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Modelling Correlation in Carbon and Energy Markets.

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Abstract

The paper examines correlations between daily returns of month-ahead baseload electricity, fuel input and carbon emission allowance (EU-ETS) prices for Great Britain. The perspective of a CCGT plant operator is assumed, producing baseload electricity with natural gas and emission allowances and selling output forward in the month-ahead market. Price correlation between power, natural gas and emission allowances as well as their dynamic behaviour is essential for the extent to which cash-flows from CCGT plants are self-hedged. Switching between input fuels with different carbon intensities is taken as the fundamental driver of this correlation. Relative marginal power generation costs are used to construct carbon price regimes during which no switching takes place. The regimes are then used as explanatory variables in a dynamic conditional correlation model. Using daily observations of month-ahead prices from April 2005 to August 2010, the results suggest that extreme weather, high commodity market volatility and seasons have no effect on correlation. However, there is evidence of significant price decoupling during periods of extreme relative carbon, coal and natural gas prices.

Keywords EU-ETS, Natural Gas, Fuel-Switching, Dynamic Conditional Correlation

JEL Classification Q41, G10

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EPRG WORKING PAPER

Modelling Correlation in Carbon and Energy Markets.

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1 Introduction

In January 2005, the *European Union Emission Trading Scheme* (EU-ETS) was launched, establishing a price for CO_2 (carbon dioxide) emissions. Due to its large share in total EU CO_2 emissions, the power generation industry is significantly impacted by carbon pricing. Marginal costs of power generation are directly affected by the price of carbon. The cost of producing one unit of electricity, based on fossil fuel generation, is now a function not only of the fuel price and the power plant's thermal efficiency, but also of the carbon price and the fuel's carbon density.

The focus of this study lies on baseload electricity in the United Kingdom, which is to a large extent generated using *Combined Cycle Gas Turbines* (CCGT), Wright (2006). The energy needs of baseload generators are mainly covered in forward markets, due to the high associated storage costs of natural gas and hard coal. Furthermore, electricity cannot be stored without significant losses and only over a short period of time and so baseload generators also sell a proportion of their output in forward power markets. The purchase of forward energy as well as the sale of forward power contracts allows the generator to lock in a given amount of profit per unit of electricity produced, that is the generator *hedges* the risk of unfavourable price movements in both energy and power markets. Following Roques et al. (2008), the cash-flows of a CCGT plant are self-hedged to the extent that power, natural gas and carbon prices naturally co-move. In particular, if higher gas and carbon prices are associated with higher power prices, that is there is strong positive co-movement, then fuel price changes may be profit neutral. It becomes

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immediately obvious that the extent to which the cash-flow of a CCGT plant is self-hedged critically depends on the nature of the co-movement of natural gas, carbon and power prices. Co-movement between prices for input fuels and the price of CO_2 emission allowances is the result of the ability to switch between input fuels in power generation, especially between hard coal and natural gas. It is commonly measured as *correlation* and is not only used in hedging decisions of power generators.

Correlations between power, carbon and fuel prices are also used in optimization of power generation plant portfolios. Roques et al. (2008) use cross-correlations and standard deviations of UK quarter-ahead fuel, power and carbon prices in a Monte-Carlo simulation of power plant net present values. They point out that, under certain circumstances regarding access to capital and the failure to secure long-term power purchase agreements, the correlation between electricity, gas and carbon markets makes 'pure' portfolios of gas power plants more attractive than diversified plant portfolios. Correlations are therefore not only important for hedging decisions on the individual plant level, but are also taken into considerations when evaluating initial capital investment decisions.

However, the relationship between the prices of natural gas, carbon emission allowances and electricity is not constant. This study will show that there are periods when the carbon, natural gas and power prices *decouple*. This reduces their co-movement and therefore the degree to which a CCGT plant is self-hedged. The ambition of this study is not to explicitly model the process driving baseload electricity prices, nor the prices for carbon emission allowances or natural gas. Rather, it will contribute to the literature in three ways. First, it will show that the pairwise correlations of energy, carbon and power prices are not constant over time. Second, it will analyze the effects of extreme weather conditions, commodity market volatility and seasonal effects on the pairwise correlations. Thirdly, it will identify periods in which the absence of an economic incentive to switch input fuels leads to a decoupling of prices and a reduction in correlation. All three aspects affect the degree of self-hedging of a CCGT power plant.

In order to model correlation and its drivers, this paper shall follow the literature in empirical financial econometrics by estimating an extended Dynamic Conditional Correlation model, based on daily observations of month-ahead energy, power and carbon futures returns.

The rest of this study is structured as follows. Section 2 describes the European Emissions Trading Scheme (EU-ETS) and its effect on the power generation industry. Previous research, with regard to both general carbon markets and short-run carbon price dynamics, is presented in section 3. Section 4 motivates the focus on energy and carbon market correlation and describes its role in the variability of marginal power generation costs. Further, it outlines the economic reasoning behind correlation regimes and defines them formally. Based on this definition, the working hypothesis will be formulated. The data and its characteristics will be discussed in section 5, which also calibrates the correlation regimes to the UK power market. Section 6 outlines the basic estimation framework. Finally, section 7 presents the estimation results and section 8 concludes. Details on extensions of the basic econometric framework as well as tabulated estimation results are provided in appendices A and B respectively.

2 The EU Emissions Trading Scheme

The EU-ETS is the biggest international carbon emission *cap-and-trade* system and aims to facilite the 1997 Kyoto Protocol emission reduction targets, by which the EU has to reduce its carbon emissions 8 % below their 1990 level by 2012.

The EU-ETS covers about 50% of total EU CO_2 and 40% of total EU greenhouse gas (GHG) emissions and became operational in January 2005. It includes the 27 EU member countries as well as Iceland, Liechtenstein and Norway. Based on a company-level, the system covers around 12,000 heavy-energy consuming installations[1] in the power sector and manufacturing [2], for all of whom participation is mandatory.

In theory, the cap-and-trade system creates incentives to reduce carbon emissions where it is least costly. This is achieved by introducing tradable emission permits, so-called *European Union Allowances* (EUA). An EUA grants the right to emit one metric tonne of CO_2 into the atmosphere and is priced in €/tCO_2. At the end of each year the covered installations have to deliver a number of EUAs corresponding to their verified annual emissions. Companies that fall short or exceed their allocated annual emission level can either buy extra allowances or sell any surplus on an over-the-counter (OTC) market or on a public exchange.

Since its beginning, the EU-ETS has been segmented into several trading periods. Phase I lasted from January 2005 until the end of 2007. It was generally regarded as a pilot phase during which several structural adjustments have taken place. Phase II started in January 2008 and will end in December 2012. Phase III will start in January 2013 and will last until December 2020.

During Phase I, there was an inter-phase banking restriction, such that unused emission allowances could not be brought forward into Phase II, and only intra-phase banking was allowed. In Phase II the banking restriction is removed and unused EUAs can be carried over into Phase III. The removal of the inter-phase banking restriction connects the price of EUA spot contracts of all trading periods and the price of futures contracts with maturity in subsequent trading periods can be connected to the current spot price via arbitrage considerations.

In the EU-ETS there is a high concentration of carbon emissions to a small number of installations, most of which belong to the power generation sector. It received approximately 55 % of total allowances in the first phase[3] and is responsible for more than a third of total EU CO_2 emissions. Therefore, the power and heat generation industry must be regarded as a key player in the EU-ETS, whose behaviour greatly influences carbon price dynamics.

Main carbon price drivers can be categorized in forces of either allowance supply or demand. Hereby, key supply factors are the number of emission allowances, allocated to individual installations in *National Allocation Plans* (NAPs) by the European Union, as well as other regulatory

[1] *Installations* are power generation or manufacturing plants with a rated thermal capacity in excess of 20MW.
[2] See EU-Commission (2009).
[3] See Chen et al. (2008).

uncertainties. The demand side, however, is more dynamic. Given the size of the power sector in the EU-ETS, allowance demand is strongly influenced by the demand for electricity. As a result, factors that influence the demand for electricity, such as (*extreme*) temperatures (heating), seasonality (lighting) and general economic activity, are also thought to drive the demand for carbon emission allowances[4]. Further, there is an electricity supply side element, which significantly influences demand for carbon emission allowances, namely *relative* fuel prices. Given a constant level of electricity demand, changes in the relative price of power generation fuels can affect allowance demand. Section 2.1 analyses this key factor in more detail, providing a formal definition of marginal power generation costs, as well as of the switch point between competing generation technologies. Finally, section 2.2 will outline how the level of competition and generation fuel mix make the preceding theoretical analysis particularly relevant to the UK power market.

2.1 Marginal Generation Cost and the Switch Point

The typical European power generator has a generation plant portfolio, which may contain nuclear, gas and coal plants as well as generation from renewable sources such as wind and hydro. Relative marginal power generation costs determine which plant will serve to produce *baseload* electricity and which *peakload*[5].

A formal definition of marginal power generation costs is given by Newbery (2005). Let MC_i be the marginal generation cost in €$/GJ_e$ of generating a given unit of electricity, burning fuel i. It is given by

$$MC_i = \frac{FC_i}{\eta_i} + \frac{EF_i}{\eta_i} \cdot EC \tag{1}$$

where FC$_i$ is the fuel cost in €$/GJ$, η_i is the plant net thermal efficiency in GJ_e/GJ[6], EF$_i$ is the GHG emission factor in $kgCO_2/GJ$ and EC is the GHG emission cost in €$/kgCO_2$ [7].

In the context of the EU-ETS, EC is the cost of carbon emissions as determined by the price of an EUA. The first part of equation (1) represents fuel-costs. Here, a higher thermal efficiency of the power plant or lower fuel costs result in lower marginal costs. The second half of equation (1) is the part of marginal generation cost that results from taking into account the price of carbon emissions. Here, lower thermal efficiency, a higher emission factor or higher costs of emission allowances drive up the marginal generation cost. Hence, the EU-ETS increases marginal costs of carbon intensive generation technologies compared to *cleaner* alternatives, such as nuclear,

[4]E.g., see Alberola et al. (2008).

[5]*Baseload* is the minimum power demand in the system. It might fluctuate over time, however, it is based on reasonable expectations of minimum customer demand. *Peakload* refers to peak electricity demand. Baseload power plants do not adapt power output to match changes in daily consumption patterns. They are typically characterized by low marginal generation costs and high reliability, CIPCO (2009).

[6]GJ_e refers to power output in gigajoule of electricity, GJ to power input in gigajoule of fuel.

[7]Eq.(1) is a simplification. MC_i is primarily determined by the *variable costs* of fuel and CO_2. However, there are other marginal cost contributors such as the variable cost of operating assets, RWE (2009).

wind or hydro.

Marginal power generation costs are obtained for all power plants in the portfolio. Plants are then ranked in order of ascending marginal costs, called the *merit order*, and profit maximizing producers start generating from the plant with lowest marginal cost. As demand increases, plants are added following the order of merit.

Theoretically, daily changes in fuel and carbon prices can change merit order through their effect on relative marginal generation costs. Given a constant demand for electricity, a change in the merit order results in changes in the annual carbon demand of producers, as they switch between input fuels with different carbon dioxide emission factors. This so-called *fuel-switching* has a direct impact on their position in the carbon emission allowance market. It is therefore reasonable to assume that producers will operate in either the OTC or the exchange traded emissions markets to react to changes in their carbon demand[8]. These operations can affect the price of EUAs significantly, given the scale of the power sector in the EU-ETS.

As discussed above, fuel-switching is driven by relative fuel and carbon emission allowance price changes. The question arises: when *exactly* does merit order change and are input fuels switched?

For the purpose of illustration, consider two competing generation technologies, hard coal and natural gas, and note that the emission factor of hard coal is approximately twice that of natural gas. Setting their marginal generation costs equal to each other and solving for the emission cost EC gives

$$EC = \frac{\eta_{coal} \cdot FC_{gas} - \eta_{gas} \cdot FC_{coal}}{\eta_{gas} \cdot EF_{coal} - \eta_{coal} \cdot EF_{gas}} \tag{2}$$

This is defined as the *switch point* by Newbery (2005) and Sijm et al. (2007). The switch point is a theoretical carbon price above which it is more profitable to burn natural gas than coal, and below which the reverse is true. If the observed price of carbon emissions, as determined by the price of an EUA, is equal to the switch point price EC, then marginal generation costs using hard coal and natural gas are indeed equal to each other.

Assume that in a situation like this, there is an increase in the price of natural gas, all else constant. Theoretically, this will increase the marginal generation costs of producing electricity by burning gas and leave the marginal generation cost of coal unchanged. Hence, coal is now preferred over gas as reflected in the change of merit order. Resulting carbon emissions will increase due to the significantly higher emission factor of coal, which will increase the price of carbon allowances[9].

For this to happen, initial marginal generation costs of gas and coal do indeed have to be

[8]Following Bunn and Fezzi (2007), agents (e.g. power generators) trade in the daily carbon market according to their dynamic expectations of the annual equilibrium carbon price.

[9]This assumes that before the price increase of natural gas, the marginal generation technology was either gas or coal, i.e. power demand was at an intermediate level. If the marginal generation technology is nuclear, in cases of very low power demand, changes in the merit order do not affect carbon emissions. In the case of very high power demand, all existing plants are fully utilized and, again, changes in merit order do not affect carbon emissions.

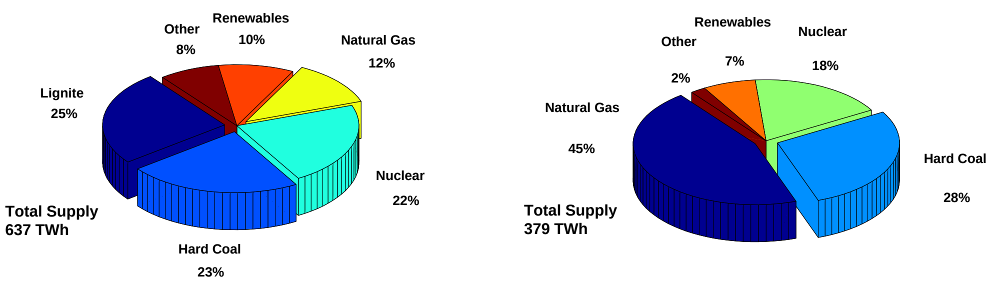
equal or reasonably close to each other. This is equivalent to the requirement that the observed carbon price is equal to or close to the switch price in equation (2). In this situation, changes in the relative fuel prices may change merit order.

If the carbon price is significantly above or below the switch price in equation (2), then marginal generation costs of coal and gas are sufficiently apart such that small changes in fuel prices should not result in changes of relative profitability of the two technologies. In this situation merit order is *static*. Hence, no fuel-switching occurs and, all else constant, demand for carbon emission allowances remains unchanged.

