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Submitted by

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A Dynamic Analysis of Price Forecast Models of Carbon Credits

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Στους γονείς μου and to Alan

Abstract

Climate change is a global issue concerning scientists and governments alike. Dealing with this issue is at the top of the international agenda. The primary cause of the human-induced greenhouse effect is found to be the carbon dioxide (CO_2), deriving mainly from burning fossil fuels, industrial activity and deforestation. Under the Kyoto Protocol, the EU has committed to reduce its total greenhouse gas emissions through a flexible mechanism, the EU Emissions Trading System (EU ETS). Here, emission allowances in the form of a new tradable asset, the European Union Allowance (EUA), can be traded in organised financial markets. Reducing effectively carbon emissions depends upon the success of such a carbon market, which requires sufficient prediction of the price behaviour. The tradable carbon credits appear to be influenced by fuel prices in the energy sector and by certain economic indicators. This thesis presents statistical models for efficient price forecasting based on the relationships between the emission spot and futures prices with energy and several industrial and economic indicators to empirically study the emission price behaviour. Due to the different Kyoto-established trading commitment phases of emission spot prices and their volatility behaviour, we propose appropriate AR–GARCH models for stochastic futures price modelling. We find that various energy and industrial variables affect the formation of the emission futures prices and should be incorporated in price forecasting models.

Keywords: ARCH, GARCH, carbon credits, forecasting, emission trading

Περίληψη

Η κλιματική αλλαγή απασχολεί τους επιστήμονες και τις κυβερνήσεις παγκόσμια. Η αντιμετώπιση αυτού του ζητήματος είναι από τις κύριες προτεραιότητες της διεθνούς ημερήσιας διάταξης. Η βασική αιτία του φαινομένου του θερμοκηπίου ανθρώπινης υπαιτιότητας θεωρείται ότι είναι το διοξείδιο του άνθρακα (CO_2), που προέρχεται κυρίως από την καύση των ορυκτών καυσίμων, από την έντονη βιομηχανική δραστηριότητα και την αποψίλωση. Σύμφωνα με το πρωτόκολλο του Κιότο, η ΕΕ έχει δεσμευτεί να μειώσει τις συνολικές εκπομπές αερίων του CO_2 μέσω ενός ευέλικτου μηχανισμού, του συστήματος εμπορίας εκπομπών του CO_2 (EU ETS). Έτσι, τα Δικαιώματα Ρύπων ως μία νέα μορφή εμπορεύσιμου κεφαλαίου με την ονομασία " Δικαίωμα Ρύπων της Ευρωπαϊκής Ένωσης", (EUA) μπορούν να εμπορευτούν στις οργανωμένες χρηματοοικονομικές αγορές. Η αποτελεσματική μείωση των εκπομπών του CO_2 εξαρτάται από την επιτυχία μιας τέτοιας αγοράς δικαιωμάτων ρύπων, η οποία απαιτεί την ικανοποιητική πρόβλεψη της συμπεριφοράς των τιμών τους. Τα εμπορεύσιμα δικαιώματα ρύπων του CO_2 εμφανίζονται να επηρεάζονται από τις τιμές καυσίμων στον ενεργειακό τομέα και από ορισμένους οικονομικούς δείκτες. Αυτή η διατριβή μελετά τις βασικές τους ιδιότητες και παρουσιάζει στατιστικά μοντέλα για την αποδοτική πρόβλεψη των τιμών τους. Η συμπεριφορά των τιμών μελετάται εμπειρικά σε σχέση με τις τιμές των βασικών προϊόντων ενέργειας (πετρέλαιο, φυσικό αέριο, ηλεκτρισμός και λιθάνθρακας) και διαφόρων άλλων οικονομικών δεικτών, που αντιπροσωπεύουν όχι μόνο τη γενικότερη οικονομική εικόνα της Ευρώπης αλλά και καθενός βιομηχανικού τομέα χωριστά. Λόγω των διαφορετικών χρονικών περιόδων εμπορίας και συναλλαγής των δικαιωμάτων ρύπων, όπως αυτές έχουν καθιερωθεί από το πρωτόκολλο του Κιότου, και εξαιτίας της έντονης μεταβλητότητας των τιμών τους προτείνονται κατάλληλα υποδείγματα AR-GARCH για τη σωστή πρόβλεψη των τιμών των δικαιωμάτων των ρύπων. Διαπιστώνεται ότι ορισμένες από τις τιμές των προϊόντων της ενέργειας και των οικονομικών

δεικτών επηρεάζουν τις τιμές των δικαιωμάτων των ρύπων και των παραγώγων τους και πρέπει να συμπεριληφθούν στα μοντέλα πρόβλεψής τους.

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Chapter 1

Introduction

Global warming is one of the major issues currently facing the world's population. There is strong evidence that this warming has been caused by human activity, mainly through the emission of greenhouse gases (GHG), in particular carbon dioxide (CO_2). This has put pressure on governments to act quickly to tackle climate change, which may have potentially catastrophic consequences for human health, the environment and the economy within the not so distant future (Stern, 2007).

In response to these risks, new policies and regulations have been introduced. One such policy is emission trading as a means to provide finance and technology to assist countries towards a clean development path. It is intended to build positive incentives into the effort to achieve coordinated action across nations. It is based on the notion that the market it creates promotes efficiency and the caps on which it is based on give greater confidence in quantity reductions than a pure tax-based mechanism (Brohé et al., 2006).

The Kyoto protocol together with the decisions made during the Conference of the Parties to the United Nations Framework Convention on Climate Change (UNFCCC) set the foundations for the first emissions trading scheme among nations. The EU has adopted an emission trading scheme (EU ETS) so that companies from the energy and other carbon-intensive industries reduce their CO_2 emissions efficiently. Since the introduction of the EU ETS in 2005, CO_2 emission certificates are now available as a new financial instrument. It is therefore increasingly important for traders to have a valid CO_2 spot price model to value potential derivatives. Companies also require an adequate CO_2 spot price model in order to better assess their production costs and support emissions-related investment decisions.

Emission trading is not a new idea. It appeared in the form of a new financial asset allowing firms to pollute that was issued to a number of firms in 2000 as part of a cap-and-trade model to reduce emissions in the Chicago area (Kosobud et al., 2005). The main participants in the emission allowance markets include both polluting industries, mostly electricity producers and also carbon investors. The polluting participants have the right to emit a certain volume

of CO_2 annually, which is allotted to them in the form of a newly created tradable asset named the European Union Allowance (EUA). One EUA refers to one tonne of CO_2 being emitted in to the atmosphere. If this allowance is partly used, then any surplus can be sold in the market. The cost of CO_2 emission allowance will prove to become significant in the pricing of gas, power and other emission-related commodities and economic activities (Carmona et al., 2005). According to a report of IETA in 2008, the global transactions for 2007 exceeded 2.1 billion tones of CO_2 worth approximately $11.6 billion. The growth prospects seem to be very high since it has been estimated that the global carbon market size will exceed $3 trillion (Daskalakis et al., 2009).

Carbon markets differ from other ones in that the commodity being traded here is essentially the lack or absence of CO_2 (Trück et al., 2008). Sellers are expected to produce fewer emissions than what they are allowed to so that all remaining allowances will be sold to other participants that emit more than their allocated amount. The emissions therefore become either an asset or a liability for the obligation to deliver allowances to cover those emissions.

The purpose of this work is to further extend the understanding of the carbon market. As it has been established only recently, it is still considered to be a young market, and therefore the impact it may have on the global economy is not yet known. However, the carbon market has to be successful for such a climate change mechanism to have a positive effect on the environment, so it is essential to have a valid price model for emission allowances trading and the related derivatives market.

In this thesis, various statistical models are investigated to find the best match that will offer maximum price forecasting. In order to achieve a good pricing model, those factors that may have an influence on the emission spots and futures prices need to be identified. These factors are identified in the European energy market (oil, gas, electricity and coal) and also in the stock markets; the latter are economic indicators of either divisions of the main economy (industrial production, utilities, etc.) or they can be representatives of the general European economic activity, i.e. FTSEurofirst300. This choice is based on the idea that a successful carbon market has to reflect any possible price fluctuations in the energy and the stock markets, so that its participants will better assess their production costs and support future emission-related decisions.

The methodology followed includes an analysis of the study variables, which provides a thorough examination of their properties and reveals their possible long-run and short-run

relationships. Appropriate GARCH models are then investigated for maximising the price forecasting process.

The outline of this thesis is as follows:

- Chapter 2. A detailed literature review of previous research is presented. The research is concentrated on the identification of the main drivers for carbon prices. In particular, we check the price determinants that are recommended by authors, the methodology followed, the kind of data used and the key results.
- Chapter 3. The main variables of the thesis are presented. Possible correlations are also investigated.
- Chapter 4. We apply three unit root tests to check for stationarity in the variables of the study.
- Chapter 5. The issue of causality among the variables of study is examined.
- Chapter 6. The Johansen cointegration test is used to check for possible cointegration relationships among the variables.
- Chapter 7. Emissions price forecasting is attempted by including the energy and the economic variables.
- Chapter 8. Conclusions, along with some final remarks are drawn.

Chapter 2

Literature Background

2.1 Introduction

To date, the study of the carbon energy markets has been divided into the following areas:

- Atheoretical, where raw data of the EUA's spot or the futures contracts prices have been taken and quantitative methods have been applied to see which statistical model fits best.
- Theoretical, where economic theory has been applied to model the behaviour of such markets and the allocation of the emission credits.
- Research concentrated on the EU policies of carbon trading
- Research dealing with the background theory of trading and general regulations outside the EU Directive.

In Table 1 below, the names of authors are listed for each of these categories. The classification of their papers is not rigid as there is inevitably some overlap in the areas of study. In particular, much of the work in policy and regulation relies heavily on theoretical modelling. We can also observe that although there is a lot of research regarding policies and theoretical modelling of carbon markets, there are few mathematical models that deal with more practical aspects, such as price forecasting of the emission credits. This is mainly due to the market being still young, and therefore the available historical market data is rather short.

The rest of this chapter is as follows: In section 2.2, a short summary of the statistical papers is provided. Similarly, sections 2.3, 2.4 and 2.5 summarise the major findings of the theoretical papers, the EU policies and regulation papers and the emission trading papers respectively. In section 2.6, some of the mentioned papers are selected to indentify the key parameters that may have an influence to the emission allowances. Finally, in section 2.7 the key conclusions are drawn.

Table 1: Authors

Statistical models	Theoretical models	EU policies and regulations	General emission trading
Benz, Trück (2009) Borak, Härdle, Trück and Weron (2006) Daskalakis, Psychoyios and Markellos (2009) Obermayer (2009) Paolella and Taschini (2006) Uhrig-Homburg and Wagner (2007) Alberola, Chevallier and Chèze (2008)	Bahn, Büeler, kypreos and Luethi (1997) Bernstein, Montgomery and Tuladhar (2006) Büeler (1997) Carmona, Fehr, Hinz and Porchet Chesney and Taschini (2009) Daskalakis and Markellos (2008) Fehr and Hinz (2006) Haurie and Viguier (2003) Leimbach (2003) Seifert, Uhrig-Homburg and Wagner (2008) Kemp and Swierzbinski (2007) Viguier, Vielle, Haurie and Bernard (2006)	Bataller and Pardo (2004) Betz, Eichhammer and Schleigh (2004) Böhringer, Hoffmann, Lange, Löschel and Moslener (2004) Böhringer, Hoffmann and Manrique-de-Lara-Peñate (2006) Chao and Wilson (1993) Ellerman, Buchner and Carraro (2007) Enevoldsen, Ryelund, Andersen (2007) Georgopolou, Sarafidis, Mirasgedis and Lalas (2006) Godal, Klaassen (2006) Grubb and Neuhoff (2006) Grubb, Azar and Persson (2005) Hidalgo,Szabo, Ciscar and Soria (2003) Insley (2003) Jacoby, Reiner (1997) Klepper and Peterson (2004) Larson, Ambrosi, Dinar, Rahman, Entler (2008) Liaskas, Mavrotas,	Adeyemi, Hunt (2007) Barker, Ekins and Foxon (2007) Betz and Sato (2006) Bierbrauer, Men, Rachev, Trück (2007) Boemare, Quirion (2002) Böhringer and Lange (2005) Böhringer, Lange (2005) Bunn and Fezzi (2007) Bünn, Karakatsani (2003) Clarke, Weyant, Birky (2006) Cronshaw, Kruse (1996) Demailly (2006) Ellerman (2005) Ellerman and Joskow (2008) Feng, Zhao (2006)

		Mandaraka, Diakoulaki (2000) Mansanet-Bataller, Pardo (2008) Matthes, Doble, Macadam, Taylor, Zanoni and Chodor (2005) Milunovich, Stegman, Cotton (2007) Neuhoff, Grubb, Keats (2005) Rogge, Schleich and Betz (2006) Schennach (2000) Schleigh, Ehrhart, Hoppe, Seifert (2006) Svendsen, Vesterdal (2003) Vesterdal, Svendsen (2004) Wirl (2006) Zetterberg, Nilsson, Åhman, Kumlin and Birgersdotter (2004) Zhao (2003)	Floros, Vlachou (2005) Greening, Boyd, Roop (2007) Gupta, Maranas (2003) Hultman (2003) Jacoby, Reilly, McFarland, Paltsev (2006) Kara, Syri, Lehtilä, Helymen, Kekkonen, Ruska, Forsström (2008) Kavuncu and Knabb (2005) Kling, Rubin (1997) Kosobud (2005) Leiby, Rubin (2001) Murphy, Rivers, Jaccard (2007) Neuhoff, Ferrario, Grubb, Gabel and Keats (2006) Neuhoff, Keats ad Sato (2006) Newell, Jaffe, Stavins (2006) Nordhaus and Boyer (1998) Popp (2006)

			Quirion (2003) Rubin (1996) Schleich and Betz (2005) Sclavounos (2007) Sijm, Neuhoff, Chen (2006) Stavins (1993) Taschini (2009) Wing (2006) Yang, Nordhaus (2006) Yate, Cronshaw (2001)

2.2 Statistical models

A review of the most relevant statistical papers is provided below:

1. Benz and Trück (2009) concentrated their research on the short-term spot price behaviour of CO_2 emission allowances. In particular, they focused on the price dynamics and the volatility changes of the stochastic price process. They justified this by claiming that the carbon market is steadily getting more complex and therefore there is a growing interest not only in the long-term emission price dynamics but in the short-time price dynamics of the assets as well.

Overall, they assumed that allowance price and returns exhibit different periods of price behaviour that included price jumps or spikes and also phases of high volatility and heteroscedasticity in the returns. They concluded that issues like shift in prices, non-normality or short periods of extreme volatility have to be incorporated into adequate pricing or forecasting models for CO_2 emission allowances or returns.

2. Trück, Borak et al., (2006) refer to the risks companies face when holding EUA allowances: market risks that include price (fluctuating allowance prices) and volume risks (not knowing up front the need for energy), credit risks that include counterparty risks (with a

counterparty that may be failing to receive or deliver in compliance with the contract), operational risks (human failures or other external risks) and finally reputational risks (when failing to comply with the emissions, a company's reputation gets jeopardized and customers get disappointed).

They claim that so far there is no study on the relationship between emission allowance spot prices and futures prices and convenience yields (difference between those two). They also investigate the changing market dynamics and the volatility term structure of the spot and futures prices, especially during the pilot period (2005-2008) and the Kyoto commitment period (2008-2012).

Emission allowances differ from classical stocks (Benz and Truck, 2006 describe them) and a step to specify them is to consider them as a factor of production and to look for an appropriate pricing model in the common factor pricing models (e.g. coal, oil, electricity), instead of typical financial stock pricing models.

They find that correlations between the spot and the futures prices decrease with time to maturity and the term structure of prices shows significant changes through time. The market has changed from initial backwardation to contango, where the futures prices during the Kyoto commitment period have exceeded the spot prices. Overall, there is increasing price volatility with maturity for both the commitment and the pilot trading period, which contradicts the time-to-maturity or Samuelson effect that suggests a typically declining term structure in the volatility of futures prices as maturity increases. The observed convenience yields are highly significant for the Kyoto period and less so for the pilot period, where there is high kurtosis and skewness.

They used a two-factor model (spot price level and its volatility) for the convenience yields. They find a significant positive relationship between the spot price level and the convenience yields and a negative correlation between the spot price volatility and the convenience yields. By using an MA(1)-GARCH(1,1) model they find that there is also heteroskedasticity in the daily changes of the convenience yields for the pilot period. They recommend for the extreme price changes, like those of the shock period in April and May 2005 to implement a jump component for the yields as their model cannot explain them. They also argue that the current contango market situation with negative convenience yields can be explained as expectations on the price risk of CO_2 emission allowances and the notion of forthcoming new allocation plans in the EU for the Kyoto protocol.

3. Daskalakis, Psychoyios and Markellos (2009) realised that when the carbon market was under scrutiny (over-allocation of emission allowances together with banking prohibition lead to a huge drop in the spot price in 2006) there existed a very high historical volatility. They also found that the behaviour of EUA spot prices is very similar between the two markets under study, something that is expected since arbitrage would wipe out any differences. Then, they took evidence from the futures markets traded in the Dutch European climate Exchange (ECX) and also Nord Pool. They examined the performance of EUA futures against that of various major asset classes for comparison in order to understand the risks and the determining factors of this new commodity. They found that the futures returns from both markets were negatively correlated with equity market returns. This implied that EUA futures may offer significant diversification opportunities to European equity investors. They argued that this contradicted the findings in the paper of Kosobud et al. (2005) who found no statistically significant correlation between monthly returns of SO_2 emission allowance spot prices in the US and returns from various financial investments.

4. Obermayer (2009) attempted to shed further light on price formation in the EU ETS carbon credits market. He explored relationships between credits and energy complex assets, including electrical power, coal, natural gas, and oil. Relationships were analyzed using various statistical tools and methods, and explored in terms of fundamental economic relationships, correlation, and co-integration. Furthermore, the applicability of certain statistical tools, specifically correlation and multivariate regression were examined. The switching price, according to the fundamentals theory, was found to be a poor indicator for valuing EUAs. Co-integration was found to be a more powerful tool for valuing EUAs, which are found to be cointegrated with oil and natural gas but not with power.

5. Paolella and Taschini (2008) provided an econometric approach to emission allowance spot market returns. The authors argued that approaches based on the analysis of a variety of factors, in particular the supply and demand fundamentals and the spot-future parity have led to doubtful conclusions because of complications of the market and the specific behaviour of the emission allowance commodity.

Therefore, they have taken a different approach that analyses instead the statistical characteristics of the historical price information. In particular, they investigated:

- the riskiness of the asset via estimation of the tail thickness of the unconditional distribution (ignoring volatility clustering), and

- a particularly well-suited GARCH-type model for the conditional distribution of the returns on the emission allowance spot prices.

Basic analysis of the data showed, by calculating the sample autocorrelation function for the returns of SO_2 data, very little correlation (the negative and positive returns cancel out each other). On the other hand, the autocorrelation function of the absolute returns showed a much stronger correlation (large returns of either sign are correlated as are small returns), which in turn demonstrated volatility clustering.

Considering the behaviour of the returns conditional on the emission spot prices, they recommend the use of a stable-Paretian GARCH model. To motivate the use of a simple conditional time-series model (GARCH) for the returns, the authors examined whether the occurrence of zero returns can be considered to be random. The occurrence of any correlations amongst the zeros would necessitate the use of a more complicated model (e.g. Markov-switching structures). They found that for the last two thirds of the time-series data there is no statistically significant evidence for correlation amongst the zeros and therefore made the assumption that the zeros occur randomly. However, it should be noted that the first third of the data contains more zeros and the time-series as a whole does not support the hypothesis of no correlation amongst the zeros. This is one of the main limitations of their model.

6. Uhrig-Homburg, Wagner, (2007) studied the relationship between the spot and futures market in the EU ETS. These are found to be linked by the cost-of-carry approach. They also found that futures markets lead the price discovery process of CO_2 emission certificates.

This empirical analysis is based on the co-integration methodology and after the break in the data in the end of 2005 a fairly stable relationship emerged between spot and futures prices in accordance with the cost-of-carry approach (long-term). For the short-term dynamics study, deviations from the equilibrium relationship may have existed for some time. However, the authors find from the co-integration study that this equilibrium is restored quickly. They also estimate a suitable vector error correction model using the most liquid spot and futures contract to see whether the futures market can serve as a price discovery vehicle for the spot prices.

They refer to other authors regarding the spot price dynamics of EUAs: Benz/Truck (2006), Fehr/Hinz (2006), Paolella/Taschini (2006), Seifert/Uhrig-Homburg/Wagner (2006). As

opposed to the above authors, their focus is not on the spot price dynamics but rather on the relationship between spot and futures markets for EUAs, first studied by Daskalakis (2006). However, Daskalakis didn't test the cost-of-carry relationship of spot and futures prices within the current trading period (2005-2007) but rather adopt an equilibrium pricing model for futures prices in the trading period 2008-2012 based in current spot prices. Also, Borak et al (2006) analyzed convenience yields for futures prices with maturities up to 2012. The authors' analysis differ from Borak's in that they argue that futures for the second trading period are written on an underlying that is not actually being traded yet.

Daskalakis' paper shows convergence for EEX and Nordpool spot EUA prices. After some analysis, it is found that the CO_2 futures market leads the price discovery process. They also recommend for companies to price derivatives in respect with the futures 2008, since this can be traded both short and long and it matures before the first compliance date in the second trading period (2008-2012).

7. Alberola, Chevallier and Chèze (2008) talked about the daily price fundamentals of EUAs traded during the first phase of the program (2005-2007). Their results extended previous literature (Mansanet-Bataller et al., 2007) by showing that EUA spot prices reacted not only to energy prices with forecast errors, but also to unanticipated temperature changes during colder events.

The first disclosure of 2005 verified emissions on April 2006 revealing the net short/long position of each plant was accompanied by a sudden allowance price collapse. Then, from October 2006 to the end of 2007 CO_2 prices tended towards zero following the European Commission announcement of stricter Phase II allocation. This price pattern suggested that allowance trading was based on heterogeneous anticipations prior to information disclosure. Within 2005–2007, different fundamentals seem to co-exist before and after the mentioned breaks. The first 2005 compliance break highlights that when the cap is not set below business-as-usual emissions, allowance trading does not necessarily guarantee a carbon price high enough to provide incentives to reduce CO_2 emissions. Indeed, during Phase I of the EU ETS, the stringency of the cap did not appear sufficient for market agents, and consequently the allowance price collapsed. Therefore, it is essential to understand price formation mechanisms when creating such a market. The question that rises is which factors contribute to shape the price formation of this newly EUA.

They concluded from the review of theoretical models by Springer (2003) and Christiansen et al. (2005) that what identified carbon prices main drivers were policy issues, energy prices, temperature events and economic activity.

According to previous literature, energy prices are the most important drivers of carbon prices due to the ability of power generators to switch between their fuel inputs (Kanen, 2006; Christiansen et al., 2005; Bunn and Fezzi, 2007; Convery and Redmond, 2007). This option to switch from natural gas to coal in their inputs represents an abatement opportunity to reduce CO_2 emissions in the short term. High (low) energy prices contribute to an increase (decrease) of carbon prices. This logic is described by Kanen (2006) who identifies brent prices as the main driver of natural gas prices which, in turn, affect power prices and ultimately carbon prices.

To their best knowledge, only Mansanet-Bataller et al. (2007) show empirical evidence of the impact of weather variables on CO_2 price changes. Yet numerous studies have already highlighted the effect of climate on energy prices. These studies indicate the relationship between temperatures and electricity demand is non-linear. Indeed, only both temperatures increases and decreases, beyond certain thresholds, may lead to increases in power demand. With respect to seasonal average, warmer summers increase the demand for air conditioning, electricity, and the derived demand for coal. Colder winters increase the demand for natural gas and heating fuel.

Also, political and institutional decisions on the overall cap stringency, which is function of initial allocation, may have an impact on the carbon price discovery. They found that when confronted to a rise of the price of coal relative to other energy markets, firms have an incentive to adapt their energy mix towards less CO_2-intensive energy sources, which conducts to less need of EUAs.

It is also revealed that deviations from seasonal average matter more than temperatures themselves on CO_2 price changes during extreme weather events.

2.3 Theoretical models review

Those theoretical models associated with the emission carbon trading are reviewed below:

1. Bueler, (1997) studied the trade of CO_2 by integrating existing energy-economy country models called Markal-Macro, a well known model in the context of energy and climate research. The "Markal" market allocation model (late 70s- early 80s) is a linear programming problem that describes the energy sector of a country/region. The solution provided represents the energy sector management with minimum costs. This approach has a main advantage of being simple to implement and provides the possibility to parallelize the solution process. A further advantage when compared with the second method is the speed of convergence (smaller number of iterations used).

The author has concentrated on modelling the effect on the energy and investment cost rather than on the benefit of climate change mitigation. The undiscounted equilibrium prices in case of full trade are surprisingly low for considerable emission reductions. Also, if the trade of permits is allowed, then there seems to be a dramatic decrease of CO_2 abatement costs. Switcherland, the Netherlands and Sweden are being considered in the calculations and represent three different types of energy-economy structure. Finally, it is found that the equilibrium Negishi weight for different scenarios is nearly constant, meaning that is can be a good starting point for applying different scenarios when computing the equilibrium.

2. Bahn, Büeler, kypreos and Luethi (1997) added on Büeler's model by proposing a multi-regional Markal-Macro model that enables an international cooperation to curb jointly CO_2 emissions through a market of emission permits. This model was used to integrate aspects of ecological sustainability, economic welfare, efficient resource use and technological innovation. Same methods as those in Büeler's paper were used for the same countries, but this time the regional sub-problems were solved in parallel in different computers.

3. Carmona, Fehr, Hinz and Porchet (2005) provided the design and numerical analysis of a new cap-and-trade scheme for the control and reduction of pollution. They quantitatively investigated the impact of emission regulation on consumer costs and company's profits. They introduced a new mathematical framework for a competitive equilibrium. This framework is general enough to accommodate tax based abatement policies, existing cap-and-trade schemes and new market designs. It provides the necessary tools to design and

implement cap-and-trade schemes capable of reaching reasonable pollution targets at low social costs while controlling windfall profits and incentives for cleaner technologies.

In the mathematical model, dynamic features of a cap-and-trade system are introduced, such as marginal costs, emission factor measuring the volume of pollutants per unit of good, production capacity, penalties and profits. Here, the main example of produced good is electricity and it is assumed that the production costs are non-negative, adapted and integrable processes. The market is driven by an exogenous and inelastic demand for goods (electricity) that has to be met exactly and is modelled by adapted stochastic processes.

They also provided a market equilibrium (by definition and proof), where the demand for each product is covered, all financial positions are in the zero net supply, and each firm is satisfied by its own strategy.

4. Chesney and Taschini, (2009) had a reference to Schennach's (2000) paper, which was one of the first ones that analysed the permit price in a stochastic continuous-time and infinite-time horizon model, where the actual path of the permit price and pollution emissions may be different from their expected path. They obtained results where when new info becomes available, the optimisation problem needs to be re-evaluated and possibly creating discontinuity in the emission permits price.

They make reference to various empirical studies of the historical time series of the permit price. In Daskalakis et al (2009) several different diffusion and jump-diffusion processes were fitted to the European CO_2 future time series. Benz and Truck (2009) analyse the short-term spot price behaviour of the return time series. In contrast, Paolella and Taschini (2008) advocate the use of a new GARCH-type structure for the analysis of inherent heteroskedasticity dynamics in the returns of SO_2 in the US and of CO_2 emission permits in the EU ETS.

The authors generate endogenously the price dynamics of emission permits under asymmetric info, allowing banking and borrowing. Like Fehr and Hinz (2006), they also differentiate between short-term and long-term abatement measures. Since in the short-term it is difficult to modify production processes or outputs, it is assumed that each firm's pollution emission follows an exogenously given stochastic process. They prove that the price path of emission permits depends in the future probability of a shortfall in permits, the penalty that will be paid in the event of a shortfall and the discount rate. The idea is that the price at each time *t* should

reflect firms' perception about scarcity or excess of permits in the market based on the info available at time *t.*

Regulatory and technological uncertainties prevent from an identification of the best strategy in the short-term. Also, observed extreme volatility in the European and the US permit markets suggests an urgent need for the development of effective hedging techniques.

5. Bernstein, Montgomery and Tuladhar (2006) examined the feasibility of an approach that does avoid the problem of targets and timetables, and concentrates on solving the most obvious gap in the Kyoto Protocol: how to change the future trajectory of emissions from the non- Annex B, Eastern European, and Former Soviet Union countries. They introduced a model of economic growth including embodied technical progress to examine whether a policy of accelerating investment in non-Annex B countries, together with technology transfer to ensure that the new investment embodies energy technologies comparable to those adopted in new investments in OECD countries, can produce emission reductions and enhance economic growth for those countries. The model indicates that significant emission savings are possible.

6. Daskalakis and Markellos (2008) examined for the first time the efficiency of EU ETS during the first two years of its operation. The analysis was based on serial correlation and variance ratio tests. The market efficiency is assessed by measuring the profitability of two popular technical analysis trading rules based on the variable length moving average and the trading range break-out. Their profitability is compared to that of naïve investment strategies based on a random walk forecasts and on a buy-and-hold approach.

Based on their results, they assume that the spot EUA prices are non-stationary with a single unit root. Also, they find high volatility in both markets due to over-allocation of EUAs. They find that the prices of intra-phase futures contracts can be described by the cost-of-carry model with a zero convenience yield and the prices of inter-phase futures contracts are best described using an equilibrium pricing approach with a stochastic yield and jumps.

The analysis shows that the emission allowance returns are serially predictable and that simple trading strategies can be used to exploit these predictabilities and to produce risk-adjusted profits. This can be the case because the market is new and immature and also because of the restrictions on short-selling and banking of EUAs.

7. Fehr and Hinz (2006) suggested a model for price formation of carbon emission rights. Their approach was based on the realization that the carbon price development reflects the private economic interests of installations, concerned by emission regulations.

Thus, the main aspect in their modelling was to face the individual strategy optimization of market participants, exposed to carbon price risk. They believed that the major emission reduction resource is the fuel switching (in the simplest case, from coal to gas) in heating and electricity production. On this account, commodity price models (in particular, fuel price models) formed an intrinsic part of carbon price modelling. Consequently, they attempted to find out how the emission allowances price evolution is quantitatively related to the fuel price development. They used a single switching price process, under the assumption that the cheapest technology would be applied first to save carbon.

8. Haurie and Viguier (2003) proposed a computable stochastic equilibrium model to represent the possible competition between Russia and China on the international market of carbon emissions permits. The model included a representation of the uncertainty concerning the date of entry of developing countries (e.g. China) on this market in the form of an event tree. Assuming that this date of entry is an uncontrolled event, we model the competition as a dynamic game played on an event tree and we look for a solution called *S*-adapted equilibrium. They compared the solution obtained from realistic data describing the demand curves for permits and the marginal abatement cost curves in different countries, under different market and information structures: (i) Russia's monopoly, (ii) Russia–China competition in a deterministic framework, (iii) Russia–China competition in a stochastic framework.

9. Leimbach (2003) argued that most climate policy models are unable to reflect non-economic factors, such as:

- Fairness issues
- Equity
- Morality

in a formalised way.

The main model is coupled by an economic sub-model (Leimbach and Toth, 2003) and a climate sub-model (Bruckner et al., 2003). It determines the emission path that keeps the system within the 'guard-rails' (a climate window that restricts the increase in global mean

temperature to 2°C and the rate of change in global mean temperature to 0.2^{o}C per decade) at least costs.

Their main results are:

- long transition phases between status quo and equal per capita allocation of emission rights are less costly
- trade restrictions require stronger reduction efforts in industrial countries in the short-term,
- unrestricted trade is superior from an economic and equity point of view
- trade restrictions may cause a considerable amount of emission rights to remain unused
- emissions trading can significantly change the terms of trade
- combining recklessly equal per capita allocation and trade restrictions distorts fairness and efficiency
- CPA (i.e. China) might become a competitor on the permit market, demanding a huge amount of emission rights.

10. Seifert, Uhrig-Homburg and Wagner (2008) claimed that it is essential to know the price dynamics of CO_2 emission certificates for risk management applications in a changing and more complex market. Currently it is difficult to deduce essential properties of a potential CO_2 price process from currently available historical data as it is rather short and may appear distorted by potential one-time effects due to the market's immature state. They therefore proposed a theoretical model that incorporates the most important properties of the EU ETS that should be accounted when modelling a CO_2 spot price process. In particular they questioned whether such a process should exhibit seasonal components, have upper or lower price bounds, show mean reversion or be random. The authors concluded that when taking some realistic assumptions about the features of the emission trading scheme they were able to build an efficient theoretical model for the CO_2 spot prices, which could be used for a potential derivatives valuation. They also found practical limitations in solving the characteristic PDE.

11. Kemp and Swierzbinski (2007) proposed the sale of long-term put options for carbon by the UK Government as an element of a programme for encouraging long-term investments to reduce carbon emissions (including carbon capture and enhanced oil recovery/storage

schemes). They argued that what was needed was “a key role for Government to put in place a framework which, by placing a value on carbon, provides a financial incentive for businesses and households to incorporate the climate change impact of their activities. A carbon price is essential for making lower carbon emissions a business imperative”.

They argued that to encourage long-term investment in carbon-abatement activities there needs to be more certainty on emissions allocations which have an obvious effect on the market value of the related allowances. Currently there is so much uncertainty surrounding the prospective value of allowances that they almost certainly cannot be usefully employed in making long-term investment decisions. Against this background there is a case for intervention by the Government (or its agent) to reduce this uncertainty. In this paper a scheme which can achieve this is proposed and discussed. It is stressed that the proposal is only one element in what might be a package of measures including tax and other capital incentives.

12. Viguier, Vielle, Haurie and Bernard (2006) proposed a two-level game model to assess the strategic allocation of greenhouse gas (GHG) emission allowances in the EU-wide market that will be implemented, following the Kyoto agreement. They claimed that there are market imperfections in the European economies that can challenge the efficiency of trading, for example some countries can be worse off with trading than without because of imperfections due to pre-existing tax distortions. Another source of imperfection comes from the limitation of the emission permits market to some sectors of the economy. These market imperfections may create a situation where some dominant countries strategize their allocation of allowances.

It was shown that EU Member States characterized by high abatement costs might be tempted to “subsidize” their energy-intensive industries through the initial allocation of emission allowances across domestic sectors. Despite, this incentive to act strategically is relatively low since strategic behaviours have a limited impact on the payoffs of the players. These results seem to be robust as the choice of admissible strategies in the different games has a limited impact on players’ behaviours.

2.4 Studies of EU policy and regulation

The key EU policies regarding the regulations of the carbon trading and their allocation methods according to the EU ETS are reviewed below:

1. Mansanet-Bataller and Pardo (2004) analyzed the impact of National Allocation Plans announcements on carbon prices and their volatility during the period October 2004 through May 2007. Following McKenzie et al. (2004), two event study approaches were used. The first one consisted of estimating the abnormal returns as coefficients of the dummy variables that corresponded to event days in a regression. The second approach was the Constant Mean Return model that measured the abnormal returns from a benchmark. In this study, they followed these two approaches when applying statistical event study methodology using daily carbon futures returns. However, the particularities of the data series led to the methodology adaptation to the existence of a huge amount of very closed and unscheduled announcements affecting a sole price series. In order to minimize big surprises during the prediction period when applying the Constant Mean Return model, they proposed the Truncated Mean model. This approach is a modification of the Constant Mean Return model in which the abnormal returns in the estimation period are obtained using a truncated mean. They found that both Phase I and Phase II announcements have an influence on carbon returns on the day of the announcement and in a few cases on the following days. They have also detected significant returns on the days before the official announcement. Related to the variations in the volatility of carbon returns, there were no observed differences before and after the announcement.

2. Betz, Eichhammer and Schleigh (2004**)** showed the main design issues of 16 NAPs are presented for Phase I of the EU ETS, which were either submitted to the European Commission (EC) by the EU member states or were available as draft versions in early May 2004. They applied some quantitative and qualitative analysis that showed the following:

- The EU ETS program seemed unlikely to result in major emission reductions during the first period of trading
- There was a big allowance offered by some member states at the cost of other sectors which were not part of the program and also at the cost of the general tax payer
- Different interpretations of the installations by different member states may lead to competitive distortions

- EU ban on banking and ex-post adjustments of allocated quantities for new installations may prove to be economically inefficient.
- Transaction costs are expected to be higher than those for compliance

3. Böhringer, Hoffmann, Lange, Löschel and Moslener (2004) quantitatively analyzed aspects of efficiency and sectoral burden sharings that may have resulted from different allocation rules.

They implemented a flexible web-based simulation model where the user can specify the design of National Allocation Plans for each EU-Member State and then evaluate the cost implications at the regional and sectoral level. Their analysis focused on the hybrid nature of the EU trading scheme, i.e. a mixture of different regulatory regimes: some sectors (industry and energy) are included in the trading scheme while others (e.g., transport, services) are not. The co-existence of an emissions trading and a non-trading part of the economy poses the problem of partitioning the overall emissions budget between the two parts of the economy. Their results showed that this can dramatically increase the compliance costs of emission regulation.

Their simulations highlighted the need to re-consider the current guidelines for National Allocation Plans in order to avoid substantial excess costs of regulation and drastic sectoral burden shifting. The hybrid regulation together with compensation (free allowance allocation) of energy-intensive industries may have been necessary in an initial stage to promote market-based regulation of carbon emissions. In the medium-run, comprehensive coverage of all carbon emitters should materialise the full potential of efficiency gains.

4. Böhringer, Hoffmann and Manrique-de-Lara-Peñate (2006) based their analysis on numerical simulations for Germany and quantified the excess costs of segmented carbon regulation. The EU-ETS covers only a part of CO_2 emission sources (production and processing of iron and steel, cement, ceramic, glass, electricity and gas), which implies a segmented environmental regulation scheme. Under such a scheme, the domestic regulator must have perfect information on the international price of tradable emission allowances and the marginal abatement cost curves across all domestic emission sources that are not included in the emissions scheme to implement the cost-minimising NAP (National Allocation Plan).

5. Chao and Wilson (1993) studied the market for emission allowances as this was introduced in the 1990 Clean Air Act Amendment. They assumed that there would be a fixed number of

allowances and that demand was affected by a stochastic parameter which follows a Wiener process (‘Brownian motion’). They developed a model for the dynamic behaviour of prices in this market, which also include an option value representing the value of flexibility as compared to the alternative of investing in scrubbers, immobile equipment that permanently reduces emissions. They studied some of the factors that affect emission allowance prices, like the demand for power and therefore for electricity. These result in increasing the demand for emissions. However, their model omitted important factors, such as regulatory uncertainty, banking of allowances, the futures market, auctions of extra allowances and concentrated only on SO_2 emissions in the US. However, they proposed to include CO_2 emissions to their model in the future.

6. Ellerman, Buchner and Carraro (2007) discussed the lessons from the allocation of allowances in the EU ETS. Their observations fall into three categories: those concerning the conditions encountered, the processes employed and the actual choices.

They concluded that the lack of data at the level of the installation because of aggregated energy use statistics and time constraints was the biggest challenge in the allocation process by nearly all member states. The problem of data availability was also due to the lack of legal authority to collect the data. This combined with the tight deadlines for NAP submission forced the governments to rely heavily on voluntary submissions from industry which surprisingly cooperated fully.

7. Enevoldsen, Ryelund and Andersen (2007) studied the impact of energy prices and taxes on energy efficiency and carbon emissions of ten industrial sectors in the three Scandinavian countries. They took price and tax data at a more detailed sectoral level, as well as of the more recent policy experience of CO_2 taxation in Scandinavia to explore industrial energy consumption behaviour ex-post.

They mentioned that the notion of decoupling has achieved global recognition as a significant conceptualisation of successful economy–environment integration. The decoupling of environmental pressures from economic growth has become a desired policy outcome, whether in climate policy or in a wider context. However, the question remains whether environmental improvements are possible without sacrificing some degree of economic welfare.

They argued that previous analyses have relied on average energy prices and have neglected the existence of rebates and discounts for large energy consumers. They improved the elasticity estimates through panel regression, which are useful when considering the impact of price changes on energy consumption. The authors suggested that the statistical results may be put to such use by first investigating the magnitude of energy price changes caused by the energy market liberalization and thereafter using the derived price elasticities to calculate the consequences on energy consumption and CO_2 emissions.

The conclusion is that decoupling:

- increases the price of energy relative to the price of labour and other input factors caused either by market developments or political instruments such as the introduction of energy/CO_2 taxes or cuts in labour taxes,
- changes energy prices in favour of low-carbon energy forms that arise as a consequence of either market developments or political instruments such as CO_2 taxes.

The statistical analysis provided clear evidence that energy taxes and especially CO_2 taxes will be an important instrument for decoupling of economic growth and CO_2 emissions. The study confirmed earlier findings that the demand for electricity is very inelastic, that is, CO_2 taxes will have only limited effects with respect to reducing electricity consumption. Moreover, increasing electricity consumption figured as an autonomous trend in most industry sectors.

8. Georgopolou, Sarafidis, Mirasgedis and Lalas (2006) attempted to explore the constraints and the available options that will guide the coming EU-ETS potential allocations. They questioned whether there will be an overall net deficit at EU level between supply and demand of allowances during the period 2005-2007 and if so then whether this will be covered by ETS installations. They found the above to be true and the deficit can be covered by the use of more reduction is ETS installations or the use of CDM credits or by a combination of both.

Lastly, they argued whether there is enough potential for additional emission reduction measures in ETS sectors in each member state to cover potential allocation deficits during the next allocation phase (2008-2012). Here they discovered that compared to the limitations imposed by the 2005-2007 allocations, the next phase is expected to be tougher for ETS

installations in the majority of the member states without the contribution of the KP mechanisms. Their exploitation leads to a more relaxed path towards the Kyoto targets, which in turn allows for more flexibility to ETS installations.

9. Godal and Klaasen (2006) examined the potential effects on permit prices and abatement costs of four compliance rules governing emissions trade across sources and period in the Kyoto Protocol; the banking rule, which allows excess permits to be used later (from one period to the next); the restoration rate rule that penalizes borrowing; the commitment period reserve rule that limits sales; and the suspensions rule that restricts borrowing and sales. From a qualitative analysis, they found that the permit price in the period 2008-2012 may range from the discounted permit price in the second period to the latter multiplied by the restoration rate. If there is banking then prices rise with rate of interest. If there is borrowing, then discount permit prices decrease from one period to the next. Their numerical simulations suggested that the additional costs of the compliance rules may be relatively small compared to those of an idealized efficient regime, in particular if the rules serve other purposes well, like promoting final compliance. However, they admitted that their analysis has its limitations, since issues like carbon sinks, non-energy related CO_2 emissions, non CO_2 greenhouse gases and the CDM have been omitted. If the above were involved in their analysis, then permit prices would be lowered. In their model of permit trade, the strategic behaviour on the demand side was not included, leading to higher aggregate costs. Also, emissions cost functions were assumed to be known and be free from externalities, whereas in reality they are not perfectly known.

10. Grubb and Neuhoff (2006) investigated three inter-related problems that can undermine the EU ETS: the approach to allocation; the absence of a credible commitment to 2012 continuation; and concerns about its impact on the international competitiveness of key sectors. They stressed the difference of an emissions market to any other market to be the fact that the amount available depends directly on government decisions about allocations.

Five principles underlie the practical economic impact of an emission trading system applied to CO_2:

- In general, CO_2 constraints cause economic rents, and free allocation of allowances to industry gives the potential to capture this value and profit, subject to: (a) degree of alignment of allowances with costs (e.g. not sectors outside EU ETS or affected

primarily by electricity pass-through costs); (b) constraints on cost pass-through due to imports and other factors.

- Profit and market share are not synonymous; the more that companies profit by raising prices to reflect the opportunity costs of carbon, the greater the possible erosion of their market share over time
- The details of allocation methods are important, as they may affect the incentives, pricing and efficiency of the scheme.
- The power sector can pass through the CO_2 related costs to the wholesale power markets, as expected in a competitive system, resulting in substantial profits and downstream costs where retail markets are competitive.
- Other participating sectors also have the potential to profit in similar ways, but the net impact is complicated by details of electricity retail market regulation, by international trade, and by downstream company, regional and product differentiation.

11. Grubb, Azar and Persson (2005) stressed the importance of the initial allocation of allowances as this will determine both the ultimate significance of the system, in terms of the total emissions and the associated carbon price and incentive to change. They argued that during the first phase of the EU-ETS the allocations have been weak and implied only a small cutback from the "business-as-usual" projections. This implied little emissions control in the first period and may provide a threat to the stability of the EU ETS. Weak allocation cannot prepare industries for the stronger emission reductions that will be required.

Several factors have led to the present over-allocation: corporate lobbying based upon competitiveness concerns; and the ability for each country to allocate free allowances to its own firms. For the first period, 2005–2007, this situation has been worsened by the lack of any aggregate target for national emissions, so countries did not need to make an explicit trade-off between emissions in the trading and non-trading sectors. This will not be the case in the second period, when the Kyoto target has to be met. Prospects for reasonable allocations in the second period may thus seem brighter, but the fundamental problems will still need to be addressed.

The authors proposed two methods to solve this: one is to auction the allowances, bearing in mind that full auctioning would worsen concerns about international competitiveness impacts and therefore suggested a mixed allocation system as more realistic. The second option is benchmarking, in which allocations are defined with direct reference to industry best practise.

To avoid a situation where the over-allocation of the first period is repeated and the Kyoto targets jeopardized, better coordination between allocation methods across Member States is also required. For that reason, the following should be considered:

- Methods for allocating allowances and the total amounts are negotiated and agreed at the EU level (Council of Ministers).
- Basic principles for these decisions should be that the allocations are in line with the Kyoto Protocol targets, adjusted for the amount that countries (governments) commit to buying through Kyoto's international mechanisms.
- The same principles are applied in all countries.
- A larger share is allocated through auctioning.

12. Hidalgo,Szabo, Ciscar and Soria (2003) presented a simulation model analyzing the evolution of the steel industry from 1997 to 2030, addressing steel production, demand, trade, energy consumption, CO_2 emissions, technology dynamics and retrofitting options. Three emission trading scenarios were discussed: a EU15 market, an enlarged EU market and an Annex B market. They found that as a general expectation, the larger the country coverage of the emission market, the lower the compliance costs of a given emission reduction target. So, under a EU15 market the compliance costs of fulfilling the Kyoto targets will be reduced by half. The countries that would benefit the most from such a market would be those with the higher amount of traded permits. Moving to a wider EU market, the permit price and the compliance costs would be reduced and the steel industry would still benefit from being a net buyer of allowances and all the candidate countries would receive revenues from permit sales. In the Annex B market, there are even more positive effects of emission trading and the steel sector would be expected to become a seller of allowances.

13. Insley (2003) analysed the real options approach of a firm to reduce pollution by retrofitting its plant rather than purchasing emission allowances by following a known stochastic process (geometric Brownian motion) for these prices. The author found that as volatility increased the critical price increased too, so the installing of a scrubber would be delayed. The model's timeframe allows for such a delay and the author recommends it for optimal investment decisions that feature long construction periods and embedded options with finite life spans.

14. Jacoby and Reiner (1997) analysed the consequences of a model of economic growth and emissions and its impact on the nations that comply with economic burdens set by the Climate Convention policies. They used the MIT Integrated Global System Model to explore the various targets and timetables for the control of the emissions across the member countries of Annex I (this includes the OECD countries plus the nations of the former Soviet Union and Eastern Europe).

Their model is a combination of various components: a model of economic growth and associated emissions, a coupled model of atmospheric chemistry and climate, a model of the effects of climate change on ecosystems and a model of the effects of CO_2 and other key greenhouse gases on the natural cycles. Their results indicate that:

- emission policies will affect not only the participating countries but others too and not necessarily in a negative way.
- Carbon leakage will occur when policies are applied differentially among world regions.
- Economic growth will be affected and implications will be great but highly uncertain not only for the total carbon emissions but also for the distribution of burdens and for leakage.
- As the economic differences between the OECD and non-OECD nations are large, so the benefit from trading is great. This provides space for bargaining over compensation.
- The current proposals for restrictions on the emissions yield a minor reduction of the potential global warming, so more country participation is required.

15. Klepper and Peterson (2004) attempted to indentify the main features and key impacts of the EU ETS by scanning the range of likely allocation plans using the simulation model DART (Dynamic Applied Regional Trade).

They show that the Eastern European countries will be the only countries selling allowances, even without hot-air included in the simulations. Their low cost abatement opportunities reduce the costs of reaching the Kyoto targets considerably. Concerning the division of costs of reaching the targets between the sectors in the ETS and those outside, it is found that only the least cost allocation approach leads to a welfare gain. If the allocation plan is not based on

abatement costs, but on actual or expected emissions then there is distortion between the ETS and the non-ETS sectors. Such an allocation mode would in general lead to a higher amount of allowances being generated and eventually would lead to a collapse of their price. Concerning the competitiveness effects, if the ETS were to be introduced throughout the EU and to all the industry sectors, there would be considerable welfare gains. However, simulation shows that even though this is not the case, there are still gains under the least cost approach for all the sectors, even for those that do not participate in emissions trading.

16. Larson, Ambrosi, Dinar, Rahman and Entler (2008) concentrated on describing essential institutions and policies for the new carbon markets and summarized early investment and price outcomes from these newly formed markets. They have also identified areas where markets have performed as predicted and those where markets remain incomplete.

Concerning emissions allocations, these in general are based on historical responsibility, population, single or multiple measures of development or economic need. Other policies used for reducing emissions are tradable permits or carbon taxes. In principal, carbon tax systems effectively fix the price of emissions but result in emissions variability while permits result in price variability and fix emissions levels. Another difference between carbon taxes and permit systems is the pricing of uncertainty. While uncertainty creates incentive to delay irreversible investments that reduce emissions, it also drives up the price of permits held in inventory, thereby reducing current emission levels and resulting in partly reducing the negative effects of uncertainty on investment. Tradable permits have been preferred over taxes, as they have proved to apply successfully to other problems as well (fishing quotas in New Zealand in 1986, phase-out of lead gasoline in the US, air pollution program in Los Angeles).

There are also a lot of concerns about the flexible mechanisms, that they will weaken the environmental efficacy of the climate change framework, as they have allowed for a large supply of excess allowances, which lowered the overall price of permits and lead to fewer emissions reduction in Annex B countries and lowered incentives to develop and use new technologies.

Concerning the objectives of the above mechanisms, some model structures are discussed. An important issue to consider here is whether the greenhouse gas concentration is an exogenous factor to the model. Optimisation models maximise profits while adjusting the level of emissions endogenously. This can be achieved either by adjusting levels of production and

the mix of sectoral output, or by introducing and endogenously selecting production technologies with different emission intensities. The other approach is to exogenously impose a level of greenhouse gas concentration on the model and find the most effective way to reach it. Both approaches can be either static or dynamic. Endogenous technology adoption can be part of the model while CO_2 concentration can be also addressed via level of production only.

It is found that most existing models agree that the permit trading substantially lowers the cost of meeting Kyoto objectives, while trade restrictions increase costs and potentially lead to market power concerns.

As for the carbon prices, such models suggested that reductions in emissions could be obtained by lower carbon prices. Flexible trading rules could also reduce the price of carbon permits. A common finding is that the costs for reaching emissions goals are greatly reduced by rules that allowed spatial and temporal flexibility. Al the above matters and their inter-relationships need to be taken into consideration by the policy makers.

17. Liaskas, Mavrotas, Mandaraka and Diakoulaki (2000) identified those factors that influenced changes in the level of industry CO_2 emissions. These changes are analyzed into four different categories: output level, energy intensity, fuel mix and structural change.

They found that CO_2 emissions from manufacturing have been reduced or stabilized in the EU despite the continuous growth in the industrial production (until 1993). The decrease in the energy prices after the second oil crisis lead to a decrease in the energy intensity effect. The change in the energy mix has also contributed to the reduction of emissions. Tendencies to switch to natural gas has been an important change in the fuel mix, since this fuel has the lowest emission factors compared to all other conventional fuels. The authors also discovered that there is no clear evidence that restructuring of the manufacturing sector in EU countries has had a positive influence in the abatement of emissions.

18. Mansanet-Bataller and Pardo (2008) have studied the carbon trading as set by the Kyoto Protocol and as it is functioning via the EU ETS. Three flexibility mechanisms are included in the protocol: JI (article 6), CDM (article 12) and Emissions Trading (article 17). JI deals with Annex I countries and allows for Emission Reduction Units (ERUs) to be used by these countries for meeting the emissions targets. CDM is for countries not part of Annex I (developing countries) to trade Certified Emission Reductions (CERs) to achieve compliance.

All trades are supervised by the International Transaction Log (ITL), which went live on 14th November 2007. There are different ways of trading EUAs in Europe:

a) Over–The-Counter trading (OTC), which was the first kind of trading even before the start of the EU ETS. The European Energy Exchange (EEX) calculated an index of OTC forward carbon prices, called CO_2 Index of European Carbon Index. This was a volume- weighted average price of OTC forward trading activities of market participants with delivery until 30th April 2006. Other OTC indexes have been created by the London Energy Brokers' Association (LEBA), which also calculates three more indices (LEBA carbon Index, LEBA 0800-1000 Carbon Index, LEBA Carbon Index Spot). The EEX Carbon Index was found to compare similarly with the LEBA carbon index in the first phase of the commitment.

b) Organised Market Trading, where it is possible to trade EUAs (BlueNext, EXAA, NordPool, EEX and GME). All these markets are based on accounts transactions, thus it is compulsory to have a registry in the specific market to participate in it.

The ECX offers more variety for expiry contracts dates, EEX offers only December futures contracts for each of the EU ETS years, Nord Pool offers December and March contracts for both phases and ECX proposes contracts with monthly expiry dates from September 2006 to March 2008.

Along with EUAS, CERs and ERUs can be traded, although they do not have any indexes. They are found to behave in a similar manner to the December 2008 EUAs future contract traded at ECX. The authors conclude that the EU ETS has succeeded in imposing a price on carbon emissions, that trading in spot, forward and futures markets is increasing with the addition of options contracts, a sign that the futures market is mature enough and that the CERs market will contribute to creating an equilibrium between the offer and the demand of the carbon markets. Finally, the effects on emissions are found to be mixed. From the latest report (2007) of the UNFCCC regarding data on the greenhouse gas inventories for Annex I countries, it is evident that the Annex B countries with economies in transition have actually drastically reduced their emission while the rest of the countries have increased them.

19. Matthes, Doble, Macadam, Taylor, Zanoni and Chodor (2005) wrote an extensive report on the environmental effectiveness and economic efficiency of the EU ETS. Their purpose is to provide an independent analysis of the National Allocation Plans in six member states

(Germany, Spain, Italy, the Netherlands, Poland, Spain and the UK). A comparison analysis of the different ways each member state chose to allocate the EUAs to the installations is provided. This included the principles and provisions surrounding allocation of allowances to existing installations in the scheme, to new entrants, how plant closures are treated, their interactions and plans for the use of credits form the CDM and the JI mechanisms at the level of installations. The structural analysis focuses on the power sector, as this is the main driver of the emissions increase and has been very influential in the NAP process in many of the member states.

Their results show that:

- Auctioning is found to be the most efficient allocation approach
- Fairness issues arise mostly for the allocation to new entrants
- There should be an integrated assessment for every allocation provision
- The costs of carbon create the key incentive for the operation of existing power plants and the implementation of emission abatement measures in existing plants and ex-post adjustments eliminate these incentives
- Updating is not a preferable option for future allocation in general
- A scheme of fuel-specific or technology-specific benchmarks for existing installations could ensure key incentives under an updating approach and would prevent the incentive of "gaming" (i.e. increase emissions to receive a higher allocation in future phases)
- A simpler benchmark scheme will minimize the problem of carbon price distortions
- installations with low emissions should also receive the full benchmark allocation to get the intended incentives
- The allocation to new entrants based on fuel-specific benchmarks is not considered to be appropriate and transfer provisions could constitute an alternative, however there may also be some fairness issues in the latter case
- In the case of free allocation to new entrants, this can be based on production data defined by load factor (capacity utilisation) benchmarks. This is a simpler and more

transparent approach which could avoid the problem of windfall profits arising from exaggerated installation-specific projections

- Measures to ensure the quality and the environmental integrity of CDM and JI projects are important, especially in the first years of the EU ETS.
- Although an auctioning scheme will create a uniform and transparent price signal for carbon costs, the allocation based on grandfathering creates manifold distortions and inconsistencies.
- Interaction in the allocation system is essential for the future development of NAPs.
- New entrant provisions will be the main focus for the phase II NAP.

20. Milunovich, Stegman, Cotton (2007) presented current initiatives to climate change management including a review of existing carbon trading schemes and those economic arguments that support them. They argue that there is a high degree of uncertainty associated with the nature and the consequences of climate change and also with the costs and benefits of emission reductions, all of which the existing policy proposals are not able to adequately account for. They recommend a hybrid approach (both tax and permits based approaches) to climate policy, as this has been suggested by the McKibbin-Wilcoxen Blueprint. Here, the government supplies short term permits at a fixed price which act like a tax on emissions but also issues a determined amount of permits, to create a private sector constituency with a clear financial interest to maintain and enforce the policy.

21. Neuhoff, Grubb and Keats (2005) used analytic models and a numeric simulation for the UK power sector to demonstrate how certain effects of the NAPs contribute to an inflation of the allowance price while reducing utilisation and investment in efficient technologies. The impact of CO_2 allowances on the relative costs of new technologies used in the electricity sector is crucial. It is found that for the UK, CO_2 allowances increase the electricity cost for consumers, independent if whether allowances are auctioned or grandfathered based on a historic line (simulation results are for the period 2005-2007). As the allowance prices can be inflated above the level they would take in a cap-and-trade program with pure auctioning of allowances or one-off allocation based on historic emissions.

22. Rogge, Schleich and Betz (2006) assessed the 18 NAPs for Phase 2 (2008-2012) of the EU ETS to find which member states intend to use the ETS effectively to reduce their emissions. Their analysis shows that at the macro level of the NAPs the ETS budgets in phase

2 are only about 3% lower than those in phase 1. There is also a difference in the stringency of the budgets between old and new member states. While the old member states intend to reduce their emissions by 105, the new ones get an excess allocation, which eradicates some of the old member states' efforts to tighten their budgets. Also, the cost-efficiency between trading and non-trading sectors demonstrates that the latter have to bear a disproportionately high share of the reduction effort in all EU 15 member states. This cost of achieving the burden-sharing targets would be lower if a cost-efficient split of the reduction target were determined and implemented.

