3,4,5,6,9)	18,333/1,98766
DE EL SPOT BASE – DE NCG SPOT GAS	Full sample	0,666323	0,655344	5.43 (**)	P(1,2,4,10)	14,387/1.99657
DE NCG SPOT GAS - DE EL SPOT BASE	Full sample	0,968642	0,968308	1,76	P(1,2,3,4,7,8,9,10)	1,4080/1,99469
DE EL SPOT PEAK – DE NCG SPOT GAS	Full sample	0,568243	0,555692	4.80 (**)	P(1,2,5,10)	11,454/2,00055
DE NCG SPOT GAS - DE EL SPOT PEAK	Full sample	0,968624	0,968308	1,66	P(1,2,3,4,7,8,9,10)	1,3288/1,99426

Table 19: Granger causality test between Electricity spot prices in different countries

Relationship	Period	Unrestricted (R^2)	Restricted (R^2)	Granger (F-test)	ADL(p,q), p=Y lag, q= 10 lag	Portmanteau/ DW (Unrestricted) 12 lag
UK EL SPOT BASE - NL EL SPOT BASE	Full sample	0,737807	0,730354	4.66 (**)	p(1,2,4,6,10)	7.8750/2.00227
	Period 1	0,611981	0,579884	3.00 (**)	p(1,4,6)	9.2602/1.89351
	Period 3	0,675851	0,661376	3.39 (**)	p(1,2,3,4,6,10)	6.1737/1.98314
NL EL SPOT BASE - UK EL SPOT BASE	Full sample	0,659978	0,628904	15.01 (**)	p(1,2,3,5,10)	11.985/2.0047
	Period 1	0,532964	0,453706	6.16 (**)	p(1,2,5)	10.991/1.9878
	Period 3	0,755756	0,748651	2.21 (*)	(1,3,4,5,6,8,10)	4.6078/2.0041
NL EL SPOT BASE - DE EL SPOT BASE	Full sample	0,658254	0,628904	14.19 (**)	p(1,2,3,5,10)	18.335/2.0097
	Period 1	0,493166	0,453706	2.83 (**)	p(1,2,5)	4.7686/1.98294
	Period 3	0,759509	0,748651	3.43 (**)	p(1,3,4,5,6,8,10)	8.0906/1.97417
DE EL SPOT BASE - NL EL SPOT BASE	Full sample	0,678174	0,655344	11.73(**)	p(1,2,4,10)	14.586/2.01083
	Period 1	0,534542	0,490438	3.46 (**)	p(1,2)	3.0702/1.99613
	Period 3	0,733797	0,716387	4.98 (**)	p(1,2,4,10)	9.1645/1.98219
UK EL SPOT BASE - DE EL SPOT BASE	Full sample	0,741394	0,730354	7.05 (**)	p(1,2,5,6,10)	13.228/2.01567
	Period 1	0,605882	0,579884	2.40 (*)	p(1,4,6)	5.4776/1.95516
	Period 3	0,676508	0,661376	3.55 (**)	p(1,2,3,4,6,10)	4.3331/1.98272
DE EL SPOT BASE - UK EL SPOT BASE	Full sample	0,693924	0,655344	20.85 (**)	p(1,2,4,10)	6.9424/1.9974
	Period 1	0,582223	0,490438	7.99 (**)	p(1,2)	8.6901/1.9828
	Period 3	0,727744	0,716387	3.18 (**)	p(1,2,4,10)	11.576/2.00825

Table 19 shows that there are significant Granger causality in both direction, in all three combination for the electricity spot market. Our overall conclusion is that there is a significant Granger causality relationship between the electricity spot prices, but we cannot suggest a leading market "steering" any of the others. Note that the F-statistic is highly dependent on degrees of freedom in the denominator, so that the full sample F-statistics are greater than the sub-sample F-statistics. Thus, based on the F-statistic, one should not conclude that the Granger causality is stronger in the full sample models.

We have already seen that electricity was Granger caused by natural gas in the spot markets in all three countries, but not the other way. It is significant Granger causality both ways in the electricity market and therefore no one-way "steering" of the prices.

Table 20: Granger causality between Natural Gas spot prices

Relationship	Period	Unrestricted (R^2)	Restricted (R^2)	Granger (F-test)	ADL(p,q), p=Y lag, q= 10 lag	Portmanteau/ DW (Unrestricted) 12 lag
NL TTF SPOT - UK NBP SPOT GAS	Full sample	0,972367	0,957754	87,7 (**)	P(1,2,3,7,8,9,10)	7,7783/2,0035
	Period 1	0,909734	0,850876	24 (**)	P(1,2,3,7,8,9,10)	5,3864/1.98021
UK NBP SPOT GAS - NL TTF SPOT	Full sample	0,92079	0,918108	5,62 (**)	P(1,3,4,5,6,9)	18,069/1,99361
	Period 1	0,876257	0,86799	2,49 (**)	P(1,5,6)	12,715/1,97258

In table 20 we have not included a Granger causality test with German natural gas prices. The reason is that the Dutch series has been partly used as a proxy for this series. However, we did not find a steering natural gas spot market, thus the Granger causality goes in both directions. That is true both for the full sample and in period 1.

Table 21: Granger causality between CO_2 and Electricity spot prices

Relationship	Period	Unrestricted (R^2)	Restricted (R^2)	Granger (F-test)	ADL(p,q), p=Y lag, q= 10 lag	Portmanteau/ DW (Unrestricted) 12 lag
NL EL SPOT BASE - CO2 SPOT	Period 3	0,75778	0,748651	2.86 (**)	p(1,3,4,5,6,8,10)	8.0006/1.97331
CO2 SPOT - NL EL BASE SPOT	Period 3	0,94512	0,942538	3.59 (**)	p(1,3)	15.516/1.31529
DE EL SPOT BASE - CO2 SPOT	Period 3	0,723602	0,716387	1.99 (*)	p(1,2,4,10)	19.270/2.01446
CO2 SPOT - DE EL SPOT BASE	Period 3	0,955204	0,942538	21.60 (**)	p(1,3)	15.740/1.3843
UK EL SPOT BASE - CO2 SPOT	Period 3	0,670986	0,661376	2.22 (*)	p(1,2,3,4,6,10)	7.6357/2.00426
CO2 SPOT - UK EL SPOT BASE	Period 3	0,952686	0,942538	16.39 (**)	p(1,3)	8.024/1.50844

* We also control the model for auto-correlation in residual with Portmanteau (Ljung-Box test).