2.2 Market Competition and Generation Fuel Mix in the United Kingdom

The previous sections outlined the significance of relative marginal costs of hard coal and natural gas generation for the merit order and subsequent demand for carbon emission allowances. For this analysis to be representative of existing market dynamics, two conditions in the electricity market structure have to hold, namely a high level of supply-side competition and an adequate generation fuel mix.

First, consider the generation fuel mix. Figure 1 exhibits the German and UK power generation fuel mix, reflecting usage of installed generation capacity. The two hydrocarbon fuels, whose price interactions with carbon emission allowances are under consideration in this study, natural gas and hard coal, together account for approximately 35% of total fuel input in Germany. At approximately 73% this share is much higher in the UK, which is attributed to the significant role of lignite in Germany. Lignite generation was responsible for roughly a quarter of total German power supply in 2007, RWE (2008). Following Zachmann (2007), power plant start up costs, as well as cost for reserve capacity are more important in an electricity system that is based to a larger degree on coal and lignite generation. Therefore, modelling changes in merit order as based on changes in relative marginal costs alone appears more adequate in the case of the UK market. Second, consider the level of supply-side competition. As a key member of the EU-ETS,



(a) Germany 2007 - Source: RWE (2008) (b) UK 2009 - Source: DECC (2010)

Figure 1: Fuel Mix Power Generation

the United Kingdom has experience with privatized electricity markets since the 1990s[10]. It has built a competitive supply industry with a relatively low level of market concentration, in which the number of major power producers is much higher when compared to other major EU-ETS members, such as Germany[11]. Low market concentration and the relatively low degree of integration with Continental European electricity markets means that the British power prices are set according to marginal generation costs in Great Britain and only possess a weak link to marginal generation costs on the European Continent. High degree of power market integration on the Continent does not permit this conclusion for Continental European power prices. For example, the German power market is relatively well integrated with those of France and the Netherlands. As a result, the marginal (price-setting) fuel in Germany might differ from what is suggested by the German fuel mix, facilitated by cross-border electricity trade.

Finally, the market for natural gas in the UK has reached a higher level of maturity and possesses weaker links to the price of oil, when compared to oil-indexed natural gas on the European continent.

Both the adequate fuel mix and the high level of market competition ensure a higher dependence of British electricity prices on short-run marginal generation costs, namely those of coal and gas generation. Therefore, Great Britain appears particular suitable for the following empirical investigation, which justifies the use of market data relevant to the British electricity sector[12].

3 Previous Literature on Carbon Markets

3.1 General Carbon Market Research

Since the beginning of the EU-ETS in 2005, the amount of carbon and climate change related research has continuously increased.

A key field in the literature is hereby the prediction of a medium- to long-term carbon price as this informs current investment decisions. This objective is often approached by *marginal abatement cost* models. Marginal abatement costs are the costs incurred by a firm when reducing their GHG emission by one extra unit, Klepper and Peterson (2006). In theory, these costs should determine the market price for CO_2. Therefore, attempting to predict the marginal abatement cost provides a measure for future carbon prices.

In a broader scope, *integrated assessment models* (IAMs) combine insights from scientific and economic modeling in order to predict a carbon price. Depending on the underlying assumptions and global emission reduction scenarios, IAM predictions are subject to a very high range and therefore difficult to interpret for policymakers and industry professionals[13].

[10]Newbery (1999) provides a thorough account of the restructuring process of UK gas and electricity sectors.
[11]See DECC (2010).
[12]Please see section 5 for details on all data used.
[13]See Bole (2009) for an extensive review of IAM predicitons of the carbon price.

Another area of research is directly concerned with the connection of the EU-ETS and the power generation sector. The implications of carbon-trading for the electricity price as well as pass-through of abatement costs are discussed in Sijm et al. (2006), Sijm et al. (2007) and Chen et al. (2008). Delarue and D'Haeseleer (2008) and Delarue et al. (2008) give special attention to fuel-switching behaviour of the European power sector and resulting short-term carbon abatement opportunities.

For a comprehensive overview of a wide range of model approaches to GHG emission markets, see Springer (2003). Beyond IAMs and carbon trading models, which will be discussed in section 3.2, Springer (2003) discusses three further categories of carbon price models: computable general equilibrium models, Neo-Keynesian macroeconomic models and energy system models.

3.2 Short-Run Carbon Price Dynamics

Despite the significance of the above carbon price models for medium- to long-term market perspectives, they don't account for the short-run price determinants in carbon spot and futures markets. After all, spot EUAs and futures are traded as financial assets on public exchanges or OTC and are therefore subject to an extended range of fundamentals. There is a field of research, which uses financial econometric techniques to identify these fundamentals and quantify their influence on both levels and volatility of emission allowance returns.

First, consider the carbon price level. As the supply of emission allowances is fixed, changes in demand are critical for price setting. The removal of the inter-phase banking restriction ensured the durability of emission allowances and underlined the significance of expectations. Only those factors which deviate from expectations should affect the price of an emission allowance. Previous research has identified four carbon market fundamentals, whose deviations from expectations greatly influence the price of an EUA. They are the regulatory design of the EU-ETS, energy prices, weather conditions and economic growth, through its effect on power demand.

The effect of weather conditions and energy prices on carbon prices has been investigated by Mansanet-Bataller et al. (2007) and Alberola et al. (2008). Mansanet-Bataller et al. (2007) use deviations of temperature indices from their seasonal averages to calculate periods of unanticipated extremely hot and cold days. These are thought to influence the daily carbon spot price returns through their effect on electricity demand. Their findings suggest that only *extreme* deviations from expected weather conditions have explanatory power, as they result in a higher than expected demand for electricity and therefore emission allowances.

In addition to weather conditions, forward energy prices play a key role for carbon prices. As opposed to EUAs, which are storable at the cost of interest, hydrocarbon fuels have additional costs of carry, mainly due to storage. Therefore, most energy needs of the power generation sector are met in forward markets and price changes reflect changes in industrial expectation, Alberola et al. (2008). For example, an unexpected shortfall in domestic natural gas production might increase its price both in spot and future markets and therefore simulate a move from gas to hard coal power generation, resulting in a higher than expected demand for carbon emission allowances. This will increase the prices of EUAs. Both Mansanet-Bataller et al. (2007) and Alberola et al. (2008) investigated the connection of forward price changes of emission intensive hydrocarbon fuels, such as coal and natural gas, and the price of emission allowances. Their results confirms the essential role forward energy prices play in the pricing of carbon emission allowances.

The effect of energy prices on carbon has further been confirmed by Bunn and Fezzi (2007). They studied the impact of the EU-ETS on the wholesale electricity market in the United Kingdom. The results of a co-integrated VAR estimation highlight the essential role of energy prices, especially that of natural gas, in determining the price of emission allowances[14].

The effect of regulatory design issues of the EU-ETS on the carbon price level was investigated by Alberola et al. (2008), Daskalakis et al. (2009) and Alberola and Chevallier (2007). Alberola et al. (2008) identify a structural break in the carbon price series during April 2006, following the report of verified emissions for 2005. The report pointed to a significant oversupply of allowances during 2005, which lead to a subsequent spot price collapse. Alberola and Chevallier (2007) and Daskalakis et al. (2009) estimate the effect of the banking restriction on the Phase I EUA price. Their findings suggest that the banking restriction undermines the ability of the EUA to provide an efficient carbon price signal.

The sensitivity of carbon price returns to changes in macroeconomic conditions is analyzed in Chevallier (2009). Variables with forecast power for equity and commodity returns are used in order to investigate whether carbon futures returns may be weakly forecast. While accounting for the potential impact of the 2007 financial crisis, his findings suggest that the carbon market is only remotely influenced by changes in the macroeconomic environment. However, the results confirm previous work with regard to the high significance of energy prices.

While most studies have focussed their attention on the fundamentals that drive carbon price returns, little work has been done on the drivers of *volatility*.

Benz and Trueck (2009) estimate a regime-switching volatility model, in which the switch mechanism is driven by a latent Markov process, rather than by observed fundamentals. Their findings suggest that volatility behaves in different phases, which are driven by fluctuations in the underlying demand for CO_2. They further maintain that expectations of future regulatory design and allowance allocation is an essential market driver and that the resulting uncertainty is reflected in sharp jumps in the carbon price process, which greatly increases volatility.

The effects on carbon volatility due to the introduction of carbon options has been examined by Chevallier et al. (2009). They apply various econometric specifications and structural break tests to daily carbon returns for the period 2005-2008. Further, they estimate the effect of energy prices and global commodity markets on carbon price volatility. Their results show although volatility has changed over the sample period, the change cannot be attributed to the introduction of EUA options.

Carbon and energy volatility spill-overs are investigated by Mansanet-Bataller and Soriano

[14] Further evidence in the support of this claim can be found in Kanen (2006).

(2009). Given the empirically documented link between energy and carbon returns, they argue that there is reason to believe that volatilities of those commodities are also connected. In an attempt to identify potential volatility spill-overs between carbon prices and prices for natural gas and crude oil, they apply a multivariate volatility model. The results suggest that carbon return volatility is directly affected by its own volatility and the volatility of crude oil and natural gas.

Kanamura (2010) assesses the impact of financial market turmoil on carbon market correlation with stock price indices. He applies a multivariate correlation model and detects an increase in market correlation in times when stock markets plunge, known as *contagion*. Further, his results suggest a reduction in correlation during the April 2006 oversupply event.

Although this work is closest to the present study, Kanamura (2010) does not make an attempt to identify exogenous drivers of correlation. Further, to the knowledge of this study, there is no other work so far that characterizes the process driving correlation between carbon and energy prices. The present work would like close this gap in the literature by combining aspects of both Chevallier et al. (2009) and Kanamura (2010) in order to build a multivariate correlation model with explanatory variables.

4 Motivation

4.1 The Significance of Volatility and Co-Movements

Fuel-switching behaviour of power generation firms connects fuel and carbon prices[15]. Following the example in section 2.1, a higher gas (coal) price can result in a higher (lower) carbon price, which provides a theoretical basis for co-movement between the prices of input fuels and carbon. This co-movement is measured as the *covariance*, or *correlation*, between the two prices. An example shall be given in which correlation between fuel input and carbon prices plays a key role.

Variances and correlations of fuel inputs and carbon emission allowances are of great concern to power generators (henceforth *producers*). A producer uses hydrocarbon fuels and carbon emission allowances as inputs to the process of electricity generation and is therefore dependent on these inputs. Unlike a portfolio manager, who can diversify her exposure to unfavourable price movements by changing the asset composition of her portfolio, the producer is exposed to price changes in power, energy and carbon markets. As a result, the risk-averse producer operates in *forward* markets in order to hedge the risk of unfavourable price movements. This enables her to lock in a given marginal cost of generation and profit.

The degree to which the producer will operate in such forward markets depends on her expectation with regard to future prices. Two key variables come into play. The first variable is the price volatility, which is commonly estimated as conditional variance. The higher the price volatility for a particular asset, the higher the uncertainty about future prices and therefore the

[15]Simulation results by Ellerman and Feilhauser (2008) and Delarue and D'Haeseleer (2008) provide theoretical support for this claim.

risk associated with exposure to this asset. For example, high carbon emission allowance price volatility, measured as high conditional variance, will lead the producer to operate more actively in a futures market to lock in a given marginal cost.

The second variable of interest is the asset's price co-movement with other relevant input prices, measured as its conditional covariance or correlation. The importance of correlations between power, gas and carbon prices is illustrated using the example of a CCGT power plant. The producer generates revenue through the sale of electricity on a power market. Her costs are given by the cost of natural gas and carbon emission allowances[16]. Assume that in period t, the risk averse producer sells 50% of her month-ahead output forward on the month-ahead market in order to protect herself against falling power prices. Further, the producer buys both the required quantities of natural gas and carbon emission allowances on the month-ahead market to ensure herself against price increases. This enables her to lock in an amount of profit p. In period $t+1$, the month-ahead prices of electricity, gas and carbon emission allowances have changed and the extent to which the strategy of selling 50% of output on the month-ahead market will lock in the same amount of profit p depends on the correlation of all three prices. Strong positive correlation of power and natural gas prices, as observed empirically, supports the notion that cash-flows of CCGT plants are self-hedged, Roques et al. (2008). That is, an increase in the price of natural gas is associated with an increase in the price for electricity, such that profits are protected. However, if prices are not strongly correlated or correlation changes over time then profits will change as a result of price movements. In particular, if carbon and gas prices decouple, a decrease in the price of gas will not be associated with a decrease in the price of carbon emission allowances and profits will decrease as a result.

In order to illustrate the producer's exposure to fuel and carbon emission allowance price movements, recall that the marginal generation cost (MC_i) is defined as in equation (1). Given the daily changes in fuel and carbon prices, $MC_{i,t}$ is time varying. Its variance is given by

$$\sigma^2_{MC_i} = \frac{1}{\eta_i^2}\sigma^2_{FC_i} + \frac{EF_i^2}{\eta_i^2}\sigma^2_{EC} + 2\frac{1}{\eta_i}\frac{EF_i}{\eta_i}\rho_{FC_i,EC}\sigma_{FC_i}\sigma_{EC} \tag{3}$$

where $\rho_{FC_i,EC}$ is the correlation of fuel inputs and carbon allowances and σ_i^2 are variances. Equation (3) is a measure of risk associated with marginal generation cost. It is a function of the variances as well as correlations of energy and carbon prices.

The present study will contribute to the literature in three ways. First, it will show that the pairwise correlations between power, fuel and carbon are time-varying. Second, it will analyze the effect of extreme weather, seasonal influences and commodity market volatility on those correlations. Thirdly, it will identify periods in which the absence of an economic incentive to switch input fuels leads to a decoupling of prices and a reduction in correlation. Section 4.2 will explain the last contribution in more detail.

[16] Other costs, such as the cost of capital, are ignored for the sake of simplicity.

4.2 Definition of Correlation Regimes

Previous research has focused on the determinants of carbon returns, while volatility and correlation with other energy series has obtained relatively little attention, despite their significance for both portfolio managers and power generators. The present section shall formulate the main working hypothesis and make an approach to answering the following question: what determines *correlation* of carbon emission allowances with other energy prices?

Changes in the relative price of input fuels, such as natural gas and coal, affect the optimal merit order of power generation, which leads to a fuel-switch by the profit maximising power generator. However, fuel-switching is not directly observable and must be inferred from changes to relative marginal generation costs.