At the micro level, they found that member states tend to stick to the already developed concepts and methodologies, unless these contradict the EU Commission. First, sector budgets are determined and then EUAs are allocated to individual installations, based on historical emissions (conventional grandfathering). There are some small improvements, like the increase in auctioning and the use of benchmarking for existing and new installations, but in total little evidence exists for improving environmental effectiveness and economic efficiency.

23. Schennach (2000) presented a model of the collective emission permit banking behaviour of electricity-generating units affected by the Clean Air Act Amendments of 1990. He took into account the constraint of the banking allowance, as pollution permits cannot be borrowed from the future. The results show a two-period behaviour evolution: a banking period, where units save their allocation permits for future use, followed by a period where all annual permits are immediately used. Marginal costs and the constraint of continuity are introduced in the model. The model can also describe events relevant to the SO_2 allowance market; the greater availability of low-sulphur coal, innovations in the abatement technologies and increases in electricity demand. Uncertainty is entered into the model by the form of de-regulation in the electricity market, environmental concerns and technological advances. The actual path of price and emission may turn out to be different (higher) from the expected path, especially when new information becomes available.

24. Schleigh, Ehrhart, Hoppe and Seifert (2006) investigated the implication of banning banking in EU emissions trading. The analysis is based in a simulation carried out in Germany with companies and a student control group. Their model demonstrated that banning the transfer of allowances from 2007 to 2008 (last year of phase 1 to first year of phase 2) increases overall compliance costs because costs saving cannot be traded over time.

If banking is prohibited, then the market prices will not reflect the 'true' opportunity costs, which will lead to inefficient abatement measures.

25. Svendsen and Vesterdal (2003) investigated ways of trading greenhouse gases in the EU, considering four main issues, which are target group, allocation of emissions allowances, how to mix emissions trading with other instruments and finally enforcement.

In terms of allocation, they suggest that each electricity utility gets its permits via 'grandfathering'. This approach allows the government to introduce changes without any compensation to the market participants.

Another economic instrument that can be introduced is green taxation to monitor costs in smaller industrial plants. Finally, to use enforcement in making sure that there will not be any cheats to the system, two monitoring mechanisms exist: a national reporting to the secretariat of the UNFCCC and an EU monitoring mechanism, where individual companies should report their emissions to the member states. In case of cheating, a fine around the level of 40€/tCO_2 should be sufficient to deter potential defectors in the system.

26. Vesterdal and Svendsen (2004) commented further on the permit allocation in the EU, by involving political and economic implications. First, at the national level, they looked at permit contributions from each country's emission target and at the firm level, they looked at the distribution mechanisms for permits to individual plants.

Regarding the first level, the energy sector together with the ongoing liberalisation of the gas and power sector will be the obvious candidates for permit allocations. Regarding the second level, different distribution rules can coexist. There can be a common agreement about how grandfathering can be out-phased from the system over time because there are large welfare gains if the revenue is used to reduce other taxes rather than being given away for free to the existing emitters. Thus, the revenue is distributed broadly and fairly.

27. Wirl (2006) investigated how two kinds of irreversibility, those of emissions and of stopping, affect the optimal intertemporal accumulation of greenhouse gases under uncertainty. Emissions are irreversible as once dissolved into the air they cannot be collected back. Stopping emissions is also irreversible, since this would mean the total shutdown of the entire fossil fuel industry. The implication of reversible stopping (switching) is seen within a real option framework, where flexibility requires an additional boundary condition, i.e. the continuity of the second derivative of the value function (at the threshold level). A more

realistic setting of a continuous choice of emissions at each instant of time was investigated. Irreversible emissions are found to be lower compared with the unconstrained optimisation problem. Stopping is never optimal, since with a continuous choice of emissions, arbitrary small levels of emissions allow avoiding the inevitable loss associated with a shutdown without causing a significant increase in temperature. It is also found that the consideration of switching allows for more conservative emissions policies, i.e. an earlier stopping. Furthermore, higher uncertainty lowers this threshold in the reversible case, but increases it in the case of irreversible stopping.

28. Zetterberg, Nilsson, Åhman, Kumlin and Birgersdotter (2004) analysed national allocation plans for the EU ETS in terms of:

- The consistency of the NAP in relation to the responsibility that each member state has towards Kyoto and the EU burden sharing agreement.
- The pressure on both the trading and the non-trading sectors to reach the targets
- Allocation methodology
- Other aspects of the allocation in terms of the Annex III criteria of the Directive

From their research it is concluded that several member states are far from fulfilling their emissions targets. The allocation quota is often higher than the Kyoto quota, indicating that the member states will need to reduce emissions more in the non-trading sector, resulting in unfairness treatment.

29. Zhao (2003) has developed an equilibrium model of permit trading and irreversible abatement investment to show how cost uncertainties affect investment under permits. The resulting investment incentive is compared with that under charges. The model introduces permit trading by price taking firms with stochastic abatement costs and rational expectations about permit prices. The results prove that abatement cost uncertainties reduce firms' investment incentive under trading systems and even more so under charges, especially if the investment is irreversible and the uncertainties enter the cost function in a linear manner.

2.5 General research into emission trading

Those papers that deal with how emission relate to other industries are reviewed below:

1. Adeyemi, Hunt (2007) provided an econometric modelling of industrial energy demand using the data of 15 OECD countries over the period 1962-2003 and investigated the issue of energy-saving technical change and asymmetric price responses. Their work was based on the models and procedures developed by Huntington. The results show that for the whole economy energy and oil demand, it is not possible to conclude that both asymmetric price responses and time dummies play an important role; they are 'complements' rather than substitutes. Their model demonstrates that when estimating energy demand models and considering the issue of energy-saving technical progress (and other exogenous trends) a general flexible approach should be initially adopted.

2. Barker, Ekins and Foxon (2007) provided a study modelling the UK Climate Change Agreements (CCAs) and related efficiency policies for energy-intensive industrial sectors (2000-2010). Their approach incorporates a top-down macroeconomic model of the UK economy, interrogating what energy savings are expected from these policies, what effects of these savings have on prices of other sectors and the economy in general, how is the output affected, how large is the increase in energy use and how this is associated with the direct energy-saving measures, what will be the effects on the CO_2 emissions and how much these results depend on the differences in energy price assumptions. The results show that industries can make cost-effective, energy-efficiency improvements by overcoming market failures and barriers when given incentives to do so. Negotiated targets will lead to significant reductions in CO_2 emissions and to further economic benefits to a national level, thanks to international competitiveness.

3. Betz and Sato (2006) provided a summary of several articles regarding the influence of allowance allocation and the lessons learnt from the 1st phase of the EU ETS.

Answering the questions whether the EU ETS is efficient and fair, the following were concluded:

- Kemfert et al. (2006) estimated some significant efficiency gains from trading in phase I, by using an equilibrium model, where there is no inter-sectoral or inter-regional trade. However, from the phase I experience so far, certain design features of the ETS may prevent the realisation of such gains.
- Neuhoff et al (2006) showed that most the NAPs did not consider the 'updating' dilemma.

- Ahman and Holmgren (2006) found that free distribution of allowances to new entrants coupled with the withdrawal of allocation from 'ceasing installations' creates further perverse incentives to keep inefficient plants in operation, which reduces the overall efficiency of the system. Betz et al. (2006) found that there has been some resistance to change in most member states and few changes have been made for phase II.
- EUA spot prices have been volatile from the start. Hepburn et al (2006) argued that more certainty and transparency are needed to drive long-term investment, including banking and setting a minimum price-floor in auctions.
- Certain sectors including power, cement, iron and steel have the potential to profit from free allocation, by adjusting output and pricing (Smale et al., 2006).
- Burden sharing is found to be disproportionally higher in non-trading sectors (Betz et al., 2006).

The European Commission has to evaluate the proposed NAPs and has to work together with all the member states to decide together about design issues, like auctioning or the ruled for new entrants and closure.

4. Bierbrauer, Men, Rachev and Trück (2007) used the spot and futures electricity price data from the EEX power market to test various one-factor and two-factor models in terms of demonstrating and explaining the data properly and their forecasting accuracy. Electricity futures means have been closely predicted and especially in the first six months electricity future quotes are greater than the expected future spot (contango situation), which is consistent with the observed right-skewness in the spot prices. However, the authors make a point that equivalent results of different markets seem to be quite different.

5. Boemare and Quirion (2002) reviewed several emission trading systems, either implemented or at an advanced stage of the policy process. They looked at some major designing points: sectoral and spatial coverage, permits allocation, temporal flexibility, trading organisation, monitoring, enforcement, compliance and the harmonisation versus subsidiarity issue. The aim is the evaluation of experience in emission trading and how far away these move from theory and why. They found that the European Directive proposal provides a wide spatial and sectoral coverage, the latter being narrowed down by the opt-out provision, which allows a member state to exclude some sectors from the system, provided

that they are regulated by another instrument (e.g. voluntary agreement). The opt-out provision may affect badly the efficiency of the system.

6. Böhringer and Lange (2005) derived optimal schemes for the free allocation of emissions allowances in a dynamic context (not based on historical data only) of updating. They found that in a closed trading system (where one regulatory agency controls the allocation of all emission permits and chooses the allocation rule for all participants, hence the emissions are capped and the allowance price is endogenous) efficient allocation schemes have to be independent of historic emissions. In an open trading system (where the emission price is determined by an international market), first-best required lump-sum allocation (grandfathering) and second-best is based on a Ramsey formula (based on a combination of output and emission levels). In the case of the EU emissions, harmonised emission-based allocation rules could apply to reduce inefficiencies from dynamic emissions.

7. Bunn and Fezzi (2007) analysed the relationship between electricity, gas and carbon prices in the daily spot market for the UK. They used a structural, cointegrated VAR model to give a clear economic interpretation (a system of structural equations is used, whose impulse response function and variance decomposition are used to provide an economic meaning), where all the variable are modelled as endogenous a priori, as a function of their past values. They also included atmospheric temperature and other dummy variables to catch the huge drop in carbon price at the end of April 2006. Their results show a strong cointegration among the endogenous variables. Carbon price is found to be exogenous and vital for formulating the equilibrium price of electricity and gas in the UK and it responded significantly and quickly to a shock on gas price.

8. Bünn and Karakatsani (2003) reviewed the main issues and resent research on modelling and forecasting electricity prices. The statistical characteristics of electricity prices are derived from stochastic models. However, their price structure has not been fully represented in the empirical research literature. Risk management drives the research to concentrate more on capturing the distribution of prices over a period of time, than in the actual level of prices at particular times. For the latter case, the structural approach is more appropriate.

9. Clarke, Weyant and Birky (2006) provide a review of technological change and support four important points for interpreting and incorporating this change into energy models: a) the notion that no single source dominates the process of technological change, b) a strong role for spillovers, c) indication that these spillovers are often indirect and require own-

industry activities to utilise and d) simple experience curve calibrations likely include a range of sources of technological change in addition to learning-by-doing.

The authors suggest being cautious in interpreting the policy conclusions of models that assume only a single source of technological progress or that ignore factors such as spillovers. Applied energy R&D and technology deployment are not the only long-term means of supporting climate change technology development.

10. Cronshaw and Kruse (1996) examined a competitive intertemporal market for bankable emission permits, such as SO_2 permits (US), where firms are subject to profit regulation. They found that if there is at least one firm that does not have its profits regulated then permit prices can rise no faster than the rate of interest. Only then will the firm bank their permits. If no firms have regulated profits, then equilibrium in the market will lead to maximal joint operating profits, which can be interpreted as achieving an overall emissions target at least overall cost. The opposite occurs when firms have their profits regulated, due to differences in the regulatory treatment of permit purchases or sales by different firms for rate-making purposes. Including imperfect competition and uncertainty would be important extensions to the model.

11. Demailly and Quirion (2006) investigated the possibility of competitiveness loss in the EU ETS. They concentrated on the cement industry and analysed two different allocation approaches: grandfathering and output-based allocation. The authors recommend a tax or auctioned allowances with a border-tax adjustment to offer the best of both worlds: no leakage, compared to grandfathering and no more clinker dilemma, compared to the output-based allocation.

12. Ellerman and Joskow (2008) summarised the goals the EU ETS achieved in the trial period (2005-2007). A number of useful lessons are derived from the trial period:

- Suppliers quickly included the allowance price into their pricing and output behaviour.
- Liquid bilateral markets and public allowance exchanges emerge rapidly and the need for one price for allowanced prevails.
- The fast market development is enabled by the frequent distribution of emission information and allowance utilisation.

- Price volatility can be managed by including allowance banking and borrowing and by allocating allowances for longer trading periods.
- Redistributing allowances can be managed without distorting abatement efficiency or competition despite the political lobbying over allocations. However, allocations that are tied to future emissions through investment and closure decisions can distort behaviour.
- It is necessary to include the interaction between allocation, allowance market and the unsettled state of electricity sector liberalisation and regulation to the program design to avoid errors and unintended consequences.

13. Feng and Zhao (2006) examined the social efficiency of alternative intertemporal permit trading regimes. The higher the degree of asymmetry the more potential benefit a bankable regime can get. A necessary condition for banking is that the marginal benefit curve is steeper than the marginal damage curve.

14. Floros and Vlachou (2005) studied the demand for energy in two-digit manufacturing sectors of Greece and evaluated the impact of a carbon tax on CO_2 emissions. Their model is the two-stage translog cost function, which relates the flow of gross output to capital, labour and energy. Data from the period 1982-1998 is used for the estimations. The results show that the demand for energy (electricity, diesel and mazout) is inelastic, of which diesel exhibits the highest price responsiveness. The production structure of manufacturing sectors suggests that there are possibilities to reduce direct and indirect CO_2 emissions if a carbon tax is used as a policy instrument.

15. Gupta and Maranas (2003) presented a model for incorporating market-based pollution abatement instruments in the technology selection decisions. The results show that the availability of both permits and options in the portfolio was beneficial, as it resulted in achieving its pollution abatement objective at minimum cost. The option contracts also result in a significant reduction in the risk premium observed by the firm.

16. Kara, Syri, Lehtilä, Helymen, Kekkonen, Ruska and Forsström (2008) investigated the impacts of the EU CO_2 emission trading on the Nordic electricity market and also on power plant operators, energy-intensive industries and other consumer groups. According to their calculations the annual average electricity price is expected to rise. Metal industry is likely to experience the forthcoming price increases to the full, with significant impact on its

international competitiveness. Key measures to overcome this increase in prices will be the investments in new low-emissions generation capacity, increased competition at the electricity market and continuous and sufficient investments in technology development.

17. Kavuncu and Knabb (2005) assessed the intergenerational costs and benefits of the Kyoto protocol by presenting a metric that isolated environmental costs of climate change. They found that the net benefits from stabilising emissions will arrive late (23rd-24th century) and the near-term costs appear to be relatively large. They seem to have ignored innovation to their framework, which will provide reduction in the costs of stabilisation and the benefits may arrive earlier than predicted.

18. Kling and Rubin (1997) investigated firms' incentive for banking or borrowing emission permits and compared the emission and output streams firms would choose with the socially optimal solution. Under the base case, the solution to the bankable permit problem diverges from the social optimum. If the borrowed permits are discounted then the social and private solutions converge as long as social damages are linear and unchanging.

19. Kosobud et al. (2005) looked at including credits in financial portfolios. SO_2 at that time (just before EU-ETS) is the leading example of emissions trading. The correlation coefficient between various assets confirms visual impression that the SO_2 asset varies independently from other assets. The differences observed between SO_2 and other assets form the basis of their argument that environmental credits form part of a well-diversified portfolio.

20. Murphy, Rivers and Jaccard (2007) explored the implications of an economy wide compulsory greenhouse gas reduction policy, such as tax or emissions cap and tradable permits for Canada's industrial sector. The simulation results show that policy makers should consider implementing policies that impose a constraint or a modest penalty that increases gradually with time according to an up-front announced schedule. This would help avoiding the high costs associated with prematurely forcing the retirement of existing capital stocks, while at the same time providing a strong signal for the adoption of low emission technologies when capital stock is retired and new technologies enter into the scheme.

21. Sijm, Neuhoff and Chen (2006) analysed the implications of the EU ETS for the power sector, as power companies get free allocations to cover their CO_2 emissions and pass on the costs of these allowances in the price of electricity. Empirical and model estimations show

that the increase in power prices on the market may be less than the increase in CO_2 costs per MWh generated by the marginal production unit.

2.6 Carbon price determinants

A selection of papers is specified to investigate all the variables and those parameters that may have an effect on the trading carbon prices. There are three kinds of tables, one for the statistical driven papers, one for the more theoretical papers and finally one for those papers describing EU policies and EU emissions trading.

Table 2: Statistical Papers

Authors	Year	Data	Price Determinants	Methodology	Key Results
Benz, Trück	2009	Daily EUA spot prices (January 3rd 2005-December 29th 2006)	Weather, fuel prices and spreads, economic growth, over-allocation of allowances	AR-base and normal distribution spike regime	AR-GARCH or regime-switching models are suitable for modelling the returns of CO_2 emission allowances
Paolella, Taschini	2006	SO_2 spot prices from the CCE (January 4th 1999-May 16th 2006) CO_2 spot prices from PowerNext (June 25th 2005-November 3rd 2006)	Coal and gas prices (fuel prices and spreads), weather, political conditions, number of allocations, market speculation, demand for credits, economic growth, fuel switching costs	Stable Paretian-GARCH, mixed normal GARCH, stable mixture GARCH models	knowledge of the distribution of allowance prices is essential for constructing optimal hedging and purchasing strategies in the carbon market
Daskalakis, Psychoyios, Markellos	2009	CO_2 spot prices from PowerNext and NordPool (October 25th 2005-December 28th	Banking policy (inter phase), cost to control pollution for the emitter,	Geometric Brownian motion process (with Jumps),	emission spot allowance prices are likely to be

		2007) CO_2 futures from NordPool and ECX (expiring December 2008, January 2005-December 28th 2007) Call options on futures from ECX (maturing by December 2008): inter-phase prices range from January 2007-December 2007 Intra-phase prices range from January 2008-June 2008	policy changes	Mean reverting Square-Root process (with Jumps), Mean reverting Logarithmic process, Constant Elasticity of Variance	characterized by jumps and nonstationarity
Borak, Härdle, Trück and Weron	2006	Spot and futures quotes from EEX (October 4th 2005- September 29th 2006.	Risks (operational, counterparty, reputational), banking, convenience yields, supply and demand for allowances, seasonal variations	Volatility measurement: MA-GARCH model	there is an overall increasing price volatility with maturity for both the commitment and second EU ETS periods
Obermayer	2009	EUA spot prices from EEX, power, coal, natural gas, oil from SKM SYSPower and Bloomberg. DAX index and seasonally adjusted industrial production index for the Eurozone from Bloomberg (March 2005-August 2009)	Power price	Correlation, co-integration, linear regression	Switching price not a good indicator for EUAs, no correlation with natural gas prices, correlation with power, co-integration with natural gas and oil, but not with power
Uhrig-Homburg and	2007	spot prices from the Powernext exchange	futures prices	Co-integration, unit root test for	Futures prices lead the spot

Wagner		and futures prices from the ICE/ECX (June 24th 2005 -November 15th 2006)		stationarity, Granger causality test	prices
Alberola, Chevallier and Chèze	2008	daily EUA spot prices from PowerNext (July 1st 2005-April 30th 2007)	Policy change and new information from EU ETS, energy prices, equilibrium between dark and spark power spreads, weather, temperature, policy issues, energy prices, temperature events and economic activity, information, energy prices, clean and dark spreads, weather, political and institutional decisions on the overall cap stringency (related to initial allocation)	Unit root tests, regression tests	energy prices with forecast errors, and unanticipated temperature changes during colder events drive EUA spot prices, carbon price changes are positively affected by the electricity variable, extremely hot days do not affect allowance prices, nonlinear relationship between temperatures and carbon prices

Table 3: Theoretical Papers

Authors	Date	Variables-parameters	Sector	Methodology	Key Results
Fehr, Hinz	2006	Switching fuel prices, seasonal fluctuations in switching costs	EU ETS trading energy	Equilibrium price model	No correlation between EUA and fuel prices but there must be a

					dependence
Chesney, Taschini	2009	Expected probability of scarcity/excess of permits, which depends on cost reduce output, switching fuel, technological change, penalties and allocation of allowances	CO_2 option pricing in EU ETS	Dynamic optimisation problem	the value of an option is embedded in the value of the emission permits
Carmona, Fehr, Hinz, Porchet	2006	Initial allowance allocations, marginal costs, amount of emissions, production capacity and costs (exogenous), demand for electricity (exogenous and inelastic), penalties, uncertainty of emission level	Electricity pricing in EU ETS	Equilibrium mathematical model of a cap-and-trade scheme	Prove existence and uniqueness of an equilibrium in which price processes for goods and pollution are exogenous
Daskalakis, Markellos	2008	Historical price information, banking prohibition	Spot EUA prices from PowerNext (June 24th 2005-December 29th 2006), NordPool (December 29th 2005-December 29th 2006), futures from ECX	Serial correlation analysis, variance ratio tests	Market inefficiency
Haurie, Viguier	2003	Discount factor, stock of permits banked, initial and final stock of permits, “hot-air” input (exogenous), emissions abatement	CO_2 emissions (Russia and China)	Stochastic equilibrium game	Competition involving entry of new countries can have an impact in the price formation of

		costs			emission permits without involving US
Seifert, Uhrig-Homburg, Wagner	2008	penalty costs, length of trading period, initial endowment with certificates, expected total emissions, marginal abatement costs, volatility of emission rate, banking and borrowing, the trading period break, increasing marginal abatement costs	CO_2 spot prices and returns from PowerNext (July 2005-October 2006), SO_2 spot prices from Platts (April 2004-July 2005), DAX levels from XETRA system (July 2005-October 2006)	finite horizon, continuous-time, stochastic framework	Total expected emissions drive CO_2 prices
Kosobud	2005	Policy variables (cap), marginal control cost function, supply and demand for permit allocation, efficient portfolio management	SO_2 prices from Clean Air Markets Allowance Trading. U. S. EPA, 2001	Correlation on the rates of returns	Tradable pollution permits can be considered as new assets worthy included in portfolios

Table 4: EU Policies and Regulation

Author	Year	Variable-parameters	Sector	Methodology	Key Results
Neuhoff, Grubb, Keats	2005	allowance allocation, electricity demand and prices, number of free allowances, installation (i.e. power plant) capacity, updating	UK power sector	Equilibrium mathematical modelling	EU ETS allocation reduces the wholesale electricity price

Alberola, Chevallier, Chèze	2008	policy issues, energy prices, temperature events and economic activity, information, energy prices, clean and dark spreads, weather, political and institutional decisions on the overall cap stringency (related to initial allocation)	EU ETS pilots phase (2005-2007), EUA spot prices from PowerNext (July 1st 2005-April 30th 2007), futures Month Ahead energy prices (oil, natural gas, coal and electricity)	Unit root tests, regression tests	Carbon price changes are positively affected by the electricity variable, extremely hot days do not seem to affect allowance prices, nonlinear relationship between temperatures and carbon prices
Bunn, Fezzi	2007	Gas and power spot prices, allocation supply and demand,	EU ETS EUA spot prices, electricity and gas prices for the UK (April 2005-May 2006)	structural, co-integrated vector autoregressive (SVAR) model	Elasticity on electricity prices affects carbon prices, carbon price is exogenous to the equilibrium of electricity and gas

From tables 2, 3 and 4 above, we can have a synopsis of the major findings:

- high gas prices relative to coal prices increase carbon credit prices
- EUA spot prices declined sharply following the collapse of spot prices of natural gas in Europe in September 2006
- there is strong correlation between emission allowance prices and average winter 2005-2006 gas prices

- Fuel prices and, ultimately, fuel switching, are the primary approximate fundamentals that determine the CO_2 price level
- EUA futures returns analyzed are negatively correlated with equity market returns
- Emission spot prices are correlated with a positive sign to the convenience yields
- high UK gas and oil prices caused a drastically price increase to the emission spots prices
- emission spot and futures prices follow the cost-of-carry approach in the long-term
- no correlation between the emission spots and the natural gas prices
- correlation between the emission spots and power
- co-integration between the emission spots with natural gas and oil, but not with power
- temperature changes during colder events influence EUA spot prices
- carbon price changes are positively affected by the electricity spot prices
- emission spot prices are non stationary with a single unit root
- gas has a positive impact on the EUA price changes, whereas coal has negative coefficients
- carbon price changes are positively affected by the electricity variable

2.7 Conclusions

In this chapter we provide a thorough literature survey regarding the various theoretical and empirical studies about the carbon market and how this relates to other markets, in particular to the energy markets. Although there is a lot of research regarding policies and theoretical modelling of carbon markets, few statistical models exist that deal with more practical aspects, such as price forecasting of the emission credits. This is mainly due to the fact that the carbon market is considered to be young still, therefore the available historical market data is rather short.

2.7.1 Statistical papers major findings

The analysis of the statistical models reviewed in section 2.2 explains the behaviour of the carbon price in the market. This is achieved by applying statistical tools (correlation, co-integration etc) to the spot and futures prices, where it is revealed that the futures prices are influenced by the spot prices. Some authors concentrated on the volatility changes of the stochastic price process, others concentrated on the various risks taken by the companies when trading in such permits and there has been investigation regarding the spot market returns based on the historical price formation. The relationships between the carbon credits and energy complex assets, including electrical power, coal, natural gas, and oil have also been investigated.

In general, high volatility is observed in the price formation, which followed the collapse of the market in April 2006. This increases the risks taken by the various participants, affecting production, reputation and further project investment. Also, EUA spot prices seem to react not only to energy prices with forecast errors, but also to unanticipated temperature changes during colder events. This leads inevitably to a steady price increase both for the credits and also for the electricity prices, which maximises companies' profits (but not their reputation necessarily).

2.7.2 Theoretical papers major findings

The theoretical models concentrate more on analysing the returns and the possible benefits of tradable permits rather than on their contribution to reducing the carbon emissions. They provide:

- Modelling of the effect on the energy and investment cost.
- Investigation of the impact of emission regulation on consumer costs and company's profits.
- Inclusion in an endogenously manner of the price dynamics of emission permits under asymmetric info, to indentify best strategies.
- Accession of the market efficiency for the trial period (2005-2007) of the EU ETS to produce risk-adjusted profits.

- Understanding that the carbon price development reflects the private economic interests of installations, concerned by emission regulations.
- Form of a framework to reflect non-economic factors, such as fairness issues, equity and morality.
- Analysis of the historical prices for risk management applications in a changing and more complex market.
- Pricing of carbon to encourage long-term investment in carbon-abatement activities and to eliminate the uncertainty of emissions allocations which have an obvious effect on the market value of the related allowances.

2.7.3 Major findings of the EU policies papers

The papers that deal with various EU policies and regulations for the application of the allocation of allowances to the member states have also been analysed. Due to the high degree of uncertainty associated with the nature and the consequences of climate change and also with the costs and benefits of emission reductions, a hybrid approach (both tax and permits based approaches) to climate policy has been recommended in various papers. Also, the impact of National Allocation Plans announcements on carbon prices and their volatility has been discussed.

Further analysis on the main design issues of NAPs show that the EU ETS program seemed unlikely to result in major emission reductions during the first period of trading. This was never intended anyway, as it was more the need for establishing a framework where discussions and decision making would be initiated to create all these incentives that would eventually lead to emissions reduction and to the sectors compliance.

The EU ETS decided to ban banking. This, in combination with ex-post adjustments of allocated quantities for new installations may prove to be economically inefficient. Transaction costs are expected to be higher than those for compliance.

Another issue raised was that the lack of data at the level of the installation because of aggregated energy use statistics and time constraints was the biggest challenge in the allocation process by nearly all member states. The problem of data availability was also due to the lack of legal authority to collect the data. This combined with the tight deadlines for

NAP submission forced the governments to rely heavily on voluntary submissions from industry which surprisingly cooperated fully.

Concerns were also raised about the EU ETS impact on the international competitiveness of key sectors. It was stressed that the difference of an emissions market to any other market to be the fact that the amount available depends directly on government decisions about allocations.

Other issues that had mixed reviews about their application and effect on costs and companies' profits are instruments like banking and auctioning, burden sharing, the method of allowances allocation for existing and new members.

2.7.4 Major findings from the general emission trading papers

Those papers that describe the connection between the emissions and various industrial sectors demonstrate that many issues affecting the EU ETS policies also affect other permit trading markets. There is a lot of concentration on the results of permit trading in technological change and thus to emission reduction. CO_2-intensive sectors such, iron and steel, cement and electricity power generation have been studied in some of the above articles to see whether permits would allow them to switch to cleaner technologies and how this would affect their windfall profits. Investigation was carried about the effects of these energy-saving plans on prices of other sectors and the economy in general, how is the output affected, how large is the increase in energy use and how this is associated with the direct energy-saving measures, what will be the effects on the CO_2 emissions and how much these results depend on the differences in energy price assumptions.

The issue of competitiveness was addressed by analysing different allocation approaches, such as grandfathering, where the number of allowances is independent of its current behaviour and output-based allocation, where the allocations are proportional to the firms' production level. What has been recommended was application of a tax on permits or auctioned allowances for further increase on profits and for creating incentives for technological improvement.

2.7.5 Price determinants major findings

In this chapter we concentrate on those research papers that provide information about which are the main drivers for the carbon prices. In particular, we check the price determinants that are recommended by authors, the methodology followed, the kind of data used and the key results. We draw our attention to those parameters involving the energy sector and those that reflect the economic activity in Europe. It is generally argued that the energy prices affect the carbon prices and there are correlation relationships between them (there exist a few objections to the above statement). As for the economic indicators, no certain established truth seems to exist; there is sparse evidence (Chevallier and Chèze, 2008; Obermayer, 2008) that shows little relation to the emission spots and futures prices. However, most of the research so far has concentrated on the emission spot prices during the first trading period (2005-2007), where high volatility has been observed (Daskalakis, 2009). This provides the incentive to transfer the point of interest to the second trading period (2008-2012) and check whether there are relationships (both short-term and long-run) among the carbon credits (spots and futures) and the various energy and economic variables. Finding such relations will lead to forming an appropriate price forecast model, which will essentially reflect the impact that the carbon market may have as a climate change mechanism.

Chapter 3

Variables included in the study

3.1 Introduction

The purpose of this chapter is the detailed presentation of our model variables, which we classify as emission, energy and European indices variables. The emissions variables refer to the emission spots and futures prices, as they have been traded in the European Energy Exchange (EEX) market in Leipzig, Germany. The data runs on a daily basis, for the period from 20/03/2008 to 31/12/2010. We have chosen the second period (otherwise named the 'commitment period') as this has been defined by the Kyoto Protocol (2008-2012) until a recent date, since during the first period (2005-2007) the emission spots prices showed a particularly high historical volatility (Daskalakis, 2008). The EVIEWS (version 4.1) program is used for producing the graphs presented in this chapter. In figure 1, we plot the emissions spot prices for the first Kyoto period (downloaded from the EEX market in January, 2008), where we can see that prices soared up to €30. This was after the reports about each member state's actual emissions during the previous compliance year. When the market participants realised that the member states were over-allocated for their emissions, the EUA prices dramatically dropped. This was also due to the banking prohibition between the Kyoto commitment periods, between 2007 and 2008 in particular. After the 20th March, 2008, the carbon market seems to have matured and offers thus a better data sample for our analysis.

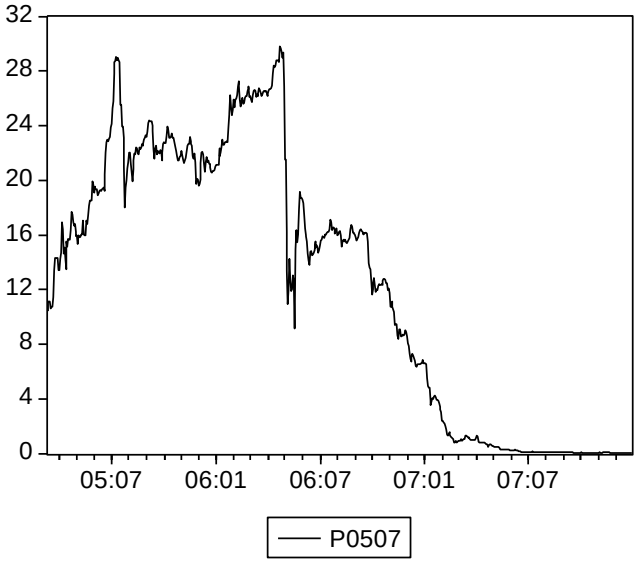


Fig.1: Emission spots prices for the period 2005-2007

In figure 1, the daily emission spot prices (P0507) during the first two years of trade (2005-2007) are displayed (05:07 refers to July, 2005 etc). The prices are quoted in Euros. Important energy variables are included in our study, which run on a daily basis for the same period as the emission variables and have also been taken from the EEX market. These include the prices of electricity and of the basic commodities used in energy production: natural gas, coal and oil (Obermayer, 2007; Paolella and Taschini, 2006).

Finally, we have included various indices associated with industrial production and general economic activity in the EU. Those indices selected represent the most active and therefore the most pollutant active European companies. They were taken from a number of different sources, such as the US Energy Information Administration (EIA), the Global Financial Data and the Eurostat.

The rest of this chapter is organised as follows: In section 3.2 we exhibit the basic statistical properties of our principal variables of interest, these being the emission spots and futures prices. In section 3.3 we introduce the energy variables that are assumed to have an influence on our main variables. In section 3.4 we introduce those European indices that may have a direct relationship with our main variables. In section 3.5 we discuss the major findings.

3.2 Presentation of the variables involved in the study

3.2.1 Emission spot prices

The emission spot prices are in fact the CO_2 emission allowances prices, which are traded in the carbon markets. They are measured in €/tCO_2 (Euros per tonne of CO_2) emitted and are traded on a daily basis. Figures 2 to 4 demonstrate the actual values (es), their logarithms (les) and the corresponding returns (res) of the emission spot prices for the period of 2008-2010, where we can observe that the prices drop after July 2008 (08:07 on the graph) and start their recovery after March 2009:

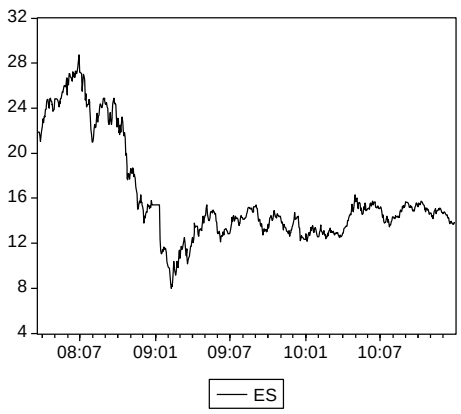


Fig.2: Actual emission spot price values

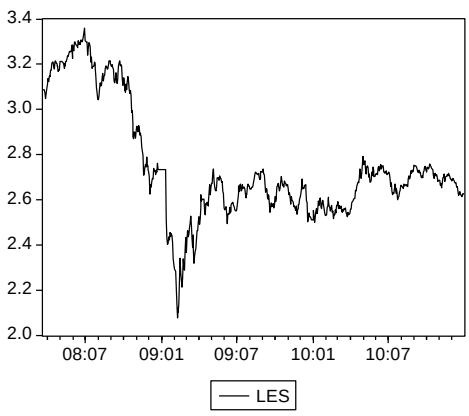


Fig.3: Logs of the emission spot prices

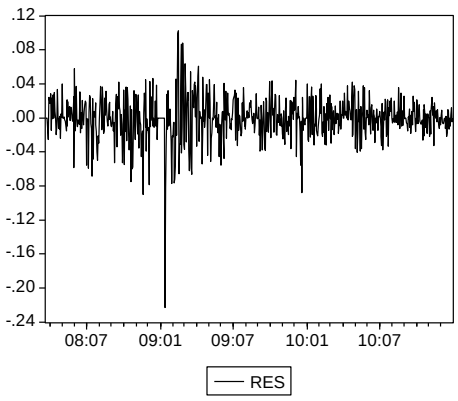


Fig.4: Returns of the emission spot prices

3.2.2 Emission futures prices

These are derivatives of the emission allowances and are also traded in the same carbon markets. They are offered as monthly, quarterly or annual contracts, the latter expiring at the end of the commitment period (2012). We chose those annual contracts expiring at 2012, as they appear to be the most liquid. Below are the figures for the plain values (ef), the logarithmic forms (lef) and the returns (ref) of the emission futures, where we can see that a fall in the futures prices coincides with that of the emissions spot prices:

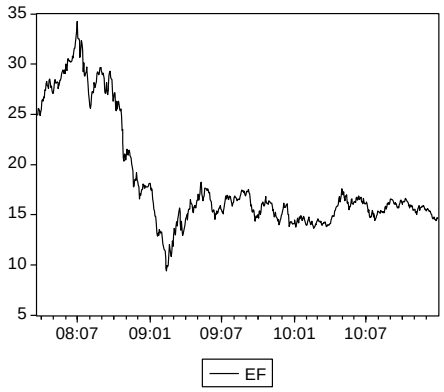


Fig.5: Actual values of emission futures

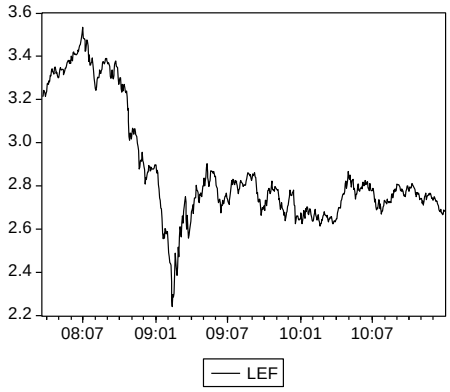


Fig.6: Log values of emission futures

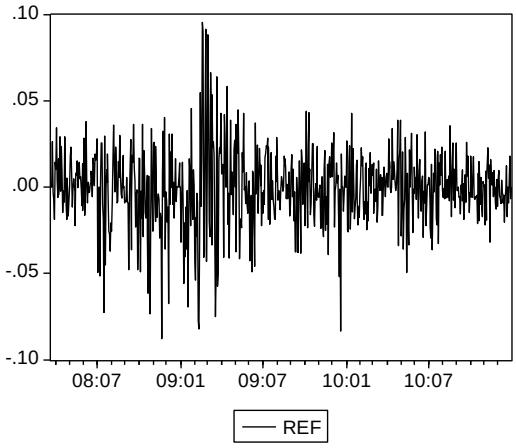


Fig.7: Returns of emission futures

In order to see the relationship between the emission spots and their futures, we produced a graph of their indices presented in Fig. 8 below:

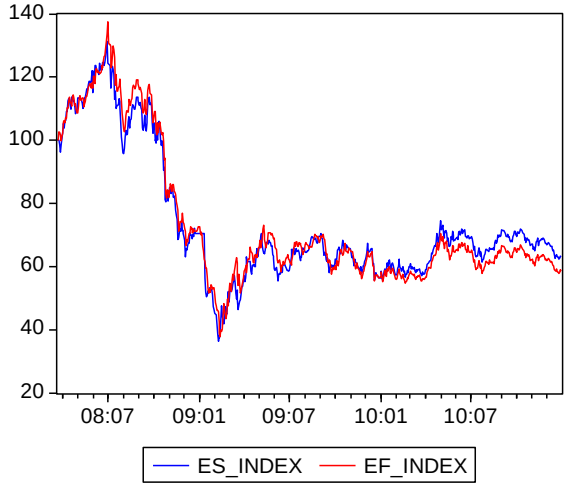


Fig.8: Emission spots and futures indices

We can clearly see in Fig. 8 that prices follow closely each other. This is also shown by their high correlation coefficient which is 0.985 (Table 9). In the same manner, we find that the correlation coefficient between the corresponding returns is found to be equal to 0.2475. The statistical properties of both the spots and the futures prices along with their returns, as well as their indices are displayed on tables 1 and 2 below:

Table 1: Statistics of actual values and returns of emission spots and futures prices

	Emission Allowances		Emission Futures	
	Spot prices	Returns	Futures	Returns
Mean	16.15766	-0.000635	18.36172	-0.000736
Median	14.63500	0.000000	16.12000	0.000000
Maximum	28.75000	0.102161	34.25000	0.095401
Minimum	7.980000	-0.223144	9.400000	-0.087809
Std. Dev.	4.531056	0.025232	5.496479	0.022182
Skewness	1.156515	-1.076595	1.231033	-0.154401
Kurtosis	3.150387	12.41933	3.104671	5.550281
Jarque-Bera	162.5250	2824.142	183.7000	199.6286
Probability	0.000000	0.000000	0.000000	0.000000
Sum	11730.46	-0.461361	13330.61	-0.534649
Sum Sq. Dev.	14884.59	0.461573	21903.18	0.356739
Observations	726	726	726	726

Table 2: Statistical properties of the indices of the emission spot and futures prices

	ES_INDEX	EF_INDEX
Mean	73.84899	73.71887
Median	66.87985	64.68700
Maximum	131.3385	137.4398
Minimum	36.45500	37.72071
Std. Dev.	20.70773	22.06290
Skewness	1.151061	1.225680
Kurtosis	3.136357	3.091516
Jarque-Bera	161.1018	182.2812
Probability	0.000000	0.000000
Sum	53688.21	53593.62
Sum Sq. Dev.	311316.2	353396.2
Observations	727	727

We can see in Table 1 that the kurtosis coefficient in both the emission spots and the emission futures actual prices and in their returns shows a leptokurtic distribution in the data. The skewness coefficient in Table 1 appears to be positive for the actual prices of the emission spots and their futures, which means that there is an asymmetry on the right side of the data distribution (the bulk of the values lies to the left of the mean). On the contrary, it is negative for their returns, which indicates an asymmetry on the left side (values lie to the right of the mean). Also, the high value of the Jarque-Bera statistic in Tables 1 and 2 shows that the error residuals of the data are not normally distributed. In Table 2 the skewness coefficient indicates an asymmetry on the right side of the distribution of the indices.

3.3 Energy variables

As energy variables we consider those commodities that are used for fuel production, i.e. natural gas, electricity, oil and coal. We have decided to consider both spots and futures prices for natural gas and electricity, since they have both been traded in the same market as our two emission variables. Physical coal futures started being traded in the same market from 2008 onwards, so we chose those instead of their spot prices. All energy variables are in daily form, for the period 20/03/2008 to 31/12/2010. The prices for gas, coal and electricity

are from the EEX market, whereas oil prices (spots and futures) have been taken from the U.S Energy Information Administration site (www.eia.gov).

3.3.1 Gas spot prices

Natural gas is one of the major fuels being used currently in Europe (Obermayer, 2007). It is also called ‘spark spread’ to distinguish it from its ‘dirtier’ alternative, this being coal, which is called ‘dark spread’. It is measured in €/ MWh. Figures 9 to 11 demonstrate the actual values (gs), their logarithms (lgs) and the corresponding returns (rgs) of the gas spot prices. Here, we observe a sharp decline around February 2009. Their recovery starts after September 2009 and the prices increase up and around 25€/ MWh, which is close to their value at the beginning of the studied period:

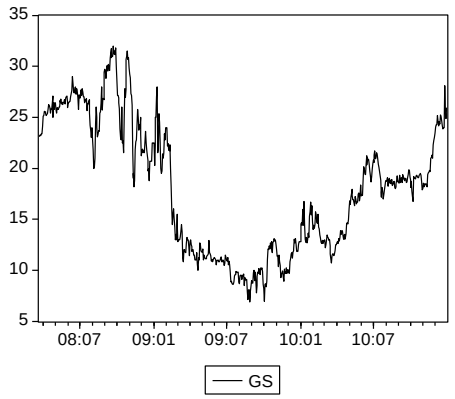


Fig.9: Actual gas spot price values

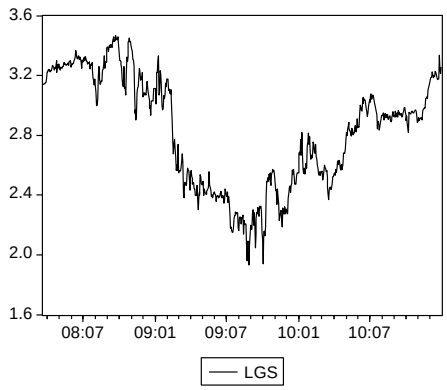


Fig.10: Logs of the gas spot prices

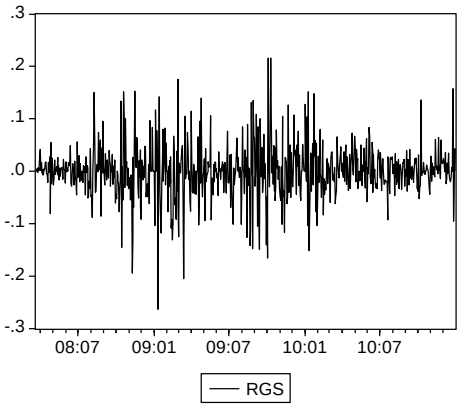


Fig.11: Returns of gas spot prices

3.3.2 Gas futures prices

These are the derivatives of the gas spot prices. They are offered as monthly, quarterly or annual contracts, the latter expiring at the end of the commitment period (2012). Again, we chose those expiring in 2012. Below are the figures for the plain values (gf), the logarithmic forms (lgf) and the returns (rgf) of the gas futures prices (in €/MWh). The decline in prices is observed around September 2008:

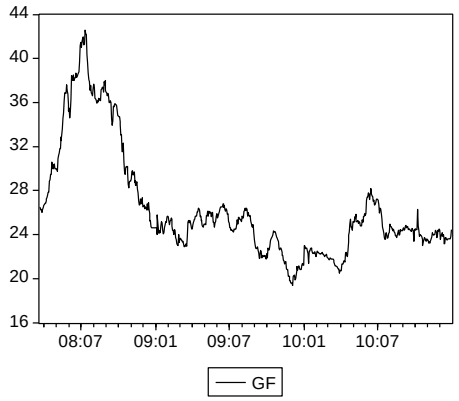


Fig.12: Actual gas futures prices

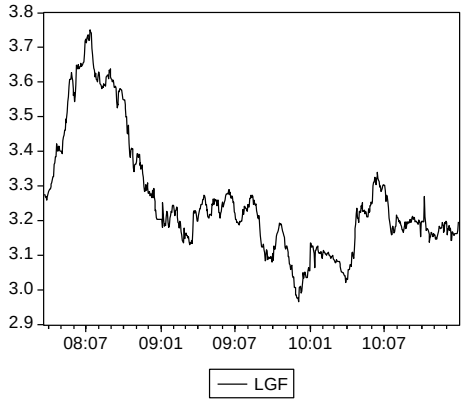


Fig.13: Logs of the gas futures prices

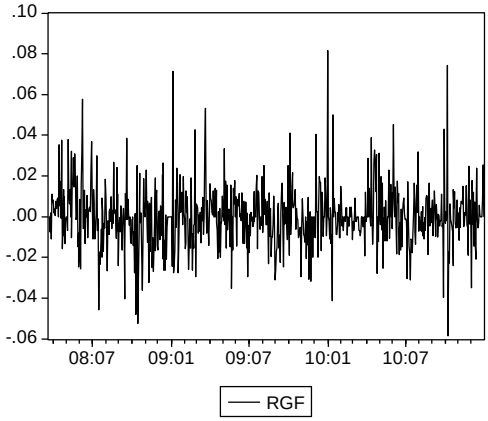


Fig.14: Returns of gas futures

In figure 15 we display the indices of the spots together with the futures. We can see from their graph that there is correlation between them, but not as strong as the one that we see in the emission spots and futures indices. Here, the correlation coefficient is 0.708.

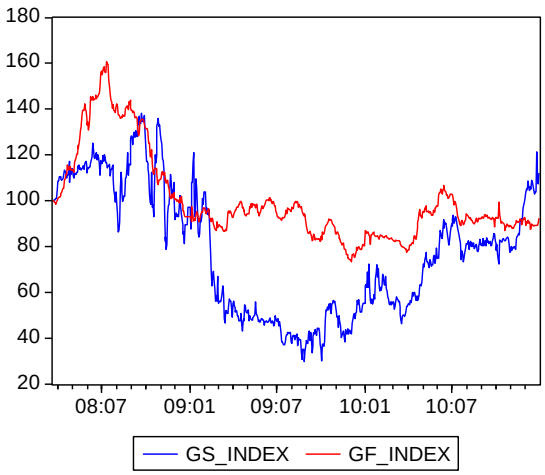


Fig.15 Indices of gas spots and futures prices

The statistical properties of both the spots and the futures prices along with their returns, as well as their indices are displayed on tables 3 and 4 below:

Table 3: Statistics of actual values and returns of gas spots and gas futures prices

	Gas spot prices		Gas futures prices	
	Spots	Returns	Futures	Returns
Mean	18.01663	0.000157	26.45455	-0.000109
Median	18.35000	0.000000	24.82500	0.000000
Maximum	32.00000	0.216379	42.55000	0.081493
Minimum	6.900000	-0.264152	19.40000	-0.058702
Std. Dev.	6.447730	0.050412	5.004367	0.014960
Skewness	0.224331	-0.026164	1.411504	0.629577
Kurtosis	1.831988	6.439411	4.124437	6.773426
Jarque-Bera	47.35788	357.9266	279.3203	478.6823
Probability	0.000000	0.000000	0.000000	0.000000
Sum	13080.07	0.114177	19206.00	-0.079035
Sum Sq. Dev.	30140.58	1.842511	18156.67	0.162256
Observations	726	726	726	726

Table 4: Statistical properties of the indices of the gas spot and futures prices

	GS_INDEX	GF_INDEX
Mean	77.85610	100.0172
Median	79.26566	93.91304
Maximum	138.2289	160.8696
Minimum	29.80562	73.34594
Std. Dev.	27.84492	18.90707
Skewness	0.221599	1.412479
Kurtosis	1.830888	4.130126
Jarque-Bera	47.35338	280.4273
Probability	0.000000	0.000000
Sum	56601.38	72712.48
Sum Sq. Dev.	562896.7	259528.4
Observations	727	727

In Table 3 the kurtosis coefficient in both the gas spots, their returns and the gas futures actual prices and in their returns shows a leptokurtic distribution in the data, but for the actual gas spot prices indicates a platykurtic distribution. The skewness coefficient appears to be positive for the actual prices of the gas spots and their futures (actual prices and returns), so there is an asymmetry on the right side of the data distribution. However, it is negative for the gas spot returns, which indicates an asymmetry on the left side. Also, the high value of the Jarque-Bera statistic in Tables 3 and 4 shows that the error residuals of the data are not normally distributed.

3.3.3 Electricity spot prices

The electricity spot prices are also traded in the EEX market in €/MWh. We have chosen the average daily prices for the market of Germany/Austria, since electricity is separately produced in each EU country and the market we got our prices from is in Germany. The figures for the plain values (els), the logarithmic forms (lels) and the returns (rels) of the electricity spot prices are provided in figures 16-18. From the graph of their actual values, we can conclude that electricity spot prices have a stable pattern, without many drops or highs:

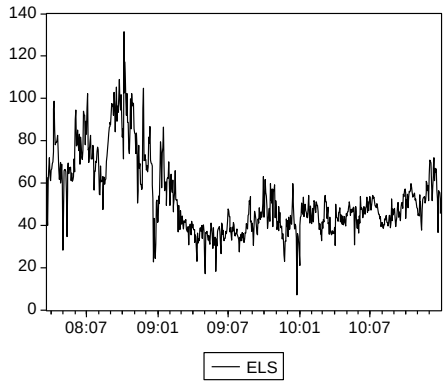


Fig.16: Actual values of electricity spots

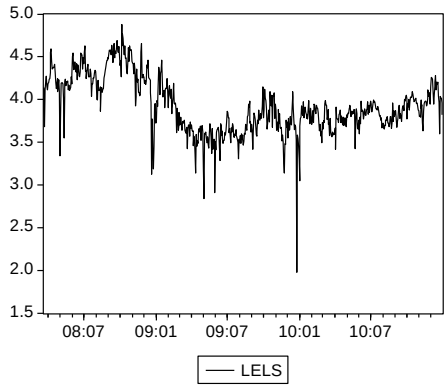


Fig.17: Logs of electricity spots

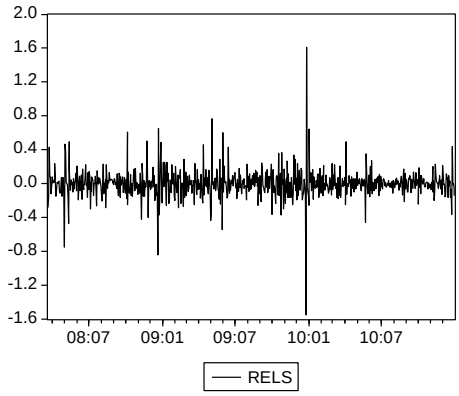


Fig.18: Returns of electricity spots

3.3.4 Electricity futures prices

We have selected those annual futures contracts ending in 2012. The actual values (elf), together with the logarithmic forms (lelf) and the returns (relf) are shown in figures 19-21, where we can observe a steady decline for the period of July 2008-February 2009, then a short climbing up and then another decline from June 2009 until now:

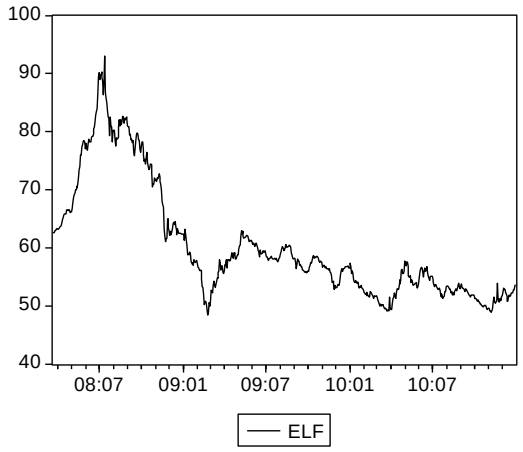


Fig.19: Actual values of electricity futures

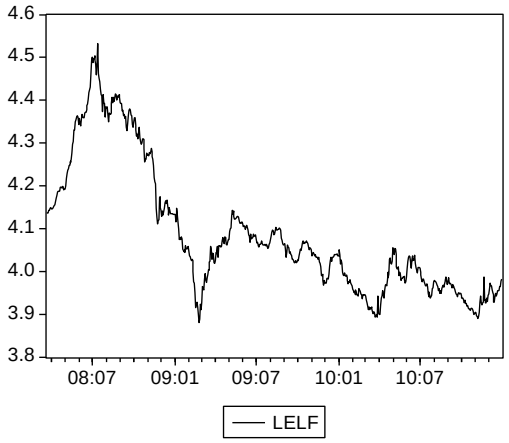


Fig.20: Logs of electricity futures

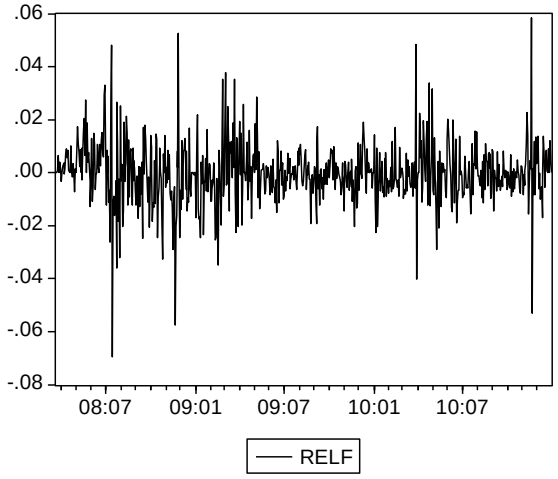


Fig.21: Returns of electricity futures

In order to see the relationship between the electricity spots and their futures, we produced a graph of their indices presented in Fig. 22 below:

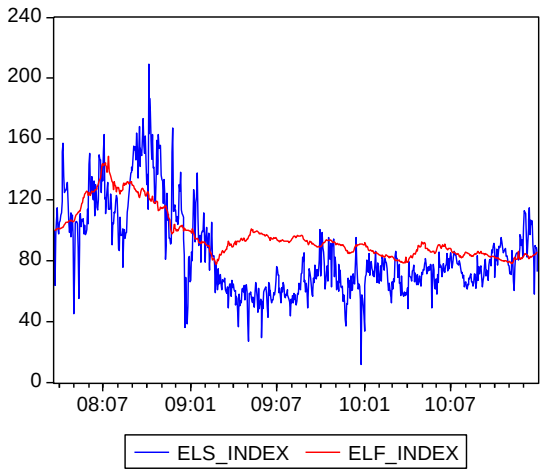


Fig.22: Indices of the electricity spots and their futures

From their graph, we can see their weak correlation and their correlation coefficient is 0.67.

The statistical properties of the spots and futures prices and their returns, as well as of their indices are displayed on tables 5 and 6 below:

Table 5: Statistics of actual values and returns of electricity spots and electricity futures prices

	Electricity spots		Electricity futures	
	Spots	Returns	Futures	Returns
Mean	53.21884	-0.000439	60.32606	-0.000213
Median	48.32500	-0.002145	57.12000	0.000000
Maximum	131.4000	1.608328	93.00000	0.058503
Minimum	7.210000	-1.555879	48.43000	-0.069569
Std. Dev.	18.13176	0.170205	9.913061	0.011566
Skewness	1.052132	0.285570	1.231831	-0.042222
Kurtosis	3.838625	25.53390	3.518641	8.360626
Jarque-Bera	155.2192	15370.11	191.7431	869.4892
Probability	0.000000	0.000000	0.000000	0.000000
Sum	38636.88	-0.318812	43796.72	-0.154417
Sum Sq. Dev.	238351.4	21.00297	71244.86	0.096984
Observations	726	726	726	726

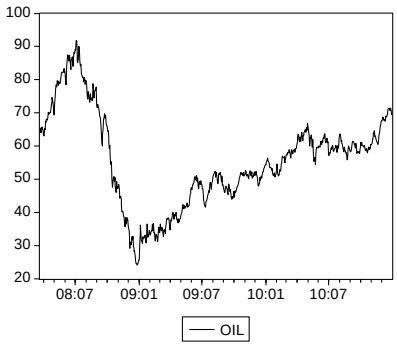
Table 6: Statistical properties of the indices of the electricity spot and futures prices

	ELS_INDEX	ELF_INDEX
Mean	84.83180	96.44943
Median	77.03586	91.35092
Maximum	209.4024	148.6811
Minimum	11.49004	77.42606
Std. Dev.	28.88082	15.83785
Skewness	1.050284	1.231639
Kurtosis	3.838049	3.521480
Jarque-Bera	154.9331	192.0395
Probability	0.000000	0.000000
Sum	61672.72	70118.74
Sum Sq. Dev.	605557.7	182108.0
Observations	727	727

In Table 5 the kurtosis coefficient in both the electricity spots and their futures (actual prices and returns) shows a leptokurtic distribution in the data. The skewness coefficient appears to be positive for the electricity spots (actual prices and returns) and their futures actual prices, indicating an asymmetry on the right side of the data distribution. However, it is negative for the electricity futures returns, which indicates an asymmetry on the left side. Also, the Jarque-Bera statistic in Tables 5 and 6 appears to be high (no normal distributed residuals).