As seen in table 21 we investigated the relationships between the spot electricity prices and the price of $C0_2$ allowances only for the last period. That is due to the collapse of the CO_2 price in the second period.

The Granger causality between CO_2 and electricity spot prices goes both directions, but there seems to be a stronger Granger causality from electricity spot prices than from CO_2 spot prices. The CO_2 price does Granger cause the electricity price in Germany and the UK on a 10 per cent significance level. One reason that electricity Granger causes the CO_2 price is that the market players first observe price signals in the electricity price before they trade emission rights.

We could not perform Granger causality tests between natural gas and CO_2 because we do not have any samples where they are integrated of same order.

6.6.3 Granger Causality for Co-integrated variables

When we are working with Granger causality in a co-integrated system, it is actually an extension of the analysis of the speed-of-adjustment estimators and it is necessary to reinterpret Granger Causality in that circumstances. "In a co-integrated system, $\{\boldsymbol{y_t}\}$ does not Granger cause $\{\boldsymbol{z_t}\}$ if lagged values of $\Delta\boldsymbol{y_{t-i}}$ do not enter the Δz_t equation and if $\boldsymbol{z_t}$ does not respond to the deviation from long-run equilibrium"(Enders, 2010). In other words, if $\boldsymbol{z_t}$ is not Granger caused by $\{\boldsymbol{y_t}\}$ it requires that $\{\boldsymbol{z_t}\}$ is weakly exogenous and that all estimators of $\Delta\boldsymbol{y_{t-i}}$´s are insignificant. Therefore we again apply the F-test for the joint significance of these parameters, similar to the one for stationary variables but now in first differences.

The test procedure could be described as follows:

$\boldsymbol{H_0} = \{\boldsymbol{z_t}\}$ Does not Granger cause $\boldsymbol{y_t}$

Control for past values of $\Delta\boldsymbol{y}$ by estimating the autoregressive model for $\Delta\boldsymbol{y_t}$ AR(p):

$\Delta\boldsymbol{y_t} = \boldsymbol{\alpha_0} + \sum_{i=1}^{p}\boldsymbol{\alpha_{11}}(\boldsymbol{i})\Delta\boldsymbol{y_{t-i}} + \boldsymbol{\varepsilon_t}$ (Restricted model)

The appropriate model could be selected by the general-to-specific approach. As an alternative we will again use OxMetrix´s advanced algorithm for model selection. After the software has selected the appropriate AR(p) model we have entered 10 distributed lags of $\boldsymbol{z_t}$:

$\Delta\boldsymbol{y_t} = \boldsymbol{\alpha_0} + \sum_{i=1}^{p}\boldsymbol{\alpha_{11}}(\boldsymbol{i})\Delta\boldsymbol{y_{t-i}} + \boldsymbol{\alpha_y}\boldsymbol{\hat{e}_{t-1}} + \sum_{i=1}^{10}\boldsymbol{\alpha_{12}}(\boldsymbol{i})\Delta\boldsymbol{z_{t-i}} + \boldsymbol{\varepsilon_t}$
(Unrestricted model)

$$\boldsymbol{F-stat}=\frac{\frac{(\boldsymbol{R_{UR}^2}-\boldsymbol{R_R^2})}{\boldsymbol{r}}}{\frac{(\boldsymbol{1}-\boldsymbol{R_{UR}^2})}{(\boldsymbol{T}-\boldsymbol{k}-\boldsymbol{1})}}$$

UR = Unrestricted model, R =Restricted model, T= observations, r= dropped variables in restricted model (=10), k= total number of variables in unrestricted model.

If F-stat is greater than F-critical from the F-distribution, we reject H_0 and conclude that $\{\boldsymbol{z_t}\}$ Granger cause $\boldsymbol{y_t}$.

Numerator degree of freedom is 10 for the F-test.

Then, we perform the same test procedure in the opposite direction, that is to investigate whether $\{\boldsymbol{y_t}\}$ does not Granger cause $\boldsymbol{z_t}$.

Critical Values:

5 per cent F-test: 1.83 (*)

1 per cent F-test: 2.32 (**)

If the test concludes auto-correlation in the residuals we need to add more lags to fix the problem. The errors (residuals) must be uncorrelated and homoscedastic to perform valid statistical inference.

Table 22: Granger causality between Electricity and Natural Gas front prices

Relationship	Period	Unrestricted (R^2)	Restricted (R^2)	Granger (F-test)	ADL(p,q), p=Y lag, q= 10 lag	Portmanteau/ DW (Unrestricted) 12 lag
NL EL FRONT MONTH BASE - DE EL FRONT MONTH BASE	Period 2	0,0438126	0,0220813	1,02	P(1 - 10) (#)	1,3842/1,99998
	Period 3	0,0402944	0,0252747	1,08	P(1,4)	2,2368/1,9928
DE EL FRONT MONTH BASE - NL EL FRONT MONTH BASE	Period 2	0,0433534	0,0175793	1,22	P(3,9)	2,5158/1,93378
	Period 3	0,0431784	0,0195233	1,71	P(1,4)	2,7099/2,01675
NL EL FRONT MONTH BASE - NL TTF FRONT MONTH	Full sample	0,0236131	0,00891606	2,26 (*)	P(1,3)	9,0052/1,99529
	Period 2	0,0469195	0,00825158	1,85 (*)	P(9)	9,7767/1,96615
	Period 3	0,0794	0,0252747	4,07 (**)	P(1,4)	3,0491/2,00443
NL TTF FRONT MONTH - NL EL FRONT MONTH BASE	Full sample	0,0189534	0,00897699	1,53	P(2,3,4)	18,377/1,97314
	Period 2	0,0372651	0,0183883	0,89	P(3,10)	18,059/2,02045
	Period 3	0,0810468	0,0602327	1,56	P(1,4,5,7)	10,825/1,9994
DE EL FRONT MONTH BASE - DE Gas Front	Full sample	0,0182079	0,00934929	1,35	P(1-10) (#)	0,33023/1,99983
	Period 2	0,045312	0,02326	1,05	P(2,3,9)	3,6934/1,87462
	Period 3	0,036107	0,019523	1,19	P(1,4)	6,4213/1,99924
DE Gas Front - DE EL FRONT MONTH BASE	Full sample	0,023779	0,005169	2,85 (**)	P(1-10) (#)	0,83098/2,00078
	Period 2	0,0638503	0,0170598	2,24 (*)	P(1-10) (#)	0,71939/2,00053
	Period 3	0,060767	0,0192351	3,03 (**)	P(1-10) (#)	0,25070/2,00304
UK NBP FRONT MONTH - NL TTF FRONT	Full sample	0,038817	0,020794	2,81 (**)	P(2,3,4,8)	7,4597/2,02668
	Period 1	0,065752	0,024674	1,45	P(2,4)	10,194/2,08434
	Period 2	0,080402	0,019471	2,96 (**)	P(1-10) (#)	2,3383/1,9895
	Period 3	0,0723629	0,0242454	3,58 (**)	P(4,5,6,7)	8,1137/2,00634
NL TTF FRONT - UK NBP FRONT MONTH	Full sample	0,025291	0,00897699	2,51 (**)	P(2,3,4)	16,282/2,08037
	Period 1	0,0529289	0,0177849	1,19	P(1-10) (#)	1,1026/1,99678
	Period 2	0,0367074	0,0183883	0,86	P(3,10)	14,368/2,12951
	Period 3	0,124418	0,060233	5,06 (**)	P(1,4,5,7)	8,1181/2,03759
NL TTF FRONT MONTH - DE Gas Front	Period 3	0,083805	0,0602327	1,78	P(1,4,5,7)	8,3370/2,00759
DE Gas Front - NL TTF FRONT MONTH	Period 3	0,19868	0,019341	15,3 (**)	P(1-10) (#)	1,0011/1,99123
UK NBP FRONT MONTH - DE Gas Front	Period 3	0,0473353	0,0312363	1,16	P(1,3,4,5,6,7)	6,4880/2,00876
DE Gas Front - UK NBP FRONT MONTH	Period 3	0,12288	0,019341	8,09 (**)	P(1-10) (#)	2,1247/2,00153