Given observed fuel price data and industry standards of typical emission factors and thermal efficiencies of various generation technologies, such as natural gas and coal, one can construct the theoretical switch price, EC_t, as defined by Newbery (2005) and given in equation (2). On comparison of this theoretical switch price to the empirical carbon prices, $P_{EUA,t}$, inference on the unobserved merit order can be made. A crucial assumption is that a profit maximising producer will switch production from using coal to using natural gas as soon as the empirical carbon emission price exceeds the theoretical switch price.

This assumption implies that unobserved fuel-switching behaviour by producers drives the correlation between input fuels and carbon emission allowances. However, in case of a static merit order, where marginal costs are significantly apart such that a change in the price of one input fuel does not lead to a change in the merit order, there is no economic incentive to switch between input fuels. As a result, the connection between fuel and carbon prices is broken. This situation is associated with periods when the empirical carbon emission price is significantly above or below the theoretical switch price. In contrast, fuel price changes may results in fuel-switching behaviour and therefore subsequent changes in the price of carbon emission allowances when marginal generation costs are sufficiently close to each other.

In practice, the calculation of the carbon switch price between competing technologies is difficult. Given the significant heterogeneity in the UK power plant portfolio, there is no *single* switch price. That is, there exists a wide range of thermal efficiencies and corresponding emission factors in the UK plant portfolio, such that a switch price will have to be calculated for each possible pair of generation technologies. The problem of heterogeneity is circumvented by looking at available data on the distribution of existing plant characteristics in the UK portfolio. Maximum and minimum values for thermal efficiencies and emission factors are used to define carbon price ranges over which the choice of generation fuel is unchanged, hence merit order is constant.

In more detail, two theoretical switch prices are defined between which the empirical carbon price is expected to move. The *upper bound* theoretical switch price, SP_u, is defined as the carbon price above which gas is the preferred technology, irrespective of the thermal characteristics of the plant portfolio. It is derived as

$$SP_u = \frac{\eta^E_{coal} \cdot FC_{gas} - \eta^I_{gas} \cdot FC_{coal}}{\eta^I_{gas} \cdot EF^E_{coal} - \eta^E_{coal} \cdot EF^I_{gas}} \tag{4}$$

where η^E_{coal} and EF^E_{coal} are the respective thermal efficiency and emission factor of the most efficient coal fired power plant in the UK plant portfolio. η^I_{gas} and EF^I_{gas} are the respective thermal efficiency and emission factor of the most inefficient natural gas fired power plant in the UK portfolio. An increasing carbon price will stimulate producers to switch input fuels from hard coal to gas. Once the carbon price has reached SP_u, even the producers with the choice between the most inefficient gas and most efficient coal plant will have switched to natural gas. That is, there exists no other technologically feasible plant portfolio which prefers coal over gas generation. As a result, a higher share of gas production will decrease the demand for carbon emission allowances and its price will start to level off.

Analogously, the *lower bound* theoretical switch price, SP_l, is defined as the carbon price below which coal is the preferred technology, irrespective of the thermal characteristics of the plant portfolio. It is derived as

$$SP_l = \frac{\eta^I_{coal} \cdot FC_{gas} - \eta^E_{gas} \cdot FC_{coal}}{\eta^E_{gas} \cdot EF^I_{coal} - \eta^I_{coal} \cdot EF^E_{gas}} \tag{5}$$

where η^I_{coal} and EF^I_{coal} are the respective thermal efficiency and emission factor of the most inefficient coal fired power plant in the UK plant portfolio. η^E_{gas} and EF^E_{gas} are the respective thermal efficiency and emission factor of the most efficient natural gas fired power plant in the UK portfolio. A decreasing carbon price will stimulate producers to switch input fuels from natural gas to hard coal generation. Once the carbon price has reached SP_l, even the producers with the choice between the most inefficient coal and most efficient natural gas plant will have switched to hard coal. That is, there exists no other technologically feasible plant portfolio which prefers gas over coal. As a result, a higher share of coal production will increase the demand for carbon emission allowances and its price will start to increase again.

Taken together, the empirically observed price of carbon emission allowances is expected to move between the two time-varying bounds SP_l and SP_u. Given the definition of the theoretical carbon switch prices, two correlation regimes are defined. The first regimes refers to a *static* merit order, in which the empirical carbon price either exceeds SP_u or falls below SP_l. In this case, either natural gas or coal are clearly preferred technologies and small changes in fuel prices will not change merit order. In this case there is no economic incentive to switch input fuels. Demand for emission allowances remains unchanged and fuel and carbon prices are *decoupled*.

The second regime corresponds to periods during which the empirical carbon price is strictly between the two bounds[17]. In this case, merit order is *mixed*, that is generation technologies

[17]Note, given $\eta^E_{fuel(i)} > \eta^I_{fuel(i)}$ and $EF^I_{fuel(i)} > EF^E_{fuel(i)}$, it follows that $SP_u > SP_l$.

are not clearly ranked in the merit order and the trade-off between two competing technologies depends on their thermal characteristics. In this regime, merit order is affected by small fuel price changes. The resulting fuel-switch affects demand for carbon emission allowances. Hence, fuel and carbon prices are *coupled*. Formally, define

$$\iota_t\left(P_{EUA,t}, SP_{l,t}, SP_{u,t}\right) = 1_t\left(SP_{l,t} < P_{EUA,t} < SP_{u,t}\right) \tag{6}$$

where $P_{EUA,t}$ is the price of a carbon allowance at time t, 1_t is the indicator function . $\iota_t(.)$ in equation (6) is equal to one in the *mixed* merit order regime, that is when prices are coupled. The dummy variable will be used in the estimation of the correlation matrix of carbon emission allowances, input fuels and electricity prices. It will help identify whether extreme relative prices of those variables affect their dynamic correlation structure. The main hypothesis to be tested is

$$H_0: \quad |corr_t(fuel, EUA|\iota_t = 1)| = |corr_t(fuel, EUA|\iota_t = 0)| \tag{7}$$

against the alternative

$$H_1: \quad |corr_t(fuel, EUA|\iota_t = 1)| > |corr_t(fuel, EUA|\iota_t = 0)| \tag{8}$$

In the mixed merit order regime ($\iota_t = 1$), an increase in the price of natural gas, say, will results in an economic incentive for some producers to switch generation to hard coal and therefore increase their demand for emission allowances. All else equal, this will increase their price. Hence, the direction of the inequality in the alternative hypothesis.

From the perspective of a CCGT plant operator, the results of evaluating the null hypothesis in equation (7) contain vital information. If in period t, relative forward fuel and carbon prices are such that merit order is constant, then prices are decoupled and their correlation is reduced. This requires a different hedging strategy in order to lock in a given profit one month ahead, when compared to coupled prices and high correlation.

5 Carbon and Energy Market Data

This section will describe the main data series used in estimation and testing of the previously stated hypothesis. The sample period covers April 22, 2005 until August 4, 2010. Taken together, this makes for a total of 1.360 daily observations. The data is obtained from the European Climate Exchange (London) and Bloomberg.

5.1 Data Specifications

5.1.1 European Emission Allowances

European Emission Allowances are traded either bilaterally over-the-counter or on public exchanges, where the most active futures exchange is the European Climate Exchange (ECX).

There are three carbon price series used in this study, daily settlement prices of future contracts with delivery in December 2007, 2009 and 2010 respectively. They are all traded on the ECX in €/ton of CO_2 and are plotted in figure 2. The December 2007 contract has a perishable underlying spot commodity, caused by the inter-phase banking restriction. Its price tends to zero as time approaches maturity. The prices of both contracts with delivery in phase II remain positive, where the slight difference in price between the two is justified by the difference in time to maturity.

The construction of a reference price for EUAs needs to take the banking restriction into account, as EUAs need to be delivered at the end of each year according to the level of verified annual emissions. This is achieved by combining the three contracts into one single EUA future price series, labelled EUA *Tracker*. During phase I, EUA Tracker is equal to the price of the December 2007 contract. In phase II, EUA Tracker switches to the December 2009 contract, until its date of maturity, after which it switches to the December 2010 contract. The newly created variable is plotted in figure 3. Although many studies employ the entire lifespan of the December 2009 contract for econometric estimation, here the December 2007 contract will be used for phase I prices, as this price bears immediate relevance to the power generation industry[18].

There are two periods in the sample which require highlighting. The first event refers to April 2006, during which the announcement of an oversupply of emission allowances sent their price plummeting from over 30 €/tCO_2 to just under 10 €/tCO_2 within a few days. This period is regarded by the literature as a structural break, introducing high exogenous volatility into the data, Alberola et al. (2008). The second event refers to the end of 2007, during which the December 2007 contract, and therefore the newly created tracker variable, fell and remained below 0.10 €/tCO_2. Given the low price level and the minimum size of a price change, this introduces high volatility.

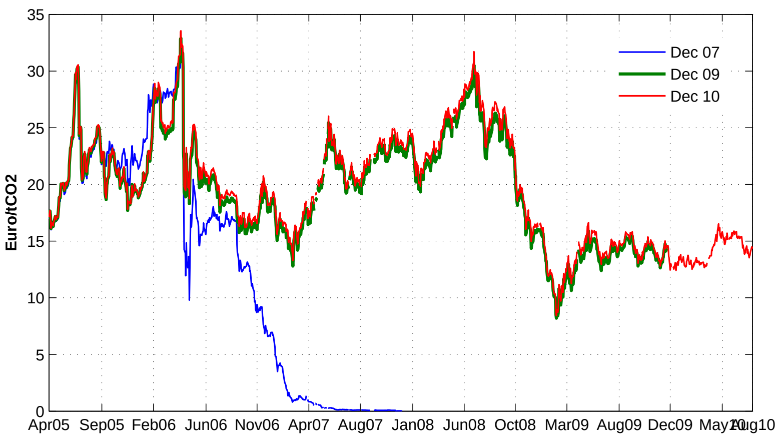


Figure 2: EUA Futures Contracts - Source: ECX

[18]See e.g. Chevallier et al. (2009) and Mansanet-Bataller and Soriano (2009).

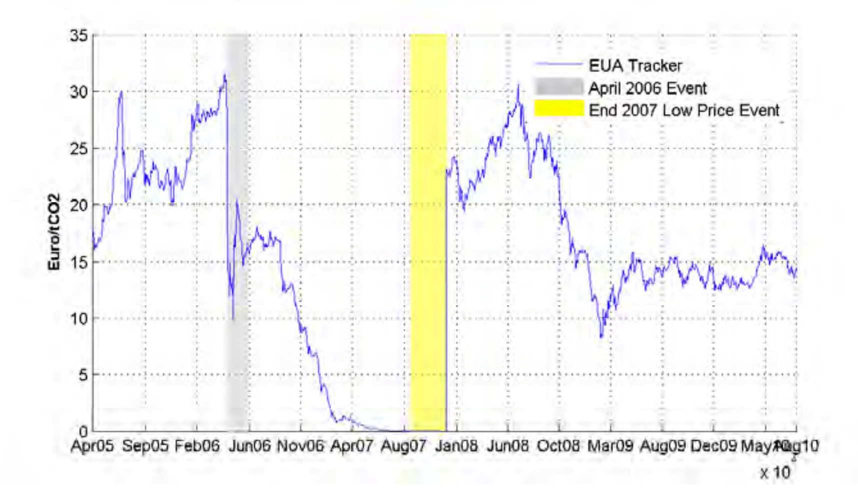


Figure 3: EUA Futures Contract Tracker

5.1.2 Energy Markets

Previous literature underlines the significance of energy prices as the main determinants of the carbon price. Section 2.2 discussed the suitability of the UK for the present analysis, which motivates the use of energy price data relevant to the UK power market. In particular, the prices of natural gas, crude oil and coal are taken as the three main fossil and carbon intensive energy sources. The price of natural gas is the daily Intercontinental Exchange (ICE) Natural Gas 1-month forward contract for the National Balancing Point (NBP) in the UK, traded in GB pence/therm. The coal price is the daily 1-month forward price of CIF ARA[19] coal futures, traded in USD/ton. The oil price used is the daily price of the ICE Brent 1-month ahead contract traded in USD/barrel. All three energy price series are plotted in figure 4, converted into Euro per GJ of energy content.

The crude oil price is included in the estimation in order to control for *contemporaneous correlation* with all other energy sources. This is this study does not take into account the lagged relationship between crude oil and natural gas, as a result of the oil-indexation of pipeline gas contracts on the European continent. Rather, it controls for the effect current oil market movements have on the current correlations between between natural gas, carbon and power prices.

As becomes immediately obvious from figure 4, the coal price is less volatility than both prices for Brent and natural gas. With exception of the period between November 2007 until November 2008, the coal price moves rather closely along 2 €/GJ. Much more volatile over the entire sample period, the oil price reached its maximum of 15.10 €/GJ in July 2008, before a sharp decline to around 7 €/GJ. The price of natural gas, however, reached its peak of 16.10 €/GJ in November 2005.

[19]CIF ARA coal is inclusive (Cost, Insurance and Freight) and delivery to large North European ports such as Amsterdam, Rotterdam and Antwerp.

The electricity price used in this study is the 1-month forward (OTC) price for *baseload* power in Great Britain. The contract prices are provided by GFI Group Ltd.,traded in GBP/MWh and plotted in figure 4. The aim of this study is to estimate correlations from the perspective of a CCGT plant operator. Following Wright (2006), CCGT generation is the main source of British baseload power, which justifies the use of baseload as opposed to *peakload* power prices.

The final variable in the dataset is the *Standard & Poor's Goldman Sachs Non-Energy Commodity Index* (SPCI) as obtained from Bloomberg. The movers of this commodity index, which is traded daily in USD, can be categorized into *industrials*, *livestock*, *precious metals* and *agriculture*[20]. Following Chevallier et al. (2009), the index volatility, computed as the rolling window standard deviation, will be used as an exogenous variable to control for global commodity market volatility. The reason for doing so is the potential correlation of one or more of the series under consideration with the SPCI movers, which introduces a bias into the correlation parameter estimation. A non-energy commodity index is used, as opposed to an index covering all commodity classes, in order to avoid problems arising from multicollinearity of right-hand-side variables.

5.1.3 Weather Controls

Mansanet-Bataller et al. (2007) documented the significant effect of weather variables on carbon prices. Weather plays a key role also in the present analysis through its effect on the electricity market. Three key weather variables are taken into account, namely air temperature, wind speed and precipitation.

Air temperature affects energy and carbon markets mainly through its effect on electricity consumption. *Extremely* hot (cold) days drive up electricity demand through increased cooling (heating) efforts, increasing the load in the power system[21]. This results in reduced possibilities to trade-off generation technologies in the plant portfolio, which then potentially affects correlation patterns of energy and carbon prices. Therefore, in line with Mansanet-Bataller et al. (2007), *extremely* hot and cold days are identified and used in form of an indicator variable in the estimation of energy and carbon price correlation.