3.3.5 Oil spot prices

Here, we have considered the Europe Brent crude oil sourced from the North Sea. It is used to price two thirds of the world's internationally traded crude oil supplies. As it is traded in $/barrel, the daily equivalent currency rates were used to convert the priced into €/barrel. The figures for the actual values (oil), the logarithmic forms (loil) and the returns of the oil spot prices (roil) are provided in figures 23-25, where we can see a sharp decline in prices starting around July 2008 until January 2009. Since then, there appears to be a continuous and steady rise:



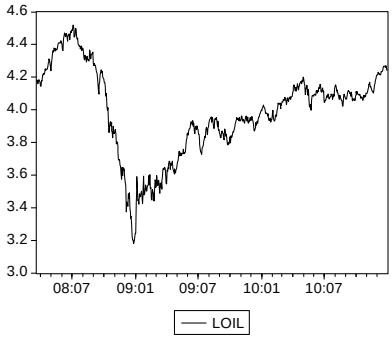


Fig.23: Actual values of electricity futures Fig.24: Logs of electricity futures

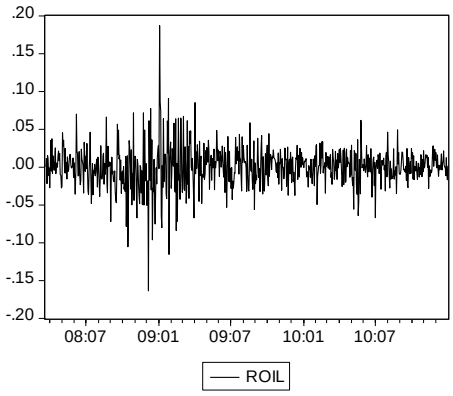


Fig.25: Returns of electricity futures

3.3.6 Oil futures prices

Oil can be traded in futures markets, as a financial mechanism to distribute risk among participants on different sides (or with different expectations) of the market, considering that the futures market is considered to be a zero-sum game, where for every buyer there will be a seller (EIA, 2011).

The prices on futures provide improvement in the price information to all aspects of the oil market and helps in limiting the uncertainty over future costs. A futures contract promises to deliver a given quantity of a standardized commodity at a specified place, price and time in the future. In reality however, oil is rarely actually delivered under a futures contract (Obermayer, 2009).

The figures for the actual values (oilf), the logarithmic forms (loilf) and the returns of the oil futures prices (roilf) are provided in figures 26-28. The futures prices seem to behave in the same way as their spots:

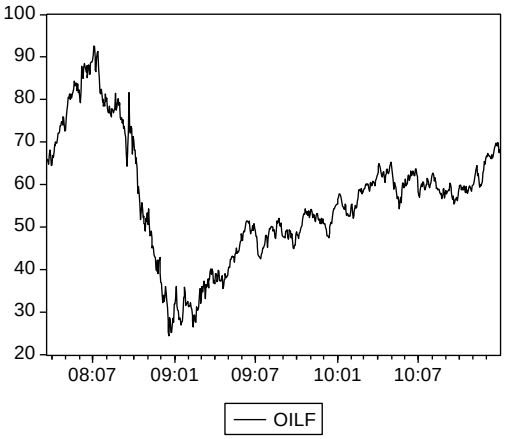


Fig.26: Actual oil futures prices

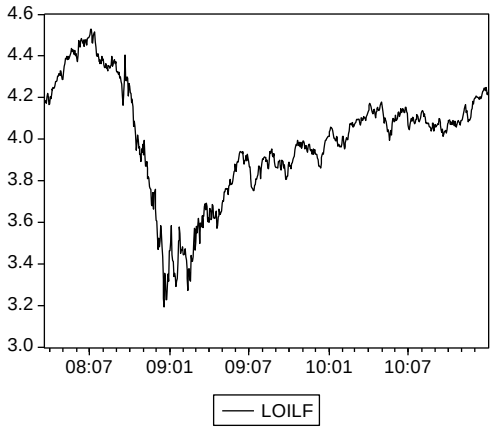


Fig.27: Logs of oil futures prices

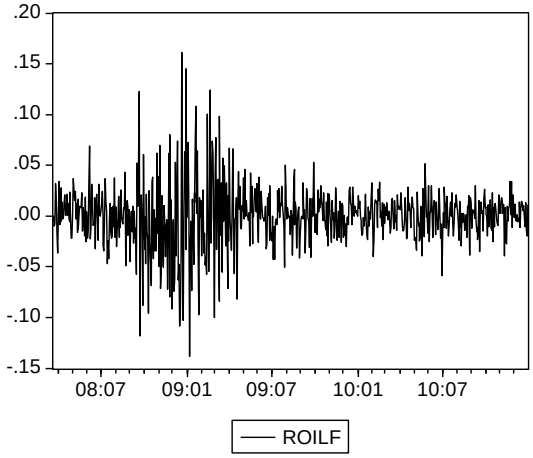


Fig.28: Returns of oil futures prices

The strong relationship between the oil spots and their futures in the form of their indices is presented in Fig. 29 below:

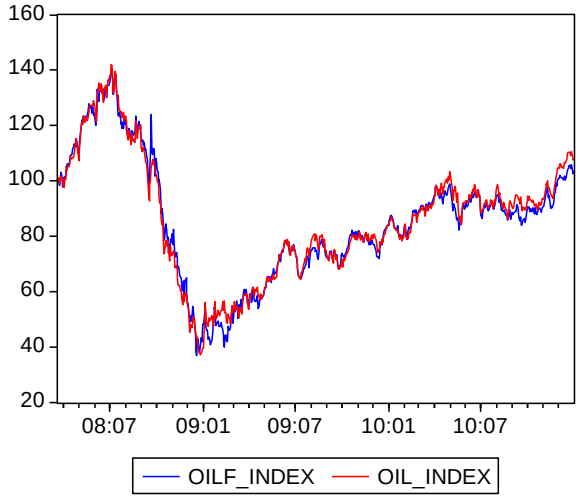


Fig.29: Indices of the oil spots and futures prices

Oil futures seem to be strongly correlated with the oil spot prices and their correlation coefficient is 0.99.

The statistical properties of the spots and futures prices and their returns, as well as of their indices are displayed on tables 7 and 8 below:

Table 7: Statistics of actual values and returns of oil spots and their futures prices

	Oil spots		Oil futures	
	Spots		Returns	
	OIL	ROIL	OILF	ROILF
Mean	55.64320	0.000103	56.37614	4.75E-05
Median	56.39781	0.000545	57.00710	0.000725
Maximum	91.78252	0.187021	92.63690	0.160893
Minimum	24.04612	-0.163479	24.34914	-0.138788
Std. Dev.	14.29274	0.027017	14.59396	0.029806
Skewness	0.187018	0.009597	0.169497	0.093226
Kurtosis	2.669257	9.035972	2.747141	7.543390
Jarque-Bera	7.541139	1102.108	5.410369	625.4841
Probability	0.023039	0.000000	0.066858	0.000000
Sum	40396.96	0.074987	40929.08	0.034508
Sum Sq. Dev.	148104.7	0.529172	154413.1	0.644083

Table 8: Statistical properties of the indices of the oil spot and futures prices

	OIL_INDEX	OILF_INDEX
Mean	86.10417	85.47472
Median	87.29766	86.44546
Maximum	141.9958	140.4186
Minimum	37.20151	36.90833
Std. Dev.	22.10295	22.11280
Skewness	0.184738	0.167139
Kurtosis	2.669592	2.747300
Jarque-Bera	7.442118	5.319187
Probability	0.024208	0.069977
Sum	62597.73	62140.12
Sum Sq. Dev.	354680.2	354996.4
Observations	727	727

In Table 7 the kurtosis coefficient in both the oil spots and their futures (actual prices) shows a platykurtic distribution in the data, whereas it indicates a leptokurtic distribution for their returns. The skewness coefficient is positive, so there is an asymmetry on the right side of the data distribution. Also, the Jarque-Bera statistic in Table 7 shows normal distributed residuals for the oil spots and their futures, whereas it appears high in their returns. In Table 8 it shows normal distribution for the indices of the oil spots and their futures.

3.3.7 Coal Futures

Annual contracts ending in 2012 are considered. The EEX market trades only futures contracts on physical coal and therefore only those will be considered in our calculations. Figures 30-32 demonstrate the actual values (cf), the logarithmic forms (lcf) and the returns of coal futures prices (rcf). Before July 2008 prices were steadily moving upwards, but since then a sharp decline followed until early in 2009 and have since been going upwards:

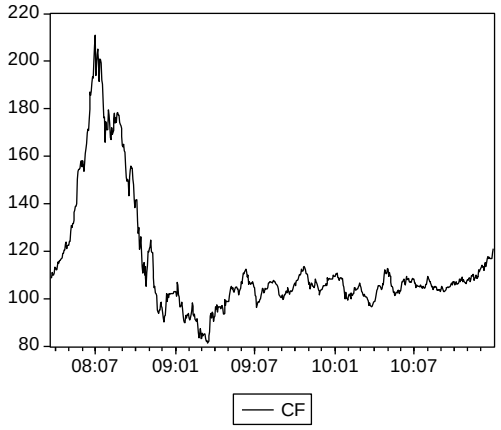


Fig.30: Actual coal futures prices

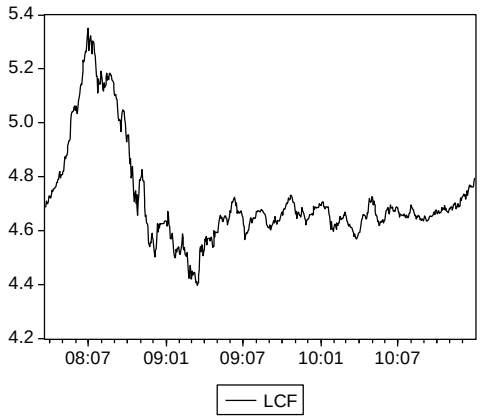


Fig.31: Logs of the coal futures prices

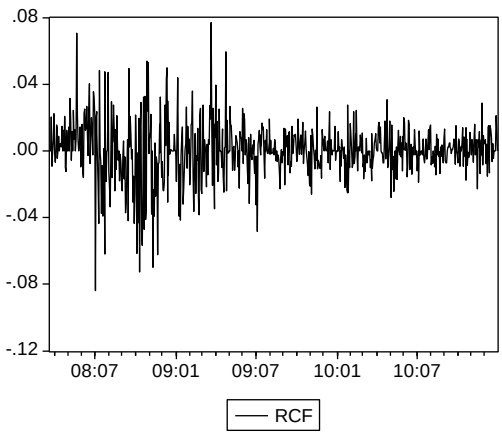


Fig.32: Returns of the coal futures prices

In table 9 below, we can clearly see the correlation possibilities among all our energy variables. We can conclude that those variables that are strongly correlated with the emission spot prices are those of their futures (0.985), the coal futures (0.854), the gas futures (0.88) and the electricity futures (0.858). Emissions spots appear to be weakly correlated with oil spots (0.74) and oil futures (0.78), the gas spots (0.72) and the electricity spot prices (0.68).

The emission futures are strongly correlated with oil futures (0.725), coal futures (0.864), gas futures (0.879) and electricity futures (0.858). They have a weaker correlation with oil spots (0.68), gas spots (0.698) and electricity spots (0.691).

Table 9: Energy variables correlations

	ES	EF	OIL	OILF	CF	GS	GF	ELS	ELF
ES	1.000000								
EF	0.985401	1.000000							
OIL	0.740504	0.680552	1.000000						
OILF	0.779128	0.724548	0.989741	1.000000					
CF	0.853558	0.864739	0.781641	0.800448	1.000000				
GS	0.717379	0.698092	0.516600	0.534394	0.606841	1.000000			
GF	0.879739	0.909979	0.617617	0.645106	0.898540	0.707989	1.000000		
ELS	0.684129	0.691295	0.399333	0.436826	0.580328	0.806770	0.671838	1.000000	
ELF	0.857827	0.914304	0.473855	0.523076	0.860385	0.618114	0.936746	0.670570	1.000000

3.4 European Indices

Here we present the list of European indices that we will include in our analysis and observe their effect on the emission allowances (spot prices and futures).

We have taken indices representing a variety of industrial activity, in our attempt to observe the impact that such an activity may have on the total carbon emissions and consequently on the formation of the emission spots and futures prices. We have also included indices that reflect the general market activity in the Euro area, as a representative of the well-being of the European economy.

Therefore, the indices are separated as follows:

- Euro Stoxx indices. These form a broad subset of the Stoxx Europe 600 Index. The number of components is variable and the indices encompass companies of 12 Eurozone countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain. We have favoured this index instead of the Stoxx Europe 600 index as a better representative of economic activity of the heavier company pollutants.
- Eurofirst300 indices. The FTSEurofirst 300 Indices are designed to represent the performance of companies that are resident and incorporated in Europe, providing investors with a set of indices that measure the performance of the 300 largest capitalised European companies.
- Other indices for a broader coverage of economic activity in the EU. These indices show a general trend in economic production and reflect the economic growth in the EU area. They are chosen based on the assumption that the economic growth follows the increase in production and leads to greater carbon emissions. It therefore provides the incentive for companies to purchase more carbon credits.

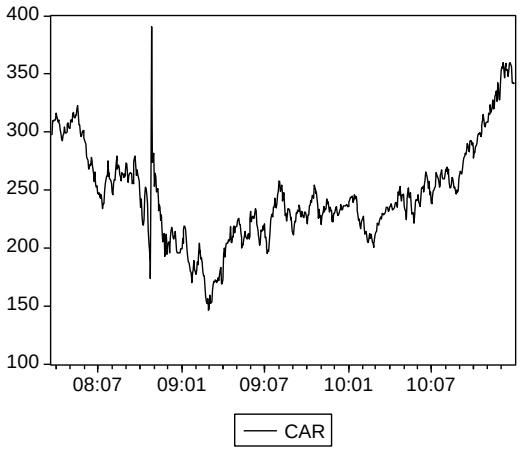
3.4.1. Euro Stoxx Indices

3.4.1.1 Euro Stoxx Automobiles Price Index

This represents the sub-supersector of Automobiles & Parts of the Consumer Goods industry. It includes:

- Automobiles, which involves makers of motorcycles and passenger vehicles, including cars, sport utility vehicles (SUVs) and light trucks. It excludes makers of heavy trucks and of recreational vehicles (RVs and ATVs).
- Auto parts, where there are manufacturers and distributors of new and replacement parts for motorcycles and automobiles, such as engines, carburettors and batteries. It excludes producers of tires.

Figures 33-35 demonstrate the actual values (car), the logarithmic forms (lcar) and the returns (rcar) of the STOXX automobiles index for the period of 20/03/2008 to 31/12/2010. Here, we can observe a large spike occurring around the 28th October, 2008:



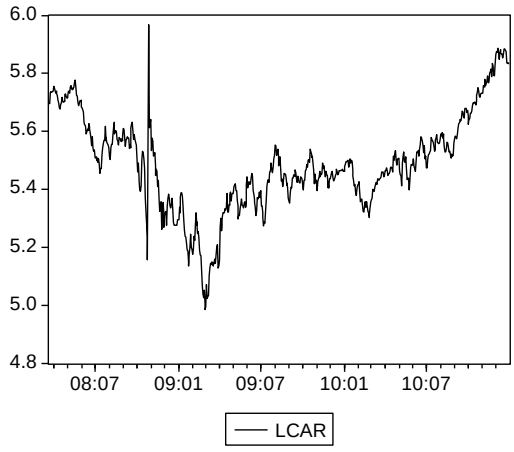


Fig.33: Actual STOXX Automobiles index values Fig.34: Logs of STOXX Automobiles index

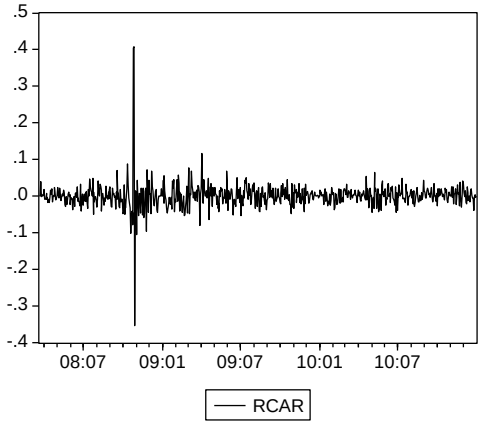


Fig.35: Returns of STOXX Automobiles index

The statistical properties of the actual index prices and their returns are displayed in table 10:

Table 10: Statistics of actual values and returns of STOXX Automobiles index

	CAR	RCAR
Mean	245.4004	0.000187
Median	238.4800	0.000000
Maximum	390.5900	0.408170
Minimum	146.0600	-0.354275
Std. Dev.	42.01424	0.034559
Skewness	0.530589	2.916916
Kurtosis	3.312055	69.04335
Jarque-Bera	37.01011	132971.7
Probability	0.000000	0.000000
Sum	178160.7	0.135417
Sum Sq. Dev.	1279767.	0.865879
Observations	726	726

In Table 10 the kurtosis coefficient in both the actual values and the returns of the automobiles index shows a leptokurtic distribution in the data. The skewness coefficient appears to be positive, indicating an asymmetry on the right side of the data distribution. Also, the Jarque-Bera statistic appears to be high (no normal distributed residuals).

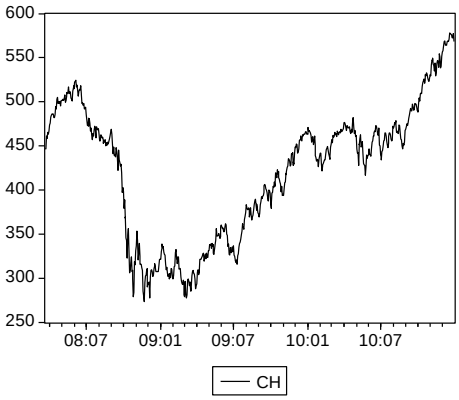
3.4.1.2 Euro Stoxx Chemicals Price Index

This supersector is part of the basic materials industry and it includes:

- Commodity chemicals, where there are producers and distributors of simple chemical products that are primarily used to formulate more complex chemicals or products, including plastics and rubber in their raw form, fibreglass and synthetic fibres.
- Speciality chemicals, which involve producers and distributors of finished chemicals for industries or end users, including dyes, cellular polymers, coatings, special plastics and other chemicals for specialized applications. They also include makers of colourings, flavours and fragrances, fertilizers, pesticides, chemicals used to make drugs, paint in its pigment form and glass in its unfinished form. Those excluded are producers of paint and glass products used for construction.

Figures 36-38 demonstrate the actual values (ch), the logarithmic forms (lch) and the returns (rch) of the STOXX Chemicals index for the period of 20/03/2008 to 31/12/2010. There is a

sharp decline beginning around September 2008 until April of the following year and has been going up again since:



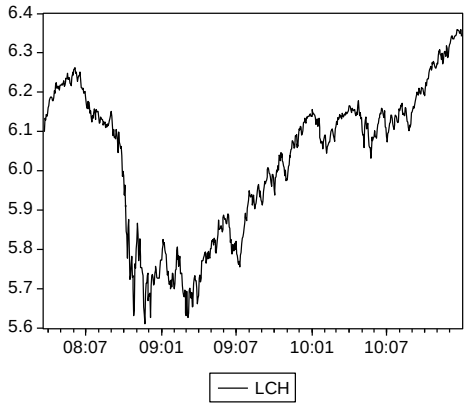


Fig.36: Actual STOXX Chemicals index values Fig.37: Logs of STOXX Chemicals index

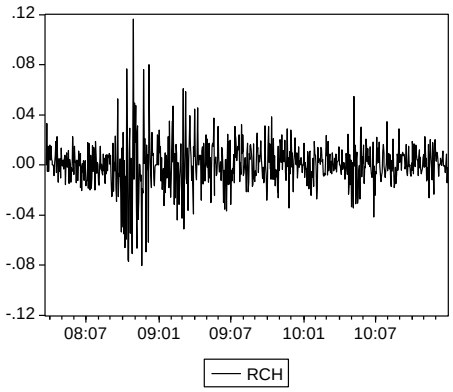


Fig.38: Returns of STOXX Chemicals index

The statistical properties of the actual index prices and their returns can be observed in table 11:

Table 11: Statistics of actual values and returns of STOXX Chemicals index

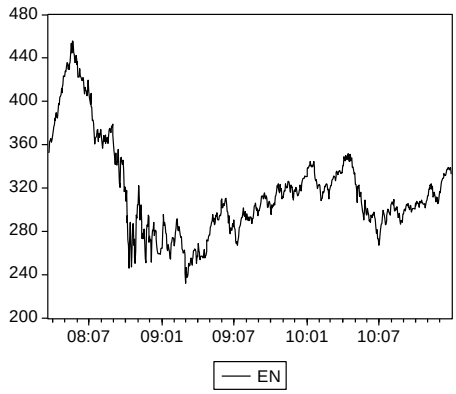
	CH	RCH
Mean	421.6710	0.000333
Median	442.8750	0.000723
Maximum	577.8200	0.116199
Minimum	273.4400	-0.080491
Std. Dev.	76.58905	0.018498
Skewness	-0.202991	-0.036322
Kurtosis	2.004091	8.353616
Jarque-Bera	34.98882	867.1611
Probability	0.000000	0.000000
Sum	306133.1	0.241522
Sum Sq. Dev.	4252764.	0.248075
Observations	726	726

In Table 11 the kurtosis coefficient confirms a platykurtic distribution in the actual values, whereas the distribution is leptokurtic in the returns of the chemicals index. The skewness coefficient appears to be negative in the actual values (asymmetry to the left), and positive to the returns (asymmetry to the right). Also, the Jarque-Bera statistic shows no normal distributed residuals.

3.4.1.3 Euro Stoxx Energy Price Index

This represents the oil & gas industry and comprises of some of the most active and with the largest capitalisation European energy solutions providers, such as Total Fina ELF, ENI, Royal Dutch Petroleum, Repsol etc.

Figures 39-41 demonstrate the actual values (en), the logarithmic forms (len) and the returns (ren) of the STOXX Energy index for the period of 20/03/2008 to 31/12/2010. Prices seem to decline around June 2008 and rise again around March 2009:



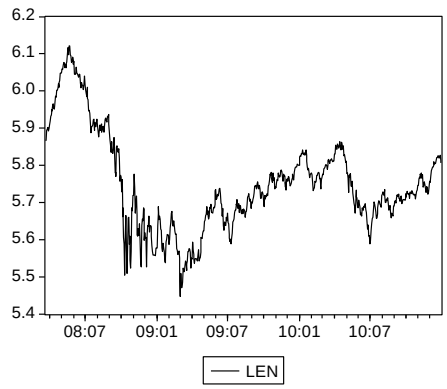


Fig.39: Actual STOXX Energy index values Fig.40: Logs of STOXX Energy index

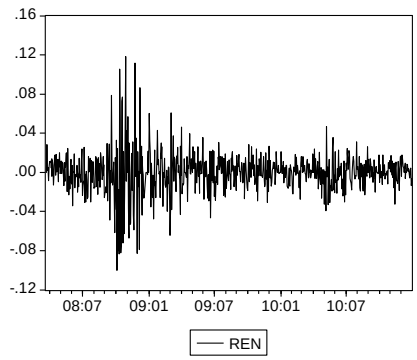


Fig.41: Returns of STOXX Energy index

The statistical properties of the actual index prices and their returns can be observed in table 12:

Table 12: Statistics of actual values and returns of STOXX Energy index

	EN	REN
Mean	316.5585	-8.16E-05
Median	307.0300	0.000000
Maximum	455.7000	0.118585
Minimum	232.1000	-0.100372
Std. Dev.	44.03545	0.020882
Skewness	1.026825	0.085142
Kurtosis	3.859845	9.363870
Jarque-Bera	149.9437	1225.967
Probability	0.000000	0.000000
Sum	229821.4	-0.059219
Sum Sq. Dev.	1405863.	0.316136
Observations	726	726

In Table 12 the kurtosis coefficient confirms a leptokurtic distribution in the actual values and the returns of the energy index. The skewness coefficient appears to be positive in both cases (asymmetry to the right) and the Jarque-Bera statistic shows no normal distributed residuals.

3.4.1.4 Euro Stoxx Industrials Price Index

This covers two major industrial supersectors: construction & materials and industrial goods and services.

The construction & materials sector consists of:

- Building Materials & Fixtures. Producers of materials used in the construction and refurbishment of buildings and structures, including cement and other aggregates, wooden beams and frames, paint, glass, roofing and flooring materials other than carpets. Includes producers of bathroom and kitchen fixtures, plumbing supplies and central air-conditioning and heating equipment. Excludes producers of raw lumber, which are classified under Forestry.
- Heavy construction. Companies engaged in the construction of commercial buildings, infrastructure such as roads and bridges, residential apartment buildings, and providers of services to construction companies, such as architects, masons, plumbers and electrical contractors.

The industrial goods and services sector covers:

- Aerospace & Defence. This includes aerospace manufacturers, assemblers and distributors of aircraft and aircraft parts primarily used in commercial or private air transport. It excludes manufacturers of communications. The defence sector incorporates producers of components and equipment for the defence industry, including military aircraft, radar equipment and weapons.
- General Industrials. This sector involves Container & Packaging, i.e. makers and distributors of cardboard, bags, boxes, cans, drums, bottles and jars and glass used for packaging and Diversified Industrials, such as industrial companies engaged in three or more classes of business within the Industrial industry that differ substantially from each other.

The Electronic & Electrical Engineering sector is made of:

- Electrical Components and Equipment. This involves makers and distributors of electrical parts for finished products, such as printed circuit boards for radios, televisions and other consumer electronics. It includes makers of cables, wires, ceramics, transistors, electric adapters, fuel cells and security cameras.
- Electronic equipment, which involves manufacturers and distributors of electronic products used in different industries. This includes makers of lasers, smart cards, bar scanners, fingerprinting equipment and other electronic factory equipment.

The Industrial Engineering sector includes:

- Commercial Vehicles & Trucks. Here, we get manufacturers and distributors of commercial vehicles and heavy agricultural and construction machinery, including rail cars, tractors, bulldozers, cranes, buses and industrial lawn mowers. Others included are non-military shipbuilders, such as builders of cruise ships and ferries.
- Industrial Machinery, where we have designers, manufacturers, distributors and installers of industrial machinery and factory equipment, such as machine tools, lathes, presses and assembly line equipment. It includes makers of pollution control equipment, castings, pressings, welded shapes, structural steelwork, compressors, pumps, bearings, elevators and escalators.

The Industrial Transportation sector involves:

- Delivery Services, mainly operators of mail and package delivery services for commercial and consumer use. This includes courier and logistic services primarily involving air transportation),
- Marine Transportation, basically providers of on-water transportation for commercial markets, such as container shipping.
- Railroads, which includes providers of industrial railway transportation and railway lines. It excludes passenger railway companies, and manufacturers of rail cars.
- Transportation Services, which are companies that manage airports, train depots, roads, bridges, tunnels, ports, and providers of logistic services to shippers of goods. It also includes companies that provide aircraft and vehicle maintenance services.

- Trucking. This consists of companies that provide commercial trucking services. It excludes road and tunnel operators and vehicle rental and taxi companies.

The Support Services sector involves:

- Business Support Services, which are providers of nonfinancial services to a wide range of industrial enterprises and governments. It includes providers of printing services, management consultants, office cleaning services, and companies that install, service and monitor alarm and security systems
- Business Training & Employment Agencies, mainly providers of business or management training courses and employment services.
- Financial Administration, which includes providers of computerized transaction processing, data communication and information services, including payroll, bill payment and employee benefit services.
- Industrial Suppliers, which are distributors and wholesalers of diversified products and equipment primarily used in the commercial and industrial sectors. It includes builder merchants.

Figures 42-44 demonstrate the actual values (ind), the logarithmic forms (lind) and the returns (rind) of the STOXX Industrial index for the period of 20/03/2008 to 31/12/2010. The biggest drop in prices occurs around September 2008, similar to the Chemicals index:

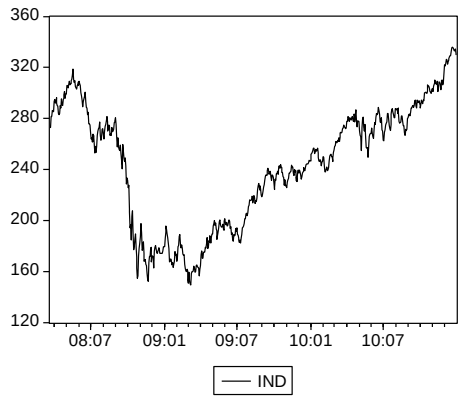


Fig.42: Actual STOXX Industrial index

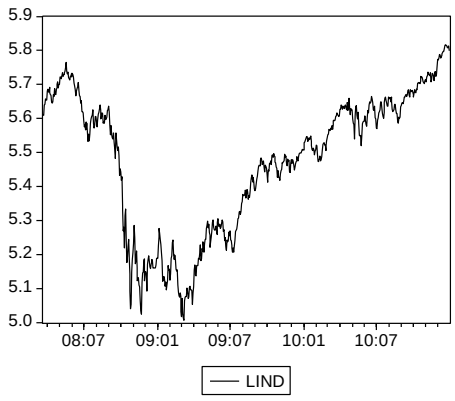


Fig.43: Logs of STOXX Industrial index

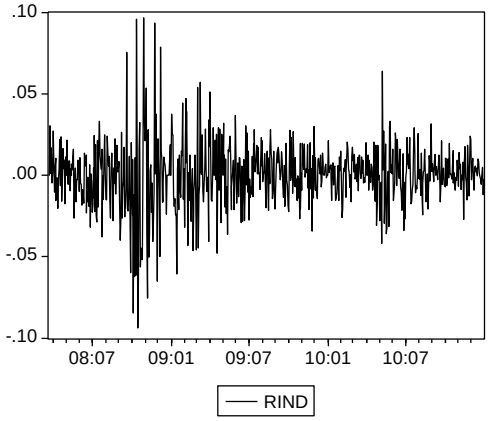


Fig.44: Returns of STOXX Industrials index

The statistical properties of the actual index prices and their returns can be observed in table 13:

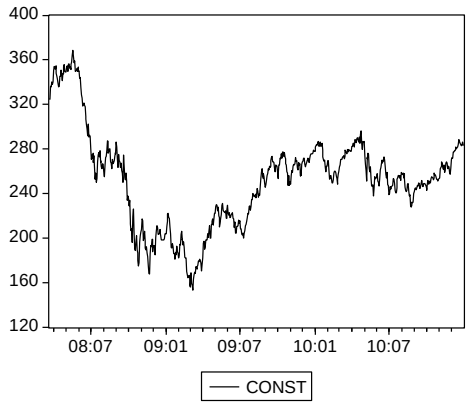
Table 13: Statistics of actual values and returns of STOXX Industrials index

	IND	RIND
Mean	243.5175	0.000261
Median	250.9900	0.000891
Maximum	335.7200	0.096588
Minimum	149.4700	-0.093918
Std. Dev.	47.86504	0.019634
Skewness	-0.255008	-0.050165
Kurtosis	1.903309	7.347546
Jarque-Bera	44.25111	572.0644
Probability	0.000000	0.000000
Sum	176793.7	0.189488
Sum Sq. Dev.	1661020.	0.279481
Observations	726	726

In Table 13 the kurtosis coefficient confirms a platykurtic distribution in the actual values, whereas the distribution is leptokurtic in the returns of the industrials index. The skewness coefficient appears to be negative in the actual values (asymmetry to the left) and the Jarque-Bera statistic shows no normal distributed residuals.

3.4.1.5 Euro Stoxx Construction Price Index

This is a sub-sector of the Industrials and will be considered separately to determine the effect it may have in our study. Figures 45-47 demonstrate the actual values (const), the logarithmic forms (lconst) and the returns (rconst) of the STOXX Construction index for the period of 20/03/2008 to 31/12/2010. There appears to be an initial drop in prices around May 2008, and then prices stabilise for a bit and drop again around September 2008. Their recovery occurs after August 2009:



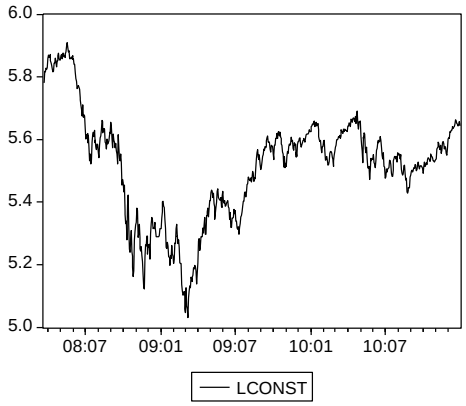


Fig.45: Actual STOXX Construction index prices Fig.46: Logs of STOXX Construction index

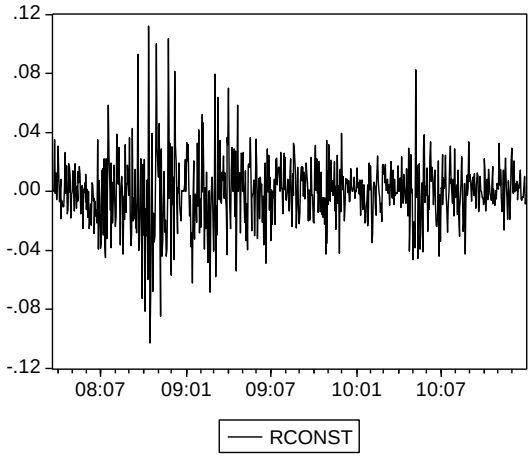


Fig.47: Returns of STOXX Construction index

The statistical properties of the actual index prices and their returns can be observed in table 14:

Table 14: Statistics of actual values and returns of STOXX Industrials index

	CONST	RCONST
Mean	251.8625	-0.000191
Median	255.3050	0.000000
Maximum	368.3100	0.111889
Minimum	152.9300	-0.103031
Std. Dev.	43.29702	0.022620
Skewness	0.293052	0.174108
Kurtosis	3.236880	6.513961
Jarque-Bera	12.08881	377.1926
Probability	0.002371	0.000000
Sum	182852.2	-0.138452
Sum Sq. Dev.	1359108.	0.370964
Observations	726	726

In Table 14 the kurtosis coefficient shows a leptokurtic distribution in the actual values and the returns of the construction index. The skewness coefficient is negative for both the actual values and the returns (asymmetry to the left). The Jarque-Bera statistic shows again no normal distributed residuals.

3.4.1.6 Euro Stoxx Basic Resources Price Index

This is a sub-sector of the basic materials industry. It is composed of the following sub-sectors:

The Forestry and Paper sector, which splits into two categories:

- Forestry, which includes owners and operators of timber tracts, forest tree nurseries and sawmills. It excludes providers of finished wood products such as wooden beams.
- Paper, which involves producers, converters, merchants and distributors of all grades of paper. It excludes makers of printed forms, which are classified under Business Support Services, and manufacturers of paper items such as cups and napkins.

The Industrial metals & Mining sector, where we have:

- Aluminium, which has companies that mine or process bauxite or manufacture and distribute aluminium bars, rods and other products for use by other industries. It excludes manufacturers of finished aluminium products, such as siding.

- Nonferrous Metals, which includes producers and traders of metals and primary metal products other than iron, aluminium and steel. It excludes companies that make finished product.
- Iron & Steel, where we have manufacturers and stockholders of primary iron and steel products such as pipes, wires, sheets and bars, encompassing all processes from smelting in blast furnaces to rolling mills and foundries. This also includes companies that primarily mine iron ores.

The Mining sector, which consists of:

- Coal mining
- Diamonds & Gemstones production
- General mining, where companies explore, extract and refine various minerals
- Gold mining
- Platinum and other precious metals mining, like silver

Figures 48-50 demonstrate the actual values (basres), the logarithmic forms (lbasres) and the returns (rbasres) of the STOXX Basic Resources index for the period of 20/03/2008 to 31/12/2010. The largest fall here starts around June 2008 and prices rise again after March 2009:

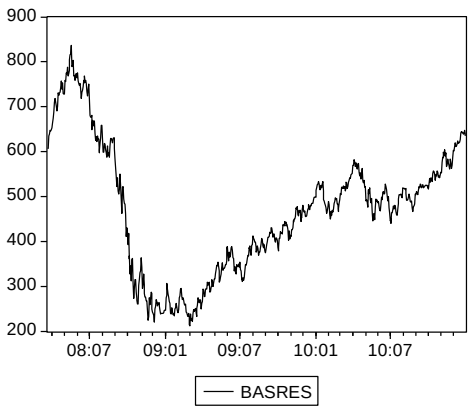


Fig.48: Actual STOXX Basic Resources index values

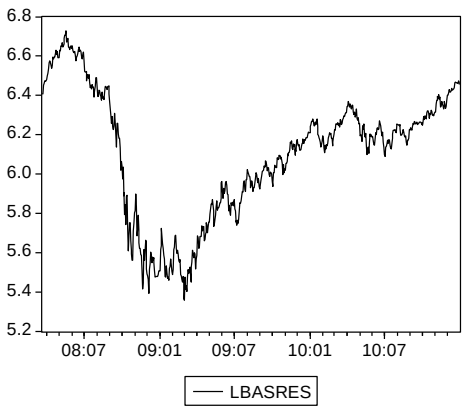


Fig.49: Logs of STOXX Basic Resources index

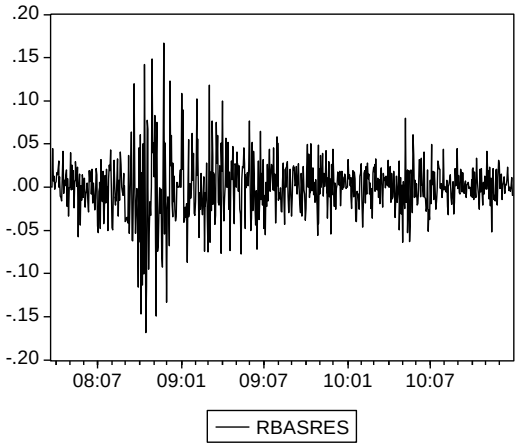


Fig.50: Returns of STOXX Basic Resources index

The statistical properties of the actual index prices and their returns can be observed in table 15 below:

Table 15: Statistics of actual values and returns of STOXX Basic Resources index

	BASRES	RBASRES
Mean	468.8615	6.31E-05
Median	478.8950	0.000000
Maximum	836.5900	0.166603
Minimum	212.0600	-0.168428
Std. Dev.	144.8779	0.033859
Skewness	0.226713	-0.094777
Kurtosis	2.426705	7.318490
Jarque-Bera	16.16143	565.2299
Probability	0.000309	0.000000
Sum	340393.4	0.045811
Sum Sq. Dev.	15217467	0.831173
Observations	726	726

In Table 15 the kurtosis coefficient indicates a platykurtic distribution in the actual values, whereas the distribution is leptokurtic in the returns of the basic resources index. The skewness coefficient appears to be negative in the returns (asymmetry to the left), and positive in the actual values (asymmetry to the right). Also, the Jarque-Bera statistic shows no normal distributed residuals.

3.4.1.7 Euro Stoxx Technology Price Index

The technology industry is composed of two sub-sectors:

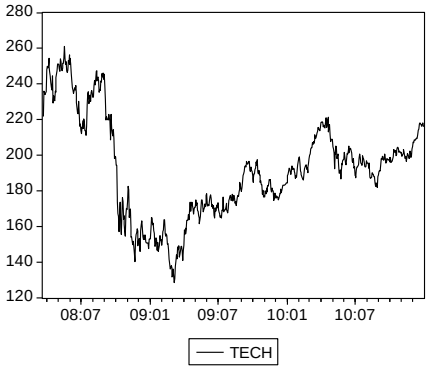
The Software & Computer Services sector, which includes:

- Computer Services, where companies provide consulting services to other businesses relating to information technology. It includes providers of computer-system design, systems integration, network and systems operations, data management and storage, repair services and technical support.
- Internet, where companies provide Internet-related services, such as Internet access providers and search engines and providers of Web site design, Web hosting, domain-name registration and e-mail services.
- Software, which involves publishers and distributors of computer software for home or corporate use. It excludes computer game producers.

The technology hardware & Equipment sector, which consists of:

- Computer Hardware, where we have manufacturers and distributors of computers, servers, mainframes, workstations and other computer hardware and subsystems, such as mass-storage drives, mice, keyboards and printers.
- Electronic office equipment, which involves manufacturers and distributors of electronic office equipment, including photocopiers and fax machines.
- Semiconductors, which includes producers and distributors of semiconductors and other integrated chips, including other products related to the semiconductor industry, such as semiconductor capital equipment and motherboards. It excludes makers of printed circuit boards.
- Telecommunications Equipment, where we get makers and distributors of high-technology communication products, including satellites, mobile telephones, fibre optics, switching devices, local and wide-area networks, teleconferencing equipment and connectivity devices for computers, including hubs and routers.

Figures 51-53 demonstrate the actual values (tech), the logarithmic forms (ltech) and the returns (rtech) of the STOXX Technology index for the period of 20/03/2008 to 31/12/2010. There are a few spikes in the graph until prices fall around September 2008. Afterwards, prices rise slowly:



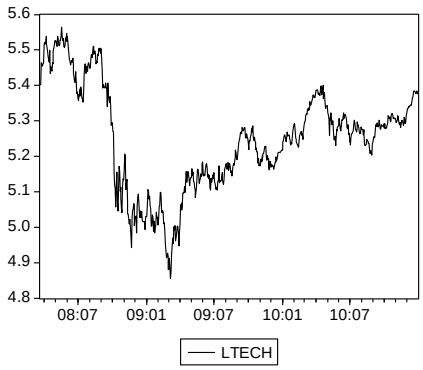


Fig. Actual STOXX Technology index values Fig. Logs of STOXX Technology index

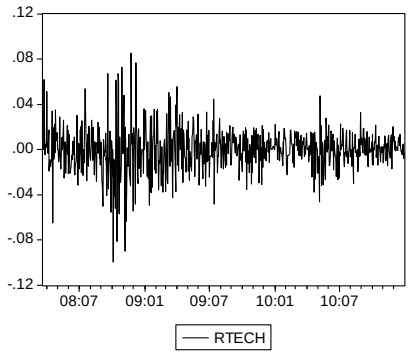


Fig. Returns of STOXX Technology index

The statistical properties of the actual index prices and their returns can be observed in table 16 below:

Table 16: Statistics of actual values and returns of STOXX Technology index

	TECH	RTECH
Mean	192.2422	-3.83E-05
Median	192.1900	0.000000
Maximum	260.9900	0.085161
Minimum	128.4000	-0.099712
Std. Dev.	28.31650	0.019255
Skewness	0.264774	-0.156926
Kurtosis	2.557247	6.614764
Jarque-Bera	14.41267	398.2418
Probability	0.000742	0.000000
Sum	139567.8	-0.027782
Sum Sq. Dev.	581322.7	0.268792
Observations	726	726

In Table 16 the kurtosis coefficient confirms a platykurtic distribution in the actual values, and a leptokurtic distribution in the returns of the technology index. The skewness coefficient appears to be negative in the returns (asymmetry to the left), and positive in the actual values of the technology index (asymmetry to the right). Again, the Jarque-Bera statistic shows no normal distributed residuals.

If we wish to compare the above indices, we re-calculate them with base=100 and we get another statistical table:

Table 17: Statistical characteristics of the new base=100 STOXX indices

	BASRES_INDEX	CAR_INDEX	CH_INDEX	CONST_INDEX	EN_INDEX	IND_INDEX	TECH_INDEX
Mean	77.31186	82.38168	94.49121	77.63919	89.72381	89.22519	86.65299
Median	78.95665	80.03826	99.27401	78.69843	87.06889	92.13833	86.61109
Maximum	137.8919	131.0837	129.4719	113.4903	129.1410	122.9879	117.6160
Minimum	34.95302	49.01836	61.26958	47.12353	65.77493	54.75693	57.86390
Std. Dev.	23.87808	14.10563	17.15067	13.35810	12.47647	17.52740	12.76177
Skewness	0.223704	0.526773	-0.204370	0.291126	1.023458	-0.257204	0.261616
Kurtosis	2.423948	3.302089	2.006656	3.224502	3.853915	1.905010	2.553186
Jarque-Bera	16.11546	36.38687	34.95051	11.79610	149.0058	44.33547	14.34049
Probability	0.000317	0.000000	0.000000	0.002745	0.000000	0.000000	0.000769
Sum	56205.72	59891.48	68695.11	56443.69	65229.21	64866.71	62996.72
Sum Sq.Dev.	413938.2	144451.3	213549.6	129546.6	113010.8	223034.2	118238.4
Observations	727	727	727	727	727	727	727

From Table 17 we can derive that the skewness coefficient demonstrates an asymmetry to the right for all the above indices, but for those of chemicals and the industrials. The kurtosis coefficient indicates a platykurtic distribution for the basic resources, the chemicals, the industrials and the technology indices and a leptokurtic distribution for the automobiles, the constructions and the energy indices. The Jarque-Bera appears to be high for all the indices (residuals are not normally distributed). The correlations among the above indices can be seen in Table 18.

Table 18: STOXX indices correlations

	BASRES_INDEX	CAR_INDEX	CH_INDEX	CONST_INDEX	EN_INDEX	IND_INDEX	TECH_INDEX
BASRES_INDEX	1.000000						
CAR_INDEX	0.771227	1.000000					
CH_INDEX	0.903285	0.827892	1.000000				
CONST_INDEX	0.918883	0.690800	0.805487	1.000000			
EN_INDEX	0.904617	0.581731	0.680210	0.891162	1.000000		
IND_INDEX	0.908183	0.837360	0.983260	0.823259	0.680049	1.000000	
TECH_INDEX	0.944429	0.722366	0.811143	0.907418	0.892598	0.848562	1.000000

We can see that there are strong correlations between the basic resources with the rest of the STOXX indices, between the automobiles index with the chemicals and the industry indices, between the chemicals and the construction and the industry indices, between the construction and the energy, industry and technology indices, between the energy and the technology indices and finally between the industry and the technology indices.

3.4.2 Eurofirst300 indices

3.4.2.1 Eurofirst300 utilities

This sector covers major European companies that provide electricity, gas and water services.

Figures 54-56 demonstrate the actual values (util300), the logarithmic forms (lutil300) and the returns (rutil300) of the Eurofirst300 Utilities index for the period of 20/03/2008 to 31/12/2010. We can observe the prices falling around June 2008. Their recovery begins after March 2009:

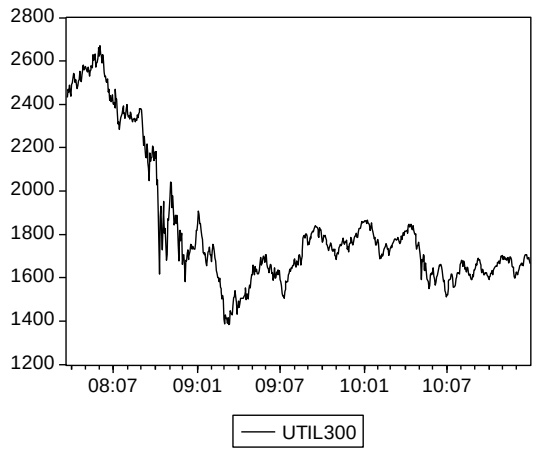


Fig.54: Actual Eurofirst300 Utilities index values

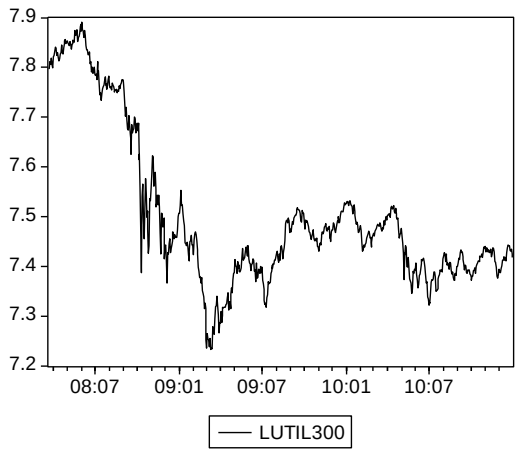


Fig.55: Logs of Eurofirst300 Utilities index

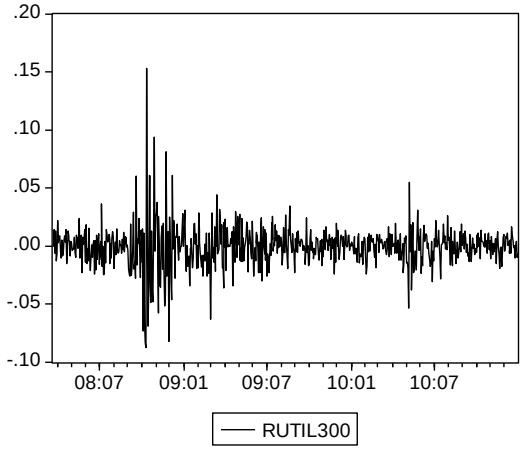


Fig.56: Returns of Eurofirst300 Utilities index

The statistical properties of the actual index prices and their returns can be observed in table 19:

Table 19: Statistics of actual values and returns of Eurofirst300 Utilities index

	UTIL300	RUTIL300
Mean	1833.394	-0.000523
Median	1729.155	7.25E-05
Maximum	2672.100	0.152699
Minimum	1384.350	-0.087633
Std. Dev.	311.6611	0.017661
Skewness	1.312564	0.525599
Kurtosis	3.506046	15.32511
Jarque-Bera	216.2082	4628.654
Probability	0.000000	0.000000
Sum	1331044.	-0.379831
Sum Sq. Dev.	70421159	0.226127
Observations	726	726

In Table 19 the kurtosis coefficient confirms a leptokurtic distribution for the actual values and the returns of the utilities index. The skewness coefficient appears to be positive in both cases (asymmetry to the right) and the Jarque-Bera statistic shows no normal distributed residuals.

3.4.2.2 Eurofirst300 oil and gas

It covers companies engaged in the exploration, production and distribution of oil and gas, including suppliers of equipment and services to the industry.

Figures 57-59 demonstrate the actual values (og300), the logarithmic forms (log300) and the returns (rog300) of the Eurofirst300 Oil & Gas index for the period of 20/03/2008 to 31/12/2010. Prices begin to decline around June 2009 and appear to start recovering after March 2009:

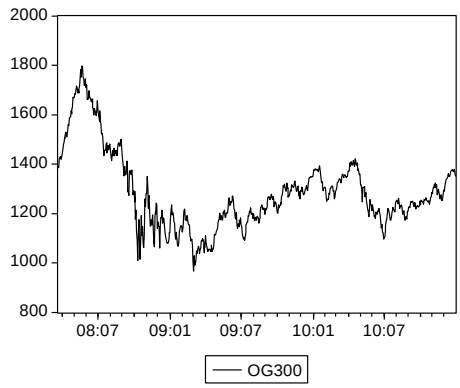


Fig.57: Actual Eurofirst300 oil & gas index values

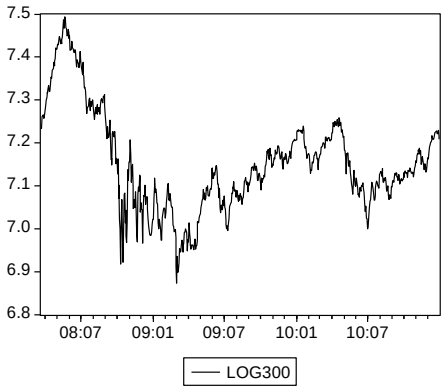


Fig.58: Logs of Eurofirst300 oil & gas index

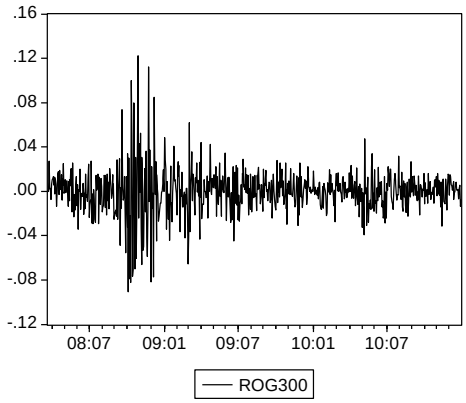


Fig.59: Returns of Eurofirst300 oil & gas index

The statistical properties of the actual index prices and their returns can be observed in table 20:

Table 20: Statistics of actual values and returns of Eurofirst300 oil & gas index

	OG300	ROG300
Mean	1285.513	-3.45E-05
Median	1256.025	0.000000
Maximum	1796.800	0.122266
Minimum	966.3800	-0.090796
Std. Dev.	157.0058	0.020446
Skewness	1.010359	0.196445
Kurtosis	3.967077	9.523228
Jarque-Bera	151.8108	1291.883
Probability	0.000000	0.000000
Sum	933282.5	-0.025049
Sum Sq. Dev.	17871847	0.303077
Observations	726	726

In Table 12 the kurtosis coefficient shows a leptokurtic distribution in both the actual values and the returns of the oil & gas index. The skewness coefficient is positive in both cases (asymmetry to the right). Again, the Jarque-Bera statistic shows no normal distributed residuals.

3.4.2.3 Eurofirst300 basic materials

This comprises of companies involved in the extraction and basic processing of natural resources other than oil and gas, i.e. coal, metal ore (including the production of basic aluminium, iron and steel products), precious metals and gemstones. This sector also includes the forestry and paper industry.

Figures 60-62 demonstrate the actual values (basmat300), the logarithmic forms (lbasmat300) and the returns (rbasmat300) of the Eurofirst300 Basic Materials index for the period of 20/03/2008 to 31/12/2010. A sharp decline occurs around July 2008 until the beginning of 2009. Since then, prices seem to recover and rise steadily:

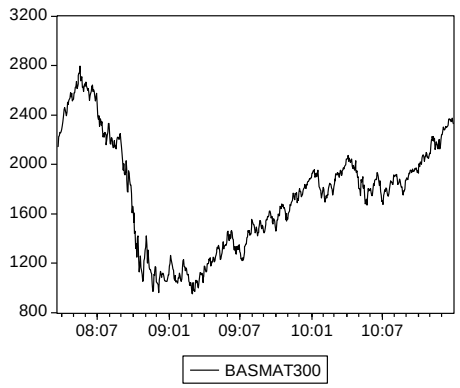


Fig.60: Actual Eurofirst300 Basic Materials index values

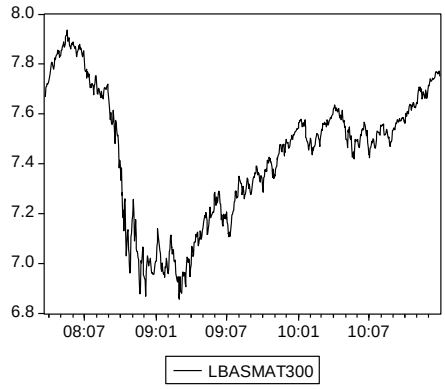


Fig.61: Logs of Eurofirst300 Basic Materials index

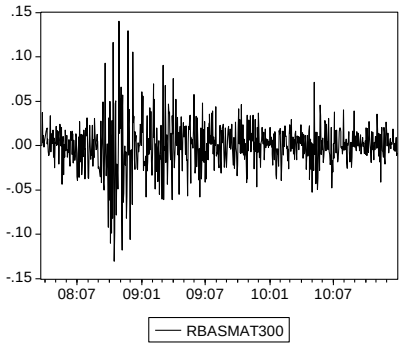


Fig.62: Returns of Eurofirst300 Basic Materials index

The statistical properties of the actual index prices and their returns can be observed in table 21:

Table 21: Statistics of actual values and returns of Eurofirst300 Basic Materials index

	BASMAT300	RBASMAT300
Mean	1750.214	0.000113
Median	1792.845	0.001011
Maximum	2795.080	0.139823
Minimum	950.5100	-0.130269
Std. Dev.	450.5558	0.026711
Skewness	0.122382	-0.134816
Kurtosis	2.194580	7.812831
Jarque-Bera	21.43548	702.8903
Probability	0.000022	0.000000
Sum	1270655.	0.081703
Sum Sq. Dev.	1.47E+08	0.517253
Observations	726	726

In Table 21 the kurtosis coefficient confirms a platykurtic distribution in the actual values, whereas the distribution is leptokurtic in the returns of the chemicals index. The skewness coefficient appears to be negative in the returns (asymmetry to the left), and positive in the actual values (asymmetry to the right). Also, the Jarque-Bera statistic appears to be high again.

3.4.2.4 Eurofirst300 Industrials

This contains companies involved in the manufacturing industries, including service providers to these companies. It also includes engineering, aerospace and defence, containers and packaging companies, electrical equipment manufacturers and commercial transport services.