** We also control the model for auto-correlation in residual with Portmanteau (Ljung-Box test).*
(#) = Had to use an AR(10) as restricted model since Autometics failed

In the front electricity market we could not conclude Granger causality in either of the directions, but since the speed-of-adjustment coefficient were significant it is not in conflict with the Granger representation theorem.

NL TTF Front Month Granger causes NL EL Front month, but not the other way. This result is expected in the same way as in the spot market analysis where the natural gas is price setter in electricity spot market, but electricity market is just one of the many uses for natural gas.

Consequently, we are surprised by the results of this relationship in Germany. Here we found that in the front market, the electricity is Granger causing the price of natural gas. However, table 1 show the relatively low share of natural gas in the German energy mix, and by taking that into account it is fair to argue that it should not dictate the electricity price in large manner. So, why is this different in the spot and front market in Germany? That is a difficult question to answer, but if we look at the Granger causality test between the different front natural gas markets we might have an answer. As the results demonstrate, for the front natural gas price between the UK and the Netherlands the Granger causality goes in both directions, meaning that both markets have a significant influence on each other. More important is it that both the Dutch and the British front natural gas price is Granger causing the German, while the German does not Granger causes any of the two. In our interpretation of this, the key is that Germany has the lowest average efficiency factor of the three countries as highlighted in figure 4. When prices of natural gas in Europe spike, adjustments in the spot markets lead to increased electricity price, which is Granger causality from natural gas to electricity in all three markets. Since the average efficiency in Germany is low, many plants will be expected to reduce its production volume, and "relatively" easy rely on other sources in the energy mix. Following the same argument for the Netherlands, which has a higher efficiency and much more reliant on natural gas, the front electricity price increase as the front natural gas prices increases. In other words, the efficient gas-fired plants in the UK and the Netherlands are more resistant to high natural gas prices and dependent on natural gas, while in Germany there should be a shift in production to other sources.

So looking ahead, the German electricity price should not be as sensitive to natural gas prices as in the UK and the Netherlands. As the price of electricity increases more German natural gas plants are expected to come into operation, which increases German demand for front natural gas, which is Granger causality from electricity to natural gas.

6.7 Part 2 summary

The problems regarding spurious regression were addressed in a comprehensive approach in part 2. First we tested whether the variables were stationary by Dickey-Fuller tests. Relationships involving non-stationary variables were later tested for co-integration. When we adjusted for seasonal effects we observed that all relationships involving non-stationary variables that we wanted to investigate were co-integrated. That gave us confidence to analyse the long-run relationships, without having spurious regression.

The estimated cross-commodity (spark spread) long-run relationships gave some interesting results. The marginal effect, estimated by the slope coefficient (beta), showed a substantial decrease in the last period. We argued that when the average marginal effect decrease, it implies that gas-fired power plants face difficulties to be fully compensated by increased electricity prices when the price of natural gas increases. Due to that we find it difficult to argue that the spark spread relationship is a stable relationship.

It should be noted that the marginal effect is based on the well-known method of ordinary least squares, such that the estimates will minimize the sum of squared residuals. Since the estimated marginal effect is a constant we only observed the "average" marginal effect for the sample. In this view we clearly recognise that it is some loss of information, which describe the dynamics faced by the management of a gas-fired plant on a daily basis. For example the flexibility to only run a plant in profitable peak hours.

In addition, we argued that if markets should be fully integrated in Europe, there should be sufficient transfer capacity between the countries. The estimated results for historical cross-country long-run relationships, or long-run market integration, were two-fold. For all practical purposes the markets are integrated when we considered front prices. On the other hand, the betas for the spot relations were far from unity. Given our hypothesis, the conclusion is that the spot markets is not fully integrated. However, we observed high explanatory powers between the spot relations, which indicate strong connections between the markets.

To further explore the dynamics we estimated the error-correction model and calculated the speed-of-adjustment parameters. The speed-of-adjustment gave an indication of how many days it takes to correct a 1 EUR/MWh deviation from the long-run relationship, by taking the inverse of the speed-of-adjustment coefficient. The result for the front market was that we observed a substantial decrease, in the number of days it takes to correct the deviation, from the first to the two last periods. In the two last periods the speed-of-adjustments are approximately 22 to 28 trading days, respectively in the Netherlands and Germany.

Following the reduction of speed-adjustment days, it means that the spark spread relationship actually has become stronger.

In the last section of part 2 we explored the Granger causality among different variables. For the spot electricity and natural gas markets the causality goes in both directions. The same was found between CO_2 and electricity spot prices, but it seemed to be a stronger Granger causality from electricity spot prices than the other way. For the front market the tests showed that natural gas prices Granger cause electricity prices, but not the other way around, except in the front market in Germany. The asymmetric response make sense considering that natural gas is an important resource for generating electricity, while generating electricity is only one of many uses for natural gas.