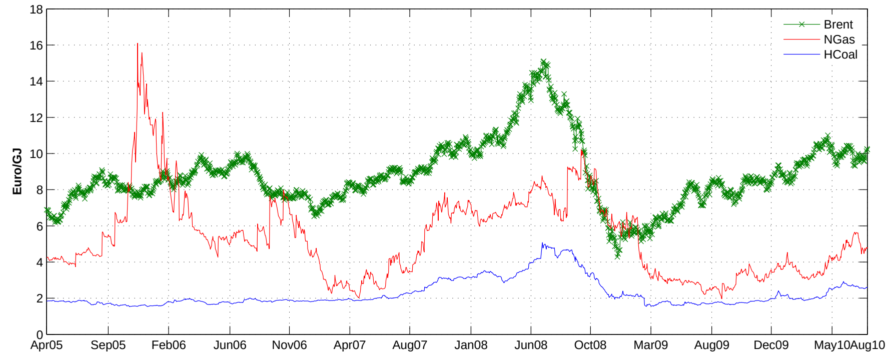
While air temperature affects electricity demand, wind speed and precipitation affect supply. Wind speed and precipitation influence the availability of wind and hydro generation respectively, which accounts for approximately 7% of the total UK fuel mix[22]. Availability of renewable (emission free) generation influences its position in the merit order and therefore total annual demand for carbon emission allowances. *Extremely* dry (rainy) and windy (non-windy) days are identified and used together with the air temperature indicator to control for the effect of weather on energy and carbon market correlation.

Applying the methodology of Mansanet-Bataller et al. (2007), population-weighted weather

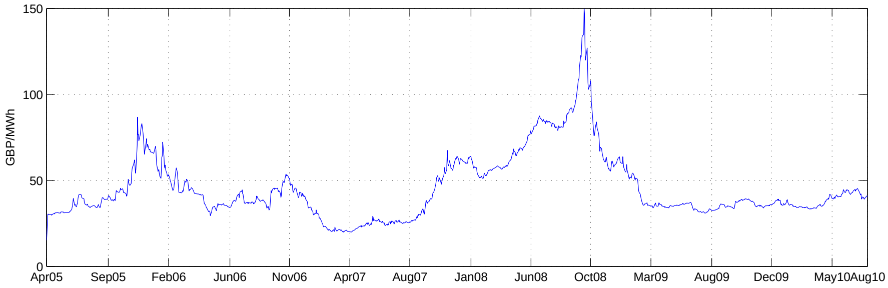
[20]The index movers are 18 non-energy commodities. Industrials: nickel, zinc, aluminium, copper, lead. Livestock: lean hogs, feed cattle, live cattle. Precious Metals: silver, gold. Agriculture: wheat, corn, coffee, soybeans, Kansas wheat, cotton, sugar, cacao.

[21]For the effects of weather on electricity demand see Hor et al. (2005).

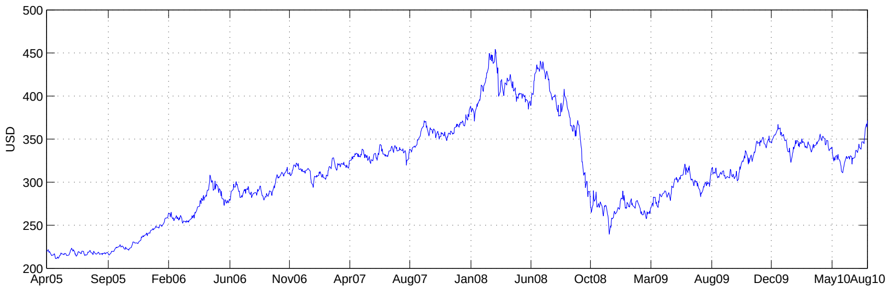
[22]See *Renewables* in figure 1.



(a) Natural Gas, Brent and Coal Prices



(b) Forward Baseload Electricity (OTC)



(c) Standard & Poor's GS Non-Energy Cmdty Index

Figure 4: Energy, Power and SPCI Data - Source: Bloomberg

indices are constructed using data from weather stations of the 30 most densely populated areas in the UK. All weather data is obtained from Bloomberg and population data is sources from the UK Census 2001, NationalStatistics (2001). Following these indices, a day is classified as *extremely* cold (hot), dry (rainy) and non-windy (windy), if all the daily observations of up to a maximum of four consecutive previous days are in the first (fifth) quintile. Table 1 outlines how many observations qualify in each of these categories.

Table 1: *Extreme* Weather Indicators

Weather	Count *Extr.* Low	Count *Extr.* High	Count Total
Temperature	112	115	227
Wind Speed	15	19	34
Precipitation	26	7	33

Extreme Low (High) = 4 previous consecutive daily observations in first (fifth) quintile.

5.2 Preliminary Statistics

Visual inspection of the the data plotted in figures 3 to 4 suggests non-stationarity, that is the data appears to be integrated of order one, $I(1)$. In order to avoid problems arising from non-stationarity, this study follows previous work by Chevallier (2009) and uses daily logarithmic returns. They are defined as

$$r_{i,t} = log\left(\frac{p_{i,t}}{p_{i,t-1}}\right) \tag{9}$$

where $p_{i,t}$ is the price of series i in period t, which is taken to be one trading day. The rest of this paper will exclusively work with daily logarithmic returns of power, energy and carbon prices, that is the econometric methodology will analyze the relationship between daily price changes rather than prices themselves. Emission allowance (EUA) returns are plotted in figure 5 and all remaining returns in figure 6. Again, two periods are highlighted in the EUA return series. The April 2006 compliance event introduced high levels of exogenous return volatility. Following Doornik and Ooms (2005), there are two ways to deal with such outliers. First, one can assume a fat tailed distribution of the return data, assigning higher probability mass to the tails of the distribution. Second, one can consider the volatility to be the result of an exogenous process. In this case, one can remove it by introducing an event dummy variable in the volatility modelling. The present analysis will adopt the latter, and introduce a dummy variable equal to one from Aril 25, 2006 until June 23, 2006, Alberola et al. (2008). Further, figure 5 highlights the low price period during the end of 2007, which will not be regarded as exogenous[23].

Special attention needs to be given to December 18, 2007. On this date the EUA tracker switches from the December 2007 to the December 2009 contract, which results in a significant price jump from nearly zero to 23.14 €/tCO_2 and therefore an abnormally high return. This jump is constructed by definition of the EUA tracker variable. No such jump is observed in any of the other returns series, which means that correlation between the emission allowance price and all other series in the model is reduced. In order to avoid introducing a bias into the estimated correlation parameters, the abnormally high return will have to be removed. This observation is

[23]During this period the price of an EUA fell below 0.10 €/tCO_2, generating abnormally high returns, as the minimum price change is 0.01 €/tCO_2

therefore treated as an exogenous outlier and is not included in the estimation.

Visual inspection of the return series leads to the conclusion that all series show evidence of volatility clustering, a form of autoregressive heteroskedasticity or ARCH effects[24]. A formal test-statistic for ARCH effects as well as descriptive statistics can be found in table 2.

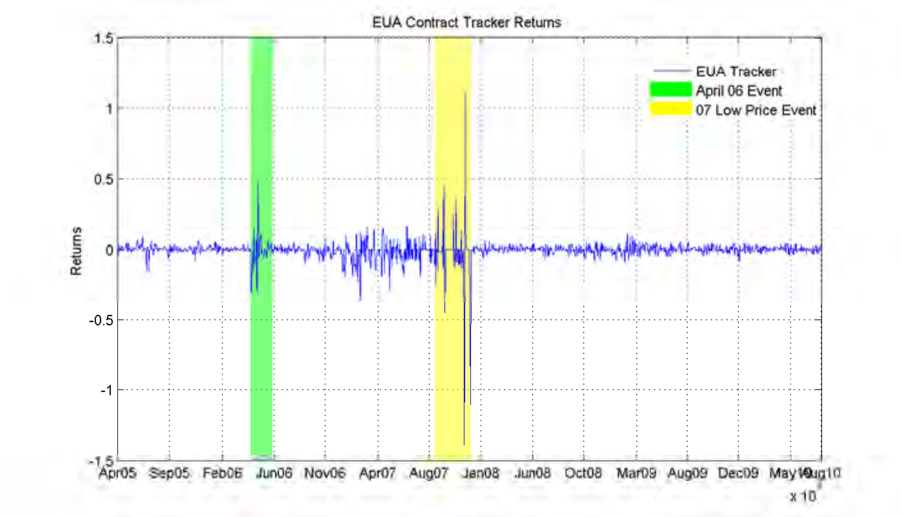


Figure 5: Returns EUA Contract Tracker

All return series have a mean close to zero. EUA returns are most volatile, closely followed by the natural gas and electricity. As shown in figure 4, the coal price return is the least volatile out of the energy data. In order to avoid spurious results in the subsequent econometric analysis of the data, one has to take account of non-stationarity. In order to detect a unit root in any of the five return series, *Augmented-Dickey-Fuller* and *Phillips-Perron* unit root tests are performed. Results are shown in table 2. Both test statistics by far exceed their critical value for the 1% significance level. Hence, one can reject the null-hypothesis of a unit root for all series, and the returns in figures 5 and 6 are all taken to be stationary.

The Ljung-Box statistic for autocorrelation indicates that one can reject the null-hypothesis of no autocorrelation for carbon, coal and oil returns, as well as for electricity. The strongest autocorrelation is in the EUA return series, whereas the commodity index and natural gas returns show no signs of statistically significant autocorrelation.

[24] ARCH stands for *Autoregressive Conditional Heteroskedasticity* and goes back to the work of Engle (1982)

Table 2: Daily Return Summary

Return Series	EUA	Ngas	Coal	Oil	Electr.	SPCI
Observations	1358	1358	1358	1358	1358	1358
Mean	-0.00583	0.00026	0.00027	0.00031	0.00025	0.00039
Median	0.00000	-0.00262	0.00000	0.00081	0.00000	0.00034
Maximum	1.09861	0.47770	0.16102	0.12707	0.27863	0.05867
Minimum	-1.38629	-0.26277	-0.20315	-0.10946	-0.21755	-0.05808
Std. Dev.	0.07785	0.04816	0.01567	0.02388	0.03099	0.01174
Skewness	-4.33189	2.60951	-0.43211	-0.09204	1.36190	-0.38568
Kurtosis	138.19000	21.30837	38.66085	5.99681	17.86345	5.31196
JB (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ADF	-8.86161	-34.87257	-30.46586	-39.38229	-25.52909	-37.89189
PP	-40.43669	-34.84420	-31.14330	-39.39300	-30.85052	-37.88619
Q(20)	142.99	29.15	99.10	50.20	83.43	25.87
$Q^2(20)$	477.37	4.40	13.40	1785.10	126.48	637.43
ARCH-LM(5)	226.95	2.05	8.13	286.35	17.17	165.31

Q(20) and $Q^2(20)$ are Ljung-Box statistics for testing autocorrelation in return and squared return series respectively for the first 20 lags. The 5% critical values of $\chi^2(5)$ and $\chi^2(20)$ distributions are 11.07 and 31.41 respectively. The 1% critical values of the ADF/PP test statistic is -3.44.

This study assumes the perspective of a CCGT plant operator and therefore puts special attention to natural gas and emission allowance returns. There are two remarkable differences between the two return series. First, the autocorrelation of the EUA returns is the strongest in the sample, whereas natural gas returns are not serially correlated. Second, the volatility of the EUA series is significantly higher than that of natural gas. These differences may largely be explained short-run storage costs. Given the removal of the inter-phase banking restriction, emission allowances are durable. They are storable only at the cost of interest. Energy commodities, such as natural gas, have additional storage costs resulting in higher costs of carry. In their work on the theory of storage, Williams and Wright (1991) argue that there is an inverse relationship between the autocorrelation of the month-ahead future price of a commodity and its storage costs. Since short-run storage costs of emission allowances are much lower when compared to those of natural gas, the difference in the level of autocorrelation is in-line with theoretical prediction[25].

The second difference, namely that in volatility, is not so straightforwardly explained. Take the relationship between spot and forward (futures) prices of a commodity. According to Hull (2008), the no-arbitrage condition ensures that

[25] A detailed analysis of the link between storage costs and commodity prices is beyond the scope of this study and can be found in Williams and Wright (1991).

$$F_t - w_{t,T} = S_t e^{(r_{t,T} - c_{t,T})(T-t)} \tag{10}$$

where F_t is the forward price at time t for delivery at time $T > t$. S_t is the spot price of the commodity at time t. $w_{t,T}$ is the cost of storing the commodity from time t to T and $r_{t,T}$ is the risk-free interest rate over the holding period. The convenience yield is given by $c_{t,T}$[26]. From this, the annual adjusted spread (z_t) can be defined as

$$z_t \equiv \frac{ln(F_t - w_{t,T}) - lnS_t}{T-t} - r_{t,T} = -c_{t,T} \leq 0 \tag{11}$$

This spread equals the annual percentage difference between the forward and spot prices at time t, adjusted for storage and interest costs over the holding period. Williams and Wright (1991) argue that there is an inverse relationship between the adjusted spread z_t and the volatility of spot and futures returns. In particular, if storage costs are low, such in the case of emission allowances, z_t is high and the spread is narrow, which results in low volatility. However, emission allowance futures return volatility exceeds that of natural gas, despite lower short-run storage costs. This contradicts the theoretical prediction. The answer to this problem lies in the outliers in the EUA return series. The April 2006 compliance event as well as the jump in December 2007 introduced exogenous volatility. Once these outliers are removed, the volatility of emission allowance returns is below that of natural gas returns and the difference is in-line with theoretical prediction.

Another aspect to be examined is the presence of heteroskedasticity, or ARCH effects. An informal test for ARCH effects in the data is the Ljung-Box statistic for autocorrelation in squared returns. Here, the results of the visual inspection are confirmed for carbon, oil, electricity and SPCI returns. ARCH effects are identified using the ARCH-Lagrangean Multiplier (ARCH-LM) test. In the ARCH-LM test, squared residuals from modelling the first moment are regressed (via OLS) on a constant and on their own lagged values. The lag-length is set to five. The ARCH-LM test statistic is $T \cdot R^2$ where R^2 is the coefficient of determination of the aforementioned least square regression, T is the sample size. Under the null hypothesis of no ARCH-effects, the test statistic has a standard asymptotic χ^2-distribution with five degrees of freedom. Again, results are displayed in Table 2. The ARCH-LM test statistic is significantly higher than its critical value for the 5% level only in the case of carbon, oil, electricity and SPCI returns. Therefore, there are statistically significant ARCH effects in those series. Natual gas and coal returns, however, show no formal sign of ARCH effects.