Figures 63-65 demonstrate the actual values (ind300), the logarithmic forms (lind300) and the returns (rind300) of the Eurofirst300 Industrials index for the period of 20/03/2008 to 31/12/2010. Similarly to the Basic Materials index above, prices begin to decline around July 2008 and start recovering again around March 2009:

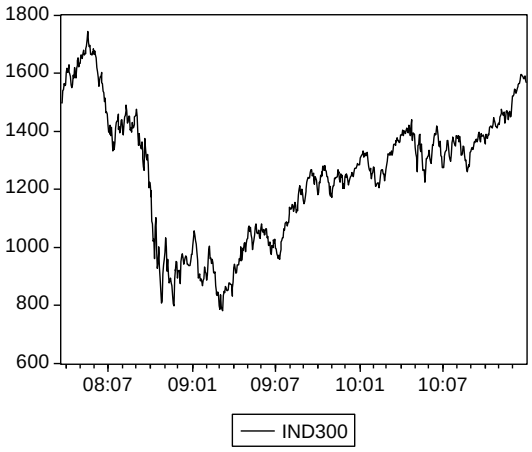


Fig.63: Actual Eurofirst300 Industrials index values

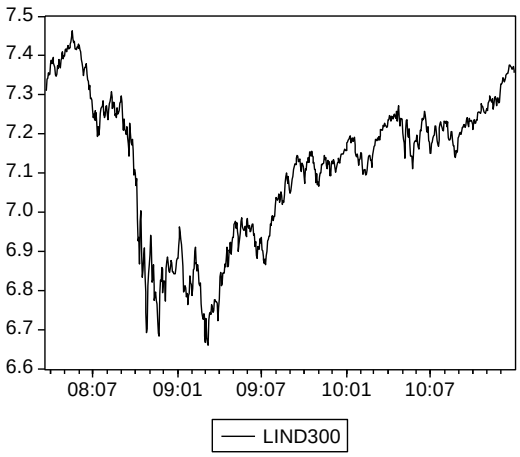


Fig. 64: Logs of Eurofirst300 Industrials index

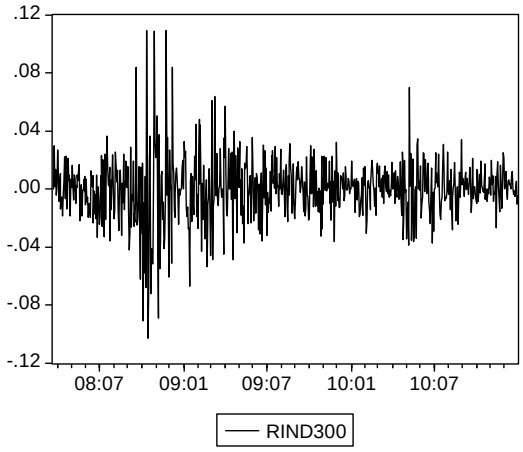


Fig.65: Returns of Eurofirst300 Industrials index

The statistical properties of the actual index prices and their returns can be observed in table 22:

Table 22: Statistics of actual values and returns of Eurofirst300 Industrials index

	IND300	RIND300
Mean	1249.523	6.27E-05
Median	1276.015	0.000654
Maximum	1744.340	0.109183
Minimum	781.0600	-0.102892
Std. Dev.	224.1692	0.021081
Skewness	-0.160783	0.064586
Kurtosis	2.199568	8.118377
Jarque-Bera	22.50892	792.9876
Probability	0.000013	0.000000
Sum	907153.5	0.045504
Sum Sq. Dev.	36432565	0.322193
Observations	726	726

In Table 22 the kurtosis coefficient shows a platykurtic distribution in the actual values, and a leptokurtic one in the returns of the industrials (300) index. The skewness coefficient appears to be negative in the actual values (asymmetry to the left), and positive in the returns (asymmetry to the right). Also, the Jarque-Bera statistic shows no normal distributed residuals. Converting the above indices with base=100 we get the following statistics:

Table 23: Statistics of Eurofirst300 indices

	UTIL300_INDEX	OG300_INDEX	BASMAT300_INDEX	IND300_INDEX
Mean	75.29866	92.83006	81.72421	83.54356
Median	71.00163	90.69136	83.69813	85.30606
Maximum	109.6953	129.7375	130.4728	116.5956
Minimum	56.83045	69.77725	44.36929	52.20780
Std. Dev.	12.81839	11.33189	21.02817	14.98611
Skewness	1.305325	1.007952	0.119590	-0.163201
Kurtosis	3.480216	3.964857	2.193236	2.198268
Jarque-Bera	213.4381	151.3012	21.44879	22.69792
Probability	0.000000	0.000000	0.000022	0.000012
Sum	54742.13	67487.45	59413.50	60736.17
Sum Sq. Dev.	119289.9	93226.87	321025.5	163047.7
Observations	727	727	727	727

From Table 23, we can derive that the skewness coefficient is positive for all the indices, except for the industrials (300) index, so the asymmetry in this case will be to the right. The kurtosis coefficient shows a leptokurtic distribution for the indices of the utilities and the oil & gas, whereas it indicates a platykurtic one for the basic materials the industrials (300) indices. We can also see that the Jarque-Bera statistic is high. In Table 24, we demonstrate the correlations of the above indices.

Table 24: Correlations among the Eurofirst300 indices

	UTIL300_INDEX	OG300_INDEX	BASMAT300_INDEX	IND300_INDEX
UTIL300_INDEX	1.000000			
OG300_INDEX	0.872716	1.000000		
BASMAT300_INDEX	0.673917	0.877569	1.000000	
IND300_INDEX	0.600838	0.817435	0.976437	1.000000

We can observe that that there are strong correlations between the utilities and the oil & gas indices, the industrials and the basic materials indices and also between the oil & gas with the basic materials and the industrials indices.

3.4.3 Other indices

3.4.3.1 Standard & Poor's Europe 350 index

The Standard & Poor's (S & P) Europe 350 Index is a free float market cap weighted index that measures the performance of equities in 17 Pan-European markets, covering approximately 70% of the total market cap. It offers an effective balance between broad market representation and liquidity. The S & P Europe 350 is part of the S & P Global 1200. It has a base date of Dec. 31, 1997 with a base value of 1000.

Figures 63-65 demonstrate the actual values (sp350), the logarithmic forms (lsp350) and the returns (rsp350) of the Standard & Poors index for the period of 20/03/2008 to 31/12/2010. The price declining occurs again around July 2008 and their recovery after March 2009:

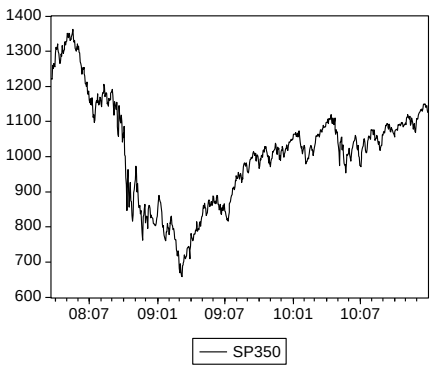


Fig.63: Actual values of Standard & Poor's index

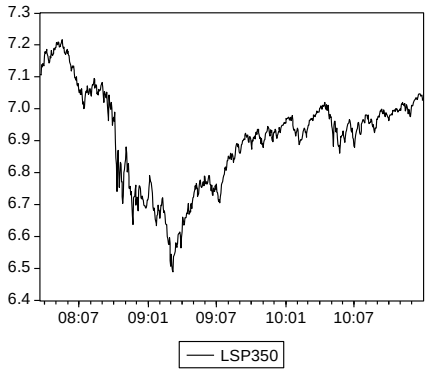


Fig.64: Logs of Standard & Poor's index

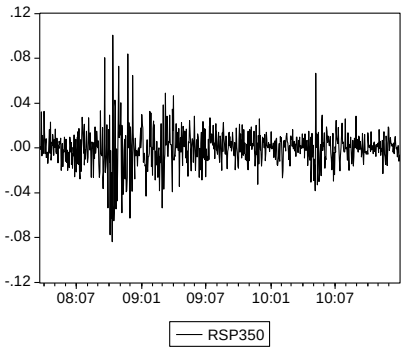


Fig.65: Returns of Standard & Poor's index

The statistical properties of the actual index prices and their returns can be observed in table 25:

Table 25: Statistics of actual values and returns of Standard & Poor's index

	RSP350	SP350
Mean	-0.000113	1012.649
Median	0.000342	1024.800
Maximum	0.100475	1362.990
Minimum	-0.083781	657.6200
Std. Dev.	0.017089	150.3964
Skewness	0.070841	0.007538
Kurtosis	8.704784	2.658582
Jarque-Bera	985.0802	3.532996
Probability	0.000000	0.170931
Sum	-0.081683	735183.1
Sum Sq. Dev.	0.211727	16398826
Observations	726	726

In Table 25 the kurtosis coefficient confirms a leptokurtic distribution in both the actual values and the returns of the S & P (350) index. The skewness coefficient is positive in both cases (asymmetry to the right) and again the Jarque-Bera statistic shows no normal distributed residuals.

3.4.3.2 DAX index

DAX is a blue-chip stock market index that incorporates thirty major German companies trading on the Frankfurt Stock Exchange. The performance of these companies is measured in terms of order book volume and market capitalization.

Since the DAX index is an indicator for the German economy, it is therefore chosen to be included in our calculations to check whether it contributes to the price formation of the EUA spot prices in the EEX spot market. We wish to check thus whether the topology of industry production (in our case Germany) influences the emission market spot prices more than the other European companies involved in the carbon market.

Figures 66-68 demonstrate the actual values (dax), the logarithmic forms (ldax) and the returns (rdax) of the DAX index for the period of 20/03/2008 to 31/12/2010. Similarly to the S & P index above, prices begin dropping around July 2008 and recovering again after March 2009:

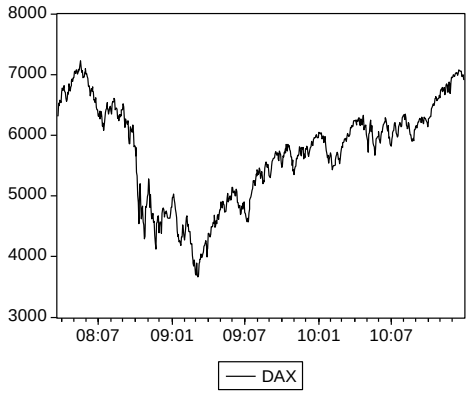


Fig.66: Actual DAX index values

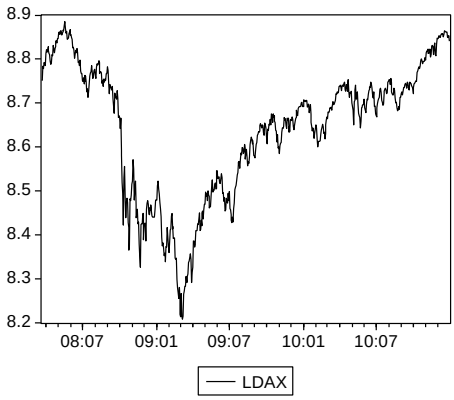


Fig.67: Logs of DAX index

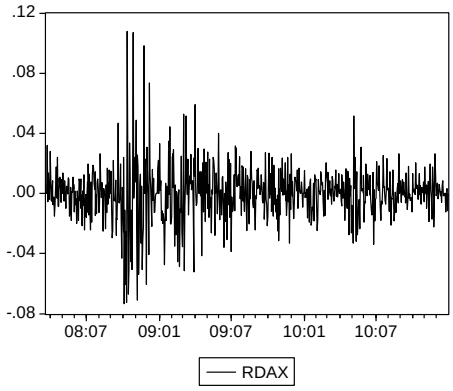


Fig.68: Returns of DAX index

The statistical properties of the actual index prices and their returns can be observed in table 26:

Table 26: Statistics of actual values and returns of the DAX index

	DAX	RDAX
Mean	5716.847	0.000124
Median	5875.940	0.000409
Maximum	7225.940	0.107975
Minimum	3666.410	-0.073355
Std. Dev.	834.2214	0.018020
Skewness	-0.393158	0.321088
Kurtosis	2.253325	9.232495
Jarque-Bera	35.56842	1187.506
Probability	0.000000	0.000000
Sum	4150431.	0.089858
Sum Sq. Dev.	5.05E+08	0.235428
Observations	726	726

In Table 26 the kurtosis coefficient confirms a platykurtic distribution in the actual values, whereas the distribution is leptokurtic in the returns of the chemicals index. The skewness coefficient appears to be negative in the actual values (asymmetry to the left), and positive to the returns (asymmetry to the right). Also, the Jarque-Bera statistic shows no normal distributed residuals.

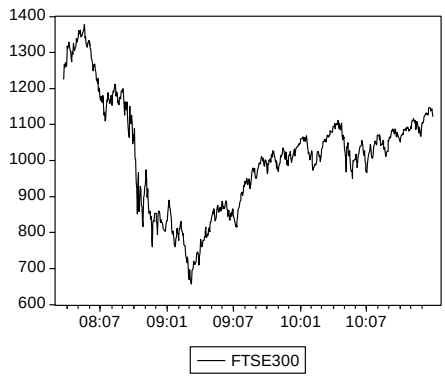
3.4.3.3 Ftseurofirst300

This index incorporates blue-chip companies that form the supersector industries discussed in 3.4.2. In total, this index covers 93.3% of the FTSE Developed Europe Index. A list of the supersectors involved in the index is listed below:

Supersector	**Description**
Automobiles & Parts	Manufacturing of cars, tyres and new or replacement parts. Vehicles used for commercial or recreational purposes are excluded.
Banks	Retail business.
Basic Resources	Extracting and processing of natural resources other than oil and gas, like coal, metal ore (including the production of basic aluminium, iron and steel products), precious metals and gemstones. It also includes the forestry and paper industry.
Chemicals	Producing and distribution of either commodity or final chemical products.
Construction & Materials	Constructing buildings and infrastructure, and production of materials and services used by this sector.
Financial Services	Corporate banking, investment services and real estate activities.
Food & Beverages	Crop growing and livestock farming to production and packing. This also includes manufacturing and distributing beverages (alcoholic and non-alcoholic), but excludes retailers.
Health Care	Providing health care, pharmaceuticals, medical equipment and medical supplies.
Industrial Goods & Services	Manufacturing industries, including service providers. It also includes engineering, aerospace and defence, containers and packaging companies, electrical equipment manufacturers and commercial transport services.
Insurance	All those companies, including brokers or agents that offer life insurance or

	reinsurance.
Media	TV and radio production and filmed entertainment. This also includes media agencies and both print and electronic publishing.
Oil & Gas	Exploring, producing and distributing oil and gas, including suppliers of equipment and services to the industry.
Personal & Household Goods	Producing durable and non-durable personal and household products, including furnishings, clothing, home electrical goods, recreational equipment and tobacco products.
Retail	Providing retail consumer goods and services, including food and medicine.
Technology	Providing computer and telecommunications hardware and related equipment, software and services, including internet access.
Telecommunications	Providing fixed-line and mobile telephone services. Manufacturers and suppliers of telecommunications equipment are excluded.
Travel & Leisure	Providing leisure services, like hotels, theme parks, restaurants, bars, cinemas and consumer travel services (airlines and auto rentals).
Utilities	Providing electricity, gas and water services.

Figures 69-71 demonstrate the actual values (ftse300), the logarithmic forms (lftse300) and the returns (rftse300) of the Ftseurofirst300 index for the period of 20/03/2008 to 31/12/2010. Prices begin their decline in July 2008 and start their recovery after February 2009:



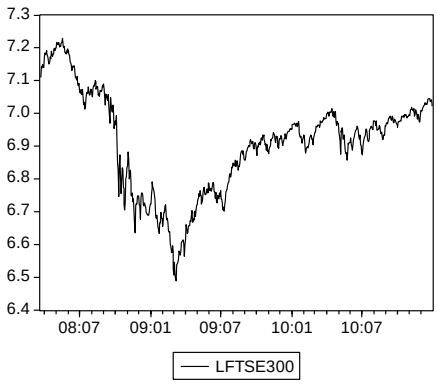


Fig.69: Actual Ftseurofirst300 index values Fig.70: Logs of Ftseurofirst300 index

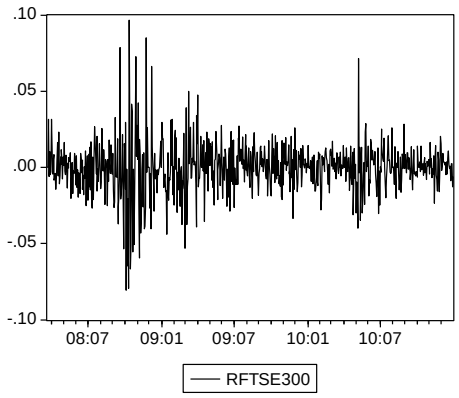


Fig.71: Returns of Ftseurofirst300 index

The statistical properties of the actual index prices and their returns can be observed in table 27:

Table 27: Statistics of actual values and returns of the Ftseurofirst300 index

	FTSE300	RFTSE300
Mean	1012.351	-0.000123
Median	1020.470	0.000000
Maximum	1378.290	0.096438
Minimum	657.3000	-0.080721
Std. Dev.	153.1182	0.017024
Skewness	0.101503	0.109936
Kurtosis	2.702375	8.571173
Jarque-Bera	3.926203	940.3611
Probability	0.140422	0.000000
Sum	734966.8	-0.089485
Sum Sq. Dev.	16997768	0.210123
Observations	726	726

In Table 27 the kurtosis coefficient indicates a platykurtic distribution in the actual values, and a leptokurtic one in the returns of the chemicals index. The skewness coefficient appears to be positive in both cases (asymmetry to the right). The Jarque-Bera statistic shows no normal distributed residuals for the returns but not for the actual values of the FTSE300 index. Converting the above indices with base = 100 we get the following statistics:

Table 28: Statistics of other indices

	DAX_INDEX	FTS300_INDEX	SP350_INDEX
Mean	90.46972	82.55242	83.01992
Median	92.97436	83.20168	84.00144
Maximum	114.3347	112.3603	111.7104
Minimum	58.01291	53.58409	53.89842
Std. Dev.	13.19538	12.49065	12.33410
Skewness	-0.395469	0.099159	0.005433
Kurtosis	2.255129	2.696046	2.653263
Jarque-Bera	35.75675	3.989971	3.645446
Probability	0.000000	0.136016	0.161585
Sum	65771.48	60015.61	60355.48
Sum Sq. Dev.	126409.7	113267.9	110446.4
Observations	727	727	727

From Table 28, we can see that the skewness coefficient is negative only for the DAX index, so the asymmetry in this case is to the left. The kurtosis coefficient shows a platykurtic distribution for all the above indices. The Jarque-Bera indicates a normal distribution for the residuals in the case of the FTSE300 and the S & P 350 indices but not for the DAX index. We can see the correlations of the indices in Table 29.

Table 29: Correlations of the general economic indices

	DAX_INDEX	FTS300_INDEX	SP350_INDEX
DAX_INDEX	1.000000		
FTS300_INDEX	0.944459	1.000000	
SP350_INDEX	0.951646	0.999308	1.000000

We can observe that there are strong correlations between the DAX with both the Ftseurofirst300 and the Standard & Poors indices and also between the Ftseurofirst300 and the Standard&Poors indices.

We can see the correlations between the emission spots and futures with all the economic variables in table 30. The emission spots are strongly correlated with the energy, technology, utilities, oil & gas and the FTSEurofirst 300 indices. They are weakly correlated with the automobiles, chemicals, industry, construction, basic resources, basic materials, industrials (300), Standard & Poors 350 and the DAX indices. The emission futures are found to be strongly correlated with the utilities index and weakly correlated to the rest of the economic indicators.

Table 30: Correlation coefficients between the emission spots and futures with the economic indicators

	spots	futures	cars	chemicals	energy	industry	construction	basic resources	technology	utilities	Oil & gas	basic materials	all industrials	Standard & Poor's	DAX	Ftseurofirst 300
spots	1															
futures	0.98	1														
cars	0.53	0.42	1													
chemicals	0.39	0.26	0.83													
energy	0.70	0.66	0.63	0.72	1											
industry	0.42	0.29	0.84	0.99	0.72	1										
construction	0.54	0.45	0.74	0.85	0.89	0.87	1									
basic materials	0.58	0.48	0.8	0.94	0.88	0.95	0.93	1								
technology	0.68	0.6	0.77	0.85	0.89	0.88	0.92	0.95	1							
utilities	0.85	0.86	0.45	0.40	0.86	0.41	0.67	0.62	0.72	1						
oil&gas	0.68	0.64	0.62	0.71	0.99	0.70	0.87	0.86	0.87	0.86	1					
basic materials	0.58	0.47	0.81	0.96	0.87	0.95	0.92	0.99	0.94	0.62	0.86	1				
all industrials	0.53	0.42	0.83	0.96	0.83	0.98	0.94	0.98	0.94	0.57	0.81	0.98	1			
Standard& Poor's	0.66	0.56	0.83	0.90	0.89	0.92	0.95	0.97	0.96	0.72	0.88	0.97	0.97	1		
DAX	0.53	0.41	0.88	0.97	0.79	0.98	0.91	0.96	0.92	0.54	0.78	0.97	0.98	0.96	1	
Ftseurofirst-300	0.68	0.59	0.82	0.90	0.90	0.91	0.94	0.96	0.96	0.74	0.89	0.97	0.96	0.99	0.96	1

3.5 Conclusions

In this chapter, we have presented the variables involved in our study and have described their statistical properties in detail. We have also checked for possible correlations. We may conclude that the emission spot prices, in relation to the energy variables are found to be strongly correlated with those of their futures and also with the futures prices of coal, gas and electricity. The emissions spots appear to be weakly correlated with oil spots and oil futures and also with the spot prices of gas and electricity.

The above findings appear to agree with some of the literature; Fehr and Hinz (2006) found no correlation between the emission spots prices and the fuel prices (in particular coal, gas and electricity spot prices). Obermayer (2007) also did not find any correlation between the emission spot and the gas spot prices. However, they also seem to contradict some other articles; Bunn and Fezzi (2007) found a link between the electricity spots and the emission spots prices. However, they concentrated in the UK market for the electricity prices. Obermayer (2007) and Alberola et al. (2008) also found correlation with the electricity spot prices. This indicates that in the second trading period, the emission spots are linked with the futures prices of the energy variables rather than with their spot prices.

Concerning the emission futures, these are strongly correlated with the emission spots, the futures prices of oil, coal, gas and electricity and both the spots and futures prices of electricity, whereas they are weakly correlated with the spots prices of oil, gas and electricity. This indicates a strong connection between the carbon and the energy derivatives markets.

In relation to the economic variables, we may conclude that the emission spots are strongly correlated with those indices that represent the energy and the utilities sectors and have a weaker correlation with the oil&gas sector and the FTSEurofirst300 stock prices. This proves the relation between the emission spots with energy and demonstrates the ability of the emission spot market to follow the changes that may occur in the energy sector and also the utilities sector, which represents electricity and gas. Similarly, the emission futures are strongly correlated to the utilities sector. However, they are more weakly correlated to the energy sector.

Chapter 4

Stationarity of the variables

4.1 Introduction

A time series X_t is said to be stationary when the following are valid (Wang, 2009):

1. The mean $E(X_t) = \mu$ is constant for all t
2. The variance $Var(X_t) = E(X_t - \mu)^2 = \sigma^2$ is constant for all t
3. The covariance $Cov(X_t, X_{t+\kappa}) = E[(X_t - \mu)(X_{t+\kappa} - \mu)] = \gamma_\kappa$ is constant for all t and $\kappa \neq 0$.

This is sometimes referred to as weakly stationary. Such time series have finite mean, variance and covariance that do not depend on time t, and the covariance depends only on the interval κ. If one or more of the above statements is not valid, then the time series is said to be non-stationary. A typical non-stationary time series is the pure random walk:

$$y_t = \mu + y_{t-1} + \varepsilon_t \quad \varepsilon_t \sim N(0, \sigma^2) \qquad (4.1)$$

where μ is a constant or drift, which can be zero. This time series in non-stationary, since $Var(y_t) = t\sigma^2 \to \infty \text{ as } t \to \infty$. The difference of a pure random walk is the Gaussian white noise:

$$\Delta y_t = \mu + \varepsilon_t \quad \varepsilon_t \sim N(0, \sigma^2) \quad (4.2)$$

Here, the variance of Δy_t is σ^2 and the mean is μ.

In general, if a time series is stationary then it is said to be integrated of order zero, or I(0). If a time series needs the difference operation once to achieve stationarity, then it is integrated of order one, or I(1). An I(0) time series has no roots on or inside the unit circle, and equivalently an I(1) series has one unit root etc.

To check for the presence of a unit root in the equation 4.2, we re-write it using a first-order autoregressive process (AR(1)):

$$y_t = \mu + \rho y_{t-1} + \varepsilon_t \qquad (4.3)$$

$$= (1 + \rho + ... + \rho^{n-1})\mu + \rho^n y_{t-n} + (1 + \rho L + ... + \rho^{n-1} L^{n-1})\varepsilon_t$$

where L is the lag operator. Equation 4.3 can be also expressed as:

$$y_t = \frac{\mu + \varepsilon_t}{(1 - \rho L)} = \frac{\mu + \varepsilon_t}{\rho((1/\rho) - L)} \qquad (4.4)$$

The above equation has a unit root r=1/ρ.

Equation 4.3 can be re-written with respect to ε_t and without μ as:

$$y_t - \rho y_{t-1} = \varepsilon_t \qquad (4.5)$$

$$= (1 - \rho L) y_t = \varepsilon_t$$

According to equation 4.5, the hypotheses for the unit root test for y_t can be written as:

$$H_o : |\rho| \geq 1, \text{ for non-stationarity} \qquad (4.6)$$

$$H_\alpha : |\rho| < 1, \text{ for stationarity}$$

When ρ = 1, then the equation 4.5 describes the random walk process. Based on the above hypothesis, we apply three different tests for stationarity, to make sure that we avoid the possibility of autocorrelation in our variables. The tests used are the Augmented Dickey-Fuller test (ADF), the Phillips-Perron test (PP) and the Kwiatkowski, Phillips, Schmidt and Shin test (KPSS). We choose the best fit regression equations according to two criteria:

- the Akaike criterion (1973): $AIC = \log(\frac{SSR}{n}) + \frac{2\kappa}{n}$ (4.7)
- the Schwarz criterion (1978): $SC = \log(\frac{SSR}{n}) + \frac{\kappa}{n}\log(n)$ (4.8)

where n is the sample size, κ is the total number of the regression parameters and SSR is the Sum of the Squares of the Residuals. The Akaike criterion (AIC) is a goodness of fit measure of a statistical model. Based on information theory, it is used to describe the trade-off between the accuracy and the complexity involved when constructing a statistical model. It includes a penalty related to the number of estimating parameters, which indicates that the

model with the minimum AIC value will offer the best fit. It can also appear in the following form (Katos, 2004):

$$AIC = -\frac{2l}{n} + \frac{2\kappa}{n} \qquad (4.9)$$

where l is the maximised value of the logarithmic likelihood:

$$l = -\frac{n}{2}\left[1 + \log(2\pi) + \log\left(\frac{SSR}{n}\right)\right] \qquad (4.10)$$

The Schwarz criterion (SC) is another measure for choosing the best fit model and is very closely related to the AIC. It also provides a penalty for increasing the model complexity and can take the form:

$$SC = -\frac{2l}{n} + \frac{\kappa \log n}{n} \qquad (4.11)$$

Where l takes the same value as in equation 4.10. The aim is to minimise both criteria (minimise the value of the variance of the residuals), therefore the best fit models are chosen where the above two criteria have the lowest values.

4.1.1 ADF test

The basic DF test (Dickey and Fuller, 1979, 1981) examines whether ρ<1 in equation 4.3, which, by subtracting the term y_{t-1} becomes:

$$\Delta y_t = \mu + (\rho - 1)y_t + \varepsilon_t \qquad (4.12)$$

$$= \mu + \theta y_{t-1} + \varepsilon_t$$

The hypothesis formed here is the following:

$$H_o : \theta = 0 \text{, there is a unit root, if } t_\theta > \tau \qquad (4.13)$$

$$H_\alpha : \theta < 0 \text{, there is no unit root, if } t_\theta < \tau$$

where θ is the regression coefficient and τ is the critical value, as this has been evaluated by MacKinnon (1991) for certain significance levels (we usually check the values at 5% significance level). For the DF test, we apply the following steps:

Step 1: we apply the method of the least squares to equation 4.12 and we make a note of the corresponding critical value τ_θ.

Step 2: we test for the existence of a unit root by following the hypothesis in 4.13. For a time series to be stationary, the critical value τ_θ has to be largely negative.

From the above we observe that the stationarity test of a time series always depends on the regression coefficient θ.

Equations 4.3 and 4.13 represent the simple case where the residual is white noise. In reality however, there is serial correlation in the residuals ε_t, which means that the DF test is not valid. In this case, Δy_t can be represented as an autoregressive process with added lagged in their differences terms, in order to eliminate the possibility of autocorrelation in the residuals. So, if we assume an autoregressive process of order p:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + ... + \phi_p Y_{t-p} + \varepsilon_t \quad (4.13)$$

Equation 4.12 can be written as:

$$\Delta y_t = \mu + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-1} + \varepsilon_t \quad (4.14)$$

Since we include these terms that appear to be lagged in their differences in equation 4.14, the DF test becomes an augmented DF test (ADF). The same critical values τ_θ are also valid for the ADF test and the same procedure is applied to test for stationarity, only now we apply the test in equation 4.14. The AIC and SC criteria can be used to check how many of these terms can be added in equation 4.14. In general, if Δy_t is of order p, then the number of terms to be added to remove any autocorrelation is p-1 (Thomas, 1997).

4.1.2 Phillips–Perron test

This test attempts to correct the t-statistic of the regression coefficient θ of the time series y_{t-1} to tackle the autocorrelation issue, instead of adding extra lagged terms. It takes the Fourier transform of the time series Δy_t and analyses its zero frequency component. The t-statistic is then calculated as:

$$t = \sqrt{\frac{r_0}{h_0}} t_\theta - \frac{(h_0 - r_0)}{2h_0\sigma} \sigma_\theta \quad (4.15)$$

where h_0 is the spectrum of Δy_t at the zero frequency, r_j is the autocorrelation function at lag j, t_θ is the t-statistic of θ, σ_θ is the standard error of θ and σ is the standard error of the test regression:

$$h_0 = r_0 + 2\sum_{\tau=1}^{M}\left(1-\frac{j}{T}\right)r_j \quad (4.16)$$

H_0 is essentially the variance of the M-period differenced series, $y_t - t_{t-M}$ and r_0 is the variance of the one-period difference, $\Delta y_t = y_t - y_{t-1}$.

The correction to the t-statistic is non parametric and considers both the heteroskedasticity and the autocorrelation in the residuals. In EViews 4.1 equation 4.16 is applied as an estimation of heteroskedasticity and autocorrelation, called Newey-West (1994) estimation.

4.1.3 KPSS test

This test is based on the statistic of the Lagrange Multiplier (LM), which accepts as a null hypothesis the stationarity of a time series and not its non-stationarity, like the rest of the unit root tests. The LM statistic can be expressed as (Katos, 2004):

$$LM = \sum_t S(t)^2 /(n^2 f_0) \quad (4.17)$$

where f_0 is an estimator of the residuals spectrum at the zero frequency and S(t) is the sum of the residuals:

$$S(t) = \sum_{r=1}^{t} \varepsilon_r \quad (4.18)$$

The estimator f_0 depends on a number of 'basic equations', which in EViews 4.1 are the following:

Bartlett: $$K(x) = \begin{cases} 1-|x|, & \text{if } |x| \le 1 \\ 0, & otherwise \end{cases} \quad (4.19)$$

Parzen: $$K(x) = \begin{cases} 1-6x^2+6|x|^3, & if\ 0 \le |x| \le (1/2) \\ 2(1-|x|)^3, & if\ (1/2) \le |x| \le 1 \\ 0, & otherwise \end{cases} \quad (4.20)$$

The rest of this chapter continues as follows: Since we have three sets of variables (energy, European indices for industrial and other sectors, general economic indices) and three sets of different stationarity tests, we divide the sections of this chapter in the following manner:

Sections 4.2, 4.3 and 4.4 demonstrate the ADF tests for our three sets of variables. Sections 4.5, 4.6 and 4.7 include the PP tests. Finally, sections 4.8, 4.9 and 4.10 deal with the KPSS tests. We draw our major conclusions in section 4.11.

4.2 ADF Stationarity Tests-Energy variables

4.2.1 EUA emission spot prices

Applying the ADF test by using EViews 4.1 for the logs and the returns of the emission spot prices, we derive Table 4.2.1. The values of the two chosen criteria (AIC and SC) are listed for every number of lags (5, 10 and 15) and considering the existence of constant, constant with trend or the case of none being used. We choose the best fit equation where those criteria appear to have the minimum values. The same procedure is followed throughout the rest of this section.

Table 4.2.1 ADF test for the logs and the returns of the emission spot prices

Lags	**Stats**	**log(es_t)**			**res_t**		
		none	constant	constant & trend	None	constant	constant & trend
q=5	AIC	-4.518*	-4.519*! [-1.672] (0.4453)	-4.517*	-4.525*!	-4.523*	-4.520*
	SC	-4.480*! [-0.706] (0.411)	-4.475*	-4.466*	-4.487*! [-11.406] (0.000)	-4.478*	-4.469
q=10	AIC	-4.513	-4.515!	-4.512	-4.516!	-4.514	-4.512
	SC	-4.443!	-4.438	-4.429	-4.446!	-4.438	-4.429
q=15	AIC	-4.504	-4.506!	-4.503	-4.503!	-4.501	-4.499
	SC	-4.401!	-4.396	-4.3874	-4.399!	-4.392	-4.383

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

Analysis of the logarithmic emission spot prices:

- According to the AIC criterion, the equation that is specified best is the one with constant and q=5 lags. The ADF t-statistic for the above fit is -1.672 with a probability of 0.445. The McKinnon test critical value is -0.439 at 1% significant level, and therefore the emission spot prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the equation that is specified best is the one with neither constant nor trend and q=5 lags. The ADF t-statistic for the above fit is -0.706 with a probability of 0.411. The McKinnon test critical value at 1% significant level is -3.439, and therefore the emission spot prices at the initial logarithmic levels are non stationary.

Analysis of the returns of the emission spot prices:

- According to the AIC and the SC criterion, the equation that is specified best is the one with neither constant nor trend and q=15 lags. The ADF t-statistic for the above fit is -11.406 with a probability of 0.000. The McKinnon test critical value at 1% significant level is -2.568, and therefore the returns of the emission spot prices are stationary.

From the analysis above we may conclude as follows:

- The emission spot prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.
- The returns of the emission spot prices are stationary, i.e., it is $res_t \sim I(0)$.

Considering the results above we may conclude that the emission spot prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(es_t) \sim I(1)$.

4.2.2 EUA futures prices

Applying the ADF test for the logs and the returns of the emission futures prices, we get following results:

Table 4.2.2: ADF test for the logs and the returns of the emission futures prices

Lags	Stats	log(ef_t)			ref_t		
		none	constant	constant & trend	none	constant	constant & trend
q=5	AIC	-4.795*	-4.796*!	-4.794*	-4.797*!	-4.795*	-4.792*
	SC	-4.757*!	-4.751*	-4.743*	-4.758*!	-4.750*	-4.741*
		[-0.923]	[-1.585]		[-10.707]		
		(0.317)	(0.490)		(0.000)		
	AIC	-4.788	-4.789!	-4.787	-4.791!	-4.789	-4.787
q=10	SC	-4.718!	-4.712	-4.704	-4.720!	-4.712	-4.703
	AIC	-4.780	-4.781!	-4.779	-4.778!	-4.777	-4.775
q=15	SC	-4.677!	-4.672	-4.663	-4.675!	-4.667	-4.659

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

From Table 4.2.2 we can conclude that:

- According to the AIC criterion, the equation that is specified best is the one with constant and q=5 lags. The ADF t-statistic for the above fit is -1.585 with a probability of 0.4896. The McKinnon test critical value is -3.439 at 1% significant level and therefore the emission futures prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the equation that is specified best is the one with neither constant nor trend and q=5 lags. The ADF t-statistic for the above fit is -0.923 with a probability of 0.3165. The McKinnon test critical value at 1% significant level is -2.568 and therefore the emission futures prices at the initial logarithmic levels are non stationary.

For the returns of the emission futures prices, the results show that:

- According to both criteria, the equation that is specified best is the one with neither constant nor trend and q=5 lags. The ADF t-statistic for the above fit is -10.707 with a probability of 0.000. Comparing it to the McKinnon test critical value (-2.568) we realise that the returns of the emission futures prices are stationary.

From the analysis above the main outcomes are that:

- The emission futures prices in logarithmic levels are non stationary.

- The returns of the emission futures prices are stationary, i.e., it is $ref_t \sim I(0)$.

From the results above we may conclude that the emission futures prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $log(ef_t) \sim I(1)$.

4.2.3 Gas spot prices

The ADF test is further applied to the logs and the returns of the gas spot prices and produces the following table:

Table 4.2.3: ADF test for the logs and the returns of the gas spot prices

Lags	Stats	$log(gs_t)$			rgs_t		
		none	constant	constant & trend	none	constant	constant & trend
q=5	AIC	-3.127	-3.128!	-3.126	-3.126!	-3.123	-3.122
	SC	-3.089*!	-3.083*	-3.075*	-3.088*!	-3.078*	-3.071*
		[-0.119]			[-10.707]		
		(0.642)			(0.000)		
q=10	AIC	-3.129!	-3.128	-3.127	-3.134*!	-3.131*	-3.132*
	SC	-3.058!	-3.0514	-3.044	-3.064	-3.055	-3.049
					[-10.345]		
					(0.000)		
q=15	AIC	-3.1324*!	-3.1319*	-3.13*	-3.133!	-3.129	-3.130
	SC	-3.029!	-3.023	-3.015	-3.029	-3.02	-3.0148
		[-0.142]					
		(0.635)					

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

For the logarithmic gas spot prices, we get two best fit equations:

- According to the AIC criterion, the equation that is specified best is the one with neither constant nor trend and q=15 lags. The ADF t-statistic here is -0.142 with a probability of 0.635. With the McKinnon value at 1% significant level of -2.568 we can say that the gas spot prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit equation is the one with neither constant nor trend and q=5 lags. The ADF t-statistic is -0.119 with a probability of 0.642 and by

comparing it to the McKinnon value (-2.568) we find that the gas spots prices at the initial logarithmic levels are non stationary.

For the returns of the gas spot prices two best fit equations are found again:

- According to the AIC criterion the best fit equation is the one with neither constant nor trend and q=10 lags. The ADF t-statistic for the above fit is -10.345 with a probability of 0.000. The McKinnon value is -2.568 and therefore the returns of the gas spot prices are stationary.
- According to the SC criterion, the equation that is specified best is the one with neither constant nor trend and q=5 lags. The ADF t-statistic here is -10.707 with a probability of 0.000. The McKinnon value is -2.568 and therefore the returns of the gas spots are stationary.

From the above we may conclude that the gas spot prices in logarithmic levels are non stationary, whereas their returns are stationary, i.e., it is $rgs_t \sim I(0)$. This leads us to the conclusion that the gas spot prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(gs_t) \sim I(1)$.

4.2.4 Gas futures prices

For the logs and the returns of the gas futures prices the following table is derived:

Table 4.2.4: ADF test for the logs and the returns of the gas futures prices

Lags	**Stats**	**$\log(gf_t)$**			**rgf_t**		
		none	constant	constant & trend	none	constant	constant & trend
q=5	AIC	-5.5549*	-5.5548*	-5.5555*!	-5.5565*!	-5.5538*	-5.5510*
	SC	-5.5169*!	-5.5104*	-5.5047*	-5.5184*!	-5.5093*	-5.5002*
		[-0.119]		[-2.077]	[-9.331]		
		(0.642)		(0.557)	(0.000)		
	AIC	-5.5396	-5.5402	-5.5407!	-5.5393!	-5.5365	-5.5337
q=10	SC	-5.4693!	-5.4635	-5.4577	-5.4689!	-5.4598	-5.4506
	AIC	-5.5213	-5.5220	-5.5222!	-5.5202!	-5.5175	-5.5147
q=15	SC	-5.4186!	-5.4128	-5.4066	-5.4174!	-5.4082	-5.399

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

For the logarithmic gas futures prices each criterion defines a best fit equation:

- In the case of the AIC criterion, the equation with constant and trend and q=5 lags is the best fit. The ADF t-statistic for the above fit is -2.077 with a probability of 0.557 and the McKinnon test critical value at 1% significant level is -3.971, so the gas futures prices at the initial logarithmic levels are non stationary.
- In the case of the SC criterion, the equation that is specified best is the one with neither constant nor trend and q=5 lags. The ADF t-statistic here is -0.119 with a probability of 0.642 and the McKinnon value is -2.568, so the gas futures prices at the initial logarithmic levels are non stationary.

For the returns of the gas spot prices, the best fit equation is the one with neither constant nor trend and q=5 lags for both the criteria. The ADF t-statistic is -9.331 with a probability of 0.000, which is smaller than the McKinnon value at 1% significant level (-2.568), therefore the returns of the gas futures prices are stationary.

We may conclude that the gas futures prices in logarithmic levels are non stationary and the returns of the gas futures prices are stationary, i.e., it is $rgf_t \sim I(0)$, which means that the gas futures prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(gf_t) \sim I(1)$.

4.2.5 Electricity spot prices

Table 4.2.5 shows the results from applying the ADF test for the logs and the returns of the electricity spot prices:

Table 4.2.5: ADF test for the logs and the returns of the electricity spot prices

Lags	**Stats**	**log(els_t)**			**$rels_t$**		
		none	constant	constant & trend	none	constant	constant & trend
q=5	AIC	-0.897*	-0.909*	-0.909*!	-0.896*!	-0.894*	-0.891*
	SC	-0.859*	-0.864*!	-0.859*	-0.858*!	-0.849*	-0.834*
			[-3.25]	[-3.602]	[-14.216]		
			(0.018)	(0.03)	(0.000)		
	AIC	-0.887	-0.895!	-0.894	-0.886!	-0.883	-0.880
		-0.816	-0.818!	-0.811	-0.815!	-0.806	-0.797
	AIC	-0.889	-0.895!	-0.892	-0.888!	-0.885	-0.883
		-0.786!	-0.785	-0.777	-0.785!	-0.776	-0.767

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

The ADF test produces two best fit equations for the logarithmic electricity spot prices, depending on each criterion:

- For the AIC criterion, the best fit equation is the one with constant and trend and q=5 lags. The ADF t-statistic is -3.602 with a probability of 0.03, which is larger than the McKinnon test critical value (-3.970), so the electricity spot prices at the initial logarithmic levels are found to be non stationary.
- For the SC criterion, the equation with constant and q=5 lags is the best fit. The ADF t-statistic for the above fit is -3.25 with a probability of 0.018 and the McKinnon value is -3.44, so the electricity spot prices at the initial logarithmic levels are non stationary.

For the returns of the electricity spot prices the best fit equation is the one with neither constant nor trend and q=5 lags according to both criteria. The ADF t-statistic for the above fit is -14.216 with a probability of 0.000 and the McKinnon value is -2.568, therefore the returns of the electricity spot prices are stationary.

From the analysis above we may conclude that the electricity spot prices in logarithmic levels are non stationary and the returns of electricity spot prices are stationary, i.e., it is $rels_t \sim I(0)$. This indicates that the electricity spot prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(els_t) \sim I(1)$.

4.2.6 Electricity futures prices

Applying the ADF test for the logs and the returns of the electricity futures prices, we get the following table:

Table 4.2.6: ADF test for the logs and the returns of the electricity futures prices

Lags	Stats	log(elf_t)			$relf_t$		
		none	constant	constant & trend	none	constant	constant & trend
q=5	AIC	-6.079*!	-6.078*	-6.082*	-6.078*!	-6.075*	-6.073*
	SC	-6.041*!	-6.034*	-6.031*	-6.0396*!	-6.031*	-6.022*
		[-0.446]			[-9.472]		
		(0.522)			(0.000)		
	AIC	-6.0699	-6.0697	-6.074!	-6.069!	-6.065	-6.064
q=10	SC	-5.999!	-5.993	-5.991	-5.999!	-5.99	-5.980
	AIC	-6.055	-6.0539	-6.057!	-6.054!	-6.051	-6.0483
q=15	SC	-5.952!	-5.945	-5.942	-5.951!	-5.942	-5.933

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

According to the results displayed in Table 4.2.6:

- For the logarithmic futures prices the best fit equation is the one with neither constant nor trend and q=5 lags according to both criteria. The ADF t-statistic is -0.446 with a probability of 0.522 and the McKinnon value is -2.568, so the electricity futures prices at the initial logarithmic levels are non stationary.
- For the returns of the electricity futures prices the best fit equation is the one with neither constant nor trend and q=5 lags. The ADF t-statistic for the above fit is -9.472 with a probability of 0.000. The McKinnon test critical value at 1% significant level is -2.568 and therefore the returns of the electricity futures prices are stationary.

The analysis shows that the electricity futures prices in logarithmic levels are non stationary., whereas the returns of the electricity futures prices are stationary, i.e., it is $relf_t \sim I(0)$. Considering these results, we may conclude that the electricity futures prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(elf_t) \sim I(1)$.

4.2.7 Oil spot prices

Table 4.2.7 demonstrates the ADF test results for the logs and the returns of the oil spot prices:

Table 4.2.7: ADF test for the logs and the returns of the oil spot prices

Lags	Stats	$\log(oil_t)$			$roil_t$		
		none	constant	constant & trend	None	constant	constant & trend
q=5	AIC	-4.3698*!	-4.3695*	-4.3684*	-4.3770*!	-4.3742*	-4.3733*
	SC	-4.3317*!	-4.3250*	-4.3176	-4.3390*!	-4.3297*	-4.3224*
		[-0.014]			[-11.514]		
		(0.678)			(0.000)		
	AIC	-4.3624!	-4.3618	-4.3609	-4.3612!	-4.3584	-4.3574
q=10	SC	-4.2922!	-4.2851	-4.2779*	-4.2909!	-4.28170	-4.2743
	AIC	-4.3522	-4.3523!	-4.3515	-4.3524!	-4.3496	-4.3486
q=15	SC	-4.2495!	-4.2431	-4.2359	-4.2495!	-4.2403	-4.2330

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

Concerning the logarithmic oil spot prices, the equation that is specified best is the one with neither constant nor trend and q=5 lags according to both criteria. The ADF t-statistic is found to be -0.014 with a probability of 0.678, which is larger than the McKinnon value at 1% significant level (-2.568), therefore the oil spot prices at the initial logarithmic levels are non stationary.

As for the returns of the oil spot prices, the best fit equation here is the one with neither constant nor trend and q=5 lags for both criteria. The ADF t-statistic is -11.514 with a probability of 0.000, which is much smaller than the McKinnon value (-2.568), so the returns of the oil spot prices are stationary.

From the analysis above we realise that:

- The oil spot prices in logarithmic levels are non stationary.
- The returns of the oil spot prices are stationary, i.e., it is $roil_t \sim I(0)$.

Considering these results we may conclude that the oil spot prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(oil_t) \sim I(1)$.

4.2.8 Oil futures

Applying the ADF test for the logs and the returns of the oil futures prices, the following table is derived:

Table 4.2.8: ADF test for the logs and the returns of the oil futures prices

Lags	Stats	log($oilf_t$)			$roilf_t$		
		none	constant	constant & trend	None	constant	constant & trend
q=5	AIC	-4.1885*!	-4.1881*	-4.1869*	-4.1874*!	-4.1846*	-4.1834*
	SC	-4.1504*!	-4.1436*	-4.1361*	-4.1492*!	-4.1401*	-4.1325*
		[-0.077]			[-11.489]		
		(0.657)			(0.000)		
	AIC	-4.1753!	-4.1748	-4.1735	-4.1752!	-4.1724	-4.1715
q=10	SC	-4.1051!	-4.0981	-4.0905	-4.1049!	-4.0957	-4.0884
	AIC	-4.1580!	-4.1578	-4.1569	-4.1586!	-4.1558	-4.1548
q=15	SC	-4.0553!	-4.0487	-4.0413	-4.0557!	-4.0465	-4.0390

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

Table 4.2.8 shows that for the logarithmic oil futures prices the equation that is specified best is the one with neither constant nor trend and q=5 lags for both criteria. The ADF t-statistic is -0.077 with a probability of 0.657 and the McKinnon value is -2.568, hence the oil spot prices at the initial logarithmic levels are non stationary.

Regarding the returns of the oil futures prices, the best fit equation is the one with neither constant nor trend and q=5 lags for both criteria. The ADF t-statistic is -11.489 with a probability of 0.000 and the McKinnon test critical value is -2.568, so the returns of the oil spot prices are stationary.

The analysis above demonstrates that the oil spot prices in logarithmic levels are non stationary and the returns of the oil spot prices are stationary, i.e., it is $roil_t \sim I(0)$. Considering these results we may conclude that the oil futures prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(oilf_t) \sim I(1)$.

4.2.9 Coal futures

The results for the logs and the returns of the coal futures prices, are displayed below:

Table 4.2.9: ADF test for the logs and the returns of the coal futures prices

Lags	Stats	$\log(cf_t)$			rcf_t		
		none	constant	constant & trend	none	constant	constant & trend
q=5	AIC	-5.318*	-5.319*!	-5.316*	-5.319*!	-5.316*	-5.314*
	SC	-5.280*!	-5.274*	-5.266*	-5.281*!	-5.278*	-5.263*
		[0.102]	[-1.628]		[-9.636]		
		(0.715)	(0.468)		(0.000)		
	AIC	-5.310	-5.312!	-5.309	-5.314!	-5.311	-5.308
q=10	SC	-5.240!	-5.235	-5.226	-5.243!	-5.234	-5.225
	AIC	-5.302	-5.303!	-5.301	-5.301!	-5.298	-5.295
q=15	SC	-5.199!	-5.194	-5.185	-5.198!	-5.189	-5.1795

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

For the logarithmic coal futures prices:

- According to the AIC criterion, the best fit equation is provided when we include constant and q=5 lags. The ADF t-statistic for the above fit is -1.628 with a probability of 0.468, and the McKinnon value is -3.439. Therefore, the coal futures prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the equation that is specified best is the one with neither constant nor trend and q=5 lags. The ADF t-statistic here is 0.102 with a probability of 0.715. The McKinnon value is -2.568, so the coal futures prices at the initial logarithmic levels are non stationary.

For the returns of the coal futures prices, the best fit equation is the one with neither constant nor trend and q=5 lags for both criteria. The ADF t-statistic is -9.636 with a probability of 0.000, which is greater than the McKinnon test critical value at 1% significant level (-2.568) and therefore the returns of the coal futures prices are stationary.

From the above we may conclude that:

- The coal futures prices in logarithmic levels are non stationary.
- The returns of the coal futures prices are stationary, i.e., it is $rcf_t \sim I(0)$.

- The coal futures prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(cf_t) \sim I(1)$.

4.3 ADF Stationarity Tests-European Sectors Indices

4.3.1 Euro Stoxx Automobiles Index

We continue with the stationarity ADF test for the logs and the returns of the automobiles index prices:

Table 4.3.1: ADF test for the logs and the returns of the automobiles index

Lags	Stats	$\log(car_t)$			$rcar_t$		
		none	constant	constant & trend	none	constant	constant & trend
q=5	AIC	-3.943*	-3.945*	-3.947*!	-3.943*!	-3.939*	-3.941*
	SC	-3.905*!	-3.900*	-3.896*	-3.905*!	-3.895*	-3.890*
		[0.103]		[-2.074]	[-13.26]		
		(0.715)		(0.56)	(0.000)		
	AIC	-3.931	-3.932	-3.936!	-3.932!	-3.929	-3.931
q=10	SC	-3.861!	-3.855	-3.853	-3.862!	-3.852	-3.848
	AIC	-3.921	-3.919	-3.924!	-3.9192!	-3.916	-3.9190
q=15	SC	-3.818!	-3.811	-3.809	-3.816!	-3.807	-3.803

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

The results for the logarithmic automobiles index prices demonstrate that:

- According to the AIC criterion, the equation that is specified best is the one with both constant and trend and q=5 lags. The ADF t-statistic for the above fit is -2.074 with a probability of 0.56. The McKinnon value is -3.97 and therefore the automobiles index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the equation that is specified best is the one with neither constant nor trend and q=5 lags. The ADF t-statistic for the above fit is 0.103 with a probability of 0.715. The McKinnon is -2.568, so the automobiles index prices at the initial logarithmic levels are non stationary.

Regarding the returns of the automobiles index prices, the best fit equation is the one with neither constant nor trend and q=5 lags according to both criteria. The ADF t-statistic (-13.26

with a probability of 0.000) is smaller than the McKinnon test critical value at 1% significant level (-2.568), hence the returns of the automobiles index prices are stationary.

From the analysis above we can say that the automobiles index prices in logarithmic levels are non stationary and the returns of the automobiles index prices are stationary, i.e., it is $rcar_t$ ~ I(0). Also, the automobiles index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(car_t)$ ~ I(1).

4.3.2 Euro Stoxx Chemicals Index

The ADF test for the logs and the returns of the chemicals index prices produces the following table:

Table 4.3.2: ADF test for the logs and the returns of the chemicals index

Lags	**Stats**	**$\log(ch_t)$**			**rch_t**		
		none	constant	constant & trend	none	constant	constant & trend
q=5	AIC	-5.1388!	-5.1366	-5.1401	-5.1373!	-5.1348	-5.1363
	SC	-5.1007*!	-5.0921*	-5.0893*	-5.0991*!	-5.0903*	-5.0854*
					[-11.67]		
					(0.000)		
	AIC	-5.1447*	-5.1428*	-5.1473*!	-5.1432*!	-5.1406*	-5.1426*
q=10	SC	-5.0744!	-5.0661	-5.0643	-5.0728!	-5.0638	-5.0594
		[0.448]		[-1.587]	[-0.813]		
		(0.811)		(0.796)	(0.000)		
	AIC	-5.1346	-5.1325	-5.1379!	-5.1332!	-5.1305	-5.1331
q=15	SC	-5.0318!	-5.0233	-5.0223	-5.0303!	-5.0212	-5.0173

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

For the logarithmic chemicals index prices:

- According to the AIC criterion, the equation that is specified best is the one with constant and trend and q=10 lags. The ADF t-statistic for the above fit is -1.587 with a probability of 0.7976. and the McKinnon value is -3.97 and therefore the chemical index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the equation that is specified best is the one with neither constant nor trend and q=5 lags. The ADF t-statistic here is 0.448 with a

probability of 0.811 and the McKinnon value is -2.568, so the chemical index prices at the initial logarithmic levels are non stationary.

Concerning the returns of the chemicals index prices:

- The AIC criterion shows the best fit equation to be the one with neither constant nor trend and q=10 lags. The ADF t-statistic is -8.013 with a probability of 0.000. The McKinnon value is -2.568 and therefore the returns of the chemical index prices are stationary.
- The SC criterion shows the best fit equation to be with neither constant nor trend and q=5 lags. Here, the ADF t-statistic is -11.67 with a probability of 0.000, which is smaller than the McKinnon test critical value at 1% significant level (-2.568), so the returns of the chemical index prices are stationary.

From the analysis above we can argue that: the chemicals index prices in logarithmic levels are non stationary, whereas the returns of the chemicals index prices are stationary, i.e., it is $rch_t \sim I(0)$. This means that the chemicals index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(ch_t) \sim I(1)$.

4.3.3 Euro Stoxx Energy Index

Table 4.3.3 demonstrates the ADF test results for the logs and the returns of the energy index prices:

Table 4.3.3: ADF test for the logs and the returns of the energy index

Lags	**Stats**	**log(en_t)**			**ren_t**		
		none	constant	constant & trend	none	constant	constant & trend
q=5	AIC	-4.9151*	-4.9175*!	-4.9148*	-4.9141*!	-4.9114*	-4.9095*
	SC	-4.877*!	-4.8730*	-4.864*	-4.8759*!	-4.8669*	-4.8586*
		[-0.235]	[-0.193]		[-11.83]		
		(0.602)	(0.32)		(0.000)		
	AIC	-4.911	-4.9136!	-4.9110	-4.912!	-4.9093	-4.9079
q=10	SC	-4.8407!	-4.836960	-4.828	-4.8416!	-4.8326	-4.8248
	AIC	-4.8993	-4.90164!	-4.8994	-4.9001!	-4.8975	-4.8964
q=15	SC	-4.79649!	-4.7924	-4.7838	-4.7972!	-4.7881	-4.7807

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

From the analysis of the logarithmic energy index prices results we can observe that :

- The AIC criterion points to the best fit equation with constant and q=5 lags. The ADF t-statistic is -1.93 with a probability of 0.32. The McKinnon value is -3.439 and therefore the energy index prices at the initial logarithmic levels are non stationary.
- The SC criterion points to the best fit equation with neither constant nor trend and q=5 lags. The ADF t-statistic for the above fit is -0.235 with a probability of 0.602 and the McKinnon value is -2.568, so the energy index prices at the initial logarithmic levels are non stationary.

The analysis of the returns of the energy index prices shows that according to both criteria the best fit equation is the one with neither constant nor trend and q=5 lags. The ADF t-statistic here is -11.83 with a probability of 0.000. The McKinnon test critical value at 1% significant level is -2.568, hence the returns of the energy index prices are stationary.

From the above we may conclude that the energy index prices in logarithmic levels are non stationary and the returns of the energy index prices are stationary, i.e., it is $ren_t \sim I(0)$. This indicates that the energy index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(en_t) \sim I(1)$.

4.3.4 Euro Stoxx Industrials Index

The results for the logs and the returns of the industrials index prices are displayed below:

Table 4.3.4: ADF test for the logs and the returns of the industrials index

Lags	Stats	$\log(ind_t)$			$rind_t$		
		none	constant	constant & trend	none	constant	constant & trend
q=5	AIC	-5.0282*	-5.0262*	-5.0310*!	-5.0268*!	-5.0243*	-5.0266*
	SC	-4.9900*!	-4.9817*	-4.9802*	-4.9887*!	-4.9798*	-4.9758*
		[0.288]		[-1.547]	[-12.076]		
		(0.769)		(0.813)	(0.000)		
	AIC	-5.0146	-5.0127	-5.0185!	-5.0145	-5.0123	-5.0157!
q=10	SC	-4.9443!	-4.9361	-4.9355	-4.9446!	-4.9355	-4.9326
	AIC	-5.0004	-4.9985	-5.0046!	-5.008!	-5.0053	-5.0071
q=15	SC	-4.8977!	-4.8894	-4.8890	-4.9051!	-4.896	-4.8914

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

Concerning the logarithmic industrials index prices, the results show that:

- According to the AIC criterion, the best fit equation is the one with constant and trend and q=5 lags. The ADF t-statistic is -1.547 with a probability of 0.813. The McKinnon value is -3.97 and therefore the industrial index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit equation is the one with neither constant nor trend and q=5 lags. The ADF t-statistic here is 0.288 with a probability of 0.769, which is greater than the McKinnon test critical value at 1% significant level (-2.568), so the industrial index prices at the initial logarithmic levels are non stationary.