7. Conclusion

The main task for this thesis was to explore the connections between electricity and natural gas prices in Germany, the Netherlands, and the UK, with an incorporation of the CO_2 allowance price. We analysed the electricity, natural gas and CO_2 allowance prices by short-term and long-term statistical concepts. The result showed evidence of cross-boarder market integration and that (clean) spark spread price relationship is reasonably stable over time. The last period showed a structural break in the (clean) spark spread relations, as we studied in section 6. Further on we hoped to identify “leading markets” by disclosing the dynamics of the price connections. At last we wanted to use estimated statistical relationships to describe the marginal effect for a natural gas-fired power plant given changes in commodity prices.

The analysis was based on a top-down approach with analysis of price-relationship in the different markets. From the statistical analysis we made several observations that we believe are important for various market participants exposed to electricity or natural gas prices. The analysis has also emphasized the importance of using several statistical techniques to explore these relationships, not only considering short-term relations.

This section will highlight the main conclusions from the analysis, based on short- and long-term relationships.

Short-term

When analysing short-term relationships between the variables we had a special focus on correlation measures, and estimated correlations in terms of returns and volatility of returns between the different variables. Within each commodity we found strong correlations, indicating tight integration of the markets. Contrary, when we performed the correlation analysis between the different commodities, we could not establish clear arguments of tight connection based short-term movements in prices.

However, when we looked at the cross-commodity correlation of volatility we found a movement towards stronger connection in the last period, indicating that electricity, natural gas and CO_2 allowances prices have become closer connected.

Since these analyses were based on short-term movements (daily basis), and that the results could not be used to infer causality, it stressed the importance of extending the analyses to statistical concepts suitable to describe relationships on a longer term.

Long-term

When we analysed long-run relationships that could explain market integration, the results were two-fold. In the front market we found clear evidence of market integration, while in the spot market the results gave less support to the hypothesis of integrated markets. However, we conclude that European electricity markets are highly integrated, and for the natural gas markets we reach the same conclusion.

In the long-term analysis we established an important finding concerning the causality between the commodities. Granger causality tests showed that natural gas prices Granger cause electricity prices, but not the other way around, except in the German front market. The asymmetric response between the commodities make sense considering that natural gas is an important resource for generating electricity, while generating electricity is only one of many uses for natural gas.

In section 6.4.2 we estimated long-run relationships and the marginal effect between electricity and natural gas prices. The slope coefficients indicate how a natural gas-fired electricity producer can transfer the average natural gas procurement cost to income from selling electricity (the spark spread). As explained in section 6.4.2, an estimated beta less than 2 indicates that a benchmarked gas-fired plant will have a marginal loss if the natural gas price increases. For the last period we observe a strong decrease in the slope coefficient. Our conclusion is that it is too soon to argue that the spark spread has reach a stable level, even though the speed-of-adjustment days has been reduced.

Considering causality, we are not able to conclude that there is a general "leading market" for any of the three price variables in the spark spread. The reason is that the results were to mixed, even though we found Granger causality in many relationships.

Suggestion for further analysis

Considering the strong decrease of the beta coefficient in the long-run relationship of the spark spread commodities in the last period, it would be very interesting to explore if the estimated slope coefficient in the last period is a permanent structural break.

In addition, an extension of the analysis that includes capacity constraints, traded volumes, and storage facilities will possibly enhance the understanding of the estimated concept. If that is combined with hourly prices instead of daily, the researcher will be able to incorporate the valuable flexibility of a natural gas-fired power plant.

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9. Appendix

9.1.1 Figure of time series

Electricity and natural gas time series used in regression analysis (level series):