As observed in many financial return series, carbon and energy returns are likely to be non-Gaussian, Mills and Markellos (2008). As displayed in Table 2, there is non-zero skewness in all return series, which is evidence of a non-symmetric distribution. Further, there is significant

[26] The benefit of holding the physical asset as opposed to a futures contract is referred to as *convenience yield*, Hull (2008).

excess kurtosis (> 3) in the returns, that is the tails of the distribution contain more probability than a Gaussian. Taken together, the return series are said to be *leptokurtic*. Formally, this study test all return series for normality applying the Jarque-Bera (JB) test statistic. The JB tests a joint hypothesis of skewness and excess kurtosis being zero. Again, the results are displayed in Table 2. The p-value for the JB statistic is zero in all six cases. Hence, the null hypothesis of normality can safely be rejected in favour of the alternative hypothesis, a non-Gaussian distribution.

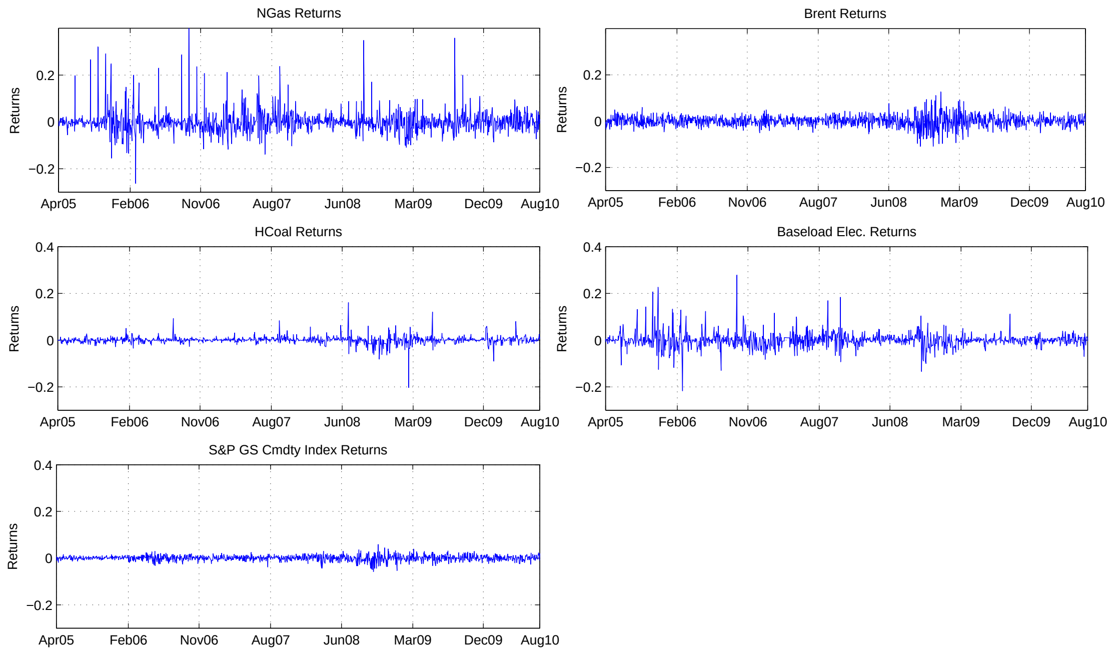


Figure 6: Energy, Electricity and Non-Energy Commodity Index Returns

5.3 Calibration of Correlation Regimes

Section 4.2 introduced both upper and lower switch bounds for the estimation of correlation regimes between carbon emission allowances and energy prices. Both prices include thermal efficiencies and emission factors which need to be calibrated to the UK plant portfolio. Calibration values are obtained from Delarue and D'Haeseleer (2008) and DECC (2010), and are exhibited in table 3.

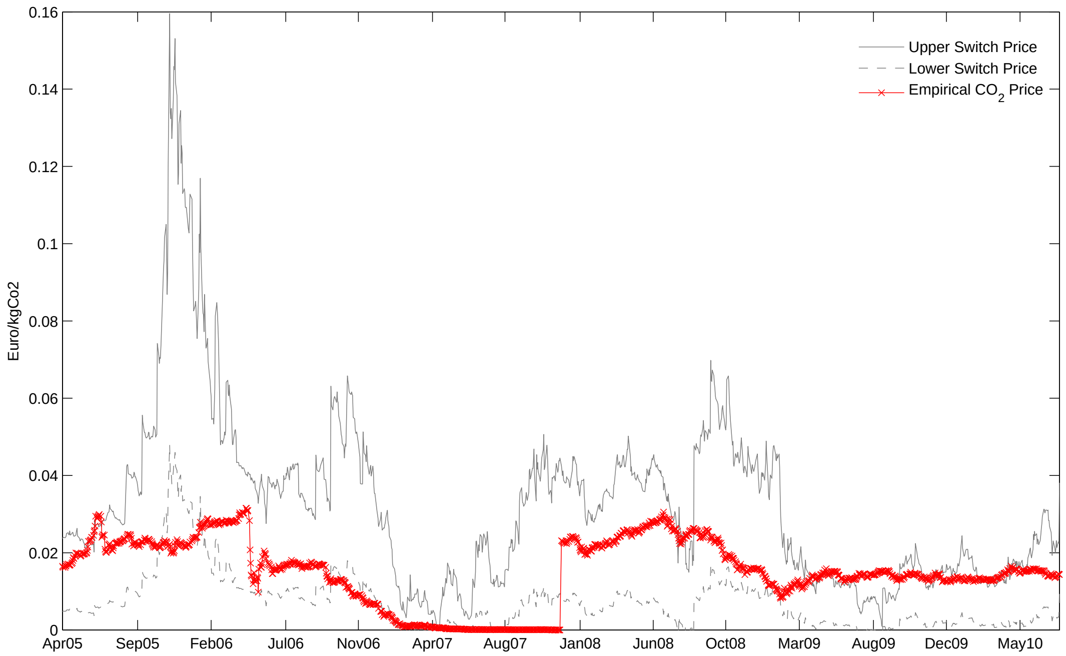
Resulting upper and lower switch bounds, based on above figures and energy and carbon price data are plotted together with the empirical carbon emission allowance price in figure 7. Periods during which the empirically price is above (below) the upper (lower) bound correspond to a decoupling of carbon and energy prices. During those periods, fuel choices of power generators are set fixed in natural gas (hard coal). The correlation between carbon emission allowance and natural gas (hard coal) prices is reduced, as no fuel-switching is taking place. Periods during which the EUA price strictly in between the two switch bounds are characterized as mixed merit. During mixed merit periods, prices of carbon emission allowances and generation fuels are coupled, as fuel-switching takes places and links price movements.

Based on these upper and lower switch bounds is the calculation of the merit order regime dummy, as given in equation (6), which is equal to one in the mixed merit order regime. Given the data, there are 877 observations in the mixed merit order regime in which prices are taken to be coupled. 481 observations are in the static merit order regime in which prices are taken to be decoupled, of which 204 correspond to a static gas and 277 to a static coal regime. Figure 7 plots the temporal distribution of all three merit order regimes. In order to provide a rigorous framework for testing the effect of static and mixed merit order on correlation, the dummy for *mixed* merit order is used in an econometric specification for the conditional correlation matrix of all energy, carbon and electricity returns. Details about the exact specification will be outlined in the next section.

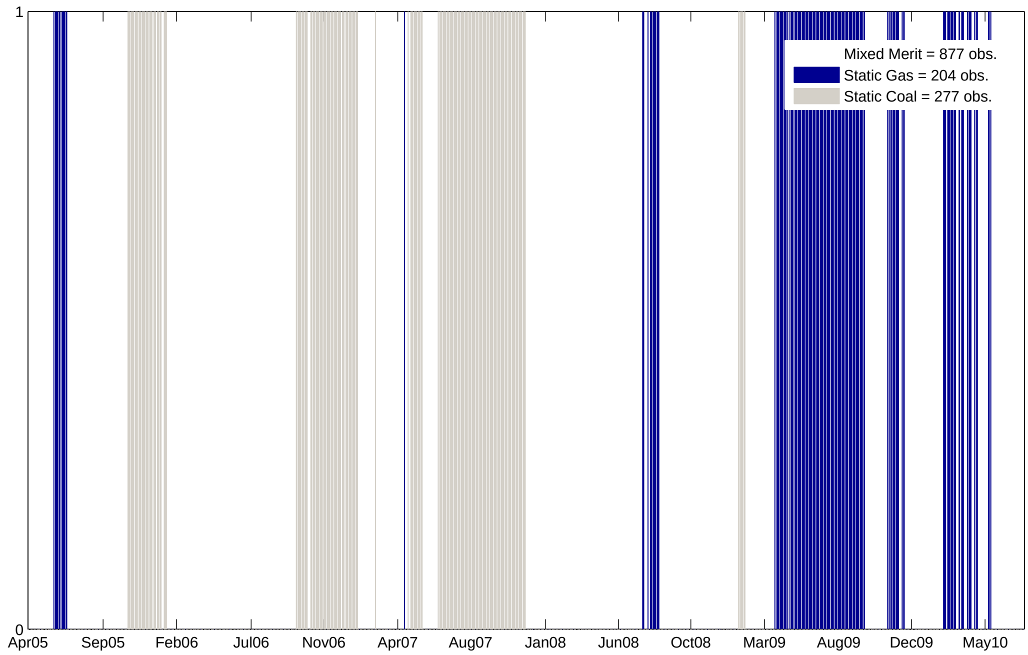
Table 3: Thermal Power Plant Characteristics

	Efficient Plant	Inefficient Plant
Natural Gas		
η	0.50	0.40
EF	117	163
Hard Coal		
η	0.38	0.34
EF	240	280

EF Emission Factor in kg/GJ, η Net Thermal Efficiency in GJ_e/GJ
Source: Delarue and D'Haeseleer (2008); DECC (2010)



(a) Theoretical Switch and Empirical CO_2 Prices



(b) Mixed Merit versus Static Coal/Gas

Figure 7: Calibration Results

6 Econometric Methods

This section will describe in detail the econometric approach taken in order to identify the existence of correlation regimes. Before imposing a parametric structure on the correlation matrix of carbon, electricity and energy returns, a suitable model for the mean has to be determined. This will be achieved in section 6.1. The residuals from the mean estimation will subsequently be used to fit a multivariate correlation model. The basic model will be described in detail in section 6.2.1. A generalization of the basic model, as well as the introduction of the merit order regime dummy and other control variables, can be found in sections A.1 and A.2 of the appendix respectively.

6.1 Estimation of the Mean

The purpose of the model for the first moment is to capture any serial correlation present in the return data. Table 2 provides the Ljung-Box test statistics for serial correlation. The statistics show evidence of significant serial correlation in the return data up to a lag length of 20 trading days. Hence, the first moment is modelled as a *Vector Autoregression* (VAR) of lag order p. Let $\mathbf{r_t}$ denote an $k \times 1$ vector of returns at time t, it is defined as $\mathbf{r_t} = \{r_{i,t}\}$, where $r_{i,t}$ is the daily logarithmic return, for $i = 1...k$, as found in equation (9). In vector notation, the VAR(p) model is then described as

$$\mathbf{r_t} = \boldsymbol{\eta_0} + \sum_{j=1}^{p} \Lambda_j \mathbf{r_{t-j}} + \boldsymbol{\epsilon_t} \tag{12}$$

where $\boldsymbol{\eta_0}$ is a $k \times 1$ vector of constants, Λ_j is a $k \times k$ matrix of coefficients and $\boldsymbol{\epsilon_t}$ is a $k \times 1$ vector of residuals. The lag length p of the VAR(p) is determined by minimizing the *Akaike Information Criterion* (AIC), testing down from $p = 20$. The model specification will be confirmed by checking the residuals in equation (12) for any remaining serial correlation.

6.2 Estimation of the Conditional Variance-Covariance Matrix

A correctly specified model for the first moment will produce serially uncorrelated residuals. However, as it is frequently the case for financial market returns, the variance of the residuals will remain time-varying, that is the returns remain *heteroskedastic*. Time-varying variance and excess kurtosis in the data motivates the use of a GARCH-type estimation framework[27]. GARCH models incorporate the heteroskedasticity of the returns into the estimation procedure and have been applied to carbon and energy market data by Benz and Trueck (2009), Chevallier et al. (2009) and Mansanet-Bataller and Soriano (2009).

The basic univariate GARCH model is defined as follows. Assume that the mean of a return

[27] GARCH stands for *Generalized Autoregressive Conditional Heteroskedasticity* and is the result of seminal work by Engle (1982) and Bollerslev (1986).

series follows an AR(p) process with drift term α_0.

$$r_{i,t} = \alpha_0 + \sum_{j=1}^{p} \alpha_j r_{i,t-j} + \epsilon_{i,t} \tag{13}$$

where $r_{i,t}$ is a daily logarithmic return of series for $i = 1...k$ and $\epsilon_{i,t}$ is a residual. Defining Ω_{t-1} as the set of available information about the process up until and including observation $t-1$, one obtains that $\epsilon_{i,t}|\Omega_{t-1} \sim N(0, \sigma^2_{i,t})$, where $\sigma^2_{i,t}$ is the conditional variance of $\epsilon_{i,t}$. It follows that

$$\epsilon_{i,t} = \sigma_{i,t}\eta_t \ , \text{ where } \quad \eta_t \sim NID(0,1) \tag{14}$$

The residual $\epsilon_{i,t}$ is fitted to a generalized autoregressive conditional heteroskedastic process, its *conditional variance* is then described as

$$\sigma^2_{i,t} = \beta_0 + \sum_{j=1}^{p} \beta_j \sigma^2_{i,t-j} + \sum_{j=1}^{q} \delta_j \epsilon^2_{i,t-i} \tag{15}$$

Equations (13) to (15) complete the specification of the $GARCH(q,p)$ model.

6.2.1 The *Dynamic Conditional Correlation* Model

A natural extension of the univariate analysis is the multivariate $GARCH(q,p)$ model. In addition to conditional variances, a multivariate specification also allows for the estimation of time-varying correlations. The mean of the 5×1 vector of carbon emission allowance, natural gas, hard coal, crude oil and electricity returns is modelled as a VAR(p), defined in equation (12) with $k = 5$, which produces a vector of serially uncorrelated, yet heteroskedastic residuals $\boldsymbol{\epsilon_t} = (\epsilon_{eua,t} \quad \epsilon_{gas,t} \quad \epsilon_{coal,t} \quad \epsilon_{oil,t} \quad \epsilon_{elec,t})'$.