Analysing the returns of the industrials index prices, the best fit equation for both criteria is the one with neither constant nor trend and q=5 lags. The ADF t-statistic is -12.076 with a probability of 0.000. The McKinnon test critical value at 1% significant level is -2.568 and therefore the returns of the industrial index prices are stationary.

From the analysis above we may conclude as follows:

- The industrial index prices in logarithmic levels are non stationary.
- The returns of the industrial index prices are stationary, i.e., it is $rind_t \sim I(0)$.
- The industrials index prices in logarithmic levels include a unit root, or this variable is said to be integrated of order one, i.e., $\log(ind_t) \sim I(1)$.

4.3.5 Euro Stoxx Construction Index

Applying the ADF test for the logs and the returns of the construction index prices, the following table is derived:

Table 4.3.5: ADF test for the logs and the returns of the construction index

Lags	Stats	log($const_t$)			$rconst_t$		
		none	constant	constant & trend	none	constant	constant & trend
q=5	AIC	-4.7334*	-4.7362*	-4.7365*!	-4.7319*!	-4.7293*	-4.7294*
	SC	-4.6953*!	-4.6918*	-4.6857*	-4.6938*!	-4.6848*	-4.6785*
		[-0.393]		[-2.047]	[-11.625]		
		(0.542)		(0.574)	(0.000)		
	AIC	-4.7184	-4.7220	-4.7231!	-4.7186!	-4.7160	-4.7170
q=10	SC	-4.6481!	-4.6454	-4.6401	-4.6482!	-4.6393	-4.6339
	AIC	-4.7038	-4.7068	-4.7083!	-4.7104!	-4.7078	-4.70798
q=15	SC	-4.6010!	-4.5976	-4.5927	-4.6075!	-4.5984	-4.5922

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

The results for the logarithmic construction index prices demonstrate that:

- For the AIC criterion, the equation that is specified best is the one with constant and trend and q=5 lags. The ADF t-statistic for the above fit is -2.047 with a probability of 0.574. The McKinnon value is -3.97, thus the construction index prices at the initial logarithmic levels are non stationary.
- For the SC criterion, the best fit equation is the one with neither constant nor trend and q=5 lags. The ADF t-statistic is 0.393 with a probability of 0.542. The McKinnon value is -2.568 and therefore the construction index prices at the initial logarithmic levels are non stationary.

The results for the returns of the construction index prices reveal that for both criteria the best fit equation is the one with neither constant nor trend and q=5 lags. The ADF t-statistic for the above fit is -11.625 with a probability of 0.000. The McKinnon value is -2.568, so the returns of the construction index prices are stationary.

From the analysis above we realise that:

- The construction index prices in logarithmic levels are non stationary.
- The returns of the construction index prices are stationary, i.e., it is $rconst_t \sim I(0)$.
- The construction index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(const_t) \sim I(1)$.

4.3.6 Euro Stoxx Basic Resources Index

The ADF test for the logs and the returns of the basic resources index prices generates the following table:

Table 4.3.6: ADF test for the logs and the returns of the basic resources index

Lags	Stats	log(basres$_t$)			rbasres$_t$		
		none	constant	constant & trend	none	constant	constant & trend
q=5	AIC	-3.9309*	-3.9301*	-3.9319*!	-3.9315*!	-3.9287*	-3.9301*
	SC	-3.8928*!	-3.8857*	-3.8810*	-3.8934*!	-3.8842*	-3.8793*
		[-0.077]		[-1.388]	[-12.39]		
		(0.657)		(0.864)	(0.000)		
	AIC	-3.9173	-3.9169	-3.9192!	-3.9191!	-3.9163	-3.9184
q=10	SC	-3.8470!	-3.8403	-3.8361	-3.8487!	-3.8396	-3.8352
	AIC	-3.9019	-3.9015	-3.9059!	-3.9123!	-3.9095	-3.9118
q=15	SC	-3.7992!	-3.7923	-3.7903	-3.8095!	-3.8002	-3.7961

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

For the logarithmic basic resources index prices:

- The AIC criterion confirms that the best fit equation is the one with constant and trend and q=5 lags. The ADF t-statistic is -1.388 with a probability of 0.864 and the McKinnon test critical value at 1% significant level is -3.97 and therefore the basic resources index prices at the initial logarithmic levels are non stationary.
- The SC criterion shows that the equation that is specified best is the one with neither constant nor trend and q=5 lags. The ADF t-statistic for the above fit is 0.077 with a probability of 0.657. The McKinnon value is -2.568, so the basic resources index prices at the initial logarithmic levels are non stationary.

Regarding the returns of the basic resources index prices the best fit equation for both criteria is the one with neither constant nor trend and q=5 lags. The ADF t-statistic is -12.39 with a probability of 0.000 and the McKinnon value is -2.568 and therefore the returns of the basic resources index prices are stationary.

The analysis above indicates that:

- The basic resources index prices in logarithmic levels are non stationary.
- The returns of the basic resources index prices are stationary, i.e., it is $rcf_t \sim I(0)$.
- The basic resources index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(basres_t) \sim I(1)$.

4.3.7 Euro Stoxx Technology Index

Applying the ADF test for the logs and the returns of the technology index prices, table 4.3.7 is obtained:

Table 4.3.7: ADF test for the logs and the returns of the technology index

Lags	Stats	log($tech_t$)			$rtech_t$		
		none	constant	constant & trend	none	constant	constant & trend
q=5	AIC	-5.0712	-5.0732!	-5.0722	-5.0749!	-5.0722	-5.0718
	SC	-5.0331*	-5.0288*!	-5.0214*	-5.0368*!	-5.0277*	-5.0209*
			[-1.859]		[-11.77]		
			(0.352)		(0.000)		
q=10	AIC	-5.0791*	-5.082*	-5.0820*!	-5.0776*!	-5.0749*	-5.0754*
	SC	-5.0088!	-5.0053	-4.999	-5.0072!	-4.9982	-4.9922
				[-1.938]	[-0.824]		
				(0.633)	(0.000)		
q=15	AIC	-5.0695	-5.0718	-5.0720!	-5.076!	-5.0732	-5.0731
	SC	-4.9667!	-4.9626	-4.9564	-4.9731!	-4.9639	-4.9573

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

The analysis for the logarithmic technology index prices confirms that:

- According to the AIC criterion, the equation that is specified best is the one with constant and trend and q=10 lags. The ADF t-statistic for the above fit is -1.938 with a probability of 0.633. The McKinnon test critical value at 1% significant level is -3.97 and therefore the technology index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit equation includes a constant and q=5 lags. The ADF t-statistic here is -1.859 with a probability of 0.352. The McKinnon value is

-3.439, so the technology index prices at the initial logarithmic levels are non stationary.

Continuing with the analysis for the returns of the technology index prices we have two best fit solutions for each criterion:

- Regarding the AIC criterion, the best fit equation is the one with neither constant nor trend and q=10 lags. The ADF t-statistic is -8.24 with a probability of 0.000 and the McKinnon test critical value at 1% significant level is -2.568 and therefore the returns of the technology index prices are stationary.
- Regarding the SC criterion, the best fit equation does not include neither constant nor trend and is with q=5 lags. The ADF t-statistic for the above fit is -11.77 with a probability of 0.000. The McKinnon value is -2.568 and therefore the returns of the technology index prices are stationary.

The analysis above shows that:

- The technology index prices in logarithmic levels are non stationary.
- The returns of the technology index prices are stationary, i.e., it is $rtech_t \sim I(0)$.
- The technology index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(tech_t) \sim I(1)$.

4.3.8 Eurofirst300 utilities

The ADF test results for the logs and the returns of the utilities index prices are displayed in Table 4.3.8 below:

Table 4.3.8: ADF test for the logs and the returns of the utilities index

Lags	Stats	log(util300$_t$)			rutil300$_t$		
		none	constant	constant & trend	None	constant	constant & trend
q=5	AIC	-5.2753*!	-5.2783*	-5.2758*	-5.2739*!	-5.2725*	-5.2712*
	SC	-5.2371*!	-5.2338*	-5.2249*	-5.2357*!	-5.228*	-5.2203*
		[-1.033]			[-11.703]		
		(0.272)			(0.000)		
	AIC	-5.2682	-5.2714!	-5.2687	-5.2665!	-5.2656	-5.26512
q=10	SC	-5.1979!	-5.1948	-5.1856	-5.1961!	-5.1888	-5.1820
	AIC	-5.2640	-5.2677!	-5.2650	-5.2621!	-5.2608	-5.2599
q=15	SC	-5.1613!	-5.1585	-5.1494	-5.1592!	-5.1515	-5.1442

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

Concerning the logarithmic utilities index prices, the equation that is specified best is the one with neither constant nor trend and q=5 lags for both criteria. The ADF t-statistic for the above fit is -1.033 with a probability of 0.272. The McKinnon test critical value at 1% significant level is -2.568 and therefore the utilities index prices at the initial logarithmic levels are non stationary.

As for the returns of the utilities index prices, the best fit equation is the one with neither constant nor trend and q=5 lags according to both criteria. The ADF t-statistic fit is -11.703 with a probability of 0.000 and the McKinnon value is -2.568, hence the returns of the utilities index prices are stationary.

From the above we may conclude as follows:

- The utilities index prices in logarithmic levels are non stationary.
- The returns of the utilities index prices are stationary, i.e., it is rutil300$_t$ ~ I(0).
- The utilities index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., log(util300$_t$) ~ I(1).

4.3.9 Eurofirst300 oil and gas

Applying the ADF test for the logs and the returns of the oil & gas index prices, the following table is derived:

Table 4.3.9: ADF test for the logs and the returns of the oil & gas index

Lags	Stats	log(og300$_t$)			rog300$_t$		
		none	constant	constant & trend	None	constant	constant & trend
q=5	AIC	-4.9625*!	-4.9655*	-4.9627*	-4.9613!	-4.9585	-4.9564
	SC	-4.9244*!	-4.9210*	-4.9119*	-4.9231*!	-4.9140*	-4.9055*
		[-0.148]			[-11.729]		
		(0.632)			(0.000)		
	AIC	-4.9606	-4.9637!	-4.9609	-4.962*!	-4.9592*	-4.9575*
q=10	SC	-4.8903!	-4.8870	-4.8779	-4.8916!	-4.8825	-4.8744
					[-9.05]		
					(0.000)		
	AIC	-4.9517	-4.9541!	-4.9517	-4.952	-4.9493	-4.9479
q=15	SC	-4.8489!	-4.8449	-4.8360	-4.8491	-4.8399	-4.8322

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

For the logarithmic oil & gas index prices, the equation that is specified best is the one with neither constant nor trend and q=5 lags for both criteria. The ADF t-statistic for the above fit is -0.148 with a probability of 0.632. The McKinnon value is -2.568, so the oil & gas index prices at the initial logarithmic levels are non stationary.

For the returns of the oil & gas index prices:

- According to the AIC criterion the best fit equation is the one with neither constant or trend and q=10 lags. The ADF t-statistic here is -9.05 with a probability of 0.000, which is smaller than the McKinnon test critical value at 1% significant level (-2.568) and therefore the returns of the oil & gas index prices are stationary.
- According to the SC criterion the best fit equation is the one with neither constant or trend and q=5 lags. The ADF t-statistic for the above fit is -11.729 with a probability of 0.000 and the McKinnon value is found to be -2.568, so the returns of the oil & gas index prices are stationary

The analysis confirms that:

- The oil & gas index prices in logarithmic levels are non stationary.
- The returns of the oil & gas index prices are stationary, i.e., it is rog300$_t$ ~ I(0).

- The oil & gas index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(og300_t) \sim I(1)$.

4.3.10 Eurofirst300 basic materials

Table 4.3.10 demonstrates the ADF test results for the logs and the returns of the basic materials index prices:

Table 4.3.10: ADF test for the logs and the returns of the basic materials index

Lags	Stats	log(basmat300$_t$)			rbasmat300$_t$		
		none	constant	constant & trend	None	constant	constant & trend
q=5	AIC	-4.407*	-4.4058*	-4.4079*!	-4.4066*!	-4.4038*	-4.4055*
	SC	-4.3688*!	-4.3614*	-4.3571*	-4.3684*!	-4.3593*	-4.3546*
		[0.02]		[-1.31]	[-12.133]		
		(0.689)		(0.885)	(0.000)		
	AIC	-4.3956	-4.3950	-4.3975!	-4.3965!	-4.3937	-4.396
q=10	SC	-4.3253!	-4.3184	-4.3145	-4.3262	-4.3170	-4.3128
	AIC	-4.3799	-4.3793	-4.3836!	-4.3854!	-4.3826	-4.3849
q=15	SC	-4.2772!	-4.2701	-4.2680	-4.2825!	-4.2733	-4.2692

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

The analysis for the logarithmic basic materials index prices proves that:

- According to the AIC criterion, the best fit equation includes both constant and trend and q=5 lags. The ADF t-statistic is -1.31 with a probability of 0.885. The McKinnon value is -3.97 and therefore the basic materials index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit equation is the one with neither constant nor trend and q=5 lags. The ADF t-statistic for the above fit is 0.02 with a probability of 0.689, which is smaller than the McKinnon value (-2.568) and so the basic materials index prices at the initial logarithmic levels are non stationary.

As for the analysis for the returns of the basic materials index prices, the best fit equation here is the one with neither constant nor trend and q=5 lags. The ADF t-statistic is -12.133

with a probability of 0.000 and the McKinnon value is -2.568, so the returns of the basic materials index prices are stationary.

From the above we may conclude that the basic materials index prices in logarithmic levels are non stationary, whereas the returns of the basic materials index prices are stationary, i.e., it is $rbasmat300_t \sim I(0)$. Also, the basic materials index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(basmat300_t) \sim I(1)$.

4.3.11 Eurofirst300 Industrials

Applying the ADF test for the logs and the returns of industrials (300) index prices, table 4.3.11 is produced:

Table 4.3.11: ADF test for the logs and the returns of the industrials (300) index

Lags	**Stats**	**log(ind300$_t$)**			**rind300$_t$**		
		none	constant	constant & trend	None	constant	constant & trend
q=5	AIC	-4.8858*	-4.8853*	-4.8883*!	-4.8845*!	-4.8817*	-4.8832*
	SC	-4.8477*!	-4.8409*	-4.8374*	-4.8463*!	-4.8372*	-4.8323*
		[-0.018]		[-1.646]	[-12.049]		
		(0.677)		(0.774)	(0.000)		
	AIC	-4.8707	-4.8707	-4.8744!	-4.8704!	-4.8676	-4.8700
q=10	SC	-4.8005!	-4.7940	-4.7913	-4.8000!	-4.7909	-4.7869
	AIC	-4.8560	-4.8559	-4.8599!	-4.8650!	-4.8622	-4.8633
q=15	SC	-4.7533!	-4.7467	-4.7443	-4.7621!	-4.7529	-4.7476

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

We get two best fit solutions for the logarithmic industrials (300) index prices:

- According to the AIC criterion, the equation that is specified best involves constant and trend and q=5 lags. The ADF t-statistic for the above fit is -1.65 with a probability of 0.774. The McKinnon test critical value at 1% significant level is -3.97 and therefore the industrials (300) index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the equation that is specified best is the one with neither constant nor trend and q=5 lags. The ADF t-statistic for the above fit is -0.018

with a probability of 0.677. The McKinnon test critical value at 1% significant level is -2.568 and therefore the industrials (300) index prices at the initial logarithmic levels are non stationary.

Concerning the returns of the industrials (300) index prices, the best fit equation is the one with neither constant nor trend and q=5 lags according to both criteria. The ADF t-statistic is -12.05 with a probability of 0.000. The McKinnon value is -2.568 and therefore the returns of the industrials (300) index prices are stationary.

We may conclude that the industrials (300) index prices in logarithmic levels are non stationary and the returns of the industrials (300) index prices are stationary, i.e., it is $rind300_t \sim I(0)$. This means that the industrials (300) index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(ind300_t) \sim I(1)$.

4.4 ADF Tests for general economy indices

4.4.1 Standard & Poor's Europe 350 index

Table 4.3.12 contains the ADF test results for the logs and the returns of the Standard & Poors index prices:

Table 4.3.12: ADF test for the logs and the returns of the Standards & Poors index

Lags	Stats	$\log(sp350_t)$			$rsp350_t$		
		none	constant	constant & trend	None	constant	constant & trend
q=5	AIC	-5.3210*	-5.3219*	-5.3227*!	-5.3202*!	-5.3175*	-5.3183*
	SC	-5.2829*!	-5.2775*	-5.2719*	-5.282*!	-5.273*	-5.2674*
		[-0.322]		[-1.659]	[-11.93]		
		(0.57)		(0.769)	(0.000)		
	AIC	-5.3134	-5.3151	-5.3167!	-5.3143!	-5.3117	-5.3136
q=10	SC	-5.2431!	-5.2384	-5.2337	-5.2439!	-5.234	-5.2305
	AIC	-5.3033	-5.3045	-5.3072!	-5.3065!	-5.3038	-5.3053
q=15	SC	-5.2006!	-5.1954	-5.1916	-5.2036!	-5.1945	-5.1895

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

The analysis for the logarithmic S & P 350 index prices shows that:

- For the AIC criterion, the best fit is the one with constant and trend and q=5 lags. The ADF t-statistic is -1.659 with a probability of 0.769, which is greater than the McKinnon value at 1% significant level (-3.97), therefore the S & P 350 index prices at the initial logarithmic levels are non stationary.
- For the SC criterion, the best fit comes with neither constant nor trend and q=5 lags. The ADF t-statistic here is -0.322 with a probability of 0.57and the McKinnon value is -2.568, therefore the S & P 350 index prices at the initial logarithmic levels are non stationary.

The analysis for the returns of the S & P 350 index prices proves that according to both the AIC and the SC criteria the best fit is the one with neither constant nor trend and q=5 lags. The ADF t-statistic for the above fit is -11.93 with a probability of 0.000. The McKinnon test critical value at 1% significant level is -2.568, so the returns of the S & P 350 index prices are stationary.

From the above, we may conclude as follows:

- The S & P 350 index prices in logarithmic levels are non stationary.
- The returns of the S & P 350 index prices are stationary, i.e., it is $rsp350_t \sim I(0)$.
- The Standard & Poors 350 index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(sp350_t) \sim I(1)$.

4.4.2 DAX index

Applying the ADF test for the logs and the returns of the DAX index prices, we get the following table:

Table 4.3.13: ADF test for the logs and the returns of the DAX index prices

Lags	Stats	log(dax_t)			$rdax_t$		
		none	Constant	constant & trend	None	constant	constant & trend
q=5	AIC	-5.1969*	-5.1964*	-5.1981*!	-5.1997*!	-5.1969*	-5.1967*
	SC	-5.1588*!	-5.152*	-5.1473*	-5.1615*!	-5.1524*	-5.1458*
		[0.097]		[-1.67]	[-10.549]		
		(0.713)		(0.764)	(0.000)		
	AIC	-5.1941	-5.194	-5.1964!	-5.1927!	-5.1899	-5.1906
q=10	SC	-5.1238!	-5.1173	-5.1134	-5.1224!	-5.1132	-5.1075
	AIC	-5.1833	-5.1825	-5.1858!	-5.1845!	-5.1817	-5.1825
q=15	SC	-5.0806!	-5.0733	-5.0701	-5.0816!	-5.0724	-5.0668

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

In Table 4.3.13, the analysis for the logarithmic DAX index prices indicates the following:

- According to the AIC criterion, the best fit includes both constant and trend and q=5 lags. The ADF t-statistic here is -1.67 with a probability of 0.764 and the McKinnon value is found to be -3.97, hence the DAX index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit is the one with neither constant nor trend and q=5 lags. The ADF t-statistic for the above fit is 0.097 with a probability of 0.713 and the McKinnon test critical value at 1% significant level is -2.568 and therefore the DAX index prices at the initial logarithmic levels are non stationary.

The analysis for the returns of the DAX index prices specifies that the best fit equation is the one with neither constant nor trend and q=5 lags for both criteria. The ADF t-statistic is -10.55 with a probability of 0.000 and the McKinnon test critical value at 1% significant level is -2.568, so the returns of the DAX index prices are stationary.

From the analysis above we may conclude that The DAX index prices in logarithmic levels are non stationary, whereas their returns are stationary, i.e., it is $rdax_t \sim I(0)$. We can also observe that the DAX index prices in logarithmic levels include a unit root, or this variable is said to be integrated of order one, i.e., $\log(dax_t) \sim I(1)$.

4.4.3 Ftseurofirst300

By applying the ADF test for the logs and the returns of ftseurofirst300 index prices we obtain the following results:

Table 4.3.14: ADF test for the logs and the returns of the Ftseurofirst300 index prices

Lags	Stats	log(ftse300$_t$)			rftse300$_t$		
		none	constant	constant & trend	None	constant	constant & trend
q=5	AIC	-5.3134*	-5.3145*	-5.3151*!	-5.3136*!	-5.3109*	-5.3117*
	SC	-5.2754*!	-5.2701*	-5.2642*	-5.2754*!	-5.2664*	-5.2609*
		[-0.338]		[-1.65]	[-11.849]		
		(0.563)		(0.78)	(0.000)		
	AIC	-5.3092	-5.311	-5.3124!	-5.3093!	-5.3068	-5.3088
q=10	SC	-5.239!	-5.2343	-5.2294	-5.239!	-5.2300	-5.2256
	AIC	-5.2991	-5.3004	-5.3030!	-5.3071!	-5.3045	-5.3059
q=15	SC	-5.1964!	-5.1912	-5.1874	-5.2042!	-5.1952	-5.1901

Note: ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation.

We have two best fit solutions for the logarithmic ftseurofirst300 index prices:

- According to the AIC criterion, the best fit comes with constant and trend and q=5 lags. The ADF t-statistic is -1.65 with a probability of 0.78. The McKinnon value is found to be -3.97, therefore the ftseurofirst300 index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit includes neither constant nor trend and q=5 lags. The ADF t-statistic for the above fit is -0.338 with a probability of 0.563 and the McKinnon value is -2.568, so the ftseurofirst300 index prices at the initial logarithmic levels are non stationary.

Regarding the analysis for the returns of the ftseurofirst300 index prices, the best fit involves neither constant nor trend and q=5 lags. The ADF t-statistic is -11.849 with a probability of 0.000 and the McKinnon value is -2.568, hence the returns of the ftseurofirst300 index prices are stationary.

From the analysis above we may conclude as follows:

- The ftseurofirst300 index prices in logarithmic levels are non stationary.
- The returns of the ftseurofirst300 index prices are stationary, i.e., it is $rftse300_t \sim I(0)$.
- The Ftseurofirst300 index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(ftse300_t) \sim I(1)$.

4.5 Testing with Phillips-Perron test- Energy

4.5.1 EUA emission spot prices

We carry on with the stationarity tests by applying the PP test for the logs and the returns of the emission spot prices. The analysis of the results is very similar to the one of the ADF test, however we use a standard number of lags, as this is provided in the PP tests in EViews 4.1. Again, we choose the best fit according to the values of the AIC and SC criteria and all the tables listed in this section have been derived accordingly.

Table 4.5.1 PP test for the logs and the returns of the emission spot prices

Stats	**$\log(es_t)$**			**res_t**		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-4.5203	-4.5209! [-1.691] (0.435)	-4.5184	-4.5266!	-4.5244	-4.5220
SC	-4.5140! [-0.794] (0.372)	-4.5083	-4.4995	-4.5203! [-24.470] (0.000)	-4.5117	-4.5030

Note:**!** is for the horizontal best fit representation.

Table 4.5.1 demonstrates the results for the logarithmic spot prices, where we can observe that:

- According to the AIC criterion, the best fit includes constant. The adjusted t-statistic for the above fit is -1.691 with a probability of 0.435 and the McKinnon test critical value at 1% significant level is -3.439, and therefore the spot prices at the initial logarithmic levels are non stationary.

- According to the SC criterion, the best fit comes with neither constant nor trend and q=5 lags. The adjusted t-statistic here is -0.794 with a probability of 0.372. The McKinnon test critical value at 1% significant level is -2.568, so the spot prices at the initial logarithmic levels are non stationary.

Concerning the returns of the emission spot prices, the best fit has neither constant nor trend according to both criteria. The adjusted t-statistic is -24.470 with a probability of 0.000, which is much greater than the McKinnon value (-2.568), therefore the returns of the spot prices are stationary.

The analysis above points to the following conclusions:

- The emission spot prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.
- The returns of the emission spot prices are stationary, i.e., it is $res_t \sim I(0)$.
- The emission spot prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(es_t) \sim I(1)$

4.5.2 Emission futures

The PP test results for the logs and the returns of the emission futures prices are displayed in Table 4.5.2:

Table 4.5.2 PP test for the logs and the returns of the emissions futures prices

Stats	**log(ef_t)**			**ref_t**		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-4.778!	-4.777	-4.775	-4.790!	-4.788	-4.785
SC	-4.772!	-4.765	-4.756	-4.784!	-4.775	-4.766
	[-0.97]			[-23.76]		
	(0.297)			(0.000)		

Note:**!** is for the horizontal best fit representation.

Regarding the logarithmic emission futures prices, the best fit is the one with neither constant nor trend. The adjusted t-statistic is -0.97 with a probability of 0.297. The McKinnon value is -2.568, therefore the futures prices at the initial logarithmic levels are non stationary.

Considering the returns of the emission futures prices, the best fit has neither constant nor trend. The adjusted t-statistic for the above fit is -23.76 with a probability of 0.000 and the McKinnon value is -2.568, therefore the returns of the futures prices are stationary.

From the analysis above we may conclude as follows:

- The emission futures prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.
- The returns of the emission spot prices are stationary, i.e., it is $ref_t \sim I(0)$.
- The emission futures prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $Log(ef_t) \sim I(1)$

4.5.3 Gas spots

Applying the PP test for the logs and the returns of the gas spot prices, the Table 4.5.3 is derived:

Table 4.5.3 PP test for the logs and the returns of the gas spot prices

Stats	**$log(gs_t)$**			**rgs_t**		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-3.136	-3.137!	-3.134	-3.134!	-3.132	-3.130
SC	-3.129!	-3.124	-3.116	-3.128!	-3.119	-3.111
	[-0.142]	[-1.653]		[-27.13]		
	(0.634)	(0.455)		(0.000)		

Note:**!** is for the horizontal best fit representation.

Here, for the logarithmic gas spot prices we have two best fit solutions:

- According to the AIC criterion, the best fit involves a constant. The adjusted t-statistic is -1.653 with a probability of 0.455. The McKinnon value is -3.439, so the gas spot prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit has neither constant nor trend. The adjusted t-statistic is -0.142 with a probability of 0.634 and the McKinnon value is -2.568, so the gas spot prices at the initial logarithmic levels are non stationary.

As for the returns, the best fit equation is the one with neither constant nor trend for both criteria. The adjusted t-statistic for the above fit is -27.13 with a probability of 0.000 and the McKinnon value is -2.568, therefore the returns of the gas spot prices are stationary.

The analysis above shows that the gas spot prices in logarithmic levels are non-stationary for both the AIC and the SC criteria, whereas their returns are stationary, i.e., it is $rgs_t \sim I(0)$. Therefore, the gas spot prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(gs_t) \sim I(1)$.

4.5.4 Gas futures

Applying the PP test for the logs and the returns of the gas futures prices, the Table 4.5.4 is derived:

Table 4.5.4 PP test for the logs and the returns of the gas futures prices

Stats	**$\log(gf_t)$**			**rgf_t**		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-5.566!	-5.5645	-5.564	-5.564!	-5.561	-5.559
SC	-5.559!	-5.552	-5.545	-5.558!	-5.549	-5.540
	[-0.237]			[-27.04]		
	(0.601)			(0.000)		

Note:**!** is for the horizontal best fit representation.

According to both the AIC and the SC criteria, the best fit for the gas futures logarithms has neither constant or trend. The adjusted t-statistic for the above fit is -0.237 with a probability of 0.601. The McKinnon value is -2.568, and therefore the gas futures prices at the initial logarithmic levels are non stationary.

The best fit equation for the returns includes neither constant nor trend, again according to both criteria. The adjusted t-statistic is -27.04 with a probability of 0.000. The McKinnon value is -2.568, and therefore the returns of the gas futures prices are stationary.

From the analysis above we may conclude as follows:

- The gas futures prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.

- The returns of the gas futures prices are stationary, i.e., it is $rgf_t \sim I(0)$.
- The gas futures prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(gf_t) \sim I(1)$

4.5.5 Electricity spots

Applying the PP test for the logs and the returns of the electricity spot prices, the Table 4.5.5 is derived:

Table 4.5.5 PP test for the logs and the returns of the electricity spot prices

Stats	**$\log(els_t)$**			**$rels_t$**		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-0.703	-0.770	-0.784!	-0.808!	-0.805	-0.802
SC	-0.697	-0.758	-0.765!	-0.801!	-0.792	-0.783
			[-8.63]	[-61.527]		
			(0.000)	(0.001)		

Note:**!** is for the horizontal best fit representation.

According to both the AIC and the SC criteria, the best fit for the logarithmic electricity spot prices contains constant and trend. The adjusted t-statistic is -8.63 with a probability of 0.000 and the McKinnon value is -3.97, therefore the electricity spot prices at the initial logarithmic levels are stationary. Concerning their returns, the best fit equation comes with neither constant nor trend and q=15 lags. The adjusted t-statistic for the above fit is -61.527 with a probability of 0.000, which is much smaller than the McKinnon test critical value at 1% significant level (-2.568), therefore the returns of the electricity spot prices are stationary.

The analysis above shows that the electricity spot prices in logarithmic levels and their returns are stationary, i.e., it is $res_t \sim I(0)$.

Considering the results above we may conclude that the electricity spot prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(els_t) \sim I(1)$.

4.5.6 Electricity futures

Table 4.5.6 includes the PP test results for the logs and the returns of the electricity futures prices:

Table 4.5.6 PP test for the logs and the returns of the electricity futures prices

Stats	log(elf_t)			$relf_t$		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-6.080	-6.079	-6.081!	-6.081!	-6.078	-6.076
SC	-6.074!	-6.066	-6.062	-6.074!	-6.066	-6.057
	[-0.46]		[-2.363]	[-26.038]		
	(0.516)		(0.399)	(0.000)		

Note:**!** is for the horizontal best fit representation.

Concerning the logarithmic electricity futures prices, we have two best fit equations:

- According to the AIC criterion, the best fit equation has both constant and trend. The adjusted t-statistic is -2.363 with a probability of 0.399. The McKinnon value is -3.97, so the electricity futures prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit equation has neither constant nor trend and q=5 lags. The adjusted t-statistic here is -0.46 with a probability of 0.516 and the McKinnon value is -2.568, therefore the electricity futures prices at the initial logarithmic levels are non stationary.

As for their returns, the best fit equation is the one with neither constant nor trend for both criteria. The adjusted t-statistic for the above fit is -26.038 with a probability of 0.000, which is smaller than the McKinnon value (-2.568), so the returns of the electricity futures prices are stationary.

The analysis for the electricity futures prices shows that they appear to be non-stationary in their logarithmic levels for both the AIC and the SC criteria. On the contrary, their returns are stationary, i.e., it is $relf_t \sim I(0)$. This indicates that the electricity futures prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(elf_t) \sim I(1)$.

4.5.7 Oil spots

The PP test for the logs and the returns of the oil spot prices produces Table 4.5.7 below:

Table 4.5.7 PP test for the logs and the returns of the oil spot prices

Stats	$\log(oil_t)$			$roil_t$		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-4.3833!	-4.3828	-4.3817	-4.3823!	-4.3796	-4.3785
SC	-4.3770!	-4.3702	-4.3628	-4.3760!	-4.3670	-4.3595
	[0.024]			[-27.45]		
	(0.690)			(0.000)		

Note:**!** is for the horizontal best fit representation.

Regarding the logarithmic oil spot prices, the best fit contains neither constant nor trend according to both criteria. The adjusted t-statistic is 0.0238 with a probability of 0.69, which is greater than the McKinnon test critical value at 1% significant level (-2.568), therefore the oil spot prices at the initial logarithmic levels are non stationary.

Concerning their returns, the best fit equation is the one with neither constant nor trend. The adjusted t-statistic here is -27.45 with a probability of 0.000. The McKinnon value is -2.568, therefore the returns of the oil spot prices are stationary.

We may conclude that the oil spot prices in logarithmic levels are non-stationary and their returns are stationary, i.e., it is $roil_t \sim I(0)$. Considering these results, oil spot prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(oil_t) \sim I(1)$

4.5.8 Oil futures

The results for the logs and the returns of the oil futures prices can be observed in Table 4.5.8 below:

Table 4.5.8 PP test for the logs and the returns of the oil futures prices

Stats	log($oilf_t$)			$roilf_t$		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-4.1868	-4.1869!	-4.1853	-4.1859!	-4.1831	-4.1815
SC	-4.1805!	-4.1743	-4.1663	-4.1795!	-4.1705	-4.1626
	[-0.042]	[-1.33]		[-27.57]		
	(0.669)	(0.613)		(0.000)		

Note:**!** is for the horizontal best fit representation.

The analysis for the logarithmic oil futures prices reveals two best fit equations:

- According to the AIC criterion, the best fit equation is the one with constant and trend. The adjusted t-statistic is -1.33 with a probability of 0.617 and the McKinnon value is -3.439, hence the oil futures prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit equation has neither constant nor trend. The adjusted t-statistic for the above fit is -0.042 with a probability of 0.669. The McKinnon value is -2.568, so the oil futures prices at the initial logarithmic levels are non stationary.

The analysis for their returns demonstrates than the best fit has neither constant nor trend. The adjusted t-statistic here is -27.57 with a probability of 0.000, which is much smaller than the McKinnon value (-2.568), therefore the returns of the oil futures prices are stationary.

From the analysis above we may conclude that:

- The oil futures prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.
- The returns of the oil futures prices are stationary, i.e., it is $roilf_t \sim I(0)$.
- The oil futures prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(oilf_t) \sim I(1)$.

4.5.9 Coal futures

Applying the PP test for the logs and the returns of the coal futures prices, the Table 4.5.9 is derived:

Table 4.5.9 PP test for the logs and the returns of the coal futures prices

Stats	**log(cf_t)**			**rcf_t**		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-5.3149!	-5.3142	-5.3116	-5.3165!	-5.3138	-5.3111
SC	-5.3086!	-5.3015	-5.2927	-5.3101!	-5.3011	-5.2921
	[0.130]			[-25.974]		
	(0.723)			(0.000)		

Note:**!** is for the horizontal best fit representation.

According to both the AIC and the SC criteria, the best fit equation for the logs of the coal futures is the one with neither constant nor trend. The adjusted t-statistic is 0.13 with a probability of 0.723 and the McKinnon test critical value at 1% significant level is -2.568, and therefore the coal futures prices at the initial logarithmic levels are non stationary.

The best fit equation for their returns appears to have neither constant nor trend according to both criteria. The adjusted t-statistic is -25.974 with a probability of 0.000. The McKinnon value is -2.568, so the returns of the coal futures prices are stationary.

From the analysis above we may conclude as follows:

- The coal futures prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.
- The returns of the coal futures prices are stationary, i.e., it is $rcf_t \sim I(0)$.
- The coal futures prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(cf_t) \sim I(1)$.

4.6 PP Stationarity Tests-European Sectors Indices

4.6.1 Euro Stoxx Automobiles Index

We then apply the PP test to the economic indices, starting with those representing each industrial sector separately. For the logs and the returns of the automobiles index prices, the Table 4.6.1 is derived:

Table 4.6.1 PP test for the logs and the returns of the Automobiles index prices

Stats	log(car_t)			$rcar_t$		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-3.8909	-3.8969	-3.8974!	-3.8896!	-3.8869	-3.8856
SC	-3.8846!	-3.8842	-3.8785	-3.8833!	-3.8742	-3.8666
	[0.203]		[-2.09]	[-30.16]		
	(0.745)		(0.55)	(0.000)		

Note:**!** is for the horizontal best fit representation.

There are two best fit equations for the logarithmic automobiles index prices:

- According to the AIC criterion, the best fit equation is the one with both constant and trend. The adjusted t-statistic is -2.09 with a probability of 0.55. The McKinnon value is -3.97, and therefore the automobiles index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit equation contains neither constant nor trends. The adjusted t-statistic is 0.203 with a probability of 0.745 and the McKinnon value is -3.439, thus the automobiles index prices at the initial logarithmic levels are non stationary.

Considering their returns and according to both the AIC and the SC criteria, the best fit equation is the one with neither constant nor trend and q=15 lags. The adjusted t-statistic for the above fit is -30.16 with a probability of 0.000 and the McKinnon value is -2.568, so the returns of the automobiles index prices are stationary.

The analysis above proves that the automobiles index prices in logarithmic levels are non-stationary for both the AIC and the SC criteria and their returns are stationary, i.e., it is $rcar_t \sim I(0)$. Considering these results, we may conclude that the automobiles index prices in

logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(car_t) \sim I(1)$.

4.6.2 Euro Stoxx Chemicals Index

Applying the PP test for the logs and the returns of the chemicals index prices, we get the table below:

Table 4.6.2 PP test for the logs and the returns of the Chemicals index prices

Stats	**$\log(ch_t)$**			**rch_t**		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-5.1409!	-5.1391	-5.1408	-5.1394!	-5.137	-5.1368
SC	-5.1346!	-5.1265	-5.1219	-5.1331!	-5.1243	-5.1179
	[0.503]			[-27.33]		
	(0.824)			(0.000)		

Note:**!** is for the horizontal best fit representation.

Considering the logarithmic chemicals index prices:

- Both the AIC and SC criteria indicate that the best fit has neither constant nor trend. The adjusted t-statistic for the above fit is 0.503 with a probability of 0.824. The McKinnon value is -2.568, therefore the chemicals index prices at the initial logarithmic levels are non stationary.

Regarding their returns:

- According to the AIC and the SC criteria, the equation that is specified best is the one with neither constant nor trend and q=15 lags. The adjusted t-statistic for the above fit is -27.33 with a probability of 0.000. The McKinnon value is -2.568, and therefore the returns of the chemicals index prices are stationary.

From the analysis above we may conclude the following:

- The chemicals index prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.
- The returns of the chemicals index prices are stationary, i.e., it is $rch_t \sim I(0)$.

- The chemicals index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(ch_t) \sim I(1)$.

4.6.3 Euro Stoxx Energy Index

Continuing with the energy index prices, the Table 4.6.3 is derived:

Table 4.6.3 PP test for the logs and the returns of the Energy index prices

Stats	**$\log(en_t)$**			**ren_t**		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-4.8985	-4.9024!	-4.8996	-4.8993!	-4.8965	-4.8942
SC	-4.8922!	-4.8897	-4.8807	-4.8929!	-4.8839	-4.8752
	[-0.168]	[-1.97]		[-28.58]		
	(0.625)	(0.3)		(0.000)		

Note:**!** is for the horizontal best fit representation.

For the logarithmic energy prices:

- According to the AIC criterion, the best fit equation is the one with constant. The adjusted t-statistic is -1.97 with a probability of 0.3 and the McKinnon value is -3.439, and therefore the energy index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit equation contains neither constant nor trend. The adjusted t-statistic here is -0.168 with a probability of 0.625 and the McKinnon value is -2.568, and therefore the energy index prices at the initial logarithmic levels are non stationary.

For the returns of the energy index prices:

- According to the AIC and the SC criterion, the best fit equation is the one with neither constant nor trend. The adjusted t-statistic for the above fit is -28.58 with a probability of 0.000, which is smaller than the McKinnon test critical value at 1% significant level (-2.568), hence the returns of the energy index prices are stationary.

We can conclude that the energy index prices in logarithmic levels are non-stationary for both the AIC and the SC criteria and their returns are stationary, i.e., it is $ren_t \sim I(0)$. This indicates

that the energy index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(en_t) \sim I(1)$.

4.6.4 Euro Stoxx Industrials Index

The PP test results for the logs and the returns of the industrials index prices are displayed in the Table 4.6:

Table 4.6.4 PP test for the logs and the returns of the Industrials prices

Stats	$\log(ind_t)$			$rind_t$		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-5.0217	-5.0200	-5.0226!	-5.0237!	-5.0211	-5.0211
SC	-5.0154!	-5.0074	-5.0037	-5.0173!	-5.0084	-5.0021
	[0.358]		[-1.437]	[-25.38]		
	(0.788)		(0.849)	(0.000)		

Note:**!** is for the horizontal best fit representation.

For the logarithmic industrials prices we have two best fit solutions:

- According to the AIC criterion, the best fit comes with constant and trend. The adjusted t-statistic is -1.437 with a probability of 0.849. The McKinnon value is -3.97, thus the industrials index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit has neither constant nor trend and q=5 lags. The adjusted t-statistic for the above fit is 0.358 with a probability of 0.788 and the McKinnon value is -2.568, and therefore the industrials index prices at the initial logarithmic levels are non stationary.

As for their returns, the best fit equation is the one with neither constant nor trend for both criteria. The adjusted t-statistic here is -25.38 with a probability of 0.000. The McKinnon value is -2.568, so the returns of the industrials index prices are stationary.

We realise that the industrials index prices in logarithmic levels are non-stationary and their returns are stationary, i.e., it is $rind_t \sim I(0)$, for both the AIC and the SC criteria. Therefore, the industrials index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(ind_t) \sim I(1)$.

4.6.5 Euro Stoxx Construction Index

For the logs and the returns of the construction index prices, we get Table 4.6.5:

Table 4.6.5 PP test for the logs and the returns of the construction index prices

Stats	log($const_t$)			$rconst_t$		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-4.7386	-4.7414!	-4.7405	-4.7376!	-4.7349	-4.7338
SC	-4.7323!	-4.7287	-4.7216	-4.7313!	-4.7222	-4.7149
	[-0.303]	[-1.944]		[-26.385]		
	(0.576)	(0.312)		(0.000)		

Note:**!** is for the horizontal best fit representation.

Considering the logarithmic construction index prices, we can observe the following:

- According to the AIC criterion, the best fit is the one with constant. The adjusted t-statistic for the above fit is -1.944 with a probability of 0.312. The McKinnon value is -3.439, hence the construction index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit equation is the one with neither constant nor trend. The adjusted t-statistic is -0.303 with a probability of 0.576. The McKinnon value is -3.439, and therefore the construction index prices at the initial logarithmic levels are non stationary.

Concerning the returns of the construction index prices, the best fit equation is the one with neither constant nor trend and q=15 lags for both criteria. The adjusted t-statistic is -26.385 with a probability of 0.000 and the McKinnon value is -2.568, and therefore the returns of the construction index prices are stationary.

The analysis above we may conclude as follows shows that:

- The construction index prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.
- The returns of the construction index prices are stationary, i.e., it is $rconst_t \sim I(0)$.

- The construction index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(const_t) \sim I(1)$.

4.6.6 Euro Stoxx Basic Resources Index

The PP test for the logs and the returns of the basic resources index prices produces Table 4.6.6 below:

Table 4.6.6 PP test for the logs and the returns of the basic resources index prices

Stats	**log(basres$_t$)**			**rbasres$_t$**		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-3.9318!	-3.9316	-3.9316	-3.9305!	-3.9277	-3.9271
SC	-3.9255!	-3.9189	-3.9126	-3.9241!	-3.9151	-3.9082
	[-0.0035]			[-27.05]		
	(0.681)			(0.000)		

Note:**!** is for the horizontal best fit representation.

According to the AIC and the SC criteria, the best fit equation for the logarithmic basic resources index prices is the one with neither constant nor trend. The adjusted t-statistic here is -0.0035 with a probability of 0.681 and the McKinnon value is -2.568, thus the basic resources index prices at the initial logarithmic levels are non stationary.

Regarding their returns, the best fit equation is the one with neither constant nor trend for both criteria. The adjusted t-statistic for the above fit is -27.05 with a probability of 0.000. The McKinnon value is -2.568, and therefore the returns of the basic resources index prices are stationary.

From the analysis above we may conclude as follows:

- The basic resources index prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.
- The returns of the basic resources index prices are stationary, i.e., it is $rbasres_t \sim I(0)$.
- The basic resources index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(basres_t) \sim I(1)$.

4.6.7 Euro Stoxx Technology Index

Applying the PP test for the logs and the returns of the technology index prices, Table 4.6.7 is derived:

Table 4.6.7 PP test for the logs and the returns of the technology index prices

Stats	**log($tech_t$)**			**$rtech_t$**		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-5.0607	-5.0625!	-5.0607	-5.0595!	-5.0568	-5.0553
SC	-5.0544!	-5.0498	-5.0417	-5.0532!	-5.0441	-5.0363
	[-0.105]	[-1.732]		[-27.34]		
	(0.647)	(0.415)		(0.000)		

Note:**!** is for the horizontal best fit representation.

We have two best fit solutions for the logarithmic technology index prices:

- According to the AIC criterion, the best fit is the one with constant. The adjusted t-statistic is -1.732 with a probability of 0.415. The McKinnon value is -3.439, and therefore the technology index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit has neither constant nor trend. The adjusted t-statistic for the above fit is -0.105 with a probability of 0.647 and the McKinnon value is -2.568, so the technology index prices at the initial logarithmic levels are non stationary.

For the returns of the technology index prices, the best fit equation is the one with neither constant nor trend for both criteria. The adjusted t-statistic here is -27.34 with a probability of 0.000, which is much smaller than the McKinnon value (-2.568), hence the returns of the technology index prices are stationary.

From the above results, we observe that the emission spot prices in logarithmic levels are non-stationary, whereas their returns are stationary, i.e., it is $rtech_t \sim I(0)$, regarding both criteria. This leads to the conclusion that the technology index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(tech_t) \sim I(1)$.

4.6.8 Eurofirst300 Utilities

The PP test results for the logs and the returns of the utilities index prices are displayed in Table 4.6.8:

Table 4.6.8 PP test for the logs and the returns of the utilities index prices

Stats	log(util300$_t$)			rutil300$_t$		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-5.2337	-5.2367!	-5.2349	-5.2321!	-5.2303	-5.2284
SC	-5.2274!	-5.2241	-5.2159	-5.2258!	-5.2176	-5.2094
	[-1.01]	[-1.937]		[-28.148]		
	(0.281)	(0.315)		(0.000)		

Note:**!** is for the horizontal best fit representation.

Concerning the logarithmic utilities index prices, we have two best fit resulting equations:

- According to the AIC criterion, the best fit equation is the one with constant. The adjusted t-statistic here is -1.937 with a probability of 0.315 and the McKinnon value is -3.439, so the utilities index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit has neither constant nor trend. The adjusted t-statistic for the above fit is -1.01 with a probability of 0.281, which is smaller than the McKinnon value (-2.568), hence the utilities index prices at the initial logarithmic levels are non stationary.

For the returns of the utilities index prices, the best fit equation is the one with neither constant nor trend regarding both criteria. The adjusted t-statistic for the above fit is -28.148 with a probability of 0.000. The McKinnon value is -2.568, therefore the returns of the utilities index prices are stationary.

From the analysis above we may conclude as follows:

- The utilities index prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.
- The returns of the utilities index prices are stationary, i.e., it is rutil300$_t$ ~ I(0).

- The utilities index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(\text{util300}_t) \sim I(1)$.

4.6.9 Eurofirst300 Oil and Gas

Table 4.6.9 demonstrates the PP test results for the logs and the returns of the oil & gas index prices:

Table 4.6.9 PP test for the logs and the returns of the oil & gas index prices

Stats	**log(og300$_t$)**			**rog300$_t$**		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-4.9407	-4.9458!	-4.9431	-4.9430!	-4.9403	-4.9378
SC	-4.9344!	-4.9331	-4.9241	-4.9367!	-4.9276	-4.9188
	[-0.087]	[-2.15]		[-29.013]		
	(0.653)	(0.225)		(0.000)		

Note:**!** is for the horizontal best fit representation.

The analysis for the logarithmic oil & gas index prices indicates the following:

- According to the AIC criterion, the best fit equation is the one with constant. The adjusted t-statistic for the above fit is -2.15 with a probability of 0.225. The McKinnon value is -3.439, and therefore the oil & gas index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit equation is the one with neither constant nor trend. The adjusted t-statistic here is -0.087 with a probability of 0.6533 and the McKinnon value is -2.568, so the oil & gas index prices at the initial logarithmic levels are non stationary.

The analysis for the returns of the oil & gas index prices specifies the best fit equation to have neither constant nor trend. The adjusted t-statistic is -29.013 with a probability of 0.000, which is much smaller than the McKinnon value (-2.568), hence the returns of the oil & gas index prices are stationary.

The results above imply that the oil & gas index prices in logarithmic levels are non-stationary for both the AIC and the SC criteria, whereas their returns appear to be stationary,

i.e., it is $rog300_t$ ~ I(0). Thus, we may conclude that the oil & gas index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $log(og300_t)$ ~ I(1).

4.6.10 Eurofirst300 Basic Materials

The results for the logs and the returns of the basic materials index prices can be observed in Table 4.6.10 below:

Table 4.6.10 PP test for the logs and the returns of the basic materials index prices

Stats	**log(basmat300$_t$)**			**rbasmat300$_t$**		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-4.4061!	-4.4054	-4.4058	-4.4048!	-4.4020	-4.4017
SC	-4.3998!	-4.3928	-4.3868	-4.3985!	-4.3894	-4.3828
	[0.088]			[-26.88]		
	(0.711)			(0.000)		

Note:**!** is for the horizontal best fit representation.

Regarding the logarithmic basic materials index prices, the best fit contains neither constant nor trend, according to both criteria. The adjusted t-statistic for the above fit is 0.088 with a probability of 0.711. The McKinnon value is -2.568, and therefore the basic materials index prices at the initial logarithmic levels are non stationary.

As for their returns, the best fit equation is the one with neither constant nor trend, according to both criteria. The adjusted t-statistic here is -26.88 with a probability of 0.000. The McKinnon value is -2.568, so the returns of the basic materials index prices are stationary.

The analysis above shows that the basic materials index prices in logarithmic levels are non-stationary for both the AIC and the SC criteria. Their returns are stationary, i.e., it is $rbasmat300_t$ ~ I(0). Considering these results, we may conclude that the basic materials index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $log(basmat300_t)$ ~ I(1).

4.6.11 Eurofirst300 Industrials

Applying the PP test for the logs and the returns of the industrials (300) index prices, the Table 4.6.11 is derived:

Table 4.6.11 PP test for the logs and the returns of the industrials (300) index prices

Stats	log(ind300$_t$)			rind300$_t$		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-4.8795	-4.8796	-4.8805!	-4.8797!	-4.877	-4.8765
SC	-4.8732!	-4.8669	-4.8615	-4.8734!	-4.8643	-4.8576
	[0.055]		[-1.576]	[-25.95]		
	(0.7)		(0.802)	(0.000)		

Note:**!** is for the horizontal best fit representation.

For the logarithmic industrials (300) index prices, the results indicate that:

- According to the AIC criterion, the best fit comes with constant and trend. The adjusted t-statistic here is -1.576 with a probability of 0.802 and the McKinnon value is -3.97, hence the industrials (300) index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit contains neither constant nor trend. The adjusted t-statistic for the above fit is 0.055 with a probability of 0.7. The McKinnon value is -2.568, and therefore the industrials (300) index prices at the initial logarithmic levels are non stationary.

For the returns of the Industrials prices, the equation that is specified best has neither constant nor trend. The adjusted t-statistic for the above fit is -25.95 with a probability of 0.000, which is much smaller than the McKinnon value (-2.568), therefore the returns of the industrials (300) index prices are stationary.

From the analysis above we may conclude as follows:

- The industrials (300) index prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.
- The returns of the industrials (300) index prices are stationary, i.e., it is rind300$_t$ ~ I(0).

- The industrials (300) index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(ind300_t) \sim I(1)$.

4.7 PP Stationarity Tests-General economy Indices

4.7.1 Standard & Poor's Europe 350 index

We continue by applying the PP test to the general economic indicators. For the logs and the returns of the S & P 350 index prices, the Table 4.7.1 is derived:

Table 4.7.1 PP test for the logs and the returns of the S & P 350 index prices

Stats	**$\log(sp350_t)$**			**$rsp350_t$**		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-5.2994	-5.3006!	-5.2998	-5.2982!	-5.2955	-5.2947
SC	-5.2931!	-5.288	-5.2809	-5.2919!	-5.2828	-5.2757
	[-0.236]	[-1.57]		[-27.53]		
	(0.601)	(0.498)		(0.000)		

Note:**!** is for the horizontal best fit representation.

We have two best fit solutions for the logarithmic S & P 350 index prices:

- According to the AIC criterion, the best fit equation is the one with constant. The adjusted t-statistic for the above fit is -1.57 with a probability of 0.498. The McKinnon value is -3.439, therefore the S & P 350 index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit equation is the one with neither constant nor trend. The adjusted t-statistic here is -0.236 with a probability of 0.601. The McKinnon value is -2.568, so the S & P 350 index prices at the initial logarithmic levels are non stationary.

As for their returns, the best fit equation is the one with neither constant nor trend. The adjusted t-statistic for the above fit is -27.53 with a probability of 0.000 and the McKinnon value is -2.568, thus the returns of the S & P 350 index prices are stationary.

The analysis above demonstrates that the S & P 350 index prices in logarithmic levels are non-stationary, whereas their returns are stationary, i.e., it is $rsp350_t \sim I(0)$, for both the AIC and the SC criteria.

Considering the results above we may conclude that the S & P 350 index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(sp350_t) \sim I(1)$.

4.7.2 DAX index

The PP test results for the logs and the returns of the DAX index prices are included in Table 4.7.2:

Table 4.7.2 PP test for the logs and the returns of the DAX index prices

Stats	$\log(dax_t)$			$rdax_t$		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-5.1933	-5.1932	-5.1935!	-5.1925!	-5.1898	-5.1888
SC	-5.1869!	-5.1806	-5.1745	-5.1862!	-5.1771	-5.1699
	[0.177]		[-1.603]	[-27.68]		
	(0.74)		(0.791)	(0.000)		

Note:**!** is for the horizontal best fit representation.

Regarding the logarithmic DAX prices:

- According to the AIC criterion, the best fit equation is the one with constant and trend. The adjusted t-statistic is -1.603 with a probability of 0.791. The McKinnon value is -3.97, hence the DAX index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit equation is the one with neither constant nor trend and q=5 lags. The adjusted t-statistic for the above fit is 0.177 with a probability of 0.74 and the McKinnon value is -2.568, so the DAX index prices at the initial logarithmic levels are non stationary.

Regarding their returns, the best fit equation is the one with neither constant nor trend. The adjusted t-statistic for the above fit is -27.68 with a probability of 0.000. The McKinnon value is -2.568, thus the returns of the DAX index prices are stationary.

From the analysis above we may conclude that the DAX index prices in logarithmic levels are non-stationary and their returns are stationary, i.e., it is $rdax_t \sim I(0)$, according to both criteria.

These results indicate that the DAX index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(dax_t) \sim I(1)$.

4.7.3 Ftseurofirst300

Table 4.7.3 displays the results for the logs and the returns of the Ftseurofirst300 index prices:

Table 4.7.3 PP test for the logs and the returns of the Ftseurofirst300 index prices

Stats	log(ftse300$_t$)			rftse300$_t$		
	none	constant	constant & trend	none	constant	constant & trend
AIC	-5.3070	-5.3082!	-5.3073	-5.3058!	-5.3031	-5.3024
SC	-5.3007!	-5.2955	-5.2884	-5.2994!	-5.2904	-5.2834
	[-0.254]	[-1.575]		[-27.5]		
	(0.59)	(0.49)		(0.000)		

Note:**!** is for the horizontal best fit representation.

Analysing the results for the logarithmic ftseurofirst300 index prices, we observe the following:

- According to the AIC criterion, the best fit is the one with constant. The adjusted t-statistic is -1.575 with a probability of 0.49 and the McKinnon value is -3.439, therefore the Ftseurofirst300 index prices at the initial logarithmic levels are non stationary.
- According to the SC criterion, the best fit has neither constant nor trend. The adjusted t-statistic for the above fit is -0.254 with a probability of 0.59 and the McKinnon value is -2.568, so the Ftseurofirst300 index prices at the initial logarithmic levels are non stationary.

Analysing the returns of the ftseurofirst300 index prices, we conclude that the best fit equation has neither constant nor trend (q=15 lags). The t-statistic here is -27.5 with a probability of 0.000. The McKinnon value is -2.568, and therefore the returns of the Ftseurofirst300 index prices are stationary.

From the analysis above we may conclude as follows:

- The Ftseurofirst300 index prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.
- The returns of the Ftseurofirst300 index prices are stationary, i.e., it is $rftse300_t \sim I(0)$.
- The ftseurofirst300 index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(ftse300_t) \sim I(1)$.

4.8 Testing with Kwiatkowski, Phillips, Schmidt and Shin test- Energy

4.8.1 EUA emission spot prices

We conclude the stationarity tests by applying the KPSS test to our variables. Again, the lags included are defined by the KPSS test in EViews 4.1, where the best fit equation is required to include at least a constant. For the logs and the returns of the emission spot prices, Table 4.8.1 is derived:

Table 4.8.1 KPSS test for the logs and the returns of the emission spot prices

Stats	**log(es)**		**res**	
	constant	constant & trend	constant	constant & trend
AIC	0.106	-0.275!	-4.520!	-4.51
SC	0.112	-0.262!	-4.514!	-4.505
		[0.548]	[0.108]	

Note:**!** is for the horizontal best fit representation.

According to the AIC and the SC criteria, the best fit equation for the logarithmic emission spot prices is the one with constant and trend. The LM-stat for the above fit is 0.548 and the McKinnon test critical value at 1% significant level is 0.216, so the emission spot prices at the initial logarithmic levels are non stationary.

The best fit equation for their returns has only constant. The LM-stat here is 0.108 with a probability of 0.000. The McKinnon value is 0.739, and therefore the returns of the emission spot prices are stationary.

From the analysis above we may conclude the following:

- The emission spot prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.
- The returns of the emission spot prices are stationary for both criteria, i.e., it is res_t ~ I(0).
- The emission spot prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $log(es_t)$ ~ I(1).

These findings agree with those found in the previous two stationarity tests.

4.8.2 EUA emission futures prices

The KPSS test results for the logs and the returns of the emission futures prices are displayed in Table 4.8.2:

Table 4.8.2 KPSS test for the logs and the returns of the emission futures prices

Stats	**$log(ef_t)$**		**ref_t**	
	constant	constant & trend	constant	constant & trend
AIC	0.193	-0.427!	-4.778!	-4.775
SC	0.199	-0.414!	-4.771!	-4.763
		[0.508]	[0.11]	

Note:**!** is for the horizontal best fit representation.