Figure 18: Electricity and natural gas seires in the Netherlands

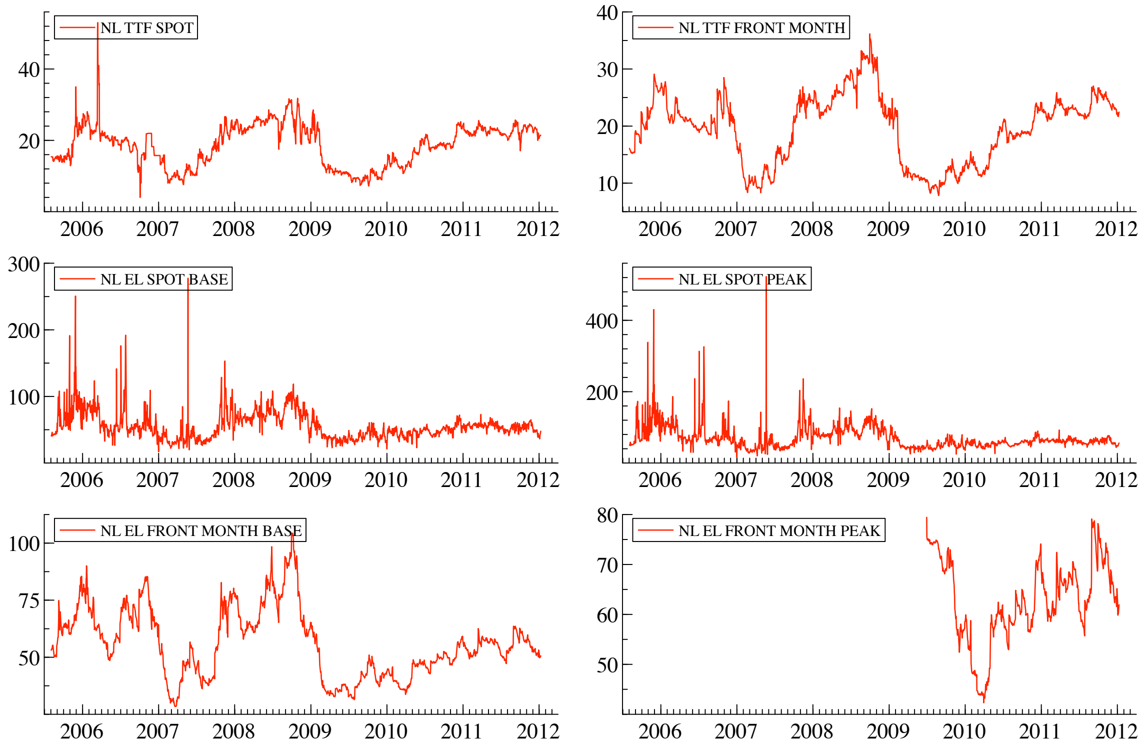


Figure 19: Electricity and natural gas seires in Germany

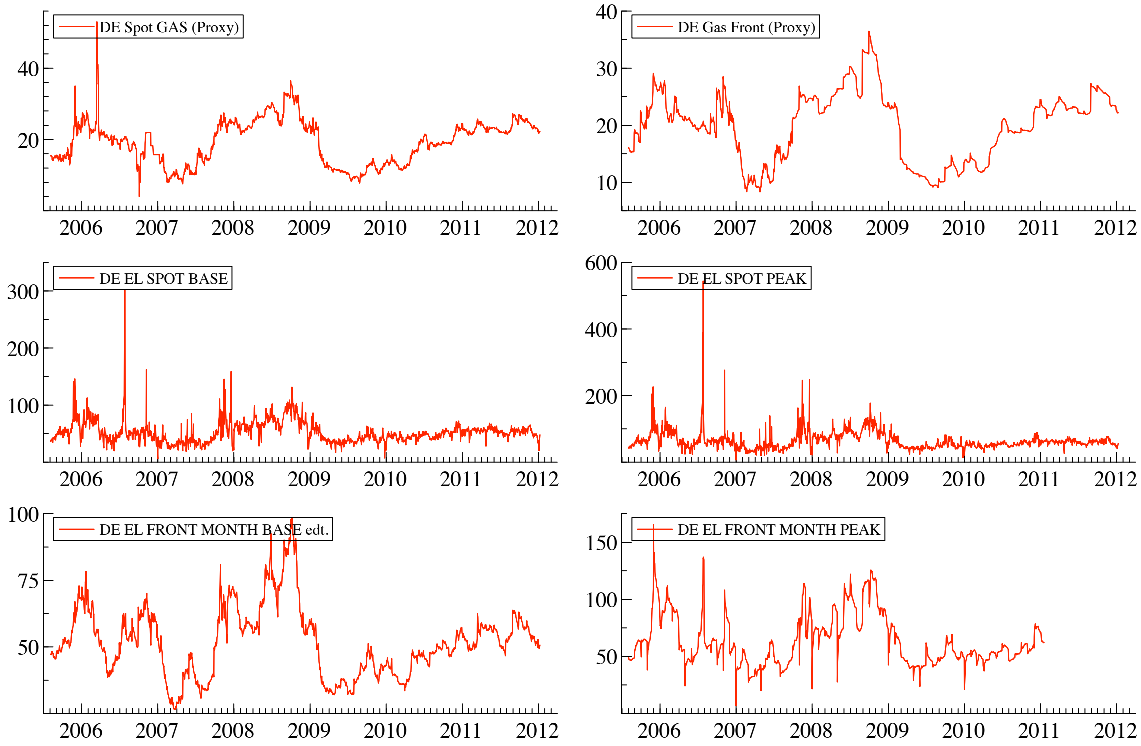
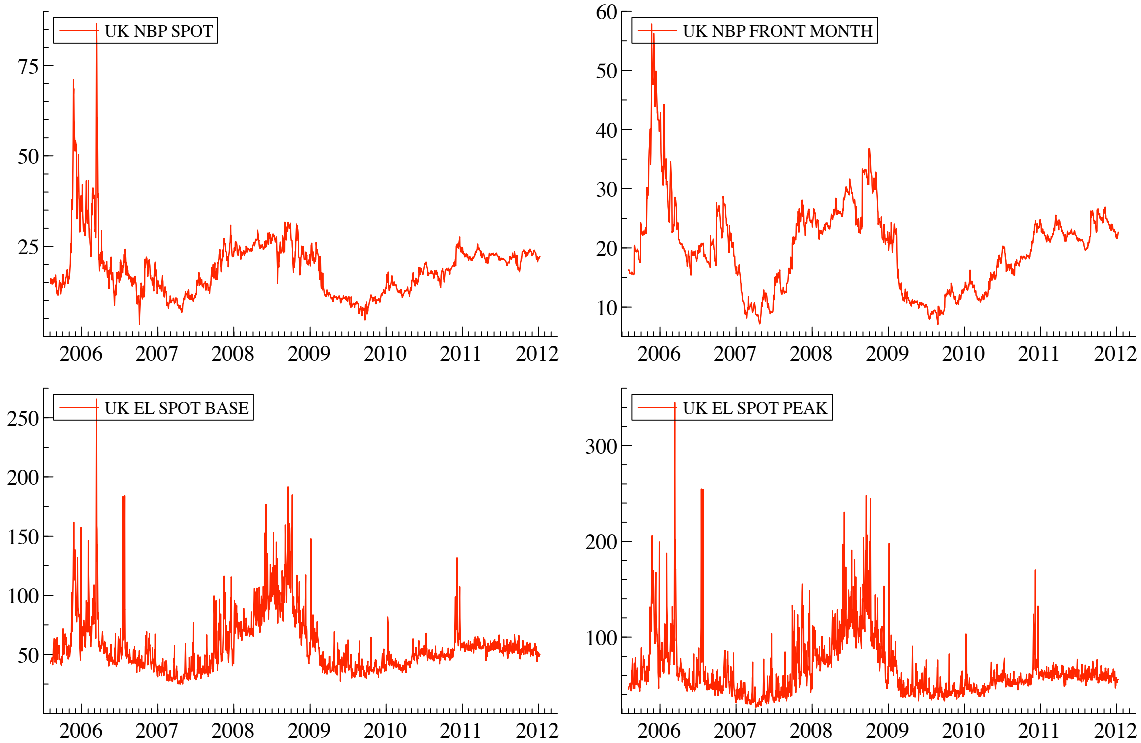


Figure 20: Electricity and natural gas seires in the UK



9.1.2 Data variables

Table 23: Time series variables

Variable	Index	Exchange	Source
NL TTF Spot	TTF Day-Ahead Index	APX-ENDEX	Thomson Reuters DataStream
NL TTF FRONT	TTF Gas Base Load TRc1	APX-ENDEX	Thomson Reuters DataStream
NL EL SPOT BASE	Power NL Base-Load Index	APX-ENDEX	Thomson Reuters DataStream
NL EL SPOT PEAK	Power NL Peak-Load Index	APX-ENDEX	Thomson Reuters DataStream
NL EL FRONT BASE	Power NL Base Load TRc1	APX-ENDEX	Thomson Reuters DataStream
UK NBP SPOT	NBP Day-Ahead Index	APX-ENDEX	Thomson Reuters DataStream
UK NBP FRONT	Natural Gas Mth.Fwd (P/Therm)	ICE	Thomson Reuters DataStream
UK EL SPOT BASE	Power UK Spot Base Load Index	APX-ENDEX	Thomson Reuters DataStream
UK EL SPOT PEAK	Power UK Spot Peak Load Index	APX-ENDEX	Thomson Reuters DataStream
DE SPOT GAS	NCG daily reference price	EEX	Thomson Reuters DataStream
DE GAS FRONT	EGIX NCG Index Mthly	EEX	Thomson Reuters DataStream
DE EL SPOT BASE	Phelix Base	EEX	Thomson Reuters DataStream
DE EL SPOT PEAK	Phelix Base	EEX	Thomson Reuters DataStream
DE EL FRONT	Monthly Baseload Continuous	EEX	Thomson Reuters DataStream
CO2 SPOT (GAS)	EU Allowances	EEX	Thomson Reuters DataStream

9.1.3 Source

We downloaded the exchange rates form FX Historical Data (http://www.fxhistoricaldata.com) that we used for the conversion to from Sterling Pound to Euro.