Given the assumption of a conditional multivariate normal distribution as the underlying return distribution, it follows that $\boldsymbol{\epsilon_t}|\Omega_{t-1} \sim N(\mathbf{0}, H_t)$, where H_t is an $k \times k$ conditional variance covariance matrix and $\mathbf{0}$ is a $k \times 1$ mean vector of zeros. Ω_{t-1} is the information set about the series up to and including period $t-1$. The residual vector $\boldsymbol{\epsilon_t}$ is conditionally heteroskedastic, that is $\boldsymbol{\epsilon_t} = H_t^{1/2}\boldsymbol{\eta_t}$, where $\boldsymbol{\eta_t}$ is an iid error process, such that $\boldsymbol{\eta_t} \sim N(\mathbf{0}, I)$.

There are various specifications for the conditional covariance matrix H_t. Among the most commonly used are the original VECH-model by Bollerslev et al. (1988), the *Constant Conditional Correlation* (CCC) model by Bollerslev (1990) and the BEKK-model by Engle and Kroner (1995)[28].

Mansanet et al. (2009) use a trivariate version of the unrestricted BEKK in order to model volatility dynamics and covariances between carbon emission allowances, natural gas and crude oil returns. The $BEKK(1,1)$ specification of the $k \times k$ conditional covariance matrix of H_t is

[28] For comprehensive surveys on multivariate GARCH models see Bauwens et al. (2003) and Silvennoinen and Tersvirta (2007).

given by

$$H_t = C'C + A'\boldsymbol{\epsilon_{t-1}}\boldsymbol{\epsilon_{t-1}}'A + B'H_{t-1}B$$

where $C = \{c_{ij}\}$ is an $k \times k$ lower-triangular matrix of constants, $A = \{a_{ij}\}$ and $B = \{b_{ij}\}$ for $i, j = 1...k$, are $k \times k$ matrices of (G)ARCH parameters. Estimates for the conditional correlation are then obtained as a function of the individual elements in $\hat{H}_t$. While this methodology has been frequently used in modelling conditional covariances among asset returns, it suffers from a problem of high dimensionality. The number of parameters increases polynomially with the number of series k. A $BEKK(p, q)$ model requires the estimation of $(p + q)k^2 + k(k + 1)/2$ parameters.

This study will therefore apply the rather parsimonious *Dynamic Conditional Correlation* (DCC) methodology based on Engle (2000) and Engle and Sheppard (2001). Essentially, the DCC specification is an extension of the CCC-model, allowing for the estimation of time-varying conditional correlations in a two-stage process. In stage one, univariate GARCH models on the individual return series produce standardized residuals, which are then used in the second stage to estimate the correlation process. A comprehensive discussion about the significance and estimation of time-varying correlations within the DCC framework can be found in Engle (2009).

Following the DCC model of Engle and Sheppard (2001), the conditional covariance matrix is re-written as

$$H_t = D_t R_t D_t$$

where D_t is the $k \times k$ diagonal matrix of time-varying standard deviations with $\sqrt{\sigma^2_{i,t}}$ on the ith diagonal, obtained from modelling each residual series as a univariate GARCH process, such as the one in equation (15). R_t is the time-varying conditional correlation matrix. Given the assumption of conditional normality[29], the log-likelihood can then be written as

$$\begin{aligned}
L(\theta) &= -\frac{1}{2}\sum_{t=1}^{T}(m\,log(2\pi) + log(|H_t|) + \boldsymbol{\epsilon_t'}H_t^{-1}\boldsymbol{\epsilon_t}) \\
&= -\frac{1}{2}\sum_{t=1}^{T}(m\,log(2\pi) + log(|D_t R_t D_t|) + \boldsymbol{\epsilon_t'}D_t^{-1}R_t^{-1}D_t^{-1}\boldsymbol{\epsilon_t}) \\
&= -\frac{1}{2}\sum_{t=1}^{T}(m\,log(2\pi) + 2log(|D_t|) + log(|R_t|) + \boldsymbol{\xi_t'}R_t^{-1}\boldsymbol{\xi_t})
\end{aligned} \tag{16}$$

where θ is a vector of parameters and $\boldsymbol{\xi_t} \sim N(\mathbf{0}, R_t)$ are the residuals standardized by their conditional standard deviations in D_t, such that $\boldsymbol{\xi_t} = D_t^{-1}\boldsymbol{\epsilon_t}$. Engle and Sheppard (2001) propose

[29] If the true conditional distribution of the residual vector $\boldsymbol{\epsilon_t}$ is not normal, equation (16) is the *quasi*-likelihood function. Its purpose is purely for estimation, which yields the asymptotically normal and consistent Quasi-Maximum Likelihood (QML) estimator. These qualities justify the widespread use of QML despite known non-Gaussian return distributions.

the following dynamic correlation structure:

$$Q_t = (1 - \sum_{j=1}^{P} \alpha_j - \sum_{j=1}^{Q} \beta_j)\bar{Q} + \sum_{j=1}^{P} \alpha_j (\boldsymbol{\xi_{t-j} \xi'_{t-j}}) + \sum_{j=1}^{Q} \beta_j Q_{t-j} \tag{17}$$

where $\bar{Q}$ is the $k \times k$ unconditional covariance matrix of the standardized residuals from the first stage. α_j measures the extent to which standardized innovations affect the correlation process. β_j is a decay parameter[30]. P and Q are the respective lag-lengths of the innovation and decay parameter and can be set independently. The dynamic conditional correlation is then given as

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{18}$$

where Q_t^* is a $k \times k$ diagonal matrix composed of the square root of the diagonal elements of Q_t. R_t is the conditional correlation matrix of the residuals resulting from the VAR(p) estimation of the first moment. Further, R_t is the conditional covariance matrix of these residuals, once standardized by their conditional variances. A typical element of R_t is of the form

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}$$

In the context of the present estimation $i, j = carbon, gas, coal, oil, elec$, therefore the resulting conditional correlation matrix is given by

$$R_t = \begin{bmatrix} 1 & \rho_{eua,gas,t} & \rho_{eua,coal,t} & \rho_{eua,oil,t} & \rho_{eua,elec,t} \\ \rho_{gas,eua,t} & 1 & \rho_{gas,coal,t} & \rho_{gas,oil,t} & \rho_{gas,elec,t} \\ \rho_{coal,eua,t} & \rho_{coal,gas,t} & 1 & \rho_{coal,oil,t} & \rho_{coal,elec,t} \\ \rho_{oil,eua,t} & \rho_{oil,gas,t} & \rho_{oil,coal,t} & 1 & \rho_{oil,elec,t} \\ \rho_{elec,eua,t} & \rho_{elec,gas,t} & \rho_{elec,coal,t} & \rho_{elec,oil,t} & 1 \end{bmatrix} \tag{19}$$

The econometric methodology will proceed in multiple stages. The first stage estimates a regular DCC model, which then serves as base case. The correlation process in stage one follows directly from Engle and Sheppard (2001) and, setting $P = Q = 1$, is given as

$$\text{Model 1} \quad Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha(\boldsymbol{\xi}_{t-1} \boldsymbol{\xi}'_{t-1}) + \beta\, Q_{t-1} \tag{20}$$

where the individual elements are as defined before. A typical element of the correlation matrix in equation (19), is the conditional correlation of carbon emission allowance and natural gas returns, given as

$$\rho_{eua,gas,t} = \frac{q_{eua,gas,t}}{\sqrt{q_{eua,t} q_{gas,t}}} \tag{21}$$

[30]If all α_j and β_j are set to zero, one obtains the CCC model of Bollerslev (1990).

Given the specification in *Model 1*, the nominator of equation (21) is estimated as

$$q_{eua,gas,t} = (1 - \alpha - \beta)\bar{q}_{eua,gas} + \alpha(\xi_{eua,t-1}\xi_{gas,t-1}) + \beta\, q_{eua,gas,t-1} \tag{22}$$

whereas the denominator is is composed of

$$q_{eua,t} = (1 - \alpha - \beta)\bar{q}_{eua} + \alpha(\xi^2_{eua,t-1}) + \beta\, q_{eua,t-1} \tag{23}$$

$$q_{gas,t} = (1 - \alpha - \beta)\bar{q}_{gas} + \alpha(\xi^2_{gas,t-1}) + \beta\, q_{gas,t-1} \tag{24}$$

Model 1 will serve as a valid starting point, however imposes significant restrictions. The parsimony of the DCC specification is based on the assumption that all asset correlations follow the same ARMA-type structure[31], that is they are all guided by the same α and β. While this might be a valid assumption when modelling similar assets within the same asset class, the current study requires more flexility. It is a reasonable assumption that power, energy and carbon markets exhibit asset specific correlation sensitivities and therefore a generalized estimation procedure for the conditional correlation matrix is required. Section A.1 discusses the generalization of the DCC model as well as the presence of asymmetries in the correlation process. Finally, section A.2 introduces control variables into the estimation.

7 Estimation Results

This section shall present the estimation results of the empirical methodology. First, the results of the $VAR(p)$ mean estimation are described in section 7.1. Second, section 7.2 discusses the outcome of the DCC estimation for *Model 1-4*.

7.1 Results for the Mean Estimation

The correct specification of the model for the first moment of the return vector is the first step in the estimation process. Previous analysis indicated significant autocorrelation in the return data, suggesting a $VAR(p)$. Several lag length (p) selection criteria are used to compare the performance of various lag order specifications while introducing a penalty for additional right hand side variables. Since the data is expressed in daily logarithmic returns, a lag order of $p = 1$ is a lag of one trading day. As expected, the log-likelihood increases with the order of p. Both the final prediction error as well as the *Akaike Information Criterion* suggest a second order VAR, while the *Schwarz Information Criterion* suggests the optimal lag-order of $p = 0$. Despite the lag-length selection criteria suggesting $p = 2$ days, only a $VAR(3)$ produces serially uncorrelated residuals, which can be attributed to high order autocorrelation in both hard coal and electricity returns.

[31] $\approx ARMA(P, Q)$.

The estimation results for the first moment reflect the significant autocorrelation patterns in the data[32]. The highest order of autocorrelation can be observed in electricity returns, which is significant at all three lags. As expected, there is a dynamic connection between the electricity return and the returns of natural gas and hard coal. The electricity return in period t is positively associated with the next period $(t+1)$ return of hard coal and, to a larger extent, that of natural gas. Further, there exists a feedback loop from natural gas on the electricity return, which again is positive. The existence of a positive feedback loop reflects the important role of natural gas in the UK electricity market as the major fuel input for power generation and confirms the notion that investments in gas-fired generation plants are *self-hedged*[33].

A correctly specified $VAR(p)$ produces serially uncorrelated residuals. The results of an LM test for serial correlation suggest that the $VAR(3)$ is correctly specified and the produced residuals are free from remaining serial correlation.

7.2 Results for the Variance and Covariance Specifications

The saved residuals from the previous step are now subject to a test for time-varying correlation. Engle and Sheppard (2001) propose a test for dynamic conditional correlation based on an auxiliary VAR estimation. Applying the test to the current set of residuals, the null-hypothesis of constant correlation can be rejected in favour of an alternative dynamic correlation structure[34].

The first estimation step of the DCC estimation framework is to fit a $GARCH(p, q)$ for each of the return series in the model. Optimal lag orders p and q have been identified using the AIC. Results are given in table 4 in the appendix. The basic $GARCH(1, 1)$ provided optimal fit for all series, except carbon returns, which require a $q = 5$ to capture higher order autocorrelation in conditional variance.

In the second step, conditional variances from the $GARCH(1, q)$ estimations are used to standardize the residuals. Based on the standardized residuals, the DCC model (Model 1) as well as various generalizations (Model 2-3) and extensions (Model 4) are estimated. Table 5 in the appendix exhibits detailed results for all four model specifications. Resulting conditional correlations for some of the return pairs are plotted in figure 8.

Columns one to three of table 5 provide the estimates for the DCC, the G-DCC and the AG-DCC respectively. The benchmark DCC results do not allow for any heterogeneity in the correlation process across the five return series as all conditional correlations are governed by the same α and β. The results show a high decay parameter (β) and a relatively low sensitivity of the correlation process to residual innovations (α), that is the correlation process between all return pairs is rather smooth. The left-hand column of figure 8 plots the resulting conditional correlation of Model 1 against a rolling window unconditional correlation estimate, using a window length of 20 trading days. Given the short window length of the rolling window (RW) correlations and

[32] The estimation results for the $VAR(3)$ as well as results for lag length selection and tests for remaining serial correlation are omitted due to space constraints. They are available upon request.

[33] See Roques et al. (2008).

[34] Test results are available upon request.

the high decay parameter (β) in the DCC, the RW correlations show in general a much higher variance.