The best fit equation for the logarithmic emission futures prices is the one with constant and trend for both criteria. The LM-stat is 0.508 and the McKinnon value is 0.216, therefore the emission futures prices at the initial logarithmic levels are non stationary.

As for their returns, the best fit equation is the one with constant, according to both criteria. The LM-stat for the above fit is 0.11 with a probability of 0.000 and the McKinnon value is 0.739, so the returns of the emission futures prices are stationary.

The results from the analysis agree with the previous ADF and PP tests and can be summarised as follows:

- The emission futures prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.

- The returns of the emission futures prices are stationary for both criteria, i.e., it is ref_t ~ I(0).
- The emission futures prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $log(ef_t)$ ~ I(1).

4.8.3 Gas spots

Table 4.8.3 shows the results for the logs and the returns of the gas spots prices:

Table 4.8.3 KPSS test for the logs and the returns of the gas spots prices

Stats	**$log(gs_t)$**		**rgs_t**	
	constant	constant & trend	constant	constant & trend
AIC	0.8864	0.776!	-3.1358!	-3.1343
SC	0.8928	0.7886!	-3.1295!	-3.1217
		[0.704]	[0.16]	

Note:**!** is for the horizontal best fit representation.

The analysis for the logarithmic gas spot prices indicates that the best fit equation is the one with constant and trend for both criteria. The LM-stat is 0.704. The McKinnon value is 0.216, therefore the gas spot prices at the initial logarithmic levels are non stationary.

Regarding their returns, the best fit equation is the one with constant, according to both criteria. The LM-stat for the above fit is 0.16 with a probability of 0.000. The McKinnon value is 0.739, so the returns of the gas spot prices are stationary.

Therefore, we can conclude that the gas spot prices in logarithmic levels are non-stationary, whereas their returns are stationary for both criteria, i.e., it is rgs_t ~ I(0). These results demonstrate that the gas spot prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $log(gs_t)$ ~ I(1).

4.8.4 Gas futures

Applying the KPSS test for the logs and the returns of the gas futures prices, we get Table 4.8.4:

Table 4.8.4 KPSS test for the logs and the returns of the gas futures prices

Stats	$\log(gf_t)$		rgf_t	
	constant	constant & trend	constant	constant & trend
AIC	-0.6848	-1.2741	-5.5655	-5.5628
SC	-0.6785	-1.2615!	-5.5592!	-5.5502
		[0.42]	[0.112]	

Note:**!** is for the horizontal best fit representation.

For the logarithmic gas futures prices, the best fit equation is the one with constant and trend, considering both criteria. The LM-stat is 0.42 and the McKinnon value is 0.216, thus the gas futures prices at the initial logarithmic levels are non stationary.

For their returns, the best fit equation is the one with constant for both the AIC and the SC criteria. The LM-stat for the above fit is 0.112 with a probability of 0.000. The McKinnon value is 0.739, hence the returns of the gas futures prices are stationary.

We may conclude that the gas futures prices in their logarithmic levels are non-stationary for both the AIC and the SC criteria and their returns are stationary, i.e., it is $rgf_t \sim I(0)$. This indicates that the gas futures prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(gf_t) \sim I(1)$. These results are consistent with those of our previous stationarity tests.

4.8.5 Electricity spots

The KPSS test results for the logs and the returns of the electricity spot prices are displayed in Table 4.3.2:

Table 4.8.5 KPSS test for the logs and the returns of the electricity spot prices

Stats	$\log(els_t)$		$rels_t$	
	constant	constant & trend	constant	constant & trend
AIC	0.5979	0.3896	-0.7023	-0.6995
SC	0.6042	0.4023!	-0.6959!	-0.6869
		[0.533]	[0.049]	

Note:**!** is for the horizontal best fit representation.

According to the AIC and the SC criteria, the best fit equation for the logarithmic electricity spot prices is the one with constant and trend. The LM-stat here is 0.533 and the McKinnon value is 0.216, hence the electricity spot prices at the initial logarithmic levels are non stationary.

As for their returns, of the electricity spot prices, the best fit equation is the one with constant. The LM-stat for the above fit is 0.049 with a probability of 0.000. The McKinnon value is 0.739, thus the returns of the electricity spot prices are stationary.

From the analysis above, we may conclude that the electricity spot prices in their logarithmic levels are non-stationary for both the AIC and the SC criteria and their returns are stationary, i.e., it is $rels_t \sim I(0)$. This means that the electricity spot prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(els_t) \sim I(1)$. These results verify our findings from the previous stationarity tests.

4.8.6 Electricity futures

Applying the KPSS test for the logs and the returns of the electricity futures prices, we get:

Table 4.8.6 KPSS test for the logs and the returns of the futures prices

Stats	**$\log(elf_t)$**		**$relf_t$**	
	constant	constant & trend	constant	constant & trend
AIC	-0.9258	-2.0133	-6.0801	-6.0775
SC	-0.9195	-2.0007! [0.247]	-6.0738! [0.109]	-6.0649

Note:**!** is for the horizontal best fit representation.

Regarding the logarithmic electricity futures prices, the best fit equation is the one with constant and trend, according to both criteria. The LM-stat for the above fit is 0.247. The McKinnon value is 0.216, so the electricity futures prices at the initial logarithmic levels are non stationary.

Considering the returns of the electricity futures prices, the best fit equation is the one with constant, for both criteria. The LM-stat here is 0.109 with a probability of 0.000 and the McKinnon value is 0.739, therefore the returns of the electricity futures prices are stationary

The analysis above demonstrates that the electricity futures in their logarithmic levels are non stationary for both criteria, whereas their returns are stationary, i.e., it is $relf_t$ ~ I(0). This means that the electricity futures prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $log(elf_t)$ ~ I(1). The results here confirm those of the previous stationarity tests.

4.8.7 Oil spots

For the logs and the returns of the oil spot prices, we get the following results:

Table 4.8.7 KPSS test for the logs and the returns of the oil spots prices

Stats	$log(oil_t)$		$roil_t$	
	constant	constant & trend	constant	constant & trend
AIC	0.2223	0.2238	-4.3834	-4.3821
SC	0.2286!	0.2365	-4.3770!	-4.3695
	[0.515]		[0.247]	

Note:**!** is for the horizontal best fit representation.

The best fit equation for the logarithmic oil spot prices is the one with constant and trend, for both criteria. The LM-stat for the above fit is 0.515 and the McKinnon value is 0.739, so the oil spot prices at the initial logarithmic levels are stationary.

The best fit for their returns contains constant. The LM-stat here is 0.247 with a probability of 0.000. The McKinnon value is 0.739, hence the returns of the oil spot prices are stationary.

The analysis shows that the oil spot prices are non stationary for both criteria in their logarithmic levels, whereas they appear to be stationary in their returns, i.e., it is $roil_t$ ~ I(0). Therefore, the oil spot prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $log(oil_t)$ ~ I(1). Again, the results agree with those of the previous stationarity tests.

4.8.8 Oil futures

Table 4.8.8 displays the results for the logs and the returns of the oil futures prices:

Table 4.8.8 KPSS test for the logs and the returns of the oil futures prices

Stats	log($oilf_t$)		$roilf_t$	
	constant	constant & trend	constant	constant & trend
AIC	0.2530	0.2557	-4.1868	-4.1852
SC	0.2594!	0.2683	-4.1805!	-4.1726
	[0.489]		[0.224]	

Note:**!** is for the horizontal best fit representation.

The analysis for the logarithmic oil futures prices shows that the best fit equation is the one with constant and trend (both criteria). The LM-stat is 0.489 and the McKinnon value is 0.739, thus the oil futures prices at the initial logarithmic levels are stationary.

The analysis for the returns of the oil futures prices indicates that the best fit equation is the one with constant (both criteria). The LM-stat here is 0.224 with a probability of 0.000. The McKinnon value is 0.739, so the returns of the oil futures prices are stationary.

The results from the analysis above agree with the previous ADF and PP tests and can be summarised as follows:

- The oil futures prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.
- The returns of the oil futures prices are stationary for both criteria, i.e., it is $roilf_t \sim I(0)$.
- The oil futures prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(oilf_t) \sim I(1)$.

4.8.9 Coal futures

Applying the KPSS test for the logs and the returns of the coal futures prices, we get Table 4.8.9:

Table 4.8.9 KPSS test for the logs and the returns of the coal futures prices

Stats	$\log(cf_t)$		rcf_t	
	constant	constant & trend	constant	constant & trend
AIC	-0.5419	-0.7678	-5.3149	-5.3122
SC	-0.5356	-0.7552! [0.365]	-5.3086! [0.128]	-5.2996

Note:**!** is for the horizontal best fit representation.

The best fit equation for the logarithmic coal futures prices is the one with constant and trend. The LM-stat for the above fit is 0.365. The McKinnon value is 0.216, so the coal futures prices at the initial logarithmic levels are non stationary.

The best fit equation for their returns is the one with constant. The LM-stat here is 0.128 with a probability of 0.000 and the McKinnon value is 0.739, therefore the returns of the coal futures prices are stationary.

The results above show that the coal futures prices are non stationary in their logarithmic levels (both criteria), whereas they appear to be stationary in their returns, i.e., it is $rcf_t \sim I(0)$. Therefore, the coal futures prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(cf_t) \sim I(1)$. These results are consistent with those of our previous stationarity tests.

4.9 KPSS Stationarity Tests-European Sectors Indices

4.9.1 Euro Stoxx Automobiles Index

Applying the KPSS test for the logs and the returns of the automobiles index prices, we have:

Table 4.9.1 KPSS test for the logs and the returns of the automobiles index prices

Stats	$\log(car_t)$		$rcar_t$	
	constant	constant & trend	constant	constant & trend
AIC	-0.7057	-0.7422	-3.8909	-3.8896
SC	-0.6994	-0.7296! [0.573]	-3.8846! [0.333]	-3.877

Note:**!** is for the horizontal best fit representation.

From Table 4.9.1 we can observe that:

- According to the AIC and the SC criteria, the best fit equation for the logarithmic automobiles index prices is the one with constant and trend. The LM-stat for the above fit is 0.573. The McKinnon value is 0.216, so the automobiles index prices at the initial logarithmic levels are non stationary.
- For their returns, the best fit equation is the one with constant (both criteria). The LM-stat here is 0.333 with a probability of 0.000 and the McKinnon value is 0.739, thus the returns of the automobiles index prices are stationary.

The analysis above indicates that the automobiles index prices are non stationary in their logarithmic levels (both criteria) and stationary in their returns, i.e., it is $rcar_t \sim I(0)$. Therefore, the automobiles index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(car_t) \sim I(1)$. The results here agree with those of our previous stationarity tests.

4.9.2 Euro Stoxx Chemicals Index

The results for the logs and the returns of the chemical index prices are listed in table 4.9.2:

Table 4.9.2 KPSS test for the logs and the returns of the chemical index prices

Stats	**$\log(ch_t)$**		**rch_t**	
	constant	constant & trend	constant	constant & trend
AIC	-0.4833	-0.6383	-5.1409	-5.1407
SC	-0.477	-0.6256!	-5.1346!	-5.1281
		[0.563]	[0.325]	

Note:**!** is for the horizontal best fit representation.

According to the AIC and the SC criteria:

- The best fit equation for the logarithmic chemical index prices is the one with constant and trend. The LM-stat is 0.563 and the McKinnon value is 0.216, hence the chemical index prices at the initial logarithmic levels are non stationary.

- The best fit equation for their returns appears to be with constant. The LM-stat for the above fit is 0.325 with a probability of 0.000. The McKinnon value is 0.739, so the returns of the chemical index prices are stationary

The analysis confirms that the chemicals index prices are non stationary for both criteria in their logarithmic levels, whereas they appear to be stationary in their returns, i.e., it is rch_t ~ I(0). Therefore, the chemicals index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(ch_t)$ ~ I(1). Again, these results are in agreement with those of the previous stationarity tests.

4.9.3 Euro Stoxx Energy Index

Table 4.9.3 includes the KPSS test results for the logs and the returns of the energy index prices:

Table 4.9.3 KPSS test for the logs and the returns of the energy index prices

Stats	**$\log(en_t)$**		**ren_t**	
	constant	constant & trend	constant	constant & trend
AIC	-1.2017	-1.2859	-4.8985	-4.8962
SC	-1.1953	-1.2732! [0.449]	-4.8922! [0.109]	-4.8835

Note:**!** is for the horizontal best fit representation.

By analysing the results, we observe that:

- According to the AIC and the SC criteria, the best fit equation for the logarithmic energy index prices is the one with constant and trend. The LM-stat for the above fit is 0.449 and the McKinnon value is 0.216, so the energy index prices at the initial logarithmic levels are non stationary.
- According to both criteria, the best fit equation for the returns of the energy index prices is the one with constant. The LM-stat is 0.109 with a probability of 0.000 and the McKinnon value is 0.739, hence the returns of the energy index prices are stationary.

The results from the analysis above agree with the previous ADF and PP tests and are summarised as follows:

- The energy index prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.
- The returns of the energy index prices are stationary for both criteria, i.e., it is ren_t ~ I(0).
- The energy index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $log(en_t)$ ~ I(1).

4.9.4 Euro Stoxx Industrials Index

The KPSS test results for the logs and the returns of the industrials index prices are included in Table 4.9.4:

Table 4.9.4 KPSS test for the logs and the returns of the industrials index prices

Stats	**$log(ind_t)$**		**$rind_t$**	
	constant	constant & trend	constant	constant & trend
AIC	-0.3043	-0.4472	-5.0217	-5.0221
SC	-0.2979	-0.4346!	-5.0154!	-5.0095
		[0.585]	[0.377]	

Note:**!** is for the horizontal best fit representation.

For the logarithmic industrials index prices the analysis reveals that, according to the AIC and the SC criteria, the best fit includes both constant and trend. The LM-stat for the above fit is 0.585 and the McKinnon value is 0.216, so the industrials index prices at the initial logarithmic levels are non stationary.

For their returns, the best fit equation is the one with constant (both criteria). The LM-stat here is 0.377 with a probability of 0.000. The McKinnon value is 0.739, thus the returns of the industrials index prices are stationary.

The analysis above indicates that the industrials index prices are non stationary for both criteria in their logarithmic levels, whereas they appear to be stationary in their returns, i.e., it is $rind_t$ ~ I(0). Therefore, the industrials index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $log(ind_t)$ ~ I(1). Again, these results are consistent with those of the previous stationarity tests.

4.9.5 Euro Stoxx Construction Index

The results for the logs and the returns of the construction index prices are listed in Table 4.3.2 below:

Table 4.3.2 KPSS test for the logs and the returns of the construction index prices

Stats	**log($const_t$)**		**$rconst_t$**	
	constant	constant & trend	constant	constant & trend
AIC	-0.6548	-0.6524	-4.7386	-4.7376
SC	-0.6485! [0.448]	-0.6398	-4.7323! [0.221]	-4.7249

Note:**!** is for the horizontal best fit representation.

The analysis shows that:

- The best fit equation for the logarithmic levels of the construction index prices has both constant and trend, regarding both criteria. The LM-stat is 0.448 and the McKinnon value is 0.739, so the construction index prices at the initial logarithmic levels are stationary.
- The best fit equation for their returns has only constant. The LM-stat for the above fit is 0.221 with a probability of 0.000. The McKinnon value is 0.739, hence the returns of the construction index prices are stationary.

The results above show that the construction index prices are non stationary in their logarithmic levels (both criteria), whereas they appear to be stationary in their returns, i.e., it is $rconst_t \sim I(0)$. Therefore, the construction index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(const_t) \sim I(1)$. These results are consistent with those of our previous stationarity tests.

4.9.6 Euro Stoxx Basic Resources Index

Table 4.9.6 displays the results for the logs and the returns of the basic resources index prices:

Table 4.9.6 KPSS test for the logs and the returns of the basic resources index prices

Stats	log($basres_t$)		$rbasres_t$	
	constant	constant & trend	constant	constant & trend
AIC	0.6047	0.5948	-3.9318	-3.9313
SC	0.611	0.6075!	-3.9255!	-3.9186
		[0.526]	[0.347]	

Note:**!** is for the horizontal best fit representation.

Concerning the logarithmic basic resources index prices, the best fit equation is the one with constant and trend, according to both criteria. The LM-stat is 0.526 and the McKinnon value is 0.216, so the basic resources index prices at the initial logarithmic levels are non stationary.

Regarding their returns, the best fit equation is the one with constant (both criteria). The LM-stat for the above fit is 0.347 with a probability of 0.000 and the McKinnon value is 0.739, therefore the returns of the basic resources index prices are stationary.

The analysis above indicates that the basic resources index prices are non stationary for both criteria in their logarithmic levels and stationary in their returns, i.e., it is $rbasres_t \sim I(0)$. Consequently, the basic resources index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(basres_t) \sim I(1)$. These results are consistent with those of the previous stationarity tests.

4.9.7 Euro Stoxx Technology Index

Applying the KPSS test for the logs and the returns of the technology index prices, we get:

Table 4.9.7 KPSS test for the logs and the returns of the technology index prices

Stats	log($tech_t$)		$rtech_t$	
	constant	constant & trend	constant	constant & trend
AIC	-0.9858	-0.9860	-5.0607	-5.0592
SC	-0.9795	-0.9734!	-5.0544!	-5.0466
		[0.51]	[0.176]	

Note:**!** is for the horizontal best fit representation.

We can observe in Table 4.9.7 that for the logarithmic technology index prices the best fit equation contains constant and trend (both criteria). The LM-stat for the above fit is 0.51 and the McKinnon value is 0.216, thus the technology index prices at the initial logarithmic levels are non stationary. For the returns of the technology index prices, the best fit equation is the one with constant (both criteria). The LM-stat here is 0.176 with a probability of 0.000. The McKinnon value is 0.739, so the returns of the technology index prices are stationary

We can conclude from the above that the technology index prices in logarithmic levels are non-stationary, whereas their returns are stationary for both criteria, i.e., it is $rtech_t \sim I(0)$. These results demonstrate that the technology index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(tech_t) \sim I(1)$. They also are in agreement with our previous stationarity test results.

4.9.8 Eurofirst300 utilities

The results for the logs and the returns of the utilities index prices can be seen in Table 4.9.8:

Table 4.9.8 KPSS test for the logs and the returns of the utilities index prices

Stats	**log(util300$_t$)**		**rutil300$_t$**	
	constant	constant & trend	constant	constant & trend
AIC	-0.8720	-1.4519	-5.2336	-5.2317
SC	-0.8657	-1.4393!	-5.2273!	-5.2190
		[0.53]	[0.164]	

Note:**!** is for the horizontal best fit representation.

For the logarithmic utilities index prices, the best fit equation is the one with constant and trend, considering both criteria. The LM-stat for the above fit is 0.53. The McKinnon value is 0.216, and therefore the utilities index prices at the initial logarithmic levels are non stationary.

As for their returns, the best fit equation is the one with constant (both criteria). The LM-stat is 0.164 with a probability of 0.000 and the McKinnon value is 0.739, hence the returns of the utilities index prices are stationary.

The results from the analysis above agree with the previous ADF and PP tests and are summarised in the following manner:

- The utilities index prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.
- The returns of the utilities index prices are stationary for both criteria, i.e., it is $rutil300_t$ ~ I(0).
- The utilities index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $log(util300_t)$ ~ I(1).

4.9.9 Eurofirst300 oil and gas

The results regarding the logs and the returns of the oil & gas index prices are listed in Table 4.9.9 below:

Table 4.9.9 KPSS test for the logs and the returns of the oil & gas index prices

Stats	**$log(og300_t)$**		**$rog300_t$**	
	constant	constant & trend	constant	constant & trend
AIC	-1.4517	-1.5331	-4.9407	-4.9382
SC	-1.4454	-1.5205! [0.45]	-4.9344! [0.087]	-4.9256

Note:**!** is for the horizontal best fit representation.

For the logarithmic oil & gas index prices, the analysis indicates that the best fit involves constant and trend (both criteria). The LM-stat here is 0.45 and the McKinnon value is 0.216, therefore the oil & gas index prices at the initial logarithmic levels are non stationary.

For their returns, the best fit is the one with constant (both criteria). The LM-stat for the above fit is 0.087 with a probability of 0.000. The McKinnon value is 0.739, hence the returns of the oil & gas index prices are stationary.

The analysis above demonstrates that the oil & gas index prices in their logarithmic levels are non stationary for both criteria, whereas their returns are stationary, i.e., it is $rog300_t$ ~ I(0). This means that the oil & gas index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $log(og300_t)$ ~ I(1). The results here confirm those of the previous stationarity tests.

4.9.10 Eurofirst300 basic materials

We continue by applying the KPSS test for the logs and the returns of the basic materials index prices:

Table 4.9.10 KPSS test for the logs and the returns of the basic materials index prices

Stats	log(basmat300$_t$)		rbasmat300$_t$	
	constant	constant & trend	constant	constant & trend
AIC	0.2099	0.1968	-4.4061	-4.4059
SC	0.2162	0.2094!	-4.3998!	-4.3932
		[0.542]	[0.358]	

Note:**!** is for the horizontal best fit representation.

Concerning the logarithmic basic materials index prices, the best fit has constant and trend (both criteria). The LM-stat is 0.542 and the McKinnon value is 0.216, so the basic materials index prices at the initial logarithmic levels are non stationary.

Considering their returns, the best fit equation is the one with constant (both criteria). The LM-stat for the above fit is 0.358 with a probability of 0.000 and the McKinnon value is 0.739, thus the returns of the basic materials index prices are stationary.

We can conclude from the above that the basic materials index prices in logarithmic levels are non-stationary, whereas their returns are stationary for both criteria, i.e., it is rbasmat300$_t$ ~ I(0). These results demonstrate that the basic materials index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., log(basmat300$_t$) ~ I(1). They also are in agreement with our previous stationarity test results.

4.9.11 Eurofirst300 Industrials

Table 4.9.11 shows the results for the logs and the returns of the industrials 300 index prices:

Table 4.9.11 KPSS test for the logs and the returns of the industrials 300 index prices

Stats	log(ind300$_t$)		rind300$_t$	
	constant	constant & trend	constant	constant & trend
AIC	-0.5092	-0.5426	-4.8795	-4.8793
SC	-0.5028	-0.5299!	-4.8732!	-4.8666
		[0.54]	[0.315]	

Note:**!** is for the horizontal best fit representation.

The analysis, for the logarithmic industrials 300 index prices indicates that according to the AIC and the SC criteria, the best fit equation is the one with constant and trend. The LM-stat is 0.54 and the McKinnon value is 0.216, hence the industrials 300 index prices at the initial logarithmic levels are non stationary. For their returns, the best fit equation is the one with constant (both criteria). The LM-stat for the above fit is 0.315 with a probability of 0.000. The McKinnon value is 0.739, therefore the returns of the industrials 300 index prices are stationary.

We can conclude from the analysis that the industrials (300) index prices in logarithmic levels are non-stationary and their returns are stationary for both criteria, i.e., it is rind300$_t$ ~ I(0). These results demonstrate that the industrials (300) index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., log(ind300$_t$) ~ I(1).

4.10 KPSS Stationarity Tests – General economy Indices

4.10.1 Standard & Poor's Europe 350 index

We conclude the stationarity tests by applying the KPSS test to the general economic indices, starting with the logs and the returns of the Standard & Poor's index prices:

Table 4.10.1 KPSS test for the logs and the returns of the Standard & Poor's index prices

Stats	$\log(sp350_t)$		$rsp350_t$	
	constant	constant & trend	constant	constant & trend
AIC	-0.9262	-0.9236	-5.2994	-5.2985
SC	-0.9199! [0.558]	-0.9110	-5.2931! [0.296]	-5.2859

Note:**!** is for the horizontal best fit representation.

The analysis for the logarithmic Standard & Poor's index prices shows that according to the AIC and the SC criteria, the best fit equation has constant and trend. The LM-stat for the above fit is 0.558 and the McKinnon value is 0.739, therefore the Standard & Poor's index prices at the initial logarithmic levels are non stationary.

Analysing their returns, the best fit equation is the one with constant (both criteria). The LM-stat here is 0.296 with a probability of 0.000 and the McKinnon value is 0.739, so the returns of the Standard & Poor's index prices are stationary.

We can conclude from the above that the Standard & Poor's index prices in logarithmic levels are non-stationary, whereas their returns are stationary for both criteria, i.e., it is $rsp350_t \sim I(0)$. These results demonstrate that the Standard & Poor's index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(sp350_t) \sim I(1)$. They also are in agreement with our previous stationarity test results.

4.10.2 DAX index

The results for the logs and the returns of the DAX index prices can be viewed in Table 4.10.2 below:

Table 4.10.2 KPSS test for the logs and the returns of the DAX index prices

Stats	$\log(dax_t)$		$rdax_t$	
	constant	constant & trend	constant	constant & trend
AIC	-0.9125	-0.9673	-5.1933	-5.1922
SC	-0.9062	-0.9546! [0.555]	-5.187! [0.23]	-5.1796

Note:**!** is for the horizontal best fit representation.

The best fit equation for the logarithmic DAX index prices is the one with constant and trend. The LM-stat is 0.555. The McKinnon value is 0.216, thus the DAX index prices at the initial logarithmic levels are non stationary.

For their returns, the best fit equation is the one with constant (both criteria). The LM-stat for the above fit is 0.23 with a probability of 0.000 and the McKinnon value is 0.739, therefore the returns of the DAX index prices are stationary.

From the analysis above we may conclude the following:

- The DAX index prices in logarithmic levels are non-stationary for both the AIC and the SC criteria.
- The returns of the DAX index prices are stationary for both criteria, i.e., it is $rdax_t \sim I(0)$.
- The DAX index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(dax_t) \sim I(1)$.

These findings agree with those in the previous two stationarity tests.

4.10.3 Ftseurofirst300

For the logs and the returns of the Ftseurofirst300 index prices, we get the following results:

Table 4.3.2 KPSS test for the logs and the returns of the Ftseurofirst300 index prices

Stats	**$\log(ftse300_t)$**		**$rftse300_t$**	
	constant	constant & trend	constant	constant & trend
AIC	-0.9019	-0.8993	-5.307	-5.3062
SC	-0.8956! [0.55]	-0.8867	-5.3007! [0.299]	-5.2936

Note:**!** is for the horizontal best fit representation.

Regarding the logarithmic Ftseurofirst300 index prices, the best fit equation is the one with constant and trend, according to both criteria. The LM-stat here is 0.55 and the McKinnon value is 0.739, therefore the Ftseurofirst300 index prices at the initial logarithmic levels are non stationary.

Concerning the returns of the Ftseurofirst300 index prices, the best fit equation is the one with constant (both criteria). The LM-stat for the above fit is 0.299 with a probability of 0.000 and the McKinnon value is 0.739, thus the returns of the Ftseurofirst300 index prices are stationary.

The analysis shows that the Ftseurofirst300 index prices are non stationary for both criteria in their logarithmic levels, whereas they appear to be stationary in their returns, i.e., it is $rftse300_t \sim I(0)$. Therefore, the Ftseurofirst300 index prices in logarithmic levels include a unit root, or this variable is integrated of order one, i.e., $\log(ftse300_t) \sim I(1)$. Again, the results agree with those of the previous stationarity tests.

4.11 Conclusions

In this chapter, we have investigated stationarity by applying three tests: Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. By choosing a large number of lags (5, 10 and 15) we attempted to eliminate the issue of autocorrelation in the time series. This seems to provide good results.

We may conclude that all our variables are found to be non stationary on their logarithmic levels and stationary on their returns. This property indicates that our study variables are integrated of order 1 and provides the initiative to further investigate for cointegration among our main variables.

CHAPTER 5

Granger Causality Tests

5.1 Introduction

The term *causality* is used in the following manner. In a regression equation, we say that when an independent variable X_t influences a dependent variable Y_t, then we accept that any changes in the variable X_t can also bring changes to the variable Y_t. The direction of the causality can be either unidirectional (X_t influences Y_t but Y_t does not influence X_t) or it can be bilateral. Because this direction is not always known, there are various tests to prove it.

We are using the Granger test (1969), which states that the future cannot predict the present or the past and makes use of the VAR models. It tests the hypothesis that refers to the coefficients of these VAR models by applying the F-statistic of Wald:

$$F = \frac{(ESS_R - ESS_U)}{ESS_U/(n-2k-1)} \sim F(k, n-2k-1) \quad (5.1)$$

where $ESSU_R$ is the sum of the squares of the residuals of the VAR regression equation and ESS_R is the sum of the squares of the residuals of the restricted regression equation. The VAR(k) model used is the following:

$$Y_t = \alpha_{10} + \sum_{j=1}^{k} \alpha_{1j} X_{t-j} + \sum_{j=1}^{k} \beta_{1j} Y_{t-j} + \varepsilon_{1t} \quad (5.2)$$

$$X_t = \alpha_{20} + \sum_{j=1}^{k} \alpha_{2j} X_{t-j} + \sum_{j=1}^{k} \beta_{2j} Y_{t-j} + \varepsilon_{2t} \quad (5.3)$$

According to the VAR model of the above two equations we test the following:

a. If $\{\alpha_{11},\alpha_{12},.....,\alpha_{1k}\}\neq 0$ and $\{\beta_{21},\beta_{22},.....,\beta_{2k}\}=0$, then there is one unidirectional causality from X_t towards Y_t ($X \rightarrow Y$).

b. If $\{\alpha_{11},\alpha_{12},.....,\alpha_{1k}\}=0$ and $\{\beta_{21},\beta_{22},.....,\beta_{2k}\}\neq 0$, then there is one unidirectional causality from Y_t towards X_t ($Y \rightarrow X$).

c. If $\{\alpha_{11},\alpha_{12},.....,\alpha_{1k}\}\neq 0$ and $\{\beta_{21},\beta_{22},.....,\beta_{2k}\}\neq 0$, then there is a bilateral causality between X_t and Y_t ($X \leftrightarrow Y$).

d. If $\{\alpha_{11},\alpha_{12},.....,\alpha_{1k}\}=0$ and $\{\beta_{21},\beta_{22},.....,\beta_{2k}\}=0$, then there is no causality between X_t and Y_t.

The hypotheses of this test are therefore the following:

H_0: X does not Granger cause Y, i.e. $\{\alpha_{11},\alpha_{12},.....,\alpha_{1k}\}=0$, if F< critical value of F

H_α: X Granger causes Y, i.e. $\{\alpha_{11},\alpha_{12},.....,\alpha_{1k}\}\neq 0$, if F> critical value of F

and

H_0: Y does not Granger cause X, i.e. $\{\beta_{21},\beta_{22},.....,\beta_{2k}\}=0$, if F< critical value of F

H_α: Y Granger causes Y, i.e. $\{\beta_{21},\beta_{22},.....,\beta_{2k}\}\neq 0$, if F> critical value of F

The following table demonstrates the attempt to estimate the best VAR model for the number of lags to take when running the causality Granger tests.

We apply the Granger test to check for causality between the emission spots and their futures. The AIC and the SC criteria are used to choose the best fit equation. We accept the null hypothesis where the probability is shown to be above 5% of the significance level and we reject it when the probability is below 5%.

Table 5.1 Causality test between emission spots and their futures

Lags		Stats	Null Hypothesis	F-Statistic	Probability
5	AIC	-9.640	REF does not Granger Cause RES	1.37840	0.23024
	SC	-9.500*	RES does not Granger Cause REF	50.4776	0.00000
10	AIC	-9.658*	REF does not Granger Cause RES	2.43893	0.00732
	SC	-9.390	RES does not Granger Cause REF	28.9209	0.00000
15	AIC	-9.616			
	SC	-9.218			

According to the AIC criterion, the best fit VAR model is for q=10 lags. We reject the null hypothesis that emission futures do not Granger cause the emission spot prices. According to the SC criterion, the best fit VAR model is for q=5 lags. Here, we reject the null hypothesis that emission spots do not Granger cause the emission future prices.

The rest of the chapter is described as follows. We apply the Granger causality test to our variables in six sections, which are:

5.2 Emissions spots and energy

5.3 Emissions spots and industrial indicators

5.4 Emissions spots and general economy indicators

5.5 Emissions futures and energy

5.6 Emissions futures and industrial indicators

5.7 Emissions futures and general economy indicators

Our main results can be summarised in section 5.8.

5.2 Emissions spots and energy

5.2.1 Emission spots and gas spot prices

The following table demonstrates the attempt to estimate the best VAR model according to the number of lags taken when running the causality Granger test.

Table 5.2.1 Granger Causality Test between emission spots and gas spots

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-7.613*	RGS does not Granger Cause RES	1.10325	0.35723
	SC	-7.473*	RES does not Granger Cause RGS	2.62375	0.02313
10	AIC	-7.566			
	SC	-7.298			
15	AIC	-7.522			
	SC	-7.124			

We can observe that for both the AIC and SC criteria the best fit VAR model is for q=5 lags. Looking at the probabilities of our hypothesis we can conclude that gas spots do not Granger

cause the emissions spots, and reject the hypothesis that emissions spots do not Granger cause gas spots.

5.2.2 Emission spots and gas futures

Similarly, Table 5.2.2 demonstrates the estimation of the best VAR model when applying the causality Granger test.

Table 5.2.2 Granger Causality Test between emission spots and gas futures

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-10.049*	RGF does not Granger Cause RES	2.40075	0.03578
	SC	-9.909*	RES does not Granger Cause RGF	2.53677	0.02745
10	AIC	-10.001			
	SC	-9.733			
15	AIC	-9.933			
	SC	-9.535			

We can see here that for both criteria the best fit VAR model is for q=5 lags. Looking at the probabilities of our hypotheses we conclude that none of the null hypothesis is valid, i.e. we reject the hypothesis that gas futures do not Granger cause the emissions spots and vice versa.

5.2.3 Emission spots and electricity spots

The following table demonstrates the Granger test results for the best VAR model estimation between the emission and the electricity spots:

Table 5.2.3 Granger Causality Test between emission spots and electricity spots

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-5.366*	RELS does not Granger Cause RES	0.27709	0.92573
	SC	-5.226*	RES does not Granger Cause RELS	0.89501	0.48385
10	AIC	-5.298			
	SC	-5.030			
15	AIC	-5.264			
	SC	-4.866			

Here, the best fit VAR model is for q=5 lags. Looking at the probabilities of our hypothesis we can observe that both the null hypothesis are valid, i.e. we accept the hypothesis that electricity spots do not Granger cause the emissions spots and vice versa.

5.2.4 Emission spots and electricity futures

The best VAR model concerning the emission spot prices with the electricity futures is displayed in Table 5.2.4 below:

Table 5.2.4 Granger Causality Test between emission spots and electricity futures

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-10.604*	RELF does not Granger Cause RES	0.86644	0.50320
	SC	-10.464*	RES does not Granger Cause RELF	7.12136	1.6E-06
10	AIC	-10.554			
	SC	-10.285			
15	AIC	-10.488			
	SC	-10.090			

We can argue that for both criteria the best fit VAR model is for q=5 lags. Looking at the probabilities of our hypothesis we accept the null hypothesis that electricity futures prices do not Granger cause the emissions spots. Furthermore, we reject the hypothesis that emission spot prices do not Granger cause the electricity futures prices.

5.2.5 Emission spots and oil spots

Table 5.2.5 shows the results for the emission and oil spot prices:

Table 5.2.5 Granger Causality Test between emission spots and oil spots

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-8.854*	ROIL does not Granger Cause RES	1.08634	0.36653
	SC	-8.714*	RES does not Granger Cause ROIL	2.15854	0.05691
10	AIC	-8.802			
	SC	-8.534			
15	AIC	-8.749			
	SC	-8.350			

We can observe here that the best fit VAR model is for q=5 lags (both criteria). According to the probabilities of our hypothesis we accept both the null hypotheses. So, oil spot prices do not Granger cause the emissions spots and also emission spot prices do not Granger cause the electricity futures prices.

5.2.6 Emission spots and oil futures

The following table demonstrates the attempt to estimate the best VAR model for different numbers of lags taken when running the causality Granger tests between emission spots and oil futures prices:

Table 5.2.6 Granger Causality Test between emission spots and oil futures

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-8.684*	ROILF does not Granger Cause RES	0.67082	0.64570
	SC	-8.544*	RES does not Granger Cause ROILF	3.50551	0.00388
10	AIC	-8.630			
	SC	-8.362			
15	AIC	-8.564			
	SC	-8.166			

For both the AIC and SC criteria the best fit VAR model is for q=5 lags. Here, we accept the null hypothesis that oil futures prices do not Granger cause the emissions spots. We reject the null hypothesis that emission spot prices do not Granger cause the electricity futures prices.

5.2.7 Emissions spots and coal futures

The results of the Granger test between the emission spots and the coal futures are listed in Table 5.2.7 below:

Table 5.2.7 Granger Causality Test between emission spots and coal futures

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-9.843*	RCF does not Granger Cause RES	2.33253	0.04082
	SC	-9.703*	RES does not Granger Cause RCF	6.75910	3.6E-06
10	AIC	-9.787			
	SC	-9.518			
15	AIC	-9.732			
	SC	-9.334			

The best fit VAR model appears to be the one for q=5 lags. Considering the probabilities of our hypothesis we reject both the null hypotheses. Therefore, the hypothesis that coal futures

do not Granger cause emission spots is not valid and neither is the hypothesis that emission spots do not Granger cause coal futures.

5.3 Emissions spots and industrial indicators

5.3.1 Emission spots with Euro Stoxx Automobiles Price Index

We then apply the Granger test between the emission spots with the various industrials indicators. Table 5.3.1 demonstrates the best VAR model concerning the automobile index prices:

Table 5.3.1 Granger Causality Test between emission spots and Euro Stoxx Automobiles Index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-8.424*	RCAR does not Granger Cause RES	0.71891	0.60935
	SC	-8.284*	RES does not Granger Cause RCAR	1.68532	0.13578
10	AIC	-8.357			
	SC	-8.088			
15	AIC	-8.321			
	SC	-7.923			

The results show that for both the AIC and SC criteria the best fit VAR model is for q=5 lags. Looking at the probabilities of our hypothesis we accept both the null hypotheses. Therefore, automobiles index prices do not Granger cause the emissions spots and vice versa.

5.3.2 Emission spots with Euro Stoxx Chemicals Price Index

Table 5.3.2 exhibits the Granger test results for the emission spots with the chemicals index prices. We can observe here that for both criteria the best fit VAR model is for q=5 lags. Looking at the probabilities of our hypothesis we accept both the null hypotheses. Therefore, chemicals index prices do not Granger cause the emissions spots and vice versa.

Table 5.3.2 Granger Causality Test between emission spots and Euro Stoxx Chemicals Index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-9.608*	RCH does not Granger Cause RES	0.36183	0.87468
	SC	-9.469*	RES does not Granger Cause RCH	0.85201	0.51314
10	AIC	-9.574			
	SC	-9.306			
15	AIC	-9.533			
	SC	-9.135			

5.3.3 Emission spots with Euro Stoxx Energy Price Index

The best VAR model for the number of lags to take when running the causality Granger tests is shown in Table 5.3.3:

Table 5.3.3 Granger Causality Test between emission spots and Euro Stoxx Energy Index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-9.608*	REN does not Granger Cause RES	0.91215	0.47246
	SC	-9.469*	RES does not Granger Cause REN	2.72703	0.01885
10	AIC	-9.574			
	SC	-9.306			
15	AIC	-9.533			
	SC	-9.135			

For both criteria the best fit VAR model is for q=5 lags. Regarding the probabilities of our hypothesis we accept the null hypothesis that energy index prices do not Granger cause the emissions spots. Furthermore, we reject the null hypothesis that emission spots do not Granger cause the energy index prices.

5.3.4 Emission spots with Euro Stoxx Industrials Price Index

The causality Granger test results for the emission spots with the industrials index prices can be observed in Table 5.3.4:

Table 5.3.4 Granger Causality Test between emission spots and Euro Stoxx Industrials Index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-9.502*	RIND does not Granger Cause RES	0.45472	0.80996
	SC	-9.362*	RES does not Granger Cause RIND	1.00821	0.41176
10	AIC	-9.454			
	SC	-9.186			
15	AIC	-9.417			
	SC	-9.018			

We can conclude that for both the AIC and SC criteria the best fit VAR model is for q=5 lags. Here, we accept the null hypothesis that the industrials index prices do not Granger cause the emissions spots. We further accept the null hypothesis that emission spots do not Granger cause the industrials index prices.

5.3.5 Emission spots with Euro Stoxx Construction Price Index

Table 5.3.5 displays the best VAR model for the number of lags to take when running the causality Granger tests for the emission spots with the construction index prices:

Table 5.3.5 Granger Causality Test between emission spots and Euro Stoxx Construction Index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-9.206*	RCONST does not Granger Cause	0.61986	0.68471
	SC	-9.066*	RES	0.72341	0.60599
			RES does not Granger Cause		
			RCONST		
10	AIC	-9.146			
	SC	-8.878			
15	AIC	-9.113			
	SC	-8.715			

We can observe here that for criteria the best fit VAR model is for q=5 lags. Looking at the probabilities of our hypothesis we accept both the null hypotheses. So, we accept that the construction index prices do not Granger cause the emission spot prices and vice versa.

5.3.6 Emission spots with Euro Stoxx Basic Resources Price Index

The following table demonstrates the attempt to estimate the best VAR model for the number of lags to take when running the causality Granger tests for the emission spots and the basic resources index prices:

Table 5.3.6 Granger Causality Test between emission spots and Euro Stoxx Basic Resources Index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-8.410*	RBASRES does not Granger Cause RES	0.56695	0.72540
	SC	-8.271*	RES does not Granger Cause RBASRES	1.78560	0.11349
10	AIC	-8.346			
	SC	-8.077			
15	AIC	-8.304			
	SC	-7.906			

The results indicate that the best fit VAR model is for q=5 lags. According to the probabilities, we accept the null hypothesis that the basic resources index prices do not Granger cause the emission spot prices. We further accept the hypothesis that emission spot prices do not Granger cause the basic resources index prices.

5.3.7 Emission spots with Euro Stoxx Technology Price Index

The Granger test for the emission spots and the technology index prices is shown below:

Table 5.3.7 Granger Causality Test between emission spots and Euro Stoxx Technology Index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-9.544*	RTECH does not Granger Cause RES	0.83580	0.52443
	SC	-9.404*	RES does not Granger Cause RTECH	0.78002	0.56425
10	AIC	-9.512			
	SC	-9.244			
15	AIC	-9.482			
	SC	-9.083			

According to both the AIC and SC criteria the best fit VAR model is for q=5 lags. Looking at the probabilities of our hypothesis we accept both the null hypotheses. Therefore, we accept the hypothesis that the technology index prices do not Granger cause the emission spot prices and vice versa.

5.3.8 Emission spots with Eurofirst300 Utilities Price Index

Considering the utilities index price, the Granger test results are the following:

Table 5.3.8 Granger Causality Test between emission spots and Eurofirst300 Utilities Index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-9.752*	RUTIL300 does not Granger Cause RES	0.67595	0.64179
	SC	-9.613*	RES does not Granger Cause RUTIL300	1.83969	0.10290
10	AIC	-9.701			
	SC	-9.433			
15	AIC	-9.659			
	SC	-9.261			

For both criteria the best fit VAR model is for q=5 lags. The probabilities of our hypotheses point to the acceptance of the null hypothesis that the utilities index prices do not Granger

cause the emission spot prices. Furthermore, we accept the hypothesis that emission spot prices do not Granger cause the utilities index prices.

5.3.9 Emission spots with Eurofirst300 oil and gas Price Index

Continuing with the oil & gas index prices we have the following results:

Table 5.3.9 Granger Causality Test between emission spots and Eurofirst300 oil and gas Index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-9.449*	ROG300 does not Granger Cause RES	1.16346	0.32557
	SC	-9.309*	RES does not Granger Cause ROG300	2.69320	0.02016
10	AIC	-9.399			
	SC	-9.131			
15	AIC	-9.362			
	SC	-8.964			

The best fit VAR model for both criteria is when q=5 lags. Considering the probabilities of our hypotheses we accept the null hypothesis that the oil and gas index prices do not Granger cause the emission spot prices. We reject the hypothesis that emission spot prices do not Granger cause the oil and gas index prices.

5.3.10 Emission spots with Eurofirst300 basic materials Price Index

The causality Granger test results for incorporating the basic materials index prices are displayed in Table 5.3.10:

Table 5.3.10 Granger Causality Test between emission spots and Eurofirst300 basic materials Index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-8.883*	RBASMAT300 does not Granger Cause RES	0.60465	0.69641
	SC	-8.743*	RES does not Granger Cause RBASMAT300	1.29480	0.26414
10	AIC	-8.824			
	SC	-8.556			
15	AIC	-8.780			
	SC	-8.382			

We can conclude that the best fit VAR model is when q=5 lags according to both criteria. Also, considering the probabilities of our hypotheses we accept both the null hypotheses. Therefore, we accept that the basic materials index prices do not Granger cause the emission spot prices and vice versa.

5.3.11 Emission spots with Eurofirst300 Industrials Price Index

We continue by applying the Granger test between the emission spots and the industrials (300) index prices:

Table 5.3.11 Granger Causality Test between emission spots and industrials Index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-9.360*	RIND300 does not Granger Cause RES	0.45660	0.80859
	SC	-9.220*	RES does not Granger Cause RIND300	1.12244	0.34690
10	AIC	-9.308			
	SC	-9.040			
15	AIC	-9.271			
	SC	-8.873			

In this case the best fit VAR model is for q=5 lags (both criteria). According to the probabilities listed in Table 5.3.11 we accept both the null hypotheses. Therefore, we accept that the industrials (300) index prices do not Granger cause the emission spot prices and vice versa.

5.4 Emissions spots and general economy indicators

5.4.1 Emission spots with Standard & Poor's Europe 350 index

We then apply the causality Granger test to the general economic indicators, starting with the Standard & Poor's (S&P) 350 index:

Table 5.4.1 Granger Causality Test between emission spots and Standard & Poor's Europe 350 Index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-9.796*	RSP350 does not Granger Cause RES	0.79296	0.55488
	SC	-9.657*	RES does not Granger Cause RSP350	0.90316	0.47841
10	AIC	-9.7460			
	SC	-9.478			
15	AIC	-9.715			
	SC	-9.317			

The results indicate that for both criteria the best fit VAR model is when q=5 lags. Looking at the probabilities we accept both the null hypotheses. Therefore, we accept that the Standard & Poors index prices do not Granger cause the emission spot prices and vice versa.

5.4.2 Emission spots with DAX index

Table 5.4.2 demonstrates the Granger test results for the DAX index prices and the emission spots.

Table 5.4.2 Granger Causality Test between emission spots and DAX Index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-9.671*	RDAX does not Granger Cause RES	0.43961	0.82094
	SC	-9.531*	RES does not Granger Cause RDAX	1.61908	0.15261
10	AIC	-9.622			
	SC	-9.353			
15	AIC	-9.603			
	SC	-9.205			

We can observe that the best fit VAR model is for q=5 lags (both criteria). Concerning the probabilities, we accept both the null hypotheses. Therefore, we accept that the DAX index prices do not Granger cause the emission spot prices and vice versa.

5.4.3 Emission spots with Ftseurofirst300

Finally, we apply the Granger causality test for the emission spots and the Ftseurofirst300 index prices:

Table 5.4.3 Granger Causality Test between emission spots and ftseurofirst300 Index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-9.792*	RFTSE300 does not Granger Cause RES	0.91943	0.46767
	SC	-9.652*	RES does not Granger Cause RFTSE300	1.23846	0.28924
10	AIC	-9.742			
	SC	-9.473			
15	AIC	-9.711			
	SC	-9.313			

We can observe that for both the AIC and SC criteria the best fit VAR model is for q=5 lags. Looking at the probabilities of our hypothesis we accept both the null hypothesis. Therefore, we accept that the ftseurofirst300 index prices do not Granger cause the emission spot prices and vice versa.

5.5 Emissions futures and energy

5.5.1 Emission futures and gas spot prices

Similarly, we apply the Granger test between the energy variable and the emission futures, starting with the gas spot prices. The procedure for estimating the best VAR model for a specific number of lags is the same as for the emission spot prices in the previous sections:

Table 5.5.1 Granger Causality Test between emission futures and gas spot prices

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-7.891*	RGS does not Granger Cause REF	2.72452	0.01895
	SC	-7.751*	REF does not Granger Cause RGS	0.62548	0.68040
10	AIC	-7.867			
	SC	-7.598			
15	AIC	-7.818			
	SC	-7.420			

The results show that for both the AIC and SC criteria the best fit VAR model is for q=5 lags. Looking at the probabilities of our hypotheses we accept the null hypothesis that the emission futures do not Granger cause the gas spot prices. We reject the hypothesis that the gas spot prices do no Granger cause the emission futures prices.

5.5.2 Emission futures and gas futures

Table 5.5.2 demonstrates the results for including the gas futures prices:

Table 5.5.2 Granger Causality Test between emission futures and gas futures prices

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-10.420*	RGF does not Granger Cause REF	2.33177	0.04088
	SC	-10.280*	REF does not Granger Cause RGF	2.12300	0.06087
10	AIC	-10.370			
	SC	-10.102			
15	AIC	-10.300			
	SC	-9.903			

For both the AIC and SC criteria the best fit VAR model is when q=5 lags. According to the probabilities of our hypotheses we accept the null hypothesis that the emission futures do not Granger cause the gas futures. We reject the hypothesis that the gas futures do not Granger cause the emission futures.

5.5.3 Emission futures and electricity spots

When introducing the electricity spot in the causality test we get the following:

Table 5.5.3 Granger Causality Test between emission futures and electricity spot prices

Lags		Stats	Null Hypothesis	F-Statistic	Probability
5	AIC	-5.644*	RELS does not Granger Cause REF	0.77741	0.56614
	SC	-5.505*	REF does not Granger Cause RELS	0.80403	0.54693
10	AIC	-5.591			
	SC	-5.323			
15	AIC	-5.553			
	SC	-5.155			

The estimations here show that for both criteria the best fit VAR model is when we include q=5 lags. In respect to the probabilities of our hypotheses we accept both the null hypotheses. Therefore, it is valid that emission futures do not Granger cause the electricity spot prices and vice versa.

5.5.4 Emission futures and electricity futures

The Granger test results with introducing the electricity futures prices are displayed in Table 5.5.4:

Table 5.5.4 Granger Causality Test between emission futures and electricity futures prices

Lags		Stats	Null Hypothesis	F-Statistic	Probability
5	AIC	-11.102*	RELF does not Granger Cause REF	3.58457	0.00329
	SC	-10.962*	REF does not Granger Cause RELF	5.49350	5.7E-05
10	AIC	-11.047			
	SC	-10.779			
15	AIC	-10.977			
	SC	-10.579			

We can observe that for both the AIC and SC criteria the best fit VAR model is for q=5 lags. Here, we reject both the null hypotheses. Therefore, we reject the hypothesis that emission futures do not Granger cause the electricity futures prices and vice versa.

5.5.5 Emission futures and oil spots

The following table demonstrates the Granger test results regarding the emission futures with the oil spots:

Table 5.5.5 Granger Causality Test between emission futures and oil spots prices

Lags		Stats	Null Hypothesis	F-Statistic	Probability
5	AIC	-9.226*	ROIL does not Granger Cause REF	3.77431	0.00222
	SC	-9.0861*	REF does not Granger Cause ROIL	2.03023	0.07244
10	AIC	-9.160			
	SC	-8.892			
15	AIC	-9.0986			
	SC	-8.700			

The best fit VAR model is for q=5 lags. Looking at the probabilities of our hypotheses we accept the null hypothesis that emission futures do not Granger cause the oil spot prices. We reject the hypothesis that oil spot prices do not Granger cause the emission futures prices.

5.5.6 Emission futures and oil futures

Considering the oil futures in the Granger test, we get the following:

Table 5.5.6 Granger Causality Test between emission futures and oil futures prices

Lags		Stats	Null Hypothesis	F-Statistic	Probability
5	AIC	-9.035*	ROILF does not Granger Cause REF	1.70375	0.13141
	SC	-8.895*	REF does not Granger Cause ROILF	1.74678	0.12169
10	AIC	-8.973			
	SC	-8.705			
15	AIC	-8.903			
	SC	-8.505			

According to both the AIC and SC criteria the best fit VAR model is for q=5 lags. Regarding the probabilities of our hypotheses we accept both the null hypotheses. Therefore, we accept that the emission futures do not Granger cause the oil futures prices and vice versa.

5.5.7 Emissions futures and coal futures

The results in the case of the coal futures are shown in Table 5.5.7:

Table 5.5.7 Granger Causality Test between emission futures and coal futures prices

Lags		Stats	Null Hypothesis	F-Statistic	Probability
5	AIC	-10.270*	RCF does not Granger Cause REF	6.96103	2.3E-06
	SC	-10.1230*	REF does not Granger Cause RCF	2.03766	0.07144
10	AIC	-10.211			
	SC	-9.943			
15	AIC	-10.160			
	SC	-9.757			

The best fit VAR model is when we consider q=5 lags. We accept the null hypothesis that emission futures do not Granger cause the coal futures prices. We reject the hypothesis that coal futures do not Granger cause the emission futures prices.

5.6 Emissions futures and industrial indicators

5.6.1 Emission futures with Euro Stoxx Automobiles Price Index

We continue our causality tests by adding the several industrial indicators. Table 5.6.1 demonstrates the results for the automobiles index prices and the emission futures:

Table 5.6.1 Granger Causality Test between emission futures and Euro Stoxx automobiles index

Lags		Stats	Null Hypothesis	F-Statistic	Probability
5	AIC	-8.699*	RCAR does not Granger Cause REF	0.13577	0.98405
	SC	-8.559*	REF does not Granger Cause RCAR	1.72244	0.12711
10	AIC	-8.639			
	SC	-8.371			
15	AIC	-8.580			
	SC	-8.182			

We can see that the best fit VAR model is again for q=5 lags. The probabilities of our hypotheses indicate the acceptance of both the null hypotheses. Therefore, we accept the hypothesis that emission futures do not Granger cause the automobiles index prices and vice versa.

5.6.2 Emission futures with Euro Stoxx Chemicals Price Index

Regarding the chemicals index prices the Granger test results are the following:

Table 5.6.2 Granger Causality Test between emission futures and Euro Stoxx chemicals index

Lags		Stats	Null Hypothesis	F-Statistic	Probability
5	AIC	-9.971*	RCH does not Granger Cause REF	1.05592	0.38369
	SC	-9.831*	REF does not Granger Cause RCH	1.27579	0.27241
10	AIC	-9.927			
	SC	-9.658			
15	AIC	-9.866			
	SC	-9.4677			

According to both criteria the best fit VAR model is for q=5 lags. Concerning the probabilities of our hypotheses we accept both the null hypotheses. Therefore, we accept the hypothesis that emission futures do not Granger cause the chemicals index prices and vice versa.

5.6.3 Emission futures with Euro Stoxx Energy Price Index

Including the energy index prices produces Table 5.6.3:

Table 5.6.3 Granger Causality Test between emission futures and Euro Stoxx energy index

Lags		Stats	Null Hypothesis	F-Statistic	Probability
5	AIC	-9.763*	REN does not Granger Cause REF	3.07889	0.00930
	SC	-9.623*	REF does not Granger Cause REN	0.77870	0.56521
10	AIC	-9.705			
	SC	-9.4366			
15	AIC	-9.650			
	SC	-9.252			

The results here indicates that the best fit VAR model is when q=5 lags (both criteria). Depending on the probabilities of our hypotheses we accept the null hypothesis that emission

futures do not Granger cause the energy index prices. We reject the hypothesis that energy index prices do not Granger cause the emission futures prices.

5.6.4 Emission futures with Euro Stoxx Industrials Price Index

Table 5.6.4 displays the Granger tests results between the emission futures and the industrials index prices:

Table 5.6.4 Granger Causality Test between emission futures and Euro Stoxx industrials index

Lags		Stats	Null Hypothesis	F-Statistic	Probability
5	AIC	-9.882*	RIND does not Granger Cause REF	1.25760	0.28051
	SC	-9.742*	REF does not Granger Cause RIND	1.72802	0.12585
10	AIC	-9.820			
	SC	-9.552			
15	AIC	-9.759			
	SC	-9.361			

The best fit VAR model is for q=5 lags according to both criteria. We accept both the null hypotheses. Therefore, we accept the hypothesis that emission futures do not Granger cause the industrials index prices and vice versa.

5.6.5 Emission futures with Euro Stoxx Construction Price Index

Applying the Granger test for the emission futures and the construction index prices results in the following:

Table 5.6.5 Granger Causality Test between emission futures and Euro Stoxx construction index

Lags		Stats	Null Hypothesis	F-Statistic	Probability
5	AIC	-9.575*	RCONST does not Granger Cause REF	1.11924	0.34861
	SC	-9.436*	REF does not Granger Cause RCONST	1.68324	0.13629
10	AIC	-9.516			
	SC	-9.248			
15	AIC	-9.448			
	SC	-9.050			

We can observe that for both the AIC and SC criteria the best fit VAR model is for q=5 lags. We accept both of our hypotheses. Therefore, we accept that emission futures do not Granger cause the construction index prices and vice versa.

5.6.6 Emission futures with Euro Stoxx Basic Resources Price Index

Regarding the basic resources index prices we get Table 5.6.6:

Table 5.6.6 Granger Causality Test between emission futures and Euro Stoxx basic materials index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-8.790*	RBASRES does not Granger Cause RES	1.14378	0.33568
	SC	-8.650*	RES does not Granger Cause RBASRES	1.01073	0.41025
10	AIC	-8.724			
	SC	-8.455			
15	AIC	-8.657			
	SC	-8.258			

The best fit VAR model occurs when q=5 lags for both criteria. According to the probabilities of our hypotheses we accept both of them. Therefore, we accept that emission futures do not Granger cause the basic materials index prices and vice versa.

5.6.7 Emission futures with Euro Stoxx Technology Price Index

Including the technology index prices in the Granger test with the emission futures we get:

Table 5.6.7 Granger Causality Test between emission futures and Euro Stoxx technology index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-9.907*	RTECH does not Granger Cause REF	1.98596	0.07866
	SC	-9.767*	REF does not Granger Cause RTECH	2.11223	0.06212
10	AIC	-9.861			
	SC	-9.593			
15	AIC	-9.815			
	SC	-9.417			

The results demonstrate the best fit VAR model is for q=5 lags (both criteria). Considering the probabilities of our hypotheses we accept both of them. Therefore, we accept that emission futures do not Granger cause the technology index prices and vice versa.