Natural gas, Power and CO_2 prices are all downloaded from Thomson Reuters DataStream. The physical conversion is based on numbers from http://www.onlineconversion.com/energy.htm.

9.1.4 Statistical software

We have used the statistical software OxMetrics 6.01 (2009) with the regression program PcGive 13.0, created by Jurgen A. Doornik who is a Research Fellow at the Economics Department of the Univeristy of Oxford, and a director of OxMetrics Technologies Ltd.

9.1.5 Energy units

Capacity (measured in Watt) is the rate of energy conversion.

1 kW = 1000 W

1 MW = 1 000 000 W

1 GW = 1 000 000 000 W

1 TW = 1 000 000 000 000 W

For constant power, energy in watt-hours is the product of power in watts and time in hours. Often used to measure energy over a time period, e.g. MWh or TWh.

9.1.6 $C0_2$ Emission Factor

60 per cent efficiency: 1 – (60 per cent/0.8366) = 0.283 t CO_2/MWh

50 per cent efficiency: 1 –(50 per cent/0.8366) = 0.402 t CO_2/MWh

40 per cent efficiency: 1 – (40 per cent/0.8366) = 0.522 t CO_2/MWh

30 per cent efficiency: 1 – (30 per cent/0.8366) = 0.641 t CO_2/MWh

9.1.7 Converting all natural gas prices to EUR/MWh :

100 000 Btu (Therm) = 0.029 307 108 333 MWh

1 000 000 Btu (MMBtu)= 0.29 307 108 333 MWh

Exchange rates conversion: EUR = USD * (1/EURUSD)

Pound = Pence/100 (National Balancing Point)

9.1.8 Data preparation for missing data points (observations);

We used linear interpolation to adjust for unequal number of observations between two or more data samples.

After the generic series were transformed either by first differencing or log returns, they got extraordinary large spikes that did not stem from regular price formation at the exchanges. These spikes came when the front contract shift to the next month. This was corrected by replacing them by the approximate mean of the series, which is zero.

9.1.9 Age/efficiency conversion for missing data

Table 24: Efficiency/age

Years	Efficency
Age < 10	60 per cent
10 > age < 20	50 per cent
20>Age > 30	40 per cent
Age>40	30 per cent

9.1.10 Data-sample error in the futures contract for electricity in The Netherlandss (DE EL FRONT MONTH BASE)

During our error correction testing we discovered a data-sample error. Germany (Phelix) month futures and The Netherlands month futures have the last contract trading day the next to last business day before contract expires. In the data-sample from Thomson Retures Datastream the month contract for Germany (Phelix EEX Month futures) is registered with data from the previous contract for the last business day. This means that when compering the two time-series we will always compare two different monthly contracts the last business day of the month. For example in the end of January the NL-series will shows the value for the March-contract, but DE-series will show the value for the February-contract. This creates a huge spike in the difference between the two series at every end-of-month observation.

We used the following formula to solve this problem since we do not have the real observations form Phelix EEX Month Futures.

DE (t) = NL (t) * (DE (t-1) / NL (t-1))

The natural gas time series (both spot and front) from Germany is based on index series form TTF before 2007-09-27 and based on data from NCG (NetConnect Germany) from 2007-09-28 until 2012-01-09. E-ON states that the increased volume and activity in the German natural gas market has made the NCG prices credible. There is therefore a artificially high correlation between the TTF and NCG prices. The EUA (CO2) prices are converted to EUR/MWh modelling a natural gas fired power plant. The average CO2 price is the average price a natural gas fired power plant need to pay for its emission per MWh.

9.1.11 New insvestments in Natural gas-fired power plants

Table 25: New natural gas-fired power plants

Plant	MW	Year	Country	Investment/MW	Operator	Type	Efficiency
Moerdijk 2	430	2012	NL	€0.93 million	Essent (RWE)	CCGT	58 %
Magnum	1350	2012	NL	€1.11 million	Nuon (Vattenfall)	CCGT/IGCC	58 %
Diemen 34	435	2012	NL	-	Nuon (Vattenfall)	CCGT	59 %
Hemweg 9	435	2012	NL	-	Nuon (Vattenfall)	CCGT	57 %
Bergum	450	2013	NL	-	Electrabel	CCGT	45 %
Emshaven	1200	2017	NL	€1.00 million	Advanced Power	CCGT	60 %
Damhead Creek 2	1000	-	UK	€0.81 million	Scottish Power	CCGT	55 %
West Burton	1300	2012	UK	€0.62 million	EDF Energy	CCGT	-

9.1.12 Correlation returns sub-samples

Table 26: Correlation returns Period 1

Correlation return P1	NL TTF Spot	NL TTF FRONT MONTH	NL EL SPOT BASE	NL EL SPOT PEAK	NL EL FRONT MONTH BASE	UK NBP SPOT	UK NBP NBP FRONT MONTH	UK EL SPOT BASE	UK EL SPOT PEAK	DE EL SPOT BASE	DE EL SPOT PEAK	DE EL FRONT MONTH BASE	CO2 SPOT (GAS)	DE SPOT GAS	DE GAS FRONT
NL TTF Spot	1														
NL TTF FRONT	0 %	1													
NL EL SPOT BASE	2 %	-4 %	1												
NL EL SPOT PEAK	1 %	-6 %	98 %	1											
NL EL FRONT BASE	2 %	30 %	-1 %	0 %	1										
UK NBP SPOT	8 %	25 %	1 %	2 %	12 %	1									
UK NBP FRONT	1 %	44 %	-7 %	-9 %	31 %	37 %	1								
UK EL SPOT BASE	-8 %	12 %	8 %	9 %	3 %	38 %	22 %	1							
UK EL SPOT PEAK	-7 %	11 %	9 %	10 %	2 %	36 %	20 %	99 %	1						
DE EL SPOT BASE	0 %	-8 %	46 %	43 %	-11 %	-2 %	-4 %	7 %	9 %	1					
DE EL SPOT PEAK	-1 %	-7 %	44 %	42 %	-10 %	1 %	-4 %	8 %	10 %	98 %	1				
DE EL FRONT	3 %	30 %	-1 %	0 %	56 %	16 %	30 %	2 %	2 %	5 %	5 %	1			
CO2 SPOT (GAS)	4 %	16 %	-1 %	-2 %	34 %	12 %	18 %	2 %	1 %	-12 %	-9 %	25 %	1		
DE SPOT GAS	100 %	0 %	2 %	1 %	2 %	8 %	1 %	-8 %	-7 %	0 %	-1 %	3 %	4 %	1	
DE GAS FRONT	0 %	90 %	-3 %	-5 %	26 %	21 %	40 %	14 %	13 %	-6 %	-6 %	27 %	15 %	0 %	1