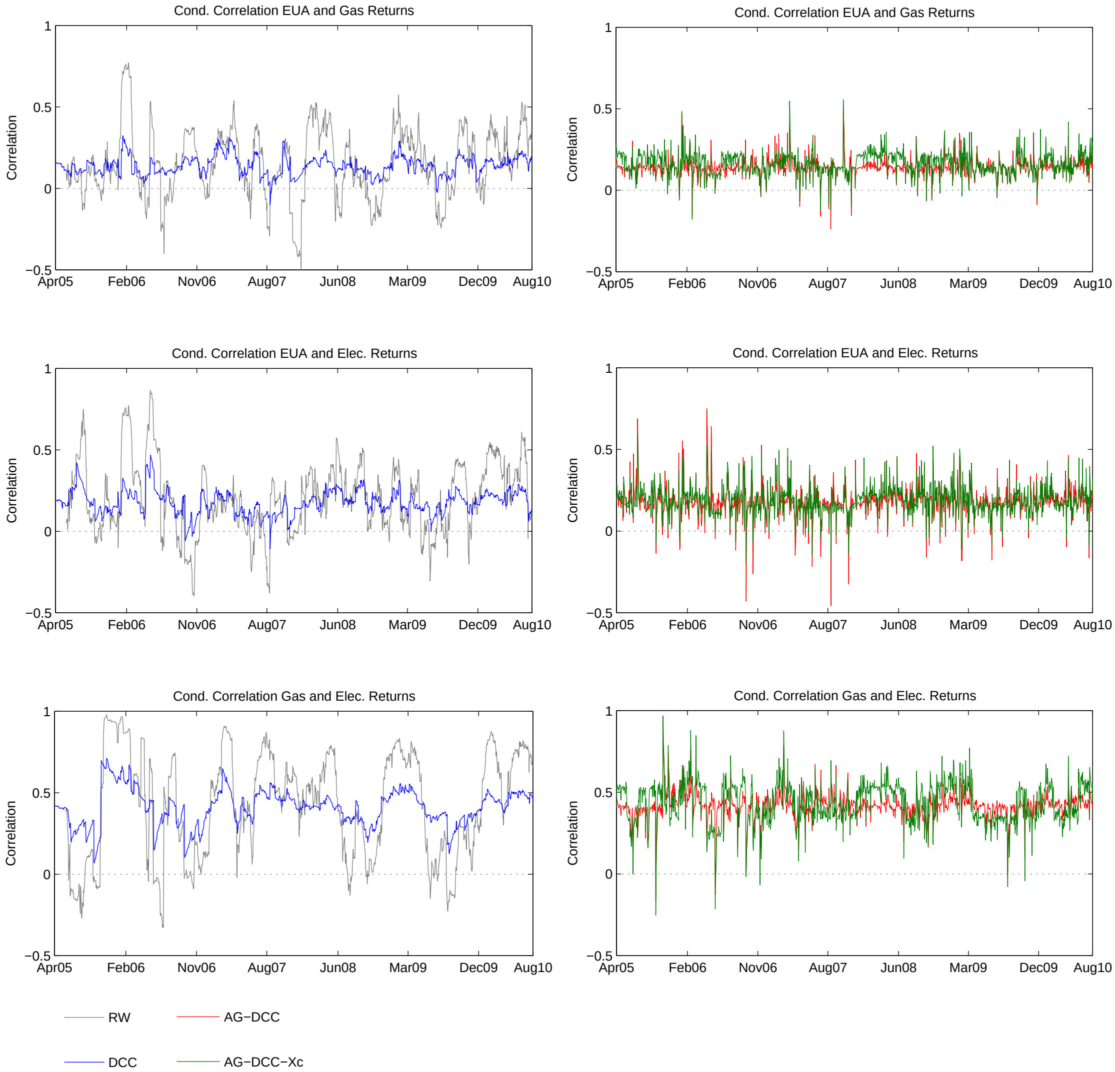


Figure 8: Estimated Conditional Correlations

The large share of natural gas in the total UK generation fuel mix and the focus on CCGT generators brings the key attention to three pairwise correlations, namely those of natural gas, emission allowance and electricity returns. As previously mentioned, the degree of correlation amongst those three return series affects the extent to which the cash-flows of a CCGT plant are *self-hedged*. In particular, sustained high and positive correlations of month-ahead natural gas and emission allowances with electricity returns means a positive correlation of month-ahead marginal cost and revenue and hence hedged profits. This is the case, as baseload producers buy fuel and sell output forward. However, the results of the DCC estimation illustrate that conditional correlation of month-ahead natural gas and electricity returns are time-varying. While the rolling window correlations (RW) for gas and electricity returns show violent movements, ranging from just under one to below zero, the DCC estimate are smoother and appear to oscillate around 0.5. This means that although correlations are time-varying, under the DCC methodology, the self-hedging property of CCGT cash-flows appears less volatile. Further, the DCC correlations between EUA and natural gas returns moves between 0.05 and 0.3. At a higher average level is the correlation between EUA and electricity returns, moving between zero and 0.4.

As described in Engle (2009), the generalization of the DCC framework to return specific sensitivity (decay) parameters (Model 2) and asymmetries (Model 3) changes the shape of conditional correlation significantly. In general, the sensitivity of the correlation processes to standardized innovations increases sharply, while the decay parameter decreases. This is illustrated by the right-hand column of figure 8. In Model 3, statistically significant asymmetric innovation sensitivities can only be detected for hard coal and crude oil returns. In both cases, the sensitivity of the correlation process to negative innovations is higher as compared to positive ones.

Finally, Model 4 introduces control variables in the AG-DCC framework. Columns 4-6 of table 5 (Appendix) exhibit the estimation results for a subset of control variable combinations, whereby the focus lies on the control parameters in the last three rows. Omitted in the result table are model specifications which include control parameters for seasonal effects (DS_t), commodity market volatility ($DCvol_t$), wind speed (DW_t) or precipitation level (DP_t). None of these variables show significant effect on the correlation structure between the five return series, either as a single explanatory variable or in combination with other controls. However, presented are the results for model specifications including the April 2006 oversupply event ($Apr06_t$), static merit order (DM_t) and extreme *low* temperature (DT_t) dummies.

Estimated by itself (AG-DCC-X-a), the April 2006 oversupply event dummy is statistically significant at the 5% level. That is, the discrete drop in the price of carbon emission allowances in April 2006 resulted in significantly reduced correlation between carbon emission allowances and all other series in the model. This result supports the findings of Kanamura (2010). They estimate, also by means of the DCC framework, a reduced correlation between carbon emission allowances and major stock indices during the April 2006 event.

The effect of the static merit order regimes is analysed in models AG-DCC-X (b) and (c). The results in the fifth column (AG-DCC-Xb) of table 5 show a statistically significant effect of the static merit order dummy when estimated by itself. Adding the April 2006 oversupply event (AG-DCC-Xc) only marginally changes the effect of the static merit order regime, which remains significant. The addition of the extreme temperature dummy (AG-DCC-Xd) does not affect the result. Therefore, a static merit order regime leads to a decoupling of fuel and carbon prices. Conditional correlation between natural gas and emission allowances is significantly reduced, which is robust to the inclusion of other relevant control variables. Figure 9 illustrates this result. The bottom panel highlights periods during which the fuel-choice of power generators is set in either natural gas or hard coal, i.e. the merit order is static. During those periods, small changes in the price of carbon emission allowances or fuel inputs do not change the merit order and no fuel-switching takes place. This leads to a decoupling of prices and a reduced conditional correlations, as estimated by the extended DCC methodology.

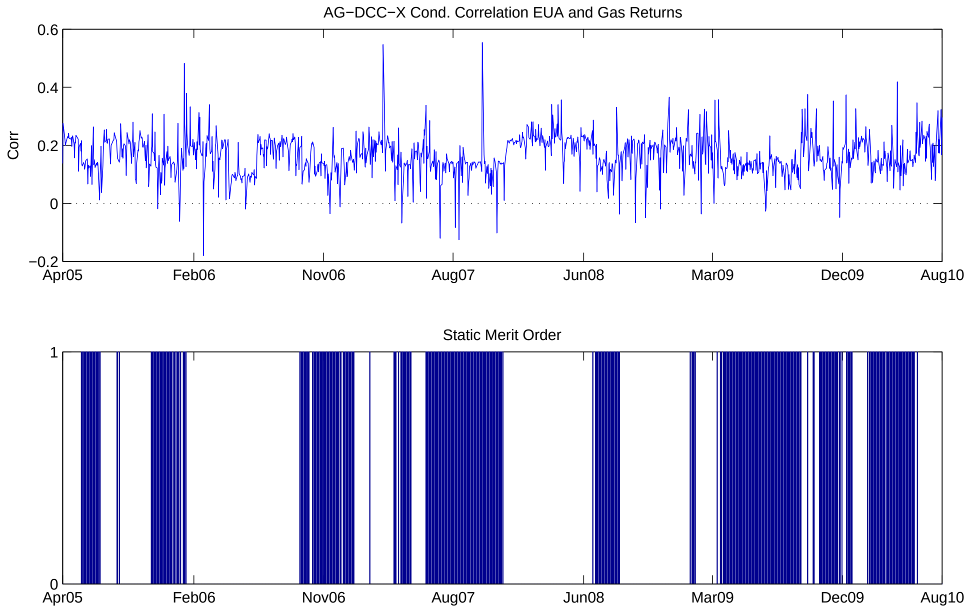


Figure 9: Estimated Effect of Decoupling on Cond. Correltation EUA/Ngas

A correctly specified multivariate GARCH model produces standardized residuals which are free from any remaining heteroskedasticity. The LM test for remaining heteroskedasticity fails to reject the null-hypothesis of *No ARCH Effects*[35]. The chosen lag lengths in the univariate GARCH estimations are therefore adequate.

In summary, given the employed methodology and data sample, this study is able to reject the null-hypothesis of no difference in correlation of month-ahead carbon emission allowance and fuel input returns across merit order regimes in favour of the alternative hypothesis, that is reduced correlation and decoupling during a static merit order. This result is of value to power generators, as the risk associated with a given generation technology is a function of this correlation. Given that changes in relative month-ahead fuel and carbon prices result in static fuel-choices, that is merit order is static, fuel input and carbon emission allowance prices *decouple* and reduce the variability of marginal generation cost. However, a reduction of conditional correlation of month-ahead electricity and natural gas returns also reduces the self-hedging property of cash-flows generated from a CCGT power plant.

[35]Test results are available upon request.

8 Conclusion

This study has investigated the dynamics of energy, power and carbon futures return correlation. In particular, it has examined the effect of static merit order in the electricity generation industry on conditional correlation of carbon emission allowance and natural gas month-ahead futures returns. Following an introduction of the EU-ETS and related fuel-switching behaviour in the power generation industry, a brief description of the existing literature outlined a prevailing gap with regard to the estimation of correlation and the determination of its drivers.

Pairwise correlations between electricity, fuel and carbon emission allowance futures returns are of key relevance to operators of CCGT power generation plants. They use forward natural gas and baseload power markets, such as the one-month ahead market, to lock in a given generation profit. Cash-flows of CCGT plants are self-hedged, to the extent that electricity, natural gas and carbon prices naturally co-move. Hence, the degree to which the same strategy of selling a given share of output forward locks in a constant profit over time depends on the correlation among fuel inputs, carbon and electricity returns.

Data characteristics, such as fat tails in the empirical distribution as well as clustering of volatility, suggested the use of a GARCH-type estimation framework. Computational advantages favoured the use of a *Dynamic Conditional Correlation* model. A generalized DCC model, which both accounts for heterogeneity in the correlation parameters across series as well for asymmetries of correlation sensitivities to standardized innovations, has been extended by a set of relevant control variables. These control variables included indicator variables for the April 2006 oversupply event in the EUA market, seasonal effects, high commodity market volatility, extreme weather conditions (air temperature, wind speed and precipitation), and finally static merit order regimes.

Based on daily return data from April 2005 to August 2010, the estimation results are summarized as follows. First, conditional correlation of all series in the sample is clearly time-varying. That is, the relationship between them changes over time, which significantly affects the self-hedging property of CCGT investments. Second, the DCC methodology yields much smoother conditional correlations when compared to unconditional correlation measures. In particular, the DCC correlation estimate of month-ahead electricity and natural gas futures returns describes a much more stable relationship between the variables when compared to a rolling window correlation measure.

Third, model extensions suggest that there exists significant heterogeneity in the correlation parameters across series and that only some control variables matter. In particular, asymmetries in the sensitivity of correlations to shocks can only be detected for hard coal and crude oil returns. Importantly, extreme weather, seasonal and high commodity market volatility controls show no statistically significant effect on correlation. As expected, the April 2006 oversupply event significantly reduces conditional correlation between the series in the model.

Finally, the static merit order control variable is significantly positive, which is the key result of this study. The main working hypothesis of identical correlation between carbon emission allowances and natural gas returns across merit order regimes is rejected in favour of the alternative hypothesis, namely a reduced correlation during static merit order regimes. This means that there is a statistically significant decoupling of electricity, fuel and carbon month-ahead returns during periods in which fuel-choices in the power sector are set in either hard coal or natural gas. During those periods there is no incentive to switch input-fuels as a response to price changes and the link between fuel and carbon prices is broken. This effect remains robust to the inclusion of other relevant controls.

Looking ahead, the estimation methodology can be improved. In particular, the AG-DCC-X model restricts control variables to be positive and only enter the denominator of each correlation element. Both restrictions ensure positive definiteness of Q_t, and therefore the conditional correlation matrix R_t, yet limit the effect of controls on correlation to be one-sided. Hence, the development of an unrestricted DCC model with control variables, which allow for a potentially two-sided effect on correlation, is desirable. Further, given that CCGT operators only sell a share of output on the month-ahead market, an investigation of correlations between electricity, natural gas and carbon future contracts along different parts of the forward curve might be of interest.

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Appendix A Extension: Econometric Specification

A.1 The *Asymmetric Generalized* DCC Model

Modelling correlation across asset classes requires some degree of flexibility in the estimation procedure. To achieve this, Hafner and Frances (2003) and Engle (2009) propose a *Generalized Dynamic Conditional Correlation* (G-DCC) model, which allows for asset specific correlation parameters. The correlation process of the G-DCC model is given by

$$\text{Model 2} \quad Q_t = (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B) + A'\boldsymbol{\xi}_{t-1}\boldsymbol{\xi}'_{t-1}A + B'\,Q_{t-1}\,B \tag{25}$$

where A and B are $k \times k$ diagonal parameter matrices, such that $A = \{\alpha_{ii}\}$ and $B = \{\beta_{ii}\}$. In order to maintain positive definiteness of Q_t, $\alpha_{ii} + \beta_{ii} < 1$ and $\alpha_{ii}, \beta_{jj} \geq 0$, $\forall i, j$. This re-parameterization of the initial DCC model allows for a high degree of heterogeneity in the correlations. Engle (2009) discusses the effect of a generalization of the form given in equation (25). Unlike in the DCC model, the G-DCC model can result in very different correlation patterns. High (low) values for α_{ii} combined with low (high) values for β_{ii} result in very flat (fluctuating) correlations of asset i with any other asset in the model[36]. A typical element of Q_t in Model 2 is given by

$$q_{ij,t} = (\bar{q}_{ij} - \alpha_{ii}\alpha_{jj}\bar{q}_{ij} - \beta_{ii}\beta_{jj}\bar{q}_{ij}) + \alpha_{ii}\alpha_{jj}(\xi_{i,t-1}\xi_{j,t-1}) + \beta_{ii}\beta_{jj}\,q_{ij,t-1} \tag{26}$$

A further generalization is achieved by allowing for asymmetries in the G-DCC model. Cappiello et al. (2006) propose the *Asymmetric Generalized Dynamic Conditional Correlation* (AG-DCC) model as[37]

$$\begin{aligned} \text{Model 3} \quad Q_t = {} & (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{N}G) \\ & + A'\boldsymbol{\xi}_{t-1}\boldsymbol{\xi}'_{t-1}A + B'\,Q_{t-1}\,B + G'\boldsymbol{\eta_{t-1}}\boldsymbol{\eta'_{t-1}}G \end{aligned} \tag{27}$$

where G is a $k \times k$ diagonal parameter matrix, such that $G = \{g_{ii}\}$. $\boldsymbol{\eta_t} = \{\eta_{i,t}\}$ is a $k \times 1$ vector with $\eta_{i,t} = min(\xi_{i,t}, 0)$. $\bar{N}$ is a $k \times k$ matrix of constants, such that $\bar{N} = T^{-1}\sum_{t=1}^{T}\boldsymbol{\eta}_t\boldsymbol{\eta}'_t$. Following Cappiello et al. (2006), the new parameter restrictions to maintain positive definiteness of Q_t are given by $\alpha_{ii} + \beta_{ii} + \eta_i\kappa < 1$ and $\alpha_{ii}, \beta_{ii}, \eta_i \geq 0$ for $i = 1...k$, where κ is the maximum eigenvalue of $\bar{Q}^{\frac{1}{2}}\bar{N}\bar{Q}^{\frac{1}{2}}$.