5.6.8 Emission futures with Eurofirst300 utilities Price Index

The following table demonstrates Granger test results for the emission futures and the utilities index prices. We can observe here that for both criteria the best fit VAR model is when q=5 lags, same as before. The probabilities of our hypotheses indicate that we should accept both of them. Therefore, we accept that emission futures do not Granger cause the utilities index prices and vice versa.

Table 5.6.8 Granger Causality Test between emission futures and Eurofirst300 utilities index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-10.080*	RUTIL300 does not Granger Cause REF	1.83995	0.10285
	SC	-9.936*	REF does not Granger Cause RUTIL300	0.40432	0.84595
10	AIC	-10.025			
	SC	-9.7566			
15	AIC	-9.969			
	SC	-9.571			

5.6.9 Emission futures with Eurofirst300 oil and gas Price Index

The Granger test results for the oil & gas index prices and the emission futures are shown in Table 5.6.9 below:

Table 5.6.9 Granger Causality Test between emission futures and Eurofirst300 oil & gas index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-9.801*	ROG300 does not Granger Cause REF	3.07831	0.00931
	SC	-9.661*	REF does not Granger Cause ROG300	0.92136	0.46641
10	AIC	-9.745			
	SC	-9.476			
15	AIC	-9.691			
	SC	-9.293			

According to both the AIC and SC criteria the best fit VAR model is when q=5 lags. We accept the null hypothesis that emission futures do not Granger cause the oil and gas index prices. We reject the hypothesis that oil and gas index prices do not Granger cause the emission futures prices.

5.6.10 Emission futures with Eurofirst300 basic materials Price Index

For the basic materials index prices we get the following Granger test results:

Table 5.6.10 Granger Causality Test between emission futures and Eurofirst300 basic materials index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-9.266*	RBASMAT300 does not Granger Cause REF	1.03072	0.39835
	SC	-9.126*	REF does not Granger Cause RBASMAT300	1.26308	0.27804
10	AIC	-9.204			
	SC	-8.935			
15	AIC	-9.134			
	SC	-8.736			

Here, the best fit VAR model is for q=5 lags (both criteria). Concerning the probabilities of our hypotheses we accept both of them. Therefore, we accept that emission futures do not Granger cause the basic materials index prices and vice versa.

5.6.11 Emission futures with Eurofirst300 Industrials Price Index

For the industrials (300) index prices Table 5.6.11 is produced:

Table 5.6.11 Granger Causality Test between emission futures and Eurofirst300 industrials index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-9.741*	RIND300 does not Granger Cause REF	1.35750	0.23835
	SC	-9.602*	REF does not Granger Cause RIND300	1.52501	0.17968
10	AIC	-9.678			
	SC	-9.410			
15	AIC	-9.615			
	SC	-9.217			

We can argue that for both criteria the best fit VAR model is when q=5 lags. The probabilities of our hypotheses direct us into accepting both of them. Therefore, we accept that emission futures do not Granger cause the industrials (300) index prices and vice versa.

5.7 Emissions futures and general economy indicators

5.7.1 Emission futures with Standard & Poor's Europe 350 index

We continue with the causality tests by incorporating the general economic indicators, starting with the S&P 350 index prices:

Table 5.7.1 Granger Causality Test between emission futures and S & P Europe 350 index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-10.157*	RSP350 does not Granger Cause REF	1.78812	0.11298
	SC	-10.018*	REF does not Granger Cause RSP350	0.88236	0.49236
10	AIC	-10.102			
	SC	-9.834			
15	AIC	-10.051			
	SC	-9.653			

The best fit VAR model is for q=5 lags regarding both criteria. We accept both of our hypotheses. Therefore, we accept that emission futures do not Granger cause the Standard & Poors Europe 350 index prices and vice versa.

5.7.2 Emission futures with DAX index

The DAX index prices provide the following causality test results:

Table 5.7.2 Granger Causality Test between emission futures and DAX index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-10.000*	RDAX does not Granger Cause REF	0.49943	0.77679
	SC	-9.860*	REF does not Granger Cause RDAX	0.98008	0.42897
10	AIC	-9.958			
	SC	-9.690			
15	AIC	-9.903			
	SC	-9.505			

For both the AIC and SC criteria the best fit VAR model is for q=5 lags. Considering the probabilities of our hypotheses we accept both of them. Therefore, we accept that emission futures do not Granger cause the DAX index prices and vice versa.

5.7.3 Emission futures with Ftseurofirst300

Finally, the Granger test for the emission futures and the Ftseurofirst300 index prices are listed in Table 5.7.3 below:

Table 5.7.3 Granger Causality Test between emission futures and ftseurofirst300 index

Lags	Stats		Null Hypothesis	F-Statistic	Probability
5	AIC	-10.160*	RFTSE300 does not Granger Cause REF	1.58515	0.16192
	SC	-10.020*	REF does not Granger Cause RFTSE300	0.93224	0.45932
10	AIC	-10.107			
	SC	-9.839			
15	AIC	-10.060			
	SC	-9.659			

We can conclude that for both criteria the best fit VAR model is when q=5 lags. Looking at the probabilities of our hypotheses we accept both of them. Therefore, we accept that emission futures do not Granger cause the ftseurofirst300 index prices and vice versa.

5.8 Summary of causality results

Table 8.1 below shows which null hypothesis we accept or reject, in the case of emission spots towards energy variables:

Table 8.1 Causality results between the emission spots and the energy variables

Energy variables	Emission spots do not Granger cause…
Emission futures	× (and vice versa)
Gas spots	× (accept the opposite)
Gas futures	× (and vice versa)
Electricity spots	✓ (and vice versa)
Electricity futures	× (accept the opposite)
Oil spots	✓ (and vice versa)
Oil futures	× (accept the opposite)
Coal futures	× (and vice versa)

In table 8.2, we demonstrate the acceptance or rejection of the null hypotheses regarding emission spots and other economic indicators:

Table 8.2 Causality results between the emission spots and the economic variables

Economic indicators	Emission spots do not Granger cause…
Euro Stoxx Automobiles Index	✓ (and vice versa)
Euro Stoxx Chemicals Index	✓ (and vice versa)
Euro Stoxx Energy Index	× (accept the opposite)
Euro Stoxx Industrials Index	✓ (and vice versa)
Euro Stoxx Construction Index	✓ (and vice versa)
Euro Stoxx Basic Resources Index	✓ (and vice versa)
Euro Stoxx Technology Index	✓ (and vice versa)
Eurofirst300 Utilities Index	✓ (and vice versa)
Eurofirst300 Oil & Gas Index	× (accept the opposite)
Eurofirst300 Basic Materials Index	✓ (and vice versa)
Eurofirst300 Industrials Index	✓ (and vice versa)
Standard & Poors Europe 350 Index	✓ (and vice versa)
DAX Index	✓ (and vice versa)
Ftseurofirst300 Index	✓ (and vice versa)

From the above we can say that the emission spots Granger cause:

1. the emission futures
2. the gas spots and their futures
3. the electricity futures
4. the oil futures
5. the coal futures
6. the Euro STOXX energy index
7. the Eurofirst 300 oil & gas index

The emission spots do not Granger cause:

1. the electricity spots
2. the oil spots
3. all the economic indices apart from the energy and the oil & gas ones.

The variables that Granger cause the emission spots are:

1. the emission futures
2. the gas futures

3. the coal futures

The variables that do not Granger cause the emission spots are:

1. the gas spots
2. the electricity spots and their futures
3. all the economic indicators

Table 8.3 below shows which null hypothesis we accept or reject, in the case of emission futures towards energy variables:

Table 8.3 Causality results between the emission futures and the energy variables

Energy variables	Emission futures do not Granger cause…
Gas spots	✓ (and reject the opposite)
Gas futures	✓ (and reject the opposite)
Electricity spots	✓ (and vice versa)
Electricity futures	× (and vice versa)
Oil spots	✓ (and reject the opposite)
Oil futures	✓ (and vice versa)
Coal futures	✓ (and reject the opposite)

In table 8.4, we demonstrate the acceptance or rejection of the null hypotheses regarding emission futures and other economic indicators:

Table 8.4 Causality results between the emission futures and the economic variables

Economic indicators	Emission spots do not Granger cause…
Euro Stoxx Automobiles Index	✓ (and vice versa)
Euro Stoxx Chemicals Index	✓ (and vice versa)
Euro Stoxx Energy Index	✓ (reject the opposite)
Euro Stoxx Industrials Index	✓ (and vice versa)
Euro Stoxx Construction Index	✓ (and vice versa)
Euro Stoxx Basic Resources Index	✓ (and vice versa)
Euro Stoxx Technology Index	✓ (and vice versa)
Eurofirst300 Utilities Index	✓ (and vice versa)
Eurofirst300 Oil & Gas Index	✓ (reject the opposite)
Eurofirst300 Basic Materials Index	✓ (and vice versa)
Eurofirst300 Industrials Index	✓ (and vice versa)
Standard & Poors Europe 350 Index	✓ (and vice versa)
DAX Index	✓ (and vice versa)
Ftseurofirst300 Index	✓ (and vice versa)

From the above we can say that the emission futures Granger cause the electricity futures. They do not Granger cause:

1. the gas spots and their futures
2. the electricity spots
3. the oil spots and their futures
4. none of the economic indicators

The variables that Granger cause the emission futures are:

1. the gas spots and their futures
2. the electricity futures
3. the oil spots
4. the coal futures
5. the energy and oil & gas indices

The variables that do not Granger cause the emission futures are:

1. the electricity spots
2. oil futures
3. all the economic indicators apart from the energy and the oil & gas variables.

Chapter 6

Co-integration analysis of the emission spot and futures prices

6.1 Introduction

If we wish to sum up our findings in the previous chapters, we deduce the following:

- In chapter 3, where we presented our variables, we found out that the emission spot prices are strongly correlated with those of their futures, the coal futures, the gas futures and the electricity futures. On the contrary, they appear to be weakly correlated with oil spots and oil futures, the gas spots and the electricity spot prices. Also, the emission futures are strongly correlated with the gas, electricity and the coal futures, and less with the oil, gas and electricity spots and the oil futures. Other strong correlations are found between the coal and the gas futures, the electricity and coal futures and finally the gas and electricity futures.
- In chapter 4, where we tested for stationarity, we discovered that all our energy, industry and general economy variables are non-stationary in their logarithmic levels, whereas their returns are found to be stationary. Therefore all our variables are found to be integrated of order one.
- In chapter 5, where we checked for causality, we have accepted the null hypothesis that gas spots, electricity spots and futures, oil spots and futures, and all the other economic indices do not Granger cause the emission spots. We have also accepted that emission futures do not Granger cause any of the energy variables or the economic indicators.

In this chapter we extend our research by further investigating the relationships between our variables based on the cointegration methodology. This explores whether two or more variables “move” together, which shows that there may be a relationship between two or more variables in equilibrium. Here, a group of non-stationary I(1) time series is said to have cointegration relationships if a certain linear combination of these time series is stationary (Wang, 2009). This enables us to check whether a short-run relationship between two or more time series can extend to a long-run relationship, which converges with time. Therefore, a

long-run relationship that appears to be in equilibrium leads to a systematic linear trend among those time series in question, which covers every part of their behaviour in time.

Concerning the relationship between the emission spots and their futures, the literature shows that emission spots influence their derivatives in a positive manner (Daskalakis et al, 2009; Wagner, 2007; Trück et al, 2006; Paolella and Taschini, 2006; Uhrig-Homburg and Wagner, 2007). They also appear to be integrated of the same order (non-stationary in logarithmic form and stationary in their returns). Therefore, we estimate their long-run equilibrium relationship by following the OLS (ordinary least squares) method (Katos, 2004):

$$Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t \quad (6.1)$$

Equation 6.1 is the cointegration regression, where ε_t represents the equilibrium error. The cointegration vector that is derived from equation 6.1 is in the form of [1, $-\beta_0$, $-\beta_1$]. Including the emission spots (as a time series X_t) and their futures (as a dependent variable Y_t) in Eviews 4.1, we get the following cointegration vector: [1, -0.065, -1.022]. The variables have been used in their logarithmic form. Therefore, equation 6.2 becomes (significance levels in brackets):

$$\text{lef}_t = 0.065 + 1.022\text{les}_t + \varepsilon_t \quad (6.2)$$

$$[0.038] \quad [0.000]$$

$$R^2 = 0.957 \quad DW = 0.284$$

Equation 6.2 can be written in respect to the equilibrium errors, which have to be stationary for the above equation to represent a long-run relationship between the emission spots time series (les_t) and their futures (lef_t) in their logarithmic levels:

$$\varepsilon_t = \text{lef}_t - 1.022\text{les}_t - 0.065 \quad (6.3)$$

After checking for stationarity by using the ADF and the PP tests, we find out that ε_t is stationary. Therefore, the emission spots and their futures are cointegrated in a long-run relationship.

However, although there is a long-run relationship between the emission spots and their futures, it is possible that these variables may be in disequilibrium in the short-run. The dynamics of this short-run disequilibrium relationship can be expressed by the 'error correction model', initially introduced by Sargan (1964):

$$\Delta Y_t = \text{lags}(\Delta Y_t, \Delta X_t) + \lambda\varepsilon_{t-1} \quad (6.4)$$

When including our variables, equation 6.4 is re-written as follows:

$$\Delta lef_t = lags(\Delta lef_t, \Delta les_t) + \lambda\varepsilon_{t-1} \qquad (6.5)$$

Equation 6.5 provides a link between the short-run and the long-run behaviour between our two variables, where we take the first differences of les_t and lef_t, which are integrated of order one, ε_t is represented according to equation 6.3 and λ is the short-run adjustment coefficient, which takes values $-1 < \lambda < 0$. The number of lags that have to be included in equation 6.4 can be estimated by the methodology suggested by Engle and Granger (1987):

- Step 1: we estimate equation 6.1, then we use the estimated cointegration vector to calculate the residual ε_t.
- Step 2: we estimated equation 6.5 by using the OLS method.

For estimating equation 6.5, we can make use of the appropriate statistical criteria, i.e. AIC, SC, to decide on the number of the lags of the first differences of the variables to be included in the equation. We find the following equation 6.6 as the one with the best fit (t-statistics in parentheses, significance levels in brackets):

$$\Delta lef_t = -0.0008 + 0.22\Delta les_t + 0.102\Delta lef_{t-1} - 0.101\Delta lef_{t-2} - 0.129\varepsilon_{t-1} \qquad (6.6)$$

$$(-1.014) \quad (7.4) \quad (2.987) \quad (-2.975) \quad (-9.542)$$

$$[0.311] \quad [0.000] \quad [0.003] \quad [0.003] \quad [0.000]$$

$$R^2 = 0.184 \qquad DW = 1.992$$

From equation 6.6, it is obvious that emission futures are influenced positively by the emission spots, something that is expected according to our hypothesis and also by their own prices on the previous day. Moreover, since the short-run adjustment coefficient appears to be significant, there is the 0.129 of deviation of the emission futures from their long-run equilibrium level that is corrected every day.

The rest of the chapter is organised as follows: We investigate the possible cointegration between emission spots and the other energy variables in section 6.2 and with the economic indices at 6.3. In sections 6.4 and 6.5 we apply the cointegration methodology between emission futures and energy variables and the other economic indicators respectively. In section 6.6, we extend the cointegrating relationship between the emission spots and their futures to include our other energy and economic variables. We summarise our results in section 6.7.

6.2 Testing for cointegration between emissions spot prices and other energy variables

In relation to the current literature, there appear to be conflicts concerning whether there is any cointegration between the emission spots and the other energy variables. Obermayer (2008) claims that emission spots are cointegrated with natural gas and oil at the 5% significance level and although he finds strong correlation between emission spots and power, he does not find any cointegration between them. Alberola et al (2008), based on previous research (Kanen, 2006; Christiansen et al., 2005; Bunn and Fezzi, 2007), argue that energy prices (electricity, natural gas, coal and oil) are the main drivers for the price of the EUA allowances and influence them in a positive manner. Kanen (2006) recognises that there is a strong correlation between power and the EUA prices and states that oil prices are the main driver for those of natural gas, which in affects the power prices in return and those influence the carbon prices. Bunn and Fezzi (2007) observe that the dramatic fall of the emission spot prices in April 2006 was a shock to the asset values of various power companies in the UK market, like in the case of British energy, where there was a loss of 5% in its stock market value. Kara et al., (2008) also find cointegration between emission spots and lagged natural gas prices when investigating the market in Finland. In contrast to the above authors, Hintermann (2009) found no cointegration between emission and fuel prices.

It is important to note that previous research covered the first commitment period, where EUA prices appeared to have high volatility and the market was considered to be very young. Therefore, we cannot have any “a priori” economic restrictions and all possible variations should be considered in our cointegration testing.

As we have more than two variables to consider, the methodology of Engle and Granger (1987) can still be applied, under the condition that there can only be one cointegration relationship among these variables. However, to cover the possibility of more than one cointegration relationships, we use the Johansen (1988) and Stock and Watson (1988) methodology:

- Step 1: We discover the order of the corresponding VAR model, depending on the AIC and SC criteria.

- Step 2: We estimate the cointegrating rank r by using the λ_{trace} statistic, which defines the levels of significance of the corresponding cointegrating vectors and according to the following null hypothesis test (Katos, 2004):

  H_o: r=0 vs. H_a: r≥1 (when λ_{trace}> critical value)

  H_o: r≤1 vs. H_a: r≥2 (when λ_{trace}< critical value) (6.7)

  H_o: r≤m-1 vs. H_a: r=m (when λ_{trace}> critical value)

The above hypothesis test involves all possible variables we can include in the cointegration model, represented by m. Critical values can be found in Johansen (1988), Johansen and Juselius (1990), Osterwald-Lenum (1992), Enders (1995).

- Step 3: we estimate the corresponding cointegrating vectors according to the cointegration rank.

If the cointegrating rank equals one (one cointegration vector), then equation 6.4 can be used for the estimation of the error correction model. However, in the case of more than one cointegration vectors, equation 6.8 is used instead, (Katos, 2004):

$$\Delta Y_t = \text{lags}(\Delta Y_t, \Delta X_{1,t} ..., \Delta X_{m,t}) + \lambda \varepsilon_{t-1} \quad (6.8)$$

At first, we investigate the possible cointegration relationships between the emission spots and the energy variables (gas, electricity and oil spots), as these are the actual EUA allowances and fuel prices respectively. Following the Johansen methodology as described above, we summarise in Table 6.1 the cointegration results between the emission spots prices and the other energy spot prices. The AIC and SC criteria show the best specification of the equation and indicate the number of possible cointegrating vectors accordingly.

Table 6.1 Summary of results with respect to assumptions for the emission spot prices

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	1	1	1	1	2
Max-Eig	1	1	1	1	1
AIC by Rank (rows) and Model (columns)					
0	-12.90192	-12.90192	-12.89140	-12.89140	-12.88342
1	-12.92299	**-12.94523***	-12.93748	-12.93610	-12.93077
2	-12.91486	-12.93461	-12.92939	-12.94415	-12.94146
3	-12.90115	-12.92008	-12.91751	-12.93255	-12.93113
4	-12.87903	-12.89905	-12.89905	-12.91315	-12.91315
SC by Rank (rows) and Model (columns)					
0	**-12.49576***	**-12.49576***	-12.45985	-12.45985	-12.42648
1	-12.46606	-12.48195	-12.45516	-12.44744	-12.42307
2	-12.40715	-12.41421	-12.39631	-12.39836	-12.38299
3	-12.34268	-12.34257	-12.33365	-12.32965	-12.32189
4	-12.26979	-12.26442	-12.26442	-12.25314	-12.25314

The assumptions of the cointegration test indicate the presence of at least one cointegrating vector at the 5% significance level. Therefore, the best fit model is the one with no data trend (linear or quadratic) and with the presence of a constant. According to the results in Table 6.1, we present in Table 6.2 the actual results of the chosen model with respect to the cointegration of the emission spot and the energy spot prices.

Table 6.2 Cointegration results between emission spots and energy spots

Hypothesized No. of CE(s)	Eigenvalue	Statistics	5 Percent Critical Value	1 Percent Critical Value
		Trace test		
		Trace Statistic		
None	0.065965	69.93044	53.12	60.16
At most 1*	0.014207	**20.66012**	34.91	41.07
At most 2	0.010351	10.32887	19.96	24.60
At most 3	0.003893	2.816538	9.24	12.97
		Max-eigenvalue test		
		Max-eigen Statistic		
None	0.065965	49.27032	28.14	33.24
At most 1*	0.014207	**10.33125**	22.00	26.81
At most 2	0.010351	7.512335	15.67	20.20
At most 3	0.003893	2.816538	9.24	12.97

*(**) denotes rejection of the hypothesis at the 5% (1%) level

From Table 6.2 we see that the trace test indicates one cointegrating equation at both 5% and 1% levels (where the trace statistic has to be smaller than the critical values at 5%), and the max-eigenvalue test indicates one cointegrating equation at both 5% and 1% levels. The normalized cointegrating coefficients are shown in Table 6.3.

Table 6.3 Normalized cointegrating coefficients (emission spots and energy)

LES	LOIL	LGS	LELS	C
1.000000	-0.255432	1.003443	-2.230683	4.184265
	(0.20493)	(0.23563)	(0.29268)	(0.91678)
	[-1.25]	[4.27]	[7.64]	[4.56]

Notes: Standard errors in parentheses
T-statistics in brackets

From the results in Table 6.3 we see that natural gas spots influence negatively the emission spots, whereas the electricity spots have a positive effect upon them. With respect to oil, it is derived that its influence upon the emission spots is non significant, since the t-statistic is found to be small.

As there is only one possible cointegration vector, we derive the following error correction equation, based on equation 6.4, with respect to the emission spots:

$$\Delta(\text{les})_t = -0.0006 + 0.0953\Delta(\text{les})_{t-1} - 0.0750\Delta(\text{les})_{t-2} + 0.0018e_{t-1} \quad (6.9)$$

$$[0.505] \quad [0.011] \quad [0.044] \quad [0.394]$$

$$R^2 = 0.015 \quad DW = 1.995$$

From equation 6.9 we see that the short-run adjustment coefficient is not significant, meaning that there is no actual deviation of the emission spot prices from their long run equilibrium level that is corrected every day. Furthermore, we observe that the emission spot prices are determined by the prices of the previous two days. This influence is positive, according to their coefficients in equation (6.9).

6.3 Testing for cointegration between emissions spot prices and other economic indicators

Previous literature suggests that there seems to be no cointegration between EUAs and various economic indicators. Obermayer (2007) used the DAX index and Hintermann (2009) included the FTSE Eurotop100 index and neither found any cointegration. However, since both authors refer to EUAs during the first Kyoto period, it is worth checking whether there is any possibility for cointegration in the second Kyoto period. Also, it is essential to involve more economic indices from various economic industry areas, to check whether there is any particular industry sector that influences directly the EUA prices.

Due to the large number of different indices, we carry out our estimations by including the more specialised industry sectors at first, which in turn are divided into those that represent three hundred companies and those that represent the most active companies. Then we continue with those indices that generally describe the economy as a whole. So, at first we include the indices of the sectors of automobiles, chemistry, energy, industry, construction, basic materials and technology, as these are described in chapter 3. Our results show that there is no cointegration among the above variables with the emission spot prices.

The next step in to include the indices that represent the 300 most active European companies (utilities, oil & gas, basic materials and industry). Table 6.4 provides a summary of the cointegration results between the emission spot prices and the mentioned industrial indicators. There appears to be a conflict in our results, where we have at least two cointegrating vectors according to the AIC criterion (with linear data trend and constant) and at least one cointegrating vector with respect to the SC criterion (with no trend and

with/without constant). Therefore, we choose the results of the AIC criterion, which is with linear trend and constant and at least two cointegrating vectors, because it seems to present more information. Table 6.5 displays the actual results of our cointegration results.

In Table 6.5 the trace test indicates two cointegrating equations at both 5% and 1% levels and the max-eigenvalue test indicates no cointegrating equation at both 5% and 1% levels. The normalized cointegrating coefficients are shown in Table 6.6. Although, there is the possibility of two cointegrating vectors at the most, we omit the second option, as it does not include the emission spots as part of the equation.

From Table 6.6, we can observe that the utilities sector is not cointegrated with the emission spots. The oil & gas, basic materials and the industrials coefficients appear to be non-significant.

Table 6.4 Summary of results with respect to assumptions for the emission spot prices and industry indicators

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	1	1	1	2	3
Max-Eig	0	0	0	0	0
AIC by Rank (rows) and Model (columns)					
0	-28.17020	-28.17020	-28.16018	-28.16018	-28.15221
1	-28.18392	-28.18176	-28.17391	-28.17644	-28.17043
2	-28.17923	-28.18114	-28.17570	**-28.18666***	-28.18330
3	-28.16378	-28.17245	-28.16976	-28.18350	-28.18288
4	-28.14202	-28.15216	-28.15223	-28.17450	-28.17545
5	-28.11440	-28.12752	-28.12752	-28.15263	-28.15263
SC by Rank (rows) and Model (columns)					
0	**-27.53557***	**-27.53557***	-27.49382	-27.49382	-27.45411
1	-27.48582	-27.47732	-27.44409	-27.44027	-27.40887
2	-27.41768	-27.40689	-27.38241	-27.38068	-27.35828
3	-27.33876	-27.32839	-27.31301	-27.30771	-27.29440
4	-27.25354	-27.23829	-27.23202	-27.22890	-27.22350
5	-27.16245	-27.14385	-27.14385	-27.13722	-27.13722

Table 6.5 Cointegration results between emission spots and industry 300 indices

Hypothesized No. of CE(s)	Eigenvalue	Statistics	5 Percent Critical Value	1 Percent Critical Value
		Trace test		
		Trace Statistic		
None **	0.045655	104.5445	87.31	96.58
At most 1 **	0.039873	70.80578	62.99	70.05
At most 2	0.026943	41.42812	42.44	48.45
At most 3	0.021237	21.70863	25.32	30.45
		Max-eigenvalue test		
		Max-eigen Statistic		
None	0.045655	33.73872	37.52	42.36
At most 1	0.039873	29.37766	31.46	36.65
At most 2	0.026943	19.71950	25.54	30.34
At most 3	0.021237	15.49810	18.96	23.65

*(**) denotes rejection of the hypothesis at the 5%(1%) level

Table 6.6 Normalized cointegrating coefficients (emission spots and industry indicators)

LES	LUTIL300	LOG300	LBASMAT300	LIND300	C
1.000000	0.000000	2.979715	-0.830035	-1.518726	0.001536
		(0.67354)	(0.59935)	(0.76569)	(0.00020)
		[-2.42517]	[0.58164]	[-2.85703]	[4.97359]

Notes: Standard errors in parentheses
T-statistics in brackets

The oil & gas index negatively influences the emission spots, whereas the industrials (lind300) index positively influences them. Based on equation 6.4, equation 6.10 shows the error correction model, with respect to the emission spots (significance level in brackets):

$$\Delta(\text{les})_t = -0.0001 + 0.095\Delta(\text{les})_{t-1} - 0.065\Delta(\text{les})_{t-2} - 0.255\Delta(\text{lutil300})_{t-1} \quad (6.10)$$

$$[0.77] \qquad [0.011] \qquad [0.081] \qquad [0.011]$$

$$-0.235\Delta(\text{lbasmat300})_{t-1} + 0.386\Delta(\text{lind300})_{t-1} - 0.00028e_{t-1}$$

$$[0.008] \qquad [0.000] \qquad [0.923]$$

$$R^2 = 0.034 \quad DW = 1.991$$

In equation 6.10 the error correction coefficient is not significant, therefore there is no actual deviation of the emission spot prices from their long run equilibrium level that is corrected

every day. Furthermore, we observe that the emission spot prices are positively influenced by their own prices of the previous day. They are negatively influenced by the previous day prices of the basic materials (lbasmat300) and the lagged prices of the utilities index (lutil300). They are positively influenced the industrials indices (lind300).

We include next the general European economy indices (Standard & Poor's350, FTSEurofirst300 and DAX). Table 6.7 lists a summary of the cointegration results between the emission spot prices and the mentioned economy indicators. Both the AIC and the SC criteria show to one cointegration vector, however we choose the best fit model (linear trend and constant) in respect to the AIC criterion, since the SC criterion points to two different models. Table 6.8 provides the actual cointegrating results of the emission spots and the general economy indices.

Table 6.7 Summary of results with respect to assumptions for the emission spot prices and general economy indicators

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	1	0	0	1	1
Max-Eig	1	0	0	1	1
AIC by Rank (rows) and Model (columns)					
0	-25.41388	-25.41388	-25.40589	-25.40589	-25.39827
1	-25.42505	-25.42632	-25.42088	-25.46618	-25.46132
2	-25.41952	-25.41803	-25.41532	**-25.47046***	-25.46826
3	-25.40682	-25.40366	-25.40174	-25.45974	-25.46012
4	-25.38598	-25.38155	-25.38155	-25.44063	-25.44063
SC by Rank (rows) and Model (columns)					
0	**-25.00772***	**-25.00772***	-24.97434	-24.97434	-24.94134
1	-24.96812	-24.96305	-24.93856	-24.97751	-24.95362
2	-24.91182	-24.89763	-24.88223	-24.92468	-24.90978
3	-24.84835	-24.82615	-24.81788	-24.85684	-24.85087
4	-24.77674	-24.74692	-24.74692	-24.78062	-24.78062

Table 6.8 Cointegration results between emission spots and general economic indices

Hypothesized No. of CE(s)	Eigenvalue	Statistics	5 Percent Critical Value	1 Percent Critical Value
		Trace test		
		Trace Statistic		
None **	0.081688	97.08720	62.99	70.05
At most 1	0.028797	35.55943	42.44	48.45
At most 2	0.014106	14.46249	25.32	30.45
At most 3	0.005807	4.205144	12.25	16.26
		Max-eigenvalue test		
		Max-eigen Statistic		
None **	0.081688	61.52777	31.46	36.65
At most 1	0.028797	21.09694	25.54	30.34
At most 2	0.014106	10.25734	18.96	23.65
At most 3	0.005807	4.205144	12.25	16.26

*(**) denotes rejection of the hypothesis at the 5%(1%) level

In Table 6.8 both the trace and the max-eigenvalue tests show the presence of at most one cointegrating vector at both 5% and 1% levels. Table 6.9 demonstrates the normalized cointegrating coefficients:

Table 6.9 Normalized cointegrating coefficients (emission spots and general economic indicators)

LES	LSP350	LFTSE300	LDAX	C
1.000000	0.000000	2.232961	-3.604729	0.001279
		(1.19542)	(1.23758)	(0.00025)
		[2.70599]	[-3.76508]	[5.85124]

Notes: Standard errors in parentheses
T-statistics in brackets

We remove the Standard & Poor's (lsp350) index from the cointegrating equation as it causes major standard errors to occur. The results suggest a negative relationship between the emission spots and the Ftseurofirst300 index (lftse300) and a positive influence from the DAX (ldax) index. Both of these findings contradict previous results. Obermayer (2007) and Hintermann (2009) found no cointegration with DAX or FTSE (Hintermann used a different FTSE indicator though). This means that during the second Kyoto period, the carbon market

has matured enough and seems to be influenced (either positively or negatively) by general European economic trends.

The error correction model is displayed in equation 6.11, with respect to the emission spots:

$$\Delta(\text{les})_t = 0.029 + 0.105\Delta(\text{les})_{t-1} - 0.074\Delta(\text{les})_{t-2} - 0.76\Delta(\text{lsp350})_{t-1} \quad (6.11)$$

$$[0.51] \quad [0.005] \quad [0.004] \quad [0.02]$$

$$+0.6\Delta(\text{lftse300})_{t-1} + 0.158\Delta(\text{ldax})_{t-1} - 0.0016e_{t-1}$$

$$[0.06] \quad [0.07] \quad [0.5]$$

$$R^2 = 0.024 \ \text{DW} = 1.996$$

In equation 6.11 the error correction coefficient is not significant, so there is no actual deviation of the emission spot prices from their long run equilibrium level that is corrected every day. Furthermore, we observe that in aggregate the emission spot prices are positively influenced by their own prices of the previous days. They are also negatively influenced by the Standard & Poor's index (lsp350).

6.4 Testing for cointegration between emission futures prices and other energy variables

In section 6.2 we found evidence of a cointegrated relationship between the emission spot prices and some of our energy variables (gas and electricity). This may indicate the presence of a similar relationship between the emission futures prices with energy. Since previous research involved only the spot prices, we cannot make any *"a priori"* assumption about the futures prices. Table 6.10 summarises the cointegrating results between the emission futures and the futures prices of our energy variables (gas, oil, electricity and coal).

Table 6.10 Summary of results with respect to assumptions for the emission futures and energy futures

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	0	0	1	1	1
Max-Eig	0	0	0	0	0
AIC by Rank (rows) and Model (columns)					
0	-27.12959	-27.12959	-27.11724	-27.11724	-27.10609
1	-27.12998	**-27.14372***	-27.13405	-27.13451	-27.12604
2	-27.12488	-27.14134	-27.13436	-27.13999	-27.13396
3	-27.10495	-27.12362	-27.11915	-27.13618	-27.13209
4	-27.08289	-27.10004	-27.09804	-27.11431	-27.11277
5	-27.05529	-27.07477	-27.07477	-27.09039	-27.09039
SC by Rank (rows) and Model (columns)					
0	**-26.49496***	**-26.49496***	-26.45088	-26.45088	-26.40800
1	-26.43189	-26.43928	-26.40422	-26.39834	-26.36448
2	-26.36332	-26.36709	-26.34108	-26.33402	-26.30894
3	-26.27993	-26.27956	-26.26240	-26.26039	-26.24361
4	-26.19440	-26.18618	-26.17782	-26.16871	-26.16083

It is clear that there is no cointegration between the emission futures and the energy futures prices. However, if we include the energy spot prices, we get two possible cointegrating vectors, according to the AIC criterion in Table 6.11. We can also see that the best fit model includes linear data trend and constant. Table 6.12 displays the actual results of our cointegration hypotheses:

Table 6.11 Summary of results with respect to assumptions for the emission futures and energy spots

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	1	1	1	2	2
Max-Eig	1	1	1	2	2
AIC by Rank (rows) and Model (columns)					
0	-13.27749	-13.27749	-13.26732	-13.26732	-13.25976
1	-13.30630	-13.32569	-13.31827	-13.31776	-13.31271
2	-13.29922	-13.31730	-13.31229	**-13.33188***	-13.32955
3	-13.28438	-13.30244	-13.30004	-13.32278	-13.32169
4	-13.26233	-13.28114	-13.28114	-13.30340	-13.30340
SC by Rank (rows) and Model (columns)					
0	**-12.87133***	**-12.87133***	-12.83577	-12.83577	-12.80283
1	-12.84937	-12.86241	-12.83595	-12.82909	-12.80500
2	-12.79151	-12.79691	-12.77920	-12.78610	-12.77108
3	-12.72591	-12.72493	-12.71618	-12.71988	-12.71244
4	-12.65308	-12.64651	-12.64651	-12.64338	-12.64338

Table 6.12 Cointegration results between emission futures and energy spot prices

Hypothesized No. of CE(s)	Eigenvalue	Statistics	5 Percent Critical Value	1 Percent Critical Value
		Trace test		
		Trace Statistic		
None **	0.072602	98.05087	62.99	70.05
At most 1 *	0.038302	43.63173	42.44	48.45
At most 2	0.015703	15.43426	25.32	30.45
At most 3	0.005534	4.006409	12.25	16.26
		Max-eigenvalue test		
		Max-eigen Statistic		
None **	0.072602	54.41915	31.46	36.65
At most 1 *	0.038302	28.19747	25.54	30.34
At most 2	0.015703	11.42785	18.96	23.65
At most 3	0.005534	4.006409	12.25	16.26

*(**) denotes rejection of the hypothesis at the 5%(1%) level

Both the trace and the max-eigenvalue test show two cointegrating equations at the 5% level and one cointegrating vector at the 1% level. The normalized cointegrating coefficients are shown in Table 6.13.

Table 6.13 Normalized cointegrating coefficients (emission futures and energy spot prices)

LEF	LOIL	LGS	LELS	C
1.000000	0.000000	1.311218	-2.953541	-0.000169
		(0.29877)	(0.40029)	(0.00035)
		[-4.69537]	[7.30537]	[3.12460]

Notes: Standard errors in parentheses
T-statistics in brackets

Our results are similar to those of the emission spots, i.e. oil spots seem to be non significant, gas spots have a negative influence on the emission futures, whereas the electricity spots affect them in a positive manner. The error correction model is displayed in equation 6.12, with respect to the emission futures:

$$\Delta(\text{lef})_t = 0.022 + 0.172\Delta(\text{lef})_{t-1} - 0.097\Delta(\text{lef})_{t-2} - 0.105\Delta(\text{loil})_{t-1} \quad (6.12)$$

$$[0.052] \quad [0.000] \quad [0.008] \quad [0.000]$$

$$-0.05\Delta(\text{lgs})_{t-1} + 0.006\Delta(\text{lels})_{t-1} - 0.002e_{t-1}$$

$$[0.005] \quad [0.245] \quad [0.045]$$

$$R^2 = 0.053 \; DW = 2.025$$

From equation 6.12, we find that since the short-run adjustment coefficient appears to be significant, there is the 0.002 of deviation of the emission futures from their long-run equilibrium level that is corrected every day. We also observe that in aggregate the emission futures are positively influenced by their prices of the two previous days. The energy variables of oil and gas have a negative effect and the electricity has a positive effect upon the emission futures.

6.5 Multiple variables cointegration between emission futures prices and other economic indicators

Following a similar approach as in section 6.3, we attempt to find possible cointegration between the emission futures and:

1. specific industrial sectors indices.
2. the most active 300 European industrial companies.
3. general economic indicators.

Implementing the first possibility, we discover that there is cointegration between the emission futures and the industrial indices, which was rejected in the case of emission spots. Table 6.14 shows a summary of the possible cointegration models.

According to both the AIC and the SC criteria, there is one cointegration relationship and the best fit model is the one with no data trend and with constant. Table 6.15 provides the actual cointegration results with respect to the various industrial sectors. The possibilities for more than four cointegration equations are not displayed:

Table 6.14 Summary of results with respect to assumptions for the emission futures and industry sectors

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	0	1	1	1	1
Max-Eig	0	0	0	0	0
AIC by Rank (rows) and Model (columns)					
0	-45.79992	-45.79992	-45.78530	-45.78530	-45.77019
1	-45.80907	**-45.81343***	-45.80150	-45.79906	-45.78629
2	-45.81127	-45.81297	-45.80343	-45.80119	-45.79119
3	-45.79820	-45.79993	-45.79305	-45.80007	-45.79212
4	-45.78005	-45.78402	-45.77953	-45.78412	-45.77838
5	-45.75281	-45.76242	-45.75969	-45.76152	-45.75854
6	-45.72154	-45.73185	-45.73163	-45.73679	-45.73658
7	-45.68259	-45.69544	-45.69750	-45.70121	-45.70130
8	-45.63898	-45.65337	-45.65337	-45.66294	-45.66294
SC by Rank (rows) and Model (columns)					
0	**-44.17527***	**-44.17527***	-44.10987	-44.10987	-44.04399
1	-44.08288	-44.08089	-44.02454	-44.01575	-43.95856
2	-43.98354	-43.97254	-43.92492	-43.91000	-43.86192
3	-43.86893	-43.85161	-43.81301	-43.80099	-43.76130
4	-43.74924	-43.72782	-43.69794	-43.67715	-43.64602
5	-43.62046	-43.59834	-43.57657	-43.54666	-43.52465
6	-43.48765	-43.45987	-43.44697	-43.41404	-43.40115
7	-43.34716	-43.31558	-43.31129	-43.27058	-43.26433
8	-43.20201	-43.16562	-43.16562	-43.12442	-43.12442

Here, the trace test indicates one cointegration equation at the 5% level and none at the 1% level, whereas the max-eigenvalue test shows no cointegration at any of the two levels. Table 6.16 displays the normalised coefficients.

Table 6.15 Cointegration results between emission futures and industrial sectors

Hypothesized No. of CE(s)	Eigenvalue	Statistics	5 Percent Critical Value	1 Percent Critical Value
		Trace test		
		Trace Statistic		
None *	0.058799	166.1872	165.58	177.20
At most 1	0.045560	122.4348	131.70	143.09
At most 2	0.033474	88.76736	102.14	111.01
At most 3	0.030701	64.18532	76.07	84.45
		Max-eigenvalue test		
		Max-eigen Statistic		
None	0.058799	43.75238	52.00	57.95
At most 1	0.045560	33.66749	46.45	51.91
At most 2	0.033474	24.58204	40.30	46.82
At most 3	0.030701	22.51327	34.40	39.79

*(**) denotes rejection of the hypothesis at the 5%(1%) level

Table 6.16 Normalized cointegrating coefficients (emission futures and industrial indices)

LEF	LCAR	LCH	LEN	LIND	LBASRES	LCONST	LTECH	C
1.000000	-3.035532	-0.336941	-1.287696	2.010540	2.639966	-1.029650	-4.063422	23.10007
	(0.52865)	(2.00232)	(1.35495)	(1.97033)	(1.09177)	(0.84046)	(1.45982)	(7.15561)
	[-5.742]	[-0.168]	[-0.95]	[1.02]	[2.418]	[-1.225]	[-2.784]	[3.228]

Notes: Standard errors in parentheses
T-statistics in brackets

Here, the automobiles (lcar) and technology (ltech) indices appear to be significant and positively influencing the emission futures, whilst the basic resources (lbasres) index is significant and negatively influences the emission futures. The error correction model for the emission futures is shown in equation 6.13.

$$\Delta(\text{lef})_t = 0.011 + 0.158\Delta(\text{lef})_{t-1} - 0.103\Delta(\text{lef})_{t-2} - 0.055\Delta(\text{lbasres})_{t-1} - 0.002e_{t-1} \quad (6.13)$$

[0.154] [0.000] [0.005] [0.03] [0.128]

$$R^2 = 0.033 \quad DW = 1.985$$

In equation 6.13, the error correction coefficient is not significant and the emission futures are in aggregate positively influenced by their prices of the two previous days. The basic resources index is found to have a negative influence upon the emission futures.

We continue with the second possibility and we summarise our preliminary results in Table 6.17. According to the AIC criterion, there are two cointegrating relationships and the best fit model is with linear trend and constant. In Table 6.18, we have the actual cointegration results between the emission futures and the indices of the 300 most active European companies.

Table 6.17 Summary of results with respect to assumptions for the emission futures and indices of 300 industrial companies

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	0	1	1	2	3
Max-Eig	0	0	0	0	0
AIC by Rank (rows) and Model (columns)					
0	-28.54766	-28.54766	-28.53816	-28.53816	-28.53031
1	-28.55903	-28.55740	-28.55020	-28.55157	-28.54559
2	-28.55297	-28.55449	-28.54935	**-28.56021***	-28.55668
3	-28.53812	-28.54561	-28.54324	-28.55641	-28.55565
4	-28.51680	-28.52563	-28.52603	-28.54708	-28.54819
5	-28.48914	-28.50132	-28.50132	-28.52534	-28.52534
SC by Rank (rows) and Model (columns)					
0	**-27.91303***	**-27.91303***	-27.87180	-27.87180	-27.83221
1	-27.86093	-27.85296	-27.82038	-27.81540	-27.78404
2	-27.79142	-27.78024	-27.75607	-27.75423	-27.73166
3	-27.71310	-27.70155	-27.68649	-27.68062	-27.66717
4	-27.62832	-27.61177	-27.60582	-27.60148	-27.59624
5	-27.53720	-27.51764	-27.51764	-27.50993	-27.50993

Table 6.18 Cointegration results between emission futures and indices of 300 industrial companies

Hypothesized No. of CE(s)	Eigenvalue	Statistics	5 Percent Critical Value	1 Percent Critical Value
		Trace test		
		Trace Statistic		
None *	0.058799	166.1872	165.58	177.20
At most 1	0.045560	122.4348	131.70	143.09
At most 2	0.033474	88.76736	102.14	111.01
At most 3	0.030701	64.18532	76.07	84.45
At most 4	0.008697	6.306381	12.25	16.26
		Max-eigenvalue test		
		Max-eigen Statistic		
None	0.058799	43.75238	52.00	57.95
At most 1	0.045560	33.66749	46.45	51.91
At most 2	0.033474	24.58204	40.30	46.82
At most 3	0.030701	22.51327	34.40	39.79
At most 4	0.008697	6.306381	12.25	16.26

*(**) denotes rejection of the hypothesis at the 5%(1%) level

The trace test shows two cointegrating equations at the 5% level and one at the 1% level. The max-eigenvalue test shows no cointegration at any level. Table 6.19 displays the normalised coefficients. The possibility where the emission futures are not included in the cointegration equation has been omitted.

Table 6.19 Normalised cointegrating coefficients (emission futures and 300 industrial indices)

LEF	LUTIL300	LOG300	LBASMAT300	LIND300	C
1.000000	0.000000	3.728407	-1.550197	-0.804653	0.001847
		(0.73675)	(0.65526)	(0.83518)	(0.00022)
		[5.057]	[-2.364]	[-0.963]	[8.575]

Notes: Standard errors in parentheses
T-statistics in brackets

The utilities sector is not included in the final cointegrating equation. The emissions futures are in the long-run positively influenced by the basic materials sector and negatively

influenced by the oil & gas index (LOG300). The error correction model is displayed in equation 6.13, with respect to the emission futures.

$$\Delta(\text{lef})_t = 0.0021 + 0.16\Delta(\text{lef})_{t-1} - 0.106\Delta(\text{lef})_{t-2} - 0.11\Delta(\log 300)_{t-1} - 0.0006e_{t-1} \quad (6.14)$$

[0.88] [0.000] [0.005] [0.009] [0.838]

$$R^2 = 0.033 \; DW = 1.992$$

The error correction coefficient is not significant and the emission futures prices are positively influenced by their one day lagged prices and negatively influenced by their previous two days prices. The oil & gas (log300) index has a negative influence upon the futures prices.

Finally, we investigate the possible cointegrating relation of the emission futures with the general economic indicators. Table 6.20 shows the general assumptions and Table 6.21 the actual cointegrating results.

Table 6.20 Summary of results with respect to assumptions for the emission futures and general economy indices

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	1	0	0	1	1
Max-Eig	1	1	1	1	1
AIC by Rank (rows) and Model (columns)					
0	-25.76327	-25.76327	-25.75559	-25.75559	-25.74794
1	-25.78025	-25.77783	-25.77273	-25.81831	-25.81342
2	-25.77124	-25.76680	-25.76442	**-25.81864***	-25.81650
3	-25.75821	-25.75163	-25.74976	-25.80715	-25.80749
4	-25.73733	-25.72954	-25.72954	-25.78781	-25.78781
SC by Rank (rows) and Model (columns)					
0	**-25.35710***	**-25.35710***	-25.32405	-25.32405	-25.29100
1	-25.32332	-25.31455	-25.29042	-25.32964	-25.30572
2	-25.26354	-25.24640	-25.23134	-25.27286	-25.25802
3	-25.19973	-25.17412	-25.16591	-25.20425	-25.19825
4	-25.12808	-25.09491	-25.09491	-25.12779	-25.12779

Again, since the SC criterion does not point to one possible best fit model, we base our estimation on the AIC criterion, which indicates one cointegrating relation and the best fit model with both linear data trend and constant.

Table 6.21 Cointegration results between emission futures and general economy indices

Hypothesized No. of CE(s)	Eigenvalue	Statistics	5 Percent Critical Value	1 Percent Critical Value
		Trace test		
		Trace Statistic		
None **	0.083914	95.25690	62.99	70.05
At most 1	0.024946	31.97688	42.44	48.45
At most 2	0.013352	13.73741	25.32	30.45
At most 3	0.005569	4.032061	12.25	16.26
		Max-eigenvalue test		
		Max-eigen Statistic		
None **	0.083914	63.28002	31.46	36.65
At most 1	0.024946	18.23947	25.54	30.34
At most 2	0.013352	9.705350	18.96	23.65
At most 3	0.005569	4.032061	12.25	16.26

*(**) denotes rejection of the hypothesis at the 5%(1%) level

Both the trace and the max-eigenvalue tests show one cointegrating equation at both the 5% and 1% levels. Table 6.22 displays the coefficients of the above equation, where we exclude the Standard & Poor's index as it provides poor estimations:

Table 6.22 Normalised cointegrating coefficients (emission futures and 300 industrial indices)

LEF	LSP350	LDAX	LFTSE300	C
1.000000	0.000000	-4.371263	3.090735	0.001619
		(1.33629)	(1.29100)	(0.00027)
		[-3.269]	[2.392]	[5.952]

Notes: Standard errors in parentheses
T-statistics in brackets

From table 6.22, we can see that the Standard & Poor's index in not included in the cointegration equation. As in the case of the emission spots, their futures are negatively connected to the Ftseurofirst300 index. Furthermore, the DAX index is significant and

positively connected with the emissions spots. Finally, the error correction model is displayed in equation 6.15, with respect to the emission futures:

$$\Delta(\text{lef})_t = 0.03 + 0.16\Delta(\text{lef})_{t-1} - 0.103\Delta(\text{lef})_{t-2} - 0.118\Delta(\text{lftse300})_{t-1} - 0.0027e_{t-1} \quad (6.14)$$

[0.485] [0.000] [0.005] [0.02] [0.474]

$$R^2 = 0.032 \text{ DW} = 1.987$$

The error correction coefficient is not significant and the emission futures prices are positively influenced by their own one day lagged prices and negatively influence by their own previous two days prices. The FTSEurofirst300 index (lftse300) has a negative effect upon the emission futures prices.

6.6 Multiple variables cointegration between emissions spot and futures prices with the energy and economic variables

In equation 6.6 from section 6.1, it is demonstrated that the emission futures are positively influenced from the emission spots and also from their own prices of the previous day. Therefore, we can continue our cointegration testing based on the above relationship and check whether their dynamics is influenced by the other energy and economic variables.

6.6.1 Cointegration between emission spot and futures prices with energy

We continue with our cointegration tests by introducing the energy spots and futures prices separately to the pair of the emission spots and their futures. We do this to identify whether the emission spots and futures have a relationship with the energy daily prices, since they get traded at the same time at the same market or are more influenced by their derivatives instead.

A summary of preliminary results is shown in Table 6.23. According to the AIC criterion, there are two cointegrating relationships and the best fit model is with linear trend and constant. In Table 6.24, we have the actual cointegration results between the emission spots-futures pair and the energy spots.

Both the trace and eigenvalue tests indicate two cointegrating equation at both the 5% and 1% levels. However, our results show one possible equation, which includes both the

emission futures (as the main dependent variable) and spots. Table 6.25 displays the coefficients of this equation.

Table 6.23 Summary of results with respect to assumptions for the emission spots-futures and energy spot prices

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	2	2	2	2	3
Max-Eig	2	2	2	2	3
AIC by Rank (rows) and Model (columns)					
0	-18.13167	-18.13167	-18.11875	-18.11875	-18.10804
1	-18.16228	-18.17341	-18.16326	-18.18483	-18.17673
2	-18.17664	-18.19783	-18.19045	-18.22099	-18.21560
3	-18.16330	-18.18305	-18.17817	**-18.22560***	-18.22279
4	-18.14201	-18.16188	-18.15961	-18.21050	-18.20928
5	-18.11444	-18.13504	-18.13504	-18.18575	-18.18575
SC by Rank (rows) and Model (columns)					
0	-17.49704*	-17.49704*	-17.45239	-17.45239	-17.40995
1	-17.46419	-17.46897	-17.43344	-17.44866	-17.41518
2	-17.41509	-17.42358	-17.39716	-17.41501	-17.39059
3	-17.33828	-17.33900	-17.32142	-17.34981	-17.33431
4	-17.25352	-17.24801	-17.23940	-17.26491	-17.25733
5	-17.16249	-17.15137	-17.15137	-17.17034	-17.17034

We can see in table 6.25 that the emission futures are negatively influenced by the electricity spots and positively influenced by the emission spots. The error correction model is displayed in equation 6.16, with respect to the emission futures and including the emission spots.

Table 6.24 Cointegration results between emission spots-futures and energy spots

Hypothesized No. of CE(s)	Eigenvalue	Statistics	5 Percent Critical Value	1 Percent Critical Value
		Trace test		
		Trace Statistic		
None **	0.092031	158.3703	87.31	96.58
At most 1 **	0.064459	88.66462	62.99	70.05
At most 2	0.034476	40.55792	42.44	48.45
At most 3	0.015256	15.22681	25.32	30.45
		Max-eigenvalue test		
		Max-eigen Statistic		
None **	0.092031	69.70567	37.52	42.36
At most 1 **	0.064459	48.10670	31.46	36.65
At most 2	0.034476	25.33112	25.54	30.34
At most 3	0.015256	11.09960	18.96	23.65

*(**) denotes rejection of the hypothesis at the 5%(1%) level

Table 6.25 Normalised cointegrating coefficients (emission spots-futures and energy spots)

LEF	LES	LOIL	LGS	LELS	C
1.000000	-0.959447	-0.012734	-0.012313	0.086655	0.000251
	(0.03348)	(0.02291)	(0.01556)	(0.02067)	(2.7E-05)
	[-28.658]	[-0.556]	[-0.79]	[4.19]	[9.447]

Notes: Standard errors in parentheses
T-statistics in brackets

$$\Delta(\text{lef})_t = -0.004 + 0.128\Delta(\text{lef})_{t-1} - 0.104\Delta(\text{lef})_{t-2} + 0.14\Delta(\text{les})_{t-1} \qquad (6.16)$$

$$[0.637] \qquad [0.001] \qquad [0.004] \qquad [0.000]$$

$$-0.085\Delta(loil)_{t-1} - 0.042\Delta(\lg s)_{t-1} + 0.003\Delta(lels)_{t-1} + 0.001\varepsilon_{t-1}$$

$$[0.006] \qquad [0.008] \qquad [0.057] \qquad [0.689]$$

$$R^2 = 0.072 \quad DW = 2.047$$

Equation 6.16 shows that the error correction coefficient is not significant and the emission futures prices are positively influenced by their own one day lagged prices and negatively influence by their own previous two days prices. The emission spots affect the futures

positively, which is expected from our hypothesis and also from the theory. Also, both the oil and gas spots affect the futures in a negative manner.

We continue with the energy futures variables. Our preliminary results are shown in table 6.26. According to the AIC criterion, there is one cointegrating relationship and the best fit model is with linear trend and constant. In Table 6.27, we have the actual cointegration results between the emission spots-futures pair and the energy futures.

Both the trace and eigenvalue tests indicate two cointegrating equation at both the 5% and 1% levels. However, our results show one possible equation, which includes both the emission futures (as the main dependent variable) and spots. Table 6.28 displays the coefficients of this equation.

Table 6.26 Summary of results with respect to assumptions for the emission spots-futures and energy futures prices

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	1	1	1	1	2
Max-Eig	1	1	1	1	1
AIC by Rank (rows) and Model (columns)					
0	-31.99242	-31.99242	-31.97738	-31.97738	-31.96352
1	-32.01323	-32.05952	-32.04723	-32.05735	-32.04621
2	-32.00769	-32.05787	-32.04830	**-32.06364***	-32.05512
3	-31.99656	-32.04930	-32.04242	-32.05805	-32.05220
4	-31.97073	-32.02531	-32.02100	-32.04903	-32.04489
5	-31.94266	-31.99622	-31.99446	-32.02162	-32.02011
6	-31.90954	-31.96486	-31.96486	-31.99217	-31.99217
SC by Rank (rows) and Model (columns)					
0	-31.07856*	-31.07856*	-31.02544	-31.02544	-30.97350
1	-31.02321	-31.06315	-31.01913	-31.02290	-30.98003
2	-30.94151	-30.97900	-30.94404	-30.94669	-30.91279
3	-30.85422	-30.88793	-30.86201	-30.85860	-30.83371
4	-30.75224	-30.78144	-30.76443	-30.76708	-30.75024
5	-30.64801	-30.66985	-30.66174	-30.65717	-30.64931
6	-30.53874	-30.55598	-30.55598	-30.54521	-30.54521

Table 6.27 Cointegration results between emission spots-futures and energy futures

Hypothesized No. of CE(s)	Eigenvalue	Statistics	5 Percent Critical Value	1 Percent Critical Value
		Trace test		
		Trace Statistic		
None **	0.109501	166.6736	114.90	124.75
At most 1	0.041421	82.94070	87.31	96.58
At most 2	0.029961	52.39769	62.99	70.05
At most 3	0.026638	30.43512	42.44	48.45
At most 4	0.008564	10.94200	25.32	30.45
		Max-eigenvalue test		
		Max-eigen Statistic		
None **	0.109501	83.73288	43.97	49.51
At most 1	0.041421	30.54300	37.52	42.36
At most 2	0.029961	21.96257	31.46	36.65
At most 3	0.026638	19.49312	25.54	30.34
At most 4	0.008564	6.209689	18.96	23.65

*(**) denotes rejection of the hypothesis at the 5%(1%) level

Table 6.28 Normalised cointegrating coefficients (emission spots-futures and energy futures)

LEF	LES	LOILF	LGF	LELF	LCF	C
1.000000	-0.787113	-0.055249	-0.014193	-0.437631	0.121720	0.000105
	(0.02510)	(0.02102)	(0.03558)	(0.06983)	(0.04263)	(2.5E-05)
	[-31.35]	[-2.68]	[-0.399]	[-6.267]	[2.855]	[4.139]

Notes: Standard errors in parentheses
T-statistics in brackets

We can see from table 6.28 that again the emission spots appear to influence the emissions futures positively and significantly. Similarly, oil, gas and electricity futures influence the emissions futures positively and significantly. In contrast, the coal futures influence the emissions futures negatively and significantly. The error correction model is displayed in equation 6.17, with respect to the emission futures by including the emission spots.

$$\Delta(\text{lef})_t = -0.002 + 0.141\Delta(\text{lef})_{t-1} - 0.101\Delta(\text{lef})_{t-2} + 0.139\Delta(\text{les})_{t-1} \quad (6.17)$$

$$[0.891] \quad [0.000] \qquad [0.006] \qquad [0.000]$$

$$-0.168\Delta(\text{lcf})_{t-1} - 0.0006\varepsilon_{t-1}$$

$$[0.001] \qquad [0.85]$$

$$R^2 = 0.066 \text{ DW} = 2.026$$

Equation 6.17 shows that the error correction coefficient is not significant and the emission futures prices are positively influenced by their own one day lagged prices and negatively influence by their own previous two days prices. It also demonstrates that the coal futures affect the emission futures in a negative manner.