Table 27: Correlation returns Period 2

Correlation return P2	NL TTF Spot	NL TTF FRONT MONTH	NL EL SPOT BASE	NL EL SPOT PEAK	NL EL FRONT MONTH BASE	UK NBP SPOT	UK NBP NBP FRONT MONTH	UK EL SPOT BASE	UK EL SPOT PEAK	DE EL SPOT BASE	DE EL SPOT PEAK	DE EL FRONT MONTH BASE	CO2 SPOT (GAS)	DE SPOT GAS	DE GAS FRONT
NL TTF Spot	1														
NL TTF FRONT	4 %	1													
NL EL SPOT BASE	14 %	-5 %	1												
NL EL SPOT PEAK	14 %	-5 %	97 %	1											
NL EL FRONT BASE	2 %	32 %	3 %	2 %	1										
UK NBP SPOT	12 %	41 %	5 %	5 %	9 %	1									
UK NBP FRONT	2 %	83 %	-5 %	-6 %	24 %	43 %	1								
UK EL SPOT BASE	3 %	6 %	13 %	14 %	-2 %	16 %	9 %	1							
UK EL SPOT PEAK	2 %	5 %	12 %	14 %	-2 %	16 %	7 %	100 %	1						
DE EL SPOT BASE	10 %	-1 %	46 %	46 %	4 %	5 %	-1 %	15 %	15 %	1					
DE EL SPOT PEAK	13 %	-4 %	44 %	46 %	2 %	5 %	-3 %	17 %	17 %	95 %	1				
DE EL FRONT	3 %	29 %	9 %	8 %	77 %	9 %	27 %	1 %	0 %	8 %	9 %	1			
CO2 SPOT (GAS)	-4 %	11 %	-3 %	-3 %	5 %	8 %	10 %	7 %	7 %	-1 %	-3 %	4 %	1		
DE SPOT GAS	53 %	29 %	9 %	9 %	11 %	13 %	26 %	4 %	3 %	4 %	5 %	15 %	-1 %	1	
DE GAS FRONT	8 %	71 %	-6 %	-5 %	15 %	33 %	70 %	2 %	1 %	2 %	2 %	18 %	9 %	12 %	1

Table 28: Correlation returns Period 3

Correlation return P3	NL TTF Spot	NL TTF FRONT MONTH	NL EL SPOT BASE	NL EL SPOT PEAK	NL EL FRONT MONTH BASE	UK NBP SPOT	UK NBP NBP FRONT MONTH	UK EL SPOT BASE	UK EL SPOT PEAK	DE EL SPOT BASE	DE EL SPOT PEAK	DE EL FRONT MONTH BASE	CO2 SPOT (GAS)	DE SPOT GAS	DE GAS FRONT
NL TTF Spot	1														
NL TTF FRONT	9 %	1													
NL EL SPOT BASE	10 %	5 %	1												
NL EL SPOT PEAK	5 %	3 %	87 %	1											
NL EL FRONT BASE	15 %	46 %	-1 %	-2 %	1										
UK NBP SPOT	6 %	40 %	3 %	-2 %	18 %	1									
UK NBP FRONT	5 %	82 %	5 %	3 %	42 %	42 %	1								
UK EL SPOT BASE	5 %	8 %	19 %	17 %	1 %	8 %	13 %	1							
UK EL SPOT PEAK	2 %	7 %	16 %	15 %	2 %	6 %	13 %	98 %	1						
DE EL SPOT BASE	5 %	1 %	49 %	49 %	1 %	0 %	1 %	12 %	9 %	1					
DE EL SPOT PEAK	4 %	1 %	56 %	63 %	1 %	-2 %	-1 %	13 %	12 %	87 %	1				
DE EL FRONT	13 %	40 %	-1 %	-2 %	87 %	17 %	37 %	-1 %	0 %	-2 %	2 %	1			
CO2 SPOT (GAS)	7 %	-6 %	-5 %	-6 %	3 %	-4 %	-6 %	-8 %	-8 %	-6 %	-9 %	0 %	1		
DE SPOT GAS	5 %	75 %	4 %	3 %	39 %	30 %	73 %	9 %	9 %	4 %	3 %	33 %	-3 %	1	
DE GAS FRONT	26 %	42 %	3 %	4 %	31 %	20 %	39 %	4 %	3 %	3 %	4 %	25 %	4 %	38 %	1