Models 2 and 3 refined the base case estimation, however, will not allow to test the key hypothesis of this study, that is the effect of static merit order regimes on correlation. The next section will outline how the estimation procedure can be extended by adding relevant control variables.

[36] α_{ii} can be regarded as the sensitivity of the correlation of asset i with other assets to correlation *innovations*, Hafner and Frances (2003).

[37] It is obvious from the specification in equation (27), that Model 3 nests Model 2 and a simple likelihood ratio test is therefore adequate to test the validity of the restrictions in Model 2.

A.2 The AG-DCC Model with Control Variables

In the final step of the estimation procedure, a vector of control variables is added to the previous generalized DCC model. This study will employ the AG-DCC-X model, proposed by Vargas (2008), given by

$$\text{Model 4} \quad Q_t = (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{N}G - K(\boldsymbol{\psi}'\bar{\boldsymbol{x}})) + A'\boldsymbol{\xi}_{t-1}\boldsymbol{\xi}'_{t-1}A + B'\,Q_{t-1}\,B + G'\boldsymbol{\eta_{t-1}}\boldsymbol{\eta'_{t-1}}G + K(\boldsymbol{\psi}'\boldsymbol{x}_{t-1}) \tag{28}$$

where K is a k-dimensional identity matrix, $\boldsymbol{x}_t$ is a $p \times 1$ vector of control variables with corresponding $p \times 1$ parameter vector $\boldsymbol{\psi} = \{\psi_j\}$. $\bar{\boldsymbol{x}}$ is a $p \times 1$ vector of constants, such that $\bar{\boldsymbol{x}} = T^{-1}\sum_{t=1}^{T}\boldsymbol{x}_t$. Following Vargas (2008) and the specification of K, Q_t in equation (28) is positive definite as long as $\psi_j \in (0, 1)$ for $j = 1...p$. The rest of this section will discuss the choice of control variables in $\boldsymbol{x}_t$, namely

$$\boldsymbol{x}_t = (Apr_{06,t} \quad DS_t \quad DCvol_t \quad DT_t \quad DW_t \quad DP_t \quad DM_t)'$$

$Apr_{06,t}$ is a dummy variable controlling for the compliance event in April 2006, it is equal to one from April 25, 2006 until June 23, 2006, and zero otherwise. DS_t is a dummy variable equal to one for observations during the first and fourth annual quarter (cold season), and zero otherwise. It examines the sensitivity of the correlation between energy and carbon returns to seasonal influences. Time of the year greatly affects electricity demand through its effect on heating and lighting and is therefore an important control in the correlation specification.

$DCvol_t$ is a control variable equal to one if the rolling window standard deviation of the *Standard & Poor's Goldman Sachs Non-Energy Commodity Index (SPCI)* at time t has been in the fifth quintile of the its distribution for the consecutive previous four days, and zero otherwise. Following Chevallier et al. (2009), this attempts to control for the effect of large global commodity market volatility[38].

DT_t is an *extreme* temperature indicator variable, equal to one if the temperature at time t has been in the first (fifth) quintile of the UK mean temperature distribution for the consecutive previous four days, and zero otherwise. DW_t (DP_t) is an *extreme* high wind (precipitation) indicator variable, equal to one if the wind speed (precipitation level) at time t has been in the fifth quintile of the UK mean wind speed (precipitation) distribution for the consecutive previous four days, and zero otherwise[39].

[38] Chevallier et al. (2009) used the standard deviation of the *Reuters/Commodity Research Bureau (CRB) Futures Index* to capture risk factors connected to global commodity markets. The present study, however, will use the *Standard & Poor's Goldman Sachs Non-Energy Commodity Index (SPCI)*. The reason for using a non-energy commodity index as opposed to the CRB Futures Index is to avoid potential problems arising from multicollinearity with right-hand-side natural gas and coal return volatilities. The rolling window standard deviation of the SPCI is calculated, using a window size of 20 trading days.

[39] See table 1 for the number of observations in each variable.

Finally, DM_t is an indicator variable, equal to one if the merit order of power generation in period t is static in either natural gas or hard coal and zero if the merit order is mixed. Using the definition mixed merit order rgimes in equation (6), $DM_t = 1 - \iota_t$.

A.3 Testing for the Existence of Merit Order Regimes

The advantage of the DCC framework is the explicit modelling of the conditional correlation processes, separate from the estimation of conditional variances in the first stage. This section will illustrate how the DCC framework allows to test our key hypothesis regarding the existence of merit order regimes in conditional correlation between carbon and energy returns. Take a typical element of Q_t in Model 4, for $i = j$ it is given by

$$\begin{aligned} q_{ij,t} &= (\bar{q}_{ij} - \alpha_{ii}\alpha_{jj}\bar{q}_{ij} - \beta_{ii}\beta_{jj}\bar{q}_{ij} - g_i g_j \bar{n}_{ij} - \boldsymbol{\psi}'\bar{\boldsymbol{x}}) \\ &\quad + \alpha_{ii}\alpha_{jj}(\xi_{i,t-1}\xi_{j,t-1}) + \beta_{ii}\beta_{jj}\, q_{ij,t-1} + g_i g_j \eta_{i,t-1}\eta_{j,t-1} + \boldsymbol{\psi}'\boldsymbol{x}_{t-1} \end{aligned} \tag{29}$$

whereas for the off-diagonal term, $i \neq j$, the control terms vanish, such that

$$\begin{aligned} q_{ij,t} &= (\bar{q}_{ij} - \alpha_{ii}\alpha_{jj}\bar{q}_{ij} - \beta_{ii}\beta_{jj}\bar{q}_{ij} - g_i g_j \bar{n}_{ij}) \\ &\quad + \alpha_{ii}\alpha_{jj}(\xi_{i,t-1}\xi_{j,t-1}) + \beta_{ii}\beta_{jj}\, q_{ij,t-1} + g_i g_j \eta_{i,t-1}\eta_{j,t-1} \end{aligned} \tag{30}$$

Some modification are necessary to clearly define the key hypothesis test. Let

$$\begin{aligned} q_{ij,t} &= \tilde{q}_{ij,t} + \boldsymbol{\psi}'(\boldsymbol{x}_{t-1} - \bar{\boldsymbol{x}}) && for\ i = j \\ q_{ij,t} &= \tilde{q}_{ij,t} && for\ i \neq j \end{aligned}$$

where for any i and j, $\tilde{q}_{ij,t}$ is defined as

$$\begin{aligned} \tilde{q}_{ij,t} &= (\bar{q}_{ij} - \alpha_{ii}\alpha_{jj}\bar{q}_{ij} - \beta_{ii}\beta_{jj}\bar{q}_{ij} - g_i g_j \bar{n}_{ij}) \\ &\quad + \alpha_{ii}\alpha_{jj}(\xi_{i,t-1}\xi_{j,t-1}) + \beta_{ii}\beta_{jj}\, q_{ij,t-1} + g_i g_j \eta_{i,t-1}\eta_{j,t-1} \end{aligned}$$

A typical element of resulting conditional correlation matrix R_t in Model 4 is then given by

$$\rho_{ij,t} = \frac{\tilde{q}_{ij,t}}{\sqrt{(\tilde{q}_{ii,t} + \boldsymbol{\psi}'(\boldsymbol{x}_{t-1} - \bar{\boldsymbol{x}}))(\tilde{q}_{jj,t} + \boldsymbol{\psi}'(\boldsymbol{x}_{t-1} - \bar{\boldsymbol{x}}))}} \tag{31}$$

where the control variables now enter in the denominator of the correlation process. Hence, equation (31) forms the basis for hypothesis testing. Hypotheses regarding the significance of any of the p control variables on the correlation processes between energy, carbon and power returns are formulated as follows[40], for $i = 1...p$

$$H_0^{(i)}: \quad \psi_i = 0$$

against the alternative

$$H_1^{(i)}: \quad \psi_i > 0$$

At the focus of the analysis is the effect of static merit order on the correlation between natural gas and carbon emission allowances. Controlling for all other factors in $\boldsymbol{x_t}$, such as season, weather and commodity market volatility, this is formulated as

$$H_0: \quad \psi_{DM} = 0 \tag{32}$$

against the alternative

$$H_1: \quad \psi_{DM} > 0 \tag{33}$$

If the estimation results reject the null hypothesis in equation (32), in favour of a significantly positive parameter ψ_{DM}, then there exists a static merit order regime, in which correlation between carbon emission allowances and natural gas returns is reduced.

[40]Recall that $\bar{\boldsymbol{x}} = T^{-1}\sum_{t=1}^{T}\boldsymbol{x}_t$ and $\boldsymbol{x}_t$ is a vector of indicator variables, such that $0 < \bar{x}_i < 1$ for $i = 1...p$. Therefore, if $x_{i,t}$ is equal to one, the element $(x_{i,t} - \bar{x}_i)$ is strictly positive and the corresponding parameter ψ_i measures to what extent the control variable i increases the denominator in equation (31).

Appendix B Tabulated Results

B.1 First Step: Univariate GARCH

Table 4: $GARCH(1, q)$ Conditional Variances

Residual Series	EUA	Gas	Coal	Oil	Eelectr.
constant	7.86E-05**	0.000957**	1.96E-06**	1.16E-05**	4.78E-05**
	[9.0E-10]	[3.0E-7]	[1.0E-12]	[1.8E-11]	[7.4E-10]
α	0.3878**	0.2090**	0.0210**	0.0762**	0.2686**
	[0.0049]	[0.0389]	[0.0001]	[0.0002]	[0.0043]
β_1	0.0886**	0.4210**	0.9724**	0.9004**	0.7314**
	[0.0117]	[0.0347]	[0.0001]	[0.0004]	[0.0035]
β_2	0.2556**	(-)	(-)	(-)	(-)
	[0.0277]				
β_3	0.0230**	(-)	(-)	(-)	(-)
	[0.0008]				
β_4	0.1656**	(-)	(-)	(-)	(-)
	[0.0142]				
β_5	0.0794**	(-)	(-)	(-)	(-)
	[0.0083]				
$\alpha + \sum_{i=1}^{q} \beta_i$	0.999998	0.630018	0.993423	0.976585	0.999998

** significant at the 5% level. * significant at the 10% level.

[...] Standard errors in parentheses.

B.2 Second Step: DCC Model 1-4

Table 5: DCC Estimation Results - Models 1 to 4

	Model 1 DCC	Model 2 GDCC	Model 3 AG-DCC	Model 4 AG-DCC-Xa	Model 4 AG-DCC-Xb	Model 4 AG-DCC-Xc
$\alpha_{(11)}$	0.0242**	0.3033**	0.3111**	0.1636**	0.2878**	0.2782**
	[3.7E-5]	[0.0141]	[0.0162]	[0.0051]	[0.0203]	[0.0271]
α_{22}	(-)	0.2397**	0.2311**	0.0095**	0.2462**	0.2620**
		[0.0097]	[0.0139]	[1.9E-5]	[0.0439]	[0.0503]
α_{33}	(-)	0.0222**	2.00E-06	2.00E-06	2.00E-06	2.00E-06
		[0.0026]	[0.0056]	[0.0225]	[0.0043]	[0.0082]
α_{44}	(-)	0.1559**	0.1556**	0.3511**	0.1561**	0.1476**
		[0.0120]	[0.0175]	[0.1711]	[0.0627]	[0.0363]
α_{55}	(-)	0.3791**	0.3904**	0.0059**	0.4242**	0.3920**
		[0.0108]	[0.0123]	[2.4E-5]	[0.0125]	[0.0068]
$\beta_{(11)}$	0.9304**	0.5252	0.4976	0.8347**	0.6665**	0.5998**
	[0.0005]	[0.5698]	[0.4291]	[0.0076]	[0.3233]	[0.2076]
β_{22}	(-)	0.7603**	0.7689**	0.9905**	0.7499**	0.7380**
		[0.0054]	[0.0062]	[9.7E-6]	[0.0510]	[0.0276]
β_{33}	(-)	0.9730**	0.4780	0.1968	0.3567	0.4415
		[0.0011]	[1.1789]	[0.7679]	[10.6549]	[1.4600]
β_{44}	(-)	0.3063	0.3241	0.1399	0.3133	0.3981
		[0.9269]	[0.6249]	[0.1294]	[4.9735]	[1.0622]
β_{55}	(-)	0.6209**	0.6096**	0.9941**	0.5758	0.6080
		[0.0328]	[0.0372]	[7.3E-6]	[0.9172]	[0.5793]
g_1	(-)	(-)	0.0470	0.0023	0.0417	0.0948
			[0.0298]	[0.0050]	[0.1842]	[0.0824]
g_2	(-)	(-)	2.00E-06	2.00E-06	2.00E-06	2.00E-06
			[0.0361]	[4.6E-5]	[0.1279]	[0.0670]
g_3	(-)	(-)	0.3535**	0.3860**	0.3542**	0.3564**
			[0.0411]	[0.0752]	[0.0864]	[0.0491]
g_4	(-)	(-)	0.7089**	0.6934**	0.6177	0.6189**
			[0.3181]	[0.2000]	[0.7149]	[0.2859]
g_5	(-)	(-)	2.00E-06	2.00E-06	2.00E-06	2.00E-06
			[0.0484]	[2.2E-5]	[0.1044]	[0.0556]
ψ_{Apr06}	(-)	(-)	(-)	0.1056**	(-)	0.5477
				[0.0026]		[1.6371]
ψ_{DM}	(-)	(-)	(-)	(-)	0.2919**	0.2898**
					[0.1149]	[0.0704]
ψ_{DT}	(-)	(-)	(-)	(-)	(-)	2.00E-06
						[0.0414]
Log-Likelihood	-15170.8658	-15172.4459	-15178.03097	-15165.4431	-15191.1725	-15195.1777

** significant at the 5% level. * significant at the 10% level. [...] Standard errors in parentheses.

The lag order of all (AG)-DCC-(X) models is set to (1,1).