9.1.13 Rolling correlations

Figure 21: 100 days rolling corr DE EL-GAS Germany

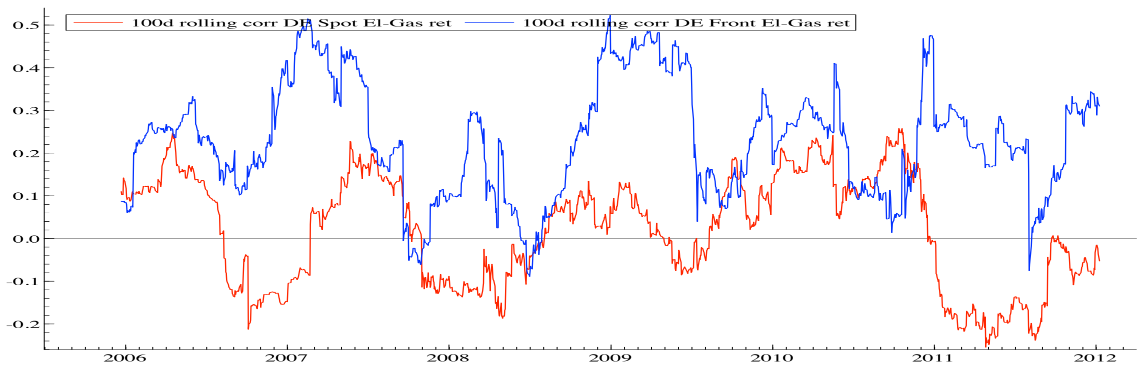


Figure 22: Dummy model of 100 days rolling corr DE Front EL-GAS Germany

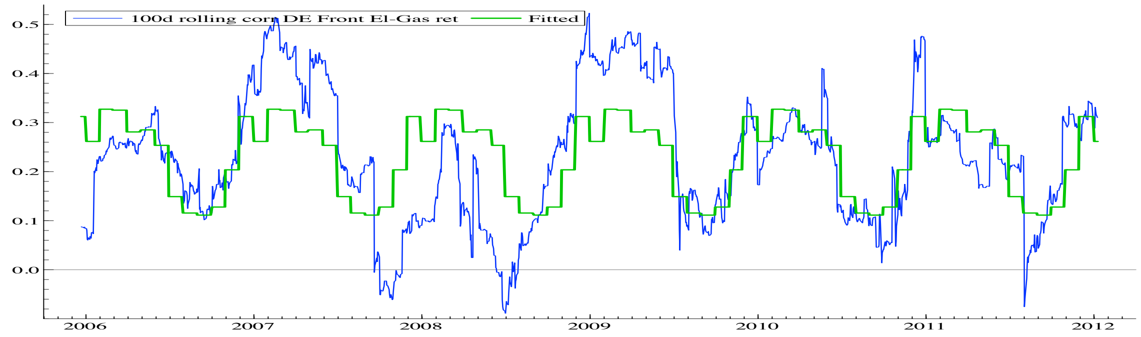
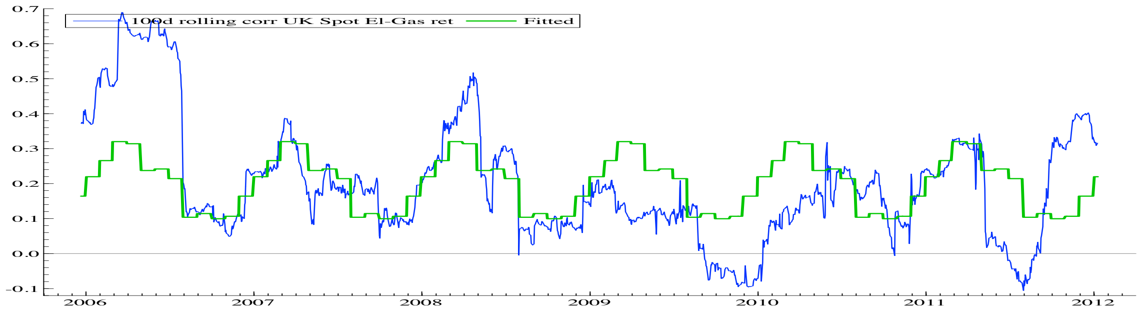


Figure 23: Dummy model of 100 days rolling corr UK Front EL-GAS the UK



9.1.14 Stationarity tests

Table 29: Sub-periods Augmented Dickey-Fuller Results

	Period	Integrated order	Level t-statistic	Selected-lags (AIC)
NL TTF SPOT	Period 1	I(0) stationary	-3.46 (**)	9
	Period 2	I(1) unit root	-1,95	1
	Period 3	I(1) unit root	-1,52	9
NL TTF FRONT MONTH	Period 1	I(1) unit root	-2,08	0
	Period 2	I(1) unit root	-1,33	4
	Period 3	I(1) unit root	-1,37	8
NL EL SPOT BASE	Period 1	I(0) stationary	-6.31 (**)	4
	Period 2	I(0) stationary	-3.96 (**)	4
	Period 3	I(0) stationary	-4.40 (**)	4
NL EL SPOT PEAK	Period 1	I(0) stationary	-9.75 (**)	1
	Period 2	I(0) stationary	-5.11 (**)	4
	Period 3	I(0) stationary	-4.27 (**)	10
NL EL FRONT MONTH BASE	Period 1	I(1) unit root	-2,51	2
	Period 2	I(1) unit root	-1,54	0
	Period 3	I(1) unit root	-2,1	4
NL EL FRONT MONTH PEAK	Period 3	I(0) stationary	-3.17 (*)	1
UK NBP SPOT	Period 1	I(0) stationary	-2.97 (*)	5
	Period 2	I(1) unit root	-2,14	3
	Period 3	I(1) unit root	-1,41	6
UK NBP FRONT MONTH	Period 1	I(1) unit root	-1,72	4
	Period 2	I(1) unit root	-1,64	0
	Period 3	I(1) unit root	-1,45	7
UK EL SPOT BASE	Period 1	I(0) stationary	-3.94 (**)	8
	Period 2	I(1) Unit root	-1,81	10
	Period 3	I(0) stationary	-3.33 (*)	10
UK EL SPOT PEAK	Period 1	I(0) stationary	-4.27 (**)	8
	Period 2	I(1) Unit root	-2,03	10
	Period 3	I(0) stationary	-4.12 (**)	10
DE Spot GAS	Period 1	I(0) stationary	-3.46 (**)	9
	Period 2	I(1) unit root	-1,23	1
	Period 3	I(1) unit root	-1,53	9
DE Gas Front	Period 1	I(1) unit root	-2,08	0
	Period 2	I(1) unit root	-1,41	1
	Period 3	I(1) unit root	-0,88	1
DE EL SPOT BASE	Period 1	I(0) stationary	-7.02 (**)	1
	Period 2	I(1) unit root	-2,59	10
	Period 3	I(0) stationary	-3.44 (**)	10
DE EL SPOT PEAK	Period 1	I(0) stationary	-7.74 (**)	1
	Period 2	I(0) stationary	-4.31 (**)	4
	Period 3	I(0) stationary	-4.47 (**)	9
DE EL FRONT MONTH BASE	Period 1	I(1) unit root	-2,8	3
	Period 2	I(1) unit root	-1,58	3
	Period 3	I(1) unit root	-2,16	4
CO2 SPOT (GAS)	Period 1	I(1) unit root	0,61	10
	Period 3	I(0) stationary	-5.99 (**)	0

9.1.15 Akaike information criterion (Akaike, 1974)

General AIC = 2 K – 2 ln (L)

K=number of parameters L = is the maximized value of the likelihood function