6.6.2 Cointegration between emission spot and futures prices with economic indicators

The cointegration tests are separated as before, i.e. we distinguish the economic variables to those that represent each industry sector separately, to those that constitute the 300 most liquid European companies and finally to those that characterise the more general economic activity in Europe.

In Table 6.29, we have the actual cointegration results between the emission spots-futures pair and the separate industrial sectors. According to both the AIC and the SC criteria, there seem to be either two cointegrating equations (trace test) or one cointegration equation (eigenvalue test), and the best fit model has no data trend, only the constant. In Table 6.30, we have the actual cointegration results between the emission spots-futures pair and the economic indices.

Table 6.29 Cointegration results between emission spots-futures and industrial sectors

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or	No Intercept	Intercept	Intercept	Intercept	Intercept
No. of CEs	No Trend	No Trend	No Trend	Trend	Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	2	2	2	2	3
Max-Eig	1	1	1	1	1
AIC by Rank (rows) and Model (columns)					
0	-50.65841	-50.65841	-50.64095	-50.64095	-50.62312
1	-50.72840	-50.72717	-50.71244	-50.71259	-50.69752
2	-50.73267	**-50.73531***	-50.72325	-50.72140	-50.70875
3	-50.73017	-50.73066	-50.72095	-50.72083	-50.71088
4	-50.71300	-50.71197	-50.70480	-50.71429	-50.70637
5	-50.68947	-50.69178	-50.68734	-50.69411	-50.68841
6	-50.65727	-50.66509	-50.66224	-50.66626	-50.66329
7	-50.62083	-50.62944	-50.62908	-50.63601	-50.63581
8	-50.57624	-50.58736	-50.58944	-50.59490	-50.59501
9	-50.52710	-50.53976	-50.53976	-50.55122	-50.55122
SC by Rank (rows) and Model (columns)					
0	-48.60221*	**-48.60221***	-48.52764	-48.52764	-48.45268
1	-48.55797	-48.55039	-48.48489	-48.47869	-48.41285
2	-48.44800	-48.43795	-48.38147	-48.36692	-48.30985
3	-48.33127	-48.31272	-48.26494	-48.24577	-48.19775
4	-48.19986	-48.17346	-48.13455	-48.11866	-48.07901
5	-48.06210	-48.03269	-48.00285	-47.97790	-47.94682
6	-47.91567	-47.88542	-47.86352	-47.82946	-47.80746
7	-47.76500	-47.72918	-47.71613	-47.67864	-47.66574
8	-47.60617	-47.56653	-47.56226	-47.51695	-47.51071
9	-47.44280	-47.39834	-47.39834	-47.35268	-47.35268

Table 6.30 Cointegration results between emission spots-futures and industrial sectors

Hypothesized No. of CE(s)	Eigenvalue	Statistics	5 Percent Critical Value	1 Percent Critical Value
		Trace test		
		Trace Statistic		
None **	0.114306	256.3310	202.92	215.74
At most 1 *	0.058964	168.6917	165.58	177.20
At most 2	0.046850	124.8128	131.70	143.09
At most 3	0.033377	90.16920	102.14	111.01
At most 4	0.031919	65.65976	76.07	84.45
At most 5	0.025608	42.23848	53.12	60.16
At most 6	0.016836	23.50850	34.91	41.07
At most 7	0.010497	11.24912	19.96	24.60
At most 8	0.005016	3.630418	9.24	12.97
		Max-eigenvalue test		
		Max-eigen Statistic		
None **	0.114306	87.63937	57.42	63.71
At most 1	0.058964	43.87889	52.00	57.95
At most 2	0.046850	34.64357	46.45	51.91
At most 3	0.033377	24.50945	40.30	46.82
At most 4	0.031919	23.42127	34.40	39.79
At most 5	0.025608	18.72998	28.14	33.24
At most 6	0.016836	12.25939	22.00	26.81
At most 7	0.010497	7.618698	15.67	20.20
At most 8	0.005016	3.630418	9.24	12.97

*(**) denotes rejection of the hypothesis at the 5%(1%) level

The trace test indicates two cointegrating equations at the 1% level. At 5% level both the trace and the eigenvalue tests demonstrate one cointegrating equation. Table 6.31 displays the coefficients of this equation:

Table 6.31 Normalised cointegrating coefficients (emission spots-futures and industrial indicators)

LEF	LES	LCAR	LCH	LIND	LEN	LCONST	LBASRES	LTECH	C
1.000000	-1.029069	0.058000	-0.065173	0.412299	-0.113167	0.123860	-0.086152	-0.237625	-0.486611
	(0.01951)	(0.03261)	(0.11202)	(0.10493)	(0.07383)	(0.04738)	(0.06027)	(0.07995)	(0.38258)
	[-52.76]	[1.78]	[-0.58]	[3.93]	[-1.53]	[2.61]	[-1.43]	[-2.97]	[-1.27]

Notes: Standard errors in parentheses
T-statistics in brackets

We can see from table 6.31 that the emission futures are influenced positively from emissions spots and the technology index (ltech) and negatively from the industrial (lind) and the construction (lconst) sectors. The error correction model is displayed in equation 6.18, with respect to the emission futures and including the emission spots. As we had many variables, we added them separately and chose the best fit according to the AIC and the SC criteria.

$$\Delta(\text{lef})_t = -0.001 + 0.121\Delta(\text{lef})_{t-1} - 0.114\Delta(\text{lef})_{t-2} + 0.148\Delta(\text{les})_{t-1} \quad (6.18)$$

$$[0.882] \qquad [0.002] \qquad [0.002] \qquad [0.000]$$

$$-0.107\Delta(\text{len})_{t-1} + 0.0002\varepsilon_{t-1}$$

$$[0.008] \qquad [0.94]$$

$$R^2 = 0.06 \text{ DW} = 2.029$$

Equation 6.18 shows that the error correction coefficient is not significant and the emission futures prices are positively influenced by their own one day lagged prices and negatively influence by their own previous two days prices. It also demonstrates that the energy sector affects the emission futures in a negative manner.

We continue with the 300 industrial companies and we summarise our preliminary results in Table 6.32. According to the AIC criterion, there are either three cointegrating relationships (trace test) or one cointegration relationship (eigenvalue test) and the best fit model is with linear trend and constant. In Table 6.33, we have the actual cointegration results between the emission futures and the indices of the 300 most active European companies.

The trace test indicates three cointegrating equations at the 5% level. At 1% level the trace test shows two cointegrating equations, whereas the eigenvalue test demonstrates one cointegrating equation. We choose the one which contains both the emission spots and their futures. Table 6.34 displays the coefficients of this equation:

Table 6.32 Summary of results with respect to assumptions for the emission spots-futures and indices of 300 industrial companies

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	1	1	2	3	4
Max-Eig	1	1	1	1	1
AIC by Rank (rows) and Model (columns)					
0	-33.42124	-33.42124	-33.40886	-33.40886	-33.39826
1	-33.46780	-33.46667	-33.45703	-33.47952	-33.47167
2	-33.47345	-33.47074	-33.46338	-33.48961	-33.48376
3	-33.46110	-33.46280	-33.45747	**-33.49259***	-33.48907
4	-33.44071	-33.44765	-33.44507	-33.48343	-33.48266
5	-33.41334	-33.42191	-33.42208	-33.46791	-33.46913
6	-33.38017	-33.39165	-33.39165	-33.44078	-33.44078
SC by Rank (rows) and Model (columns)					
0	-32.50738*	-32.50738*	-32.45691	-32.45691	-32.40824
1	-32.47778	-32.47030	-32.42893	-32.44508	-32.40549
2	-32.40727	-32.39187	-32.35913	-32.37267	-32.34143
3	-32.31877	-32.30143	-32.27706	-32.29314	-32.27058
4	-32.22222	-32.20378	-32.18850	-32.20148	-32.18801
5	-32.11869	-32.09554	-32.08935	-32.10345	-32.09833
6	-32.00937	-31.98277	-31.98277	-31.99383	-31.99383

We can see from table 6.34 that the emission futures are influenced positively from emissions spots and the basic materials sector and negatively from the industrials (lind300) and the utilities (lutil300) sectors.

Table 6.33 Cointegration results between emission spots-futures and 300 industrial companies

Hypothesized No. of CE(s)	Eigenvalue	Statistics	5 Percent Critical Value	1 Percent Critical Value
		Trace test		
		Trace Statistic		
None **	0.101186	179.0508	114.90	124.75
At most 1 **	0.045054	102.0284	87.31	96.58
At most 2 *	0.038240	68.74363	62.99	70.05
At most 3	0.026491	40.59258	42.44	48.45
At most 4	0.020279	21.20802	25.32	30.45
At most 5	0.008848	6.416341	12.25	16.26
		Max-eigenvalue test		
		Max-eigen Statistic		
None **	0.101186	77.02235	43.97	49.51
At most 1	0.045054	33.28478	37.52	42.36
At most 2	0.038240	28.15105	31.46	36.65
At most 3	0.026491	19.38456	25.54	30.34
At most 4	0.020279	14.79168	18.96	23.65
At most 5	0.008848	6.416341	12.25	16.26

*(**) denotes rejection of the hypothesis at the 5%(1%) level

Table 6.34 Normalised cointegrating coefficients (emission spots-futures and 300 industrial companies)

LEF	LES	LBASMAT300	LOG300	LIND300	LUTIL300	C
1.000000	-0.993909	-0.160048	-0.086746	0.171217	0.313905	0.000322
	(0.02483)	(0.06821)	(0.09435)	(0.08699)	(0.09397)	(4.9E-05)
	[-40.03]	[-2.35]	[-0.92]	[1.97]	[3.34]	[6.59]

Notes: Standard errors in parentheses
T-statistics in brackets

The error correction model is displayed in equation 6.19, with respect to the emission futures and including the emission spots:

$$\Delta(\text{lef})_t = -0.002 + 0.113\Delta(\text{lef})_{t-1} - 0.113\Delta(\text{lef})_{t-2} + 0.153\Delta(\text{les})_{t-1} \quad (6.19)$$

$$[0.642] \qquad [0.004] \qquad [0.002] \qquad [0.000]$$

$$-0.0803\text{E}-5\Delta(\log 300)_{t-1} + 0.0001\varepsilon_{t-1}$$

$$[0.025] \qquad [0.769]$$

$$R^2 = 0.058 \text{ DW} = 2.022$$

Equation 6.19 shows that the error correction coefficient is not significant and the emission futures prices are positively influenced by their own one day lagged prices and negatively influence by their own previous two days prices. It also demonstrates that the oil & gas sector affects the emission futures in a negative manner.

Finally, we include the general economic indices to our tests and we summarise our preliminary results in Table 6.35. According to the AIC criterion, there are two cointegrating relationships and the best fit model is with linear trend and constant. In Table 6.36, we have the actual cointegration results between the emission futures and the general economic indicators.

Table 6.35 Summary of results with respect to assumptions for the emission spots-futures and general economy indices

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Selected (5% level) Number of Cointegrating Relations by Model (columns)					
Trace	1	1	1	2	2
Max-Eig	1	1	1	2	2
AIC by Rank (rows) and Model (columns)					
0	-30.61574	-30.61574	-30.60539	-30.60539	-30.59504
1	-30.63989	-30.68996	-30.68238	-30.67968	-30.67193
2	-30.63977	-30.69623	-30.69116	**-30.73623***	-30.73124
3	-30.62488	-30.68047	-30.67814	-30.73223	-30.72997
4	-30.60623	-30.65925	-30.65744	-30.71581	-30.71608
5	-30.57967	-30.63161	-30.63161	-30.69089	-30.69089
SC by Rank (rows) and Model (columns)					
0	-29.98111	-29.98111	-29.93903	-29.93903	-29.89694
1	-29.94180	**-29.98552***	-29.95256	-29.94351	-29.91037
2	-29.87822	-29.92198	-29.89787	-29.93025	-29.90622
3	-29.79986	-29.83641	-29.82139	-29.85644	-29.84149
4	-29.71775	-29.74538	-29.73722	-29.77021	-29.76413
5	-29.62772	-29.64793	-29.64793	-29.67548	-29.67548

Table 6.36 Cointegration results between emission spots-futures and general economic indicators

Hypothesized No. of CE(s)	Eigenvalue	Statistics	5 Percent Critical Value	1 Percent Critical Value
		Trace test		
		Trace Statistic		
None **	0.099460	171.7278	87.31	96.58
At most 1 **	0.083341	96.09061	62.99	70.05
At most 2	0.026126	33.26224	42.44	48.45
At most 3	0.013952	14.14884	25.32	30.45
At most 4	0.005531	4.004774	12.25	16.26
		Max-eigenvalue test		
		Max-eigen Statistic		
None **	0.099460	75.63718	37.52	42.36
At most 1 **	0.083341	62.82837	31.46	36.65
At most 2	0.026126	19.11340	25.54	30.34
At most 3	0.013952	10.14407	18.96	23.65
At most 4	0.005531	4.004774	12.25	16.26

*(**) denotes rejection of the hypothesis at the 5%(1%) level

Both the trace and the eigenvalue tests indicate two cointegrating equations at the 5% and 1% levels. We choose the one which contains both the emission spots and their futures. Table 6.37 displays the coefficients of this equation:

Table 6.37 Normalised cointegrating coefficients (emission spots-futures and general economy indices)

LEF	LES	LSP350	LDAX	LFTSE300	C
1.000000	-1.004433	4.957834	0.272365	-5.035175	3.23E-05
	(0.02723)	(1.44441)	(0.17617)	(1.50964)	(5.8E-05)
	[-36.89]	[3.43]	[1.55]	[-3.34]	[0.56]

Notes: Standard errors in parentheses
T-statistics in brackets

We can see from table 6.37 that the emission futures are influenced negatively by the Standard & Poor's index, and they are influenced positively from emissions spots and the Ftseurofirst300 index (lftse300). The error correction model is displayed in equation 6.20, with respect to the emission futures and including the emission spots.

$$\Delta(lef)_t = -0.009 + 0.117\Delta(lef)_{t-1} - 0.114\Delta(lef)_{t-2} + 0.153\Delta(les)_{t-1} \quad (6.20)$$

[0.813] [0.003] [0.002] [0.000]

$$-0.121\Delta(lftse300)_{t-1} + 0.0001\varepsilon_{t-1}$$

[0.015] [0.826]

$$R^2 = 0.06 \; DW = 2.024$$

Equation 6.20 shows that the error correction coefficient is not significant and the emission futures prices are positively influenced by their own one day lagged prices and negatively influence by their own previous two days prices. It also demonstrates that the Ftseurofirst300 (lftse300) index affects the emission futures in a negative manner.

6.7 Conclusions

In this chapter we ran the Johansen cointegration test to check for possible cointegration relationships between the emission spot and futures prices with our energy and economic variables. Furthermore, we investigated the error correction models between the related variables reflecting their short-run relationship. We have tested for cointegration between the emission spots and:

- the emission futures. We find that the emission spots are cointegrated with their futures in a long-run relationship. In the short-run, the short-term adjustment coefficient appears to be significant, so there is deviation of the emission futures from their long run equilibrium level that is corrected every day.
- the energy spots. We find that the emission spots are cointegrated with the energy spots in a long-run relationship. In the short-run, gas spots influence negatively the emission spots, whereas the electricity spots have a positive effect upon them. Oil is found to be non significant. Also, the short-term adjustment coefficient appears to be non significant.
- the economic variables that represent each separate industrial sector, which are found not to be cointegrated with the emission spots.
- the economic variables that represent the 300 most active European companies. These are cointegrated with the emission spots in a long-run relationship. In the short-run, the emission spot prices are positively influenced by the industrials index (lind300).

They are negatively influenced by the previous day prices of the basic materials and the lagged prices of the utilities index.

- the economic variables that represent the general European economy. These are found to be cointegrated in the long-run with the emission spots. In the short-run, the emission spots negatively influenced by the Standard & Poor's index. Also, the short-term adjustment coefficient appears to be non significant.

We have also tested for cointegration between the emission futures and:

- the energy variables. We find that the futures have a long-run relationship with the energy prices. In the short-run, oil and gas seem to have a negative effect and the electricity has a positive effect upon the emission futures in the short-term. Also, the short-term adjustment coefficient appears to be significant, so there is deviation of the emission futures from their long run equilibrium level that is corrected every day.
- the economic variables that represent each separate industrial sector. We discover that the futures are cointegrated with them in the long-run. In the short-run, the basic resources index is found to have a negative influence upon the emission futures. Also, the automobiles and technology indices appear to be significant and positively influencing the emission futures, whilst the basic resources index is significant and negatively influences the emission futures. Also, the short-term adjustment coefficient appears to be non significant.
- the economic variables that represent the 300 most active European companies. These are cointegrated with the emission futures in a long-run relationship. In the short-run, the oil & gas index has a negative influence upon the futures prices. The emission futures are influenced positively the basic materials sector and negatively from the industrials and the utilities sectors. Also, the short-term adjustment coefficient appears to be non significant.
- the economic variables that represent the general European economy. These are found to be cointegrated in the long-run with the emission spots. In the short-run, the Ftseurofirst300 index has a negative effect upon the emission futures prices. Also, the short-term adjustment coefficient appears to be non significant. As in the case of the emission spots, their futures are negatively connected to the Ftseurofirst300 index. Furthermore, the DAX index is significant and positively connected with the emissions spots.

Finally, we pair up the emission spots with their futures and run more cointegration tests to check whether there is a cointegration relationship that connects them with the rest of the variables mentioned above. We may conclude the following:

- There is a long-run relationship between the pair of spots-futures and the energy spot prices. In the short-run, the emission futures are negatively influenced by the electricity spots and positively influenced by the emission spots. The oil and gas spots affect the futures in a negative manner, whereas the electricity spots seem to affect the futures in a positive way. Also, the short-term adjustment coefficient appears to be non significant.
- There is a long-run relationship between the pair of spots-futures and the energy futures prices. In the short-run, oil, gas and electricity futures influence the emissions futures positively and significantly. In contrast, the coal futures influence the emissions futures negatively and significantly.
- There is a long-run relationship between the pair of spots-futures and the economic variables that represent each separate industrial sector. In the short-run, the emission futures are influenced positively from emissions spots and the technology index (ltech) and negatively from the industrial and the construction sectors. Also, the short-term adjustment coefficient appears to be non significant.
- There is a long-run relationship between the pair of spots-futures and the economic variables that represent the 300 most active European companies. In the short-run, the oil & gas sector affects the emission futures in a negative manner. Also, the short-term adjustment coefficient appears to be non significant.
- There is a long-run relationship between the pair of spots-futures the economic variables that represent the general European economy. In the short-run, the emission futures are influenced negatively by the Standard & Poor's index, and they are influenced negatively by the FTSEurofirst300 index (lftse300). Also, the short-term adjustment coefficient appears to be non significant.

Chapter 7

Forecasting the Emission Allowances

7.1 Introduction

Up until now we have looked at the basic properties and the inter-relations of our study variables. We have analysed and checked for the presence of unit roots, causality, long-run cointegration relationships, and for short-run error correction relationships. This analysis is vital to better comprehend how these variables may interact with each other and more specifically how the energy and the economic indicators influence the carbon prices (spots and futures). This information is essential for the formation of a valid CO_2 spot price model for emission allowances trading and at the same time for a potential derivatives market. Those companies that participate in the carbon market require an adequate price model to better assess their production costs and to support future emission-related decisions. A good price model will also lead to a successful carbon market and therefore to an efficient emission reduction mechanism.

The rest of this chapter includes the following: In section 2, we attempt to forecast the emission spot prices by including our energy variables and in section 3 by including the economic indices. In sections 4 and 5 we use the above methodology for predicting the emission futures. We summarise our findings in section 6.

7.2 Forecasting the carbon price using energy prices

In chapter 6, we found that the emission spot prices are strongly cointegrated with their futures. We also know from theory (Daskalakis, 2009; Obermayer, 2008; Uhrig-Homburg and Wagner, 2007) that the emission futures depend on the spots and are influenced by them in a positive manner. Therefore, a good pricing model should involve both of these two time series. However, before attempting to find such a model, we should check first whether the energy variables and the economic indicators can provide separately a good forecast for the emission spot prices.

We begin by applying the Ordinary Least Squares (OLS) method in estimating the regression equation between the emission spot prices and the energy variables. This method is used to find the best fit curve by minimising the sum of the squares of the errors (residuals) of the regression equation. So, if the regression equation is of the following linear form:

$$Y_i = \alpha + \beta X_i + \varepsilon_i \quad (7.1)$$

where:

Y_i = dependent variable

α, β = coefficients of the equation

X_i = independent variable

ε_i= disturbance term (error)

The least squares method attempts then to minimise the sum of the squared residuals with respect to the coefficients of the equation, which can be written as:

$$\min \text{SSR}\,(\alpha,\beta) = \sum_{i=1}^{n} \varepsilon_i^2 = \sum_{i=1}^{n} (Y_i - \alpha - \beta X_i)^2 \quad (7.2)$$

where SSR= Sum of Squared Residuals.

Table 7.1 lists some possible regressions between the emission spots with the energy variables. We have also added the prices of emission spots of the previous day in our regression attempts, as this is proven to improve the fit of the equations. To check for the presence of heteroskedasticity with respect to autocorrelation in the residuals, we apply the ARCH-LM (Autoregressive Conditional Heteroskedasticity Lagrange Multiplier) test (Engle, 1982). It is based on the hypothesis that in equation 7.3, the variance $\text{Var}(\varepsilon_t) = \sigma_t^2$ of the residuals ε_t, at time t depends on the square of the disturbance term of the period t-1, i.e. it depends on ε_{t-1}^2:

$$Y_t = \beta_0 + \beta_1 X_{1t} + \ldots + \beta_k X_{kt} + \varepsilon_t \quad (7.3)$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \qquad (7.4)$$

The steps of this test involve:

Step 1: we estimate equation 7.3 using the OLS method and we save the residuals ε_t.

Step 2: we then run the following regression:

$$\varepsilon_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_q \varepsilon_{t-q}^2 \quad (7.5)$$

and we take the R^2 statistic (determination coefficient, the fraction of the variance of the dependent variable explained by the independent variables).

Step 3: Considering that

$$ARCH(q)=(n-q)R^2 \sim \chi^2(q) \quad (7.6)$$

we test for the ARCH(q) process according to the assumptions:

$H_o : \alpha_1 = \ldots = \alpha_q = 0$, accept when $(n-q)R^2 < \chi^2(q)$ (7.7)

H_α : ARCH(q), accept when $(n-q)R^2 > \chi^2(q)$

Table 7.1 Regression estimation of emission spots and energy variables (LS method)

Possible regressions between emission spots and energy variables	Significance levels(in brackets) and ARCH-LM test probability results (in parentheses)
oil	[0.0174], (0.0001)
gas	[0.298], (0.00001)
electricity	[0.05], (0.000012)
oil and gas	[0.019], [0.336], (0.000014)
oil and electricity	[0.033], [0.098], (0.000014)
gas and electricity	[0.8891], [0.095], (0.000011)
oil, gas and electricity	[0.0337], [0.989], [0.179], (0.000014)

The results in Table 7.1 show that there is autoregressive conditional heteroskedasticity in the residuals, which leads to weak forecasting by using the OLS method. Therefore, we introduce the ARCH-GARCH models (Engle, 1982) in running the regressions with the energy variables. The GARCH model is a general ARCH(q) model, where the variance σ_t^2 is not just dependent on the squares of the lagged residuals, but it also depends on the lagged variances too:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{m} \gamma_i \sigma_{t-i}^2 \quad (7.8)$$

The equation with the best fit can include all possible combinations among the energy variables (in our case all possible combination among the gas, oil and electricity spot prices), along with their lagged values (gas_{t-1}, gas_{t-2}, $electricity_{t-1}$ etc.), multiple orders of the ARCH-GARCH models (i.e. ARCH(1), ARCH(2), GARCH(1), GARCH(2) etc.) and along with the presence of standard deviation or variance (or nothing at all). Since the possibilities are plenty, we include those with the smallest values of AIC and the SC criteria in Table 7.2. The regressions that involve combinations of lagged values of the energy variables were found to be non significant, so they were excluded from the table. We have included again the emission spot values of the previous day, as they provide better statistical results.

From Table 7.2 we observe that the best fit model is provided when we include the oil and gas variables in the equation 7.8 along with variance:

$$S_t = 0.036oil_t - 0.0108gas_t + 0.986S_{t-1} + 8.192\sigma^2 - 0.082 \quad (7.9)$$

[0.000] [0.000] [0.000] [0.01] [0.000]

$$R^2 = 0.99 \quad DW = 1.793$$

$$\sigma_t^2 = 5.82E-7 + 0.051\varepsilon_{t-1}^2 + 0.949\sigma_{t-1}^2$$

[0.783] [0.000] [0.000]

where S_t represents the emission spot prices, S_{t-1} their lagged (by one day) prices and σ^2 is the variance.

Table 7.2 Possible regressions with the energy variables

	Dependent variable: Emission Spots none (1)	Dependent variable: Emission Spots with standard deviation (2)	Dependent variable: Emission Spots with variance (3)
oil	0.0224 [0.000] AIC= -4.7096 SC= -4.6717	0.0316 [0.000] AIC= -4.7255! SC= -4.6812!	0.0289 [0.000] AIC= -4.7225 SC= -4.6782
gas	-0.0027 [0.386] AIC= -4.6956 SC= -4.6577!	-0.0026 [0.396] AIC= -4.6994! SC= -4.6552	not converging
electricity	-0.0098 [0.004] AIC= -4.7028 SC= -4.6649!	-0.0094 [0.007] AIC= -4.7065 SC= -4.6622	-0.0093 [0.008] AIC= -4. 7065! SC= -4.6623
oil and gas	0.028 -0.014 [0.000] [0.000] AIC= -4.7257* SC= -4.6815*	0.037 -0.009 [0.000] [0.000] AIC= -4.7381* SC= -4.6876*	0.036 -0.0108 [0.000] [0.000] **AIC= -4.7385*!** **SC= -4.6879*!**
oil and electricity	0.023 -0.012 [0.000] [0.000] AIC= -4.7193 SC= -4.6751	0.032 -0.0102 [0.000] [0.004] AIC= -4.7329! SW= -4.6824!	0.029 -0.0113 [0.000] [0.002] AIC= -4.7321 SC= -4.6816
gas and electricity	0.0014 -0.011 [0.683] [0.005] AIC= -4.7003! SC= -4.6551!	0.0014 -0.0104 [0.696] [0.018] AIC= -4.704 SC= -4.6534	0.0014 -0.0104 [0.689] [0.018] AIC= -4.704! SC= -4.6535
oil, gas and electricity	0.027 -0.008 -0.005 [0.000] [0.007] [0.178] AIC= -4.725 SC= -4.6744	0.036 -0.008 -0.005 [0.000] [0.009] [0.243] AIC= -4.7371 SW= -4.6803	0.0353 -0.0086 -0.0054 [0.000] [0.004] [0.203] AIC= -4.7379! SC= -4.681!

Note: significance levels in brackets
***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation

We can see that both the R^2 and the DW statistics are close to desirable values (R^2 is close to 1 and DW is close to 2). However, when we plot the forecast spot prices next to the actual emission spot prices (see Figure 7.2), we do not get satisfactory forecasting statistics and the

variance of the spot prices increases without reaching equilibrium (see Figure 7.1). The values that we get for the forecasting statistics are:

1. Theil inequality coefficient = 0.082. This states that for actual values Y_t and forecast values F_t and $e_t = F_t - Y_t$ forecast errors and n number of forecasts, the Theil coefficient is given by:

$$\text{Theil} = \frac{\sqrt{\frac{1}{n}\sum(F_t - Y_t)^2}}{\sqrt{\frac{1}{n}\sum F_t^2} + \sqrt{\frac{1}{n}\sum Y_t^2}} \quad (7.10)$$

This coefficient measures the inequality between the actual and the forecast values and lies between 0 and 1. If its value is close to 0, then this suggests good forecasting. It can be decomposed into three proportions of inequality: bias, variance and covariance (their addition equals 1).

2. Bias proportion = 0.29. This calculates the systematic error and needs to be close to 0, no matter what the Theil coefficient's value is.

3. Variance proportion = 0.265. This indicates the ability of the forecasts to replicate degrees of variability in the forecast variable. If its value is close to 1, then the actual values have fluctuated considerable whereas the forecast ones have not. Therefore, the variance proportion should be close to 0.

4. Covariance proportion= 0.444. This calculates the unsystematic error, and therefore it has to be close to 1 ideally.

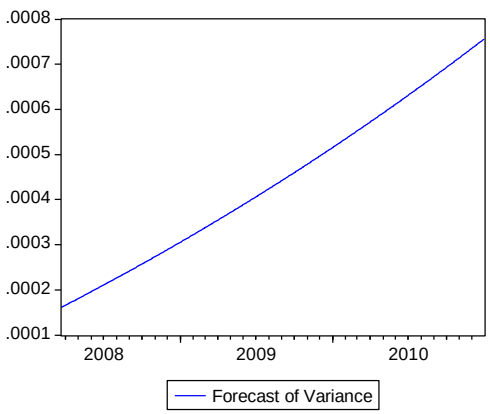


Figure 7.1: Variance of the emission spots (eqn. 7.9)

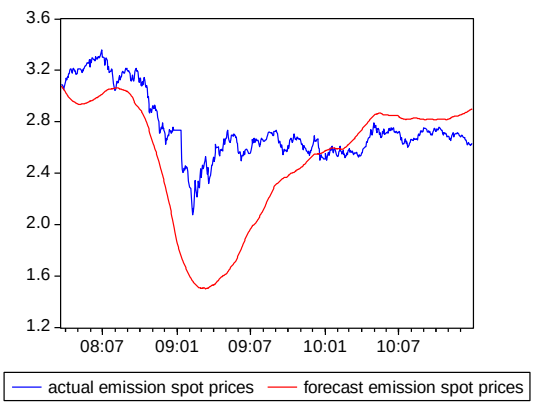


Figure 7.2: Forecast of the emission spots (eqn. 7.9)

The above results indicate that by including the oil and gas spot prices when trying to forecast the emission spot prices does not lead to good results. The emission spot prices are strongly dependent on their own lagged prices, so they seem to have their own dynamics and do not react to the energy prices. This result agrees with previous research (Hintermann, 2009), where the same energy variables were used to predict the emission spot prices without any good forecasting results. However, we can see that the variance is not converging.

7.3 Forecasting the emission spots with economic indicators

Following the methodology of section 7.2 we continue with the prediction of the emission spot prices by using our economic indicators. By including each economic variable separately to our forecasting attempts, we wish to check whether the individual industrial sectors or the general economic situation may influence the prediction of the emission spots.

Again, the possible regressions we get are numerous, therefore we include only those that appear to be significant, using the same statistical criteria (AIC and SC) as before. Table 7.3 shows our results. Since the car manufacturing and the chemicals indices are not found to be significant in our regression attempts, they are not included in the table.

We make use of the EGARCH (exponential GARCH) model. This is an alternative to the GARCH model, where the conditional standard deviations are modelled rather than the variances (Taylor, 1986; Schwert, 1989):

$$\sigma_t = \alpha_0 + \alpha_1 |\varepsilon_{t-1}| + \beta_1 \sigma_{t-1} \quad (7.11)$$

According to equation 7.11, the conditional variance becomes the square of a weighted average of absolute errors (or shocks) rather than the weighted average of squared errors (Mills and Markellos, 2008). Consequently, larger shocks will have a smaller impact on the conditional variance than in the standard GARCH model. The EGARCH model (Nelson, 1991) consists of a non-symmetric response to shocks:

$$\log(\sigma_t^2) = \alpha_0 + \alpha_1 f(\varepsilon_{t-1} / \sigma_{t-1}) + \beta_1 \log(\sigma_{t-1}^2) \quad (7.12)$$

where, $f(\varepsilon_{t-1} / \sigma_{t-1}) = \theta_1 (\varepsilon_{t-1} / \sigma_{t-1}) + (|\varepsilon_{t-1} / \sigma_{t-1}| - E|\varepsilon_{t-1} / \sigma_{t-1}|)$. θ_1 is the impulse response coefficient and E represents the variance. It is a non-symmetric response to shocks, because $\partial f / \partial \varepsilon_{t-1} = \theta_1 + 1$, when $\varepsilon_{t-1} > 0$ and $\partial f / \partial \varepsilon_{t-1} = \theta_1 - 1$, when $\varepsilon_{t-1} < 0$.

We can also notice that by using the EGARCH model instead of the simple GARCH model together with standard deviation both the statistical criteria (smaller AIC and SC, better values for R^2 and DW) and the forecast statistics (Theil coefficient, Bias, Variance and Covariance proportions) improve the forecasting in some cases. This could be due to the fact that the asymmetry in this model allows for a quicker response to price shocks. It corresponds better to price falls rather than to rises, a phenomenon known as the "leverage effect", (Mills and Markellos, 2008).

The best fit here is with the basic resources stock index, using the EGARCH model with standard deviation:

$$S_t = 0.967S_{t-1} + 0.04\text{basres} + 1.054\sigma - 0.179 \quad (7.13)$$

$$[0.000] \qquad [0.000] \qquad [0.000] \quad [0.000]$$

$$R^2 = 0.99 \quad DW = 1.828$$

$$\log(\sigma_t^2) = -0.06 + 0.0875|\varepsilon_{t-1}/\sigma_{t-1}| + 0.038(\varepsilon_{t-1}/\sigma_{t-1}) + \log(\sigma_{t-1}^2)$$

$$[0.15] \qquad [0.000] \qquad [0.002] \qquad [0.000]$$

The R^2 and the DW statistics have desirable values, however the forecasting statistics look poor: (1) Theil coefficient = 0.082, (2) Bias proportion = 0.526, (3) Variance proportion = 0.107, (4) Covariance proportion = 0.366. When plotting the variance, we can see that the variance increases without reaching equilibrium (see Figure 7.4) and the forecasted prices are nowhere near the actual emission spot prices (see Figure 7.3).

Table 7.3 Possible regressions with the economic variables

Economic variables	Dependent variable: Emission spots none (1)	Dependent variable: Emission spots with standard deviation and EGARCH model (2)
energy	0.0268 [0.002] AIC= -4.7026 SC= -4.6568	not significant
industry	not significant	0.0808

		[0.000] AIC= -4.7189 SC= -4.6684
construction	0.023 [0.00] AIC= -4.7064 SC= -4.6685	not significant
basic resources	0.0135 [0.000] AIC= -4.7051 SC= -4.6672	0.0398 [0.000] **AIC= -4.7278*!** **SC= -4.6772*!**
technology	0.0373 [0.000] AIC= -4.7106* SC= -4.6727*	0.0756 [0.000] AIC= -4.7149! SC= -4.6644!
utilities	0.0248 [0.000] AIC= -4.703! SC= -4.6651!	0.0263 [0.000] AIC= -4.6334 SC= -4.5892
oil & gas	0.0239 [0.01] AIC= -4.6994 SC= -4.6615	0.0352 [0.000] AIC= -4.7066! SC= -4.656!
basic materials	0.0119 [0.006] AIC= -4.7006! SC= -4.6627!	0.0215 [0.000] AIC= -4.6805 SC= -4.6363
all industrials	0.0147 [0.015] AIC= -4.6939 SC= -4.6619	0.0799 [0.000] AIC= -4.7136! SC= -4.6631!
Standard& Poor's	0.0263 [0.002] AIC= -4.7035! SC= -4. 6656!	0.0546 [0.000] AIC= -4.6275 SC= -4.577
DAX	0.0148 [0.016] AIC= -4.6535 SC= -4.6535!	0.0939 [0.000] AIC= -4.7005! SC= -4.6499

Ftseurofirst-300	0.027 [0.001] AIC= -4.704 SC= -4.6661!	0.0924 [0.000] AIC= -4.7136! SC= -4.6631

Note: significance levels in brackets
***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation

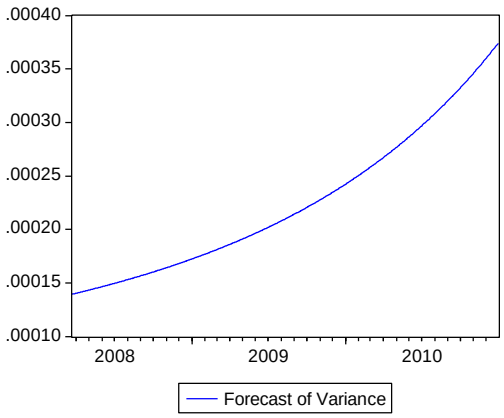


Figure 7.3: Variance of spots (eqn. 7.13)

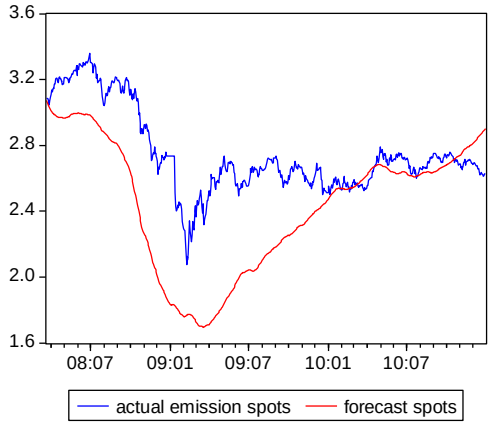


Figure 7.4: Forecast of spots (eqn. 7.13)

The above results provide the incentive to continue with our research and attempt further combinations among the economic indicators, to check whether including more than one indicator will improve the forecasting of the emission spot prices. Table 7.4 contains those regressions where the economic indicators appear to be significant.

Table 7.4 Emission spots with economic indicators-other combinations

Other combinations	Dependent variable: Emission spots none (1)	Dependent variable: Emission spots with standard deviation (2)
DAX with Chemicals	not significant	0.173 [0.000] (DAX) -0.1252 [0.000] (chemicals) AIC= -4.5484 SC= -4.4979
DAX with Basic Resources	not significant	-0.0756 [0.001] (DAX) 0.0534 [0.000] (basic resources) AIC= -4.7289* SC= -4.6783*
Standard & Poor's with Technology	not significant	0.0334 [0.000] (Standard & Poor's) 0.0565 [0.000] (technology) AIC= -4.6767 SC= -4.6261

Note: significance levels in brackets
***** represents the vertical best fit

The best fit equation comprises of the basic resources index along with DAX, using a GARCH(1,1) model with standard deviation:

$$S_t = 0.378 + 0.979S_{t-1} + 0.053basres - 0.075DAX + 0.122\sigma \quad (7.14)$$

$$[0.021] \quad [0.000] \qquad [0.000] \qquad [0.001] \qquad [0.000]$$

$$R^2 = 0.99 \quad DW = 1.803$$

$$\sigma_t^2 = -3.64E-7 + 0.0428\varepsilon_{t-1}^2 + 0.96\sigma_{t-1}^2$$

$$[0.82] \qquad [0.000] \qquad [0.000]$$

The variance in equation (7.14) decreases with time and reaches equilibrium (see Figure 7.5), but the forecasted values verse the actual values are still not good (see Figure 7.6). The new forecast statistics seem to have improved: The Theil coefficient is down to 0.0368, the Bias proportion is also down to 0.442. Similarly, the Variance proportion is reduced to 0.057, and the Covariance proportion is slightly increased to 0.5.

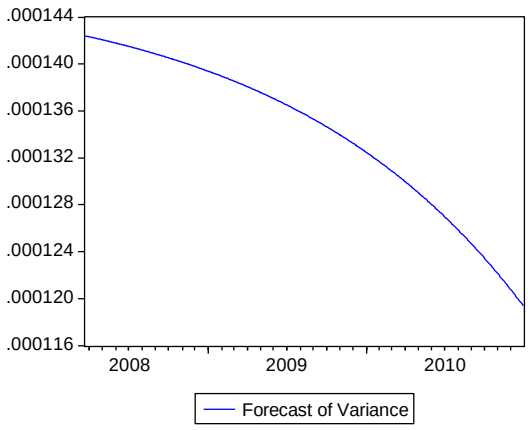


Figure 7.5 Variance of the spots (eqn. 7.14)

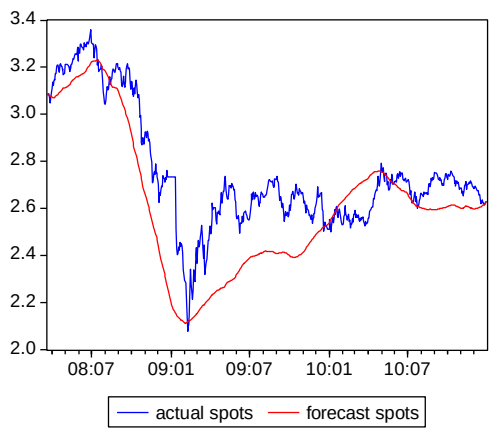


Figure 7.6 Forecast of the spots (eqn. 7.14)

We still get very poor forecasting results. This is because we have not included the emission futures in the regression equations. It seems that the carbon market, although it has matured in the second commitment period, has formed its own dynamics, where the relationship between the emission spots and their futures is very strong and appears to be immune to

outside variables. It is apparent that, in order to predict the emission spots, their futures have to be considered in the forecast equation.

7.4 Forecasting the emission futures using energy variables

We already know from theory (Daskalakis, 2009; Trück, 2006; Taschini, 2006) that there is a strong relationship between the emission futures and the spot prices. Hence, for the prediction of the futures prices we need to include in our forecasting attempts the emission spots prices since they are found to be strongly correlated and cointegrated with each other. Firstly, their relationship has to be established.

A thorough empirical examination that was carried over by Uhrig-Homburg and Wagner (2007) reveals that the emission spots are linked with their futures by the cost-of-carry approach. This type of relationship between the emission spots S_t at time t and their futures $F_t(T)$ contracts maturing at time T, with a constant interest rate of r is demonstrated by the equation 7.4 below (Uhrig-Homburg and Wagner, 2007; Daskalakis, 2009):

$$F_t(T) = e^{r(T-t)} S_t \qquad (7.15)$$

With the emission futures as our dependent variable, we then try to estimate a more accurate relationship, by using standard GARCH(1,1) models and the ML-ARCH method. This is possible since our variables are all found to be integrated of order one. We also incorporate the logarithmic first and second time-lags of the emission spots, in order to check whether the futures prices are influenced from the previous one and two-day period gap of the spot prices (both get priced at the end of every working day of the week). We display the resulting equation along with the significance levels in brackets, along with the statistical values of R^2 and the Durbin-Watson (DW). We also include the resulting variance equation. Furthermore, Figures 7.7 and 7.8 present the variance of futures prices and the forecast of futures respectively.

$$F_t(T) = 0.474S_t + 0.259S_{t-1} + 0.3S_{t-2} + 0.614ma(1) + 1.542\sigma + 0.598 \quad (7.16)$$

$$[0.000] \quad [0.000] \quad [0.000] \quad [0.000] \quad [0.000] \quad [0.817]$$

$$R^2 = 0.989 \quad DW = 1.274$$

$$\sigma_t^2 = 1.88E-6 + 0.116e_{t-1}^2 + 0.887\sigma_{t-1}^2$$

$$[0.19] \quad [0.000] \quad [0.000]$$

All the other variables appear to be statistically significant. We can see that the R^2 is close to the value of one, which is desirable, however the DW value is far from 2, meaning that it can be possibly improved:

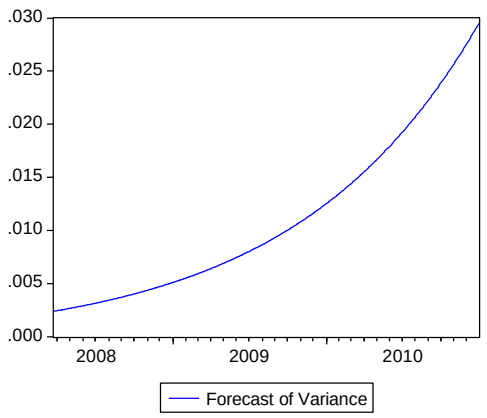


Figure 7.7: Variance of the futures prices (eqn.7.16)

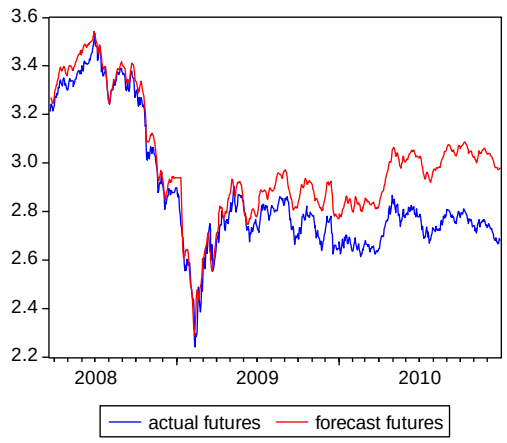


Figure 7.8: Forecast of futures (eqn. 7.16)

We can conclude from figures 7.7 and 7.8 that equation 7.16 provides a weak forecasting attempt for the futures, based on just the spot prices of the current date and the previous two days. This is also because the variance of the futures price is increasing without reaching equilibrium. This provides the incentive to change equation 7.16, by adding the futures prices from the previous day (F_{t-1}) among the predicting variables. The estimated equation is shown in 7.17:

$$F_t(T) = 0.179S_{t-1} + 0.838F_{t-1} + 0.096ma(1) + 1.155\sigma - 0.05 \quad (7.17)$$

$$[0.000] \quad [0.000] \quad [0.018] \quad [0.000] \quad [0.000]$$

$$R^2 = 0.994 \ DW = 2.009$$

$$\sigma_t^2 = 404E-6 + 0.06e_{t-1}^2 + 0.923\sigma_{t-1}^2$$

$$[0.174] \quad [0.000] \quad [0.000]$$

Figures 7.9 and 7.10 demonstrate this improvement in the variance and the forecasting of the futures prices, respectively:

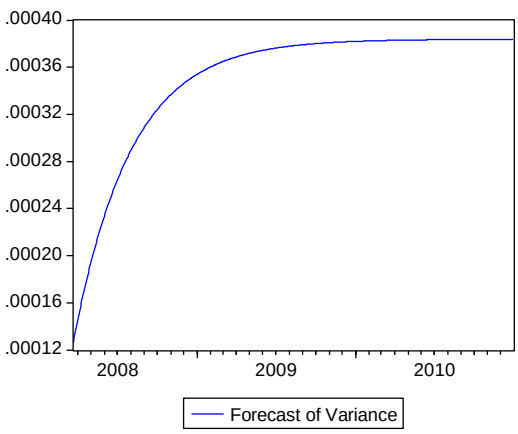


Figure 7.9: Variance of futures (eqn. 7.17)

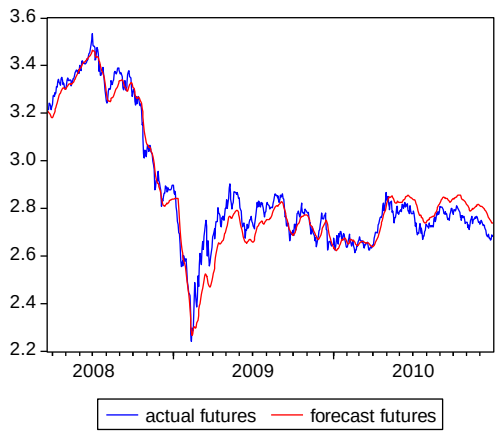


Figure 7.10: Futures forecast (eqn. 7.17)

Considering the above we incorporate the energy variables in equation 7.17. Since we are trying to predict the emission futures, it would be interesting to consider both the spots and the futures prices of the energy variables, to see which ones can provide a better forecasting. We can also add lagged values of the energy variables to check how much the emission futures depend on prices of previous days. Therefore, we can consider the following methodology:

1) Include energy spot prices

   a) Estimate the resulting equation with lagged emission spot prices (S_{t-1}, S_{t-2}, etc.)

b) Estimate the resulting equation with lagged emission futures prices (F_{t-1}, F_{t-2}, etc.)

2) Include lagged energy spot prices (gas_{t-1}, oil_{t-1}, $electricity_{t-1}$, etc.)

   a) Estimate the resulting equation with lagged emission spot prices

   b) Estimate the resulting equation with lagged emission futures prices

3) Include energy futures prices

   a) Estimate the resulting equation with lagged emission spot prices

   b) Estimate the resulting equation with lagged emission futures prices

4) Include lagged energy futures prices

   a) Estimate the resulting equation with lagged emission spot prices

   b) Estimate the resulting equation with lagged emission futures prices

The resulting regressions are shown for each energy variable individually in tables 7.5., 7.6, 7.7 and 7.8 for oil, gas, electricity and coal respectively. Again, we have considered those where the energy variables appear to be significant and provide the best forecast, depending also on the forecasting statistics and the AIC and SC criteria. The values in the columns represent the coefficient of each energy variable and the significance levels appear in brackets.

Table 7.5 Regressions between the emission futures and oil

	Energy variable: oil			
Variables	GARCH	GARCH with standard deviation	EGARCH	EGARCH with standard deviation
oil_t, S_t, S_{t-1}, S_{t-2}	-0.119 [0.000] AIC= -4.5612 SC= -4.5042	-0.045 [0.000] AIC=-5.0076 SC= -4.9443	-0.119 [0.000] AIC= -4.555013 SC= -4.491755	0.02 [0.001] AIC= -5.2306! SC= -5.161!
oil_t, S_t, F_{t-1}	-0.032 [0.000] AIC= -5.2322 SC= -5.1816	-0.011 [0.001] AIC= -5.308 SC= -5.2511	not significant	0.052 [0.000] AIC= -5.5114! SC= -5.4482!
oil_{t-1}, S_t, S_{t-1}, S_{t-2}	-0.137 [0.000] AIC= -4.627 SC= -4.5701	-0.082 [0.000] AIC= -4.9149 SC= -4.8516	not significant	0.014 [0.01] AIC= -5.2093! SC= -5.1397!
oil_{t-1}, S_t, F_{t-1}	-0.041 [0.000] AIC= -5.2585* SC= -5.2079*	-0.017 [0.000] AIC= -5.3148* SC= -5.2579*	not significant	0.033 [0.000] AIC= -5.4881! SC= -5.425!
oilf, S_t, S_{t-1}, S_{t-2}	-0.126 [0.000] AIC= -4.5109 SC= -4.4539	-0.081 [0.000] AIC= -4.8128 SC= -4.7495	not significant	0.057 [0.000] AIC= -5.2802! SC= -5.2106!
oilf, S_t, F_{t-1}	-0.027 [0.000] AIC= -5.217 SC= -5.1665	not significant	not significant	0.064 [0.000] **AIC= -5.5303!*** **SC= -5.4671!***
$oilf_{t-1}$, S_t, S_{t-1}, S_{t-2}	-0.122 [0.000] AIC= -4.5632 SC= -4.5063	-0.099 [0.000] AIC= -4.7415 SC= -4.6783	not significant	0.035 [0.000] AIC= -5.2695! SC= -5.1999!
$oilf_{t-1}$, S_t, F_{t-1}	-0.035 [0.000] AIC= -5.2379 SC= -5.1873	-0.013 [0.000] AIC= -5.1873 SC= -5.2539	not significant	0.044 [0.000] AIC= -5.5024! SC= -5. 4392!

Note: significance levels in brackets
***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation

The best fit equation appears to be the one using the oil futures along with the EGARCH model and standard deviation and including the emission spots and the lagged futures prices:

$$F_t = 0.557S_t + 0.426F_{t-1} + 0.064oilf + 0.163ma(1) + 3.713\sigma - 0.2 \quad (7.18)$$

$$[0.000] \quad [0.000] \quad [0.000] \quad [0.000] \quad [0.000] \quad [0.000]$$

$$R^2 = 0.994 \quad DW = 1.608$$

$$\log(\sigma_t^2) = -0.033 + 0.052|\varepsilon_{t-1}/\sigma_{t-1}| + 0.054(\varepsilon_{t-1}/\sigma_{t-1}) + 1.001\log(\sigma_{t-1}^2)$$

$$[0.102] \quad [0.000] \quad [0.000] \quad [0.000]$$

The variance in equation (7.18) decreases with time and reaches equilibrium (see Figure 7.11). The new forecast statistics together with the forecast of futures (see Figure 7.12) seem to have improved slightly as well, although they are not close to ideal values: the Theil coefficient is reduced further to 0.013, however the Bias proportion has slightly gone up to 0.488. The Variance proportion is down to 0.0545, and the Covariance proportion has also gone down to 0.45.

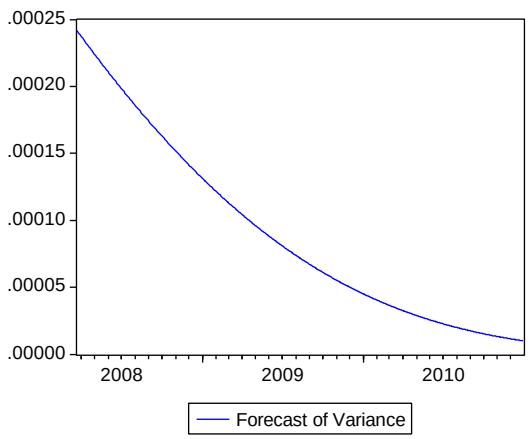


Figure 7.11: Variance of the futures (eqn. 7.18)

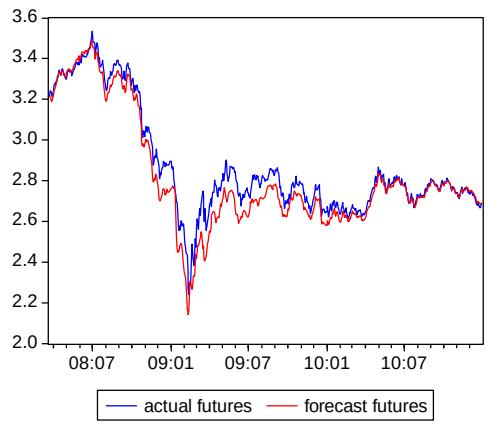


Figure 7.12: Futures forecast (eqn. 7.18)

From table 7.6 we get two best fits: one is when we include lagged gas spot prices with lagged emission futures prices, by using the GARCH model with standard deviation, and the other when we include lagged futures gas prices with lagged emission futures prices

(previous two days), by using the EGARCH model with standard deviation. The first fit is shown in equation (7.19).

$$F_t(T) = 0.28S_t + 0.76F_{t-1} - 0.019gas_{t-1} + 1.352\sigma - 0.055 \quad (7.19)$$

$$[0.000] \quad [0.000] \quad [0.000] \quad [0.000] \quad [0.000]$$

$$R^2 = 0.995 \quad DW = 1.884$$

$$\sigma_t^2 = 2.19E-6 + 0.0676e_{t-1}^2 + 0.925\sigma_{t-1}^2$$

$$[0.154] \quad [0.000] \quad [0.000]$$

Table 7.6 Regressions between the emission futures and gas

	Energy variable: gas			
Variables	GARCH	GARCH with standard deviation	EGARCH	EGARCH with standard deviation
gas_t, S_t, S_{t-1}, S_{t-2}, S_{t-3}	-0.081 [0.000] AIC= -4.5884 SC= -4.5251	-0.046 [0.000] AIC= -4.9784 SC= -4.9088	not significant	-0.021 [0.000] AIC= -5.23! SC= -5.154!
gas_t, S_t, F_{t-1}	-0.021 [0.000] AIC= -5.2674 SC= -5.2169	-0.011 [0.001] AIC= -5.308 SC= -5.2511	not significant	-0.019 [0.000] AIC= -5.3861! SC= -5.3356!
gas_{t-1}, S_t, S_{t-1}, S_{t-2}, S_{t-3}	-0.084 [0.000] AIC= -4.6146 SC= -4.5512	-0.048 [0.000] AIC= -5.0301 SC= -4.9605	not significant	-0.034 [0.000] AIC= -5.2651! SC= -5.1955!
gas_{t-1}, S_t, F_{t-1}	-0.023 [0.000] AIC= -5.2788* SC= -5.2282*	-0.019 [0.000] **AIC= -5.3881!*** **SC= -5.3375!***	not significant	-0.0155 [0.000] AIC= -5.0331 SC= -4.9762
gasf, S_t, S_{t-1}, S_{t-2}	0.268 [0.000] AIC= -4.5444 SC= -4.4875	0.282 [0.000] AIC= -4.5548 SC= -4.4915	not significant	0.317 [0.000] AIC= -4.7272! SC= -4.6577!
gasf, S_t, F_{t-1}	-0.021 [0.02] AIC= -5.1892 SC= -5.1386	-0.0088 [0.000] AIC= -5.3441! SC= -5.2872!	not significant	not significant
$gasf_{t-1}$, S_t, S_{t-1}, S_{t-2}	0.179 [0.000] AIC= -4.438 SC= -4.3811	0.24 [0.000] AIC= -4.4388 SC= -4.3756	not significant	0.27 [0.000] AIC= -4.5809! SC= -4.5113!
$gasf_{t-1}$, S_t, F_{t-1}	not significant	-0.022 [0.000] AIC= -5.3191 SC= -5.2685	not significant	(with F_{t-2}) -0.028 [0.047] **AIC= -5.4975!*** **SC= -5.428***

Note: significance levels in brackets
***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation

The variance in equation (7.19) increases with time and reaches equilibrium (see Figure 7.13). The new forecast statistics, together with the forecasting ability of the model (see Figure 7.14), seem to have improved substantially: The Theil coefficient has dropped dramatically down to 0.009, along with the Bias proportion (0.046) and also the Variance proportion (0.012). Also, the Covariance proportion is increased up to 0.94.

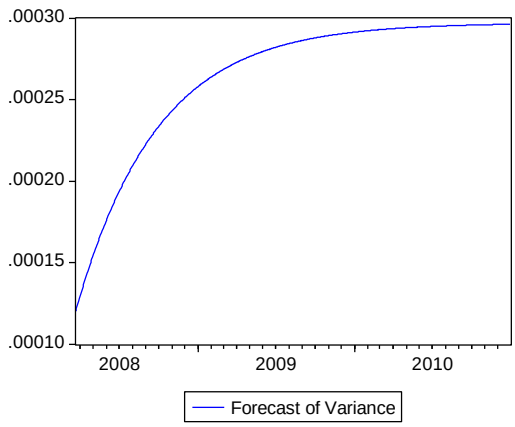


Figure 7.13: Variance of the futures (eqn. 7.19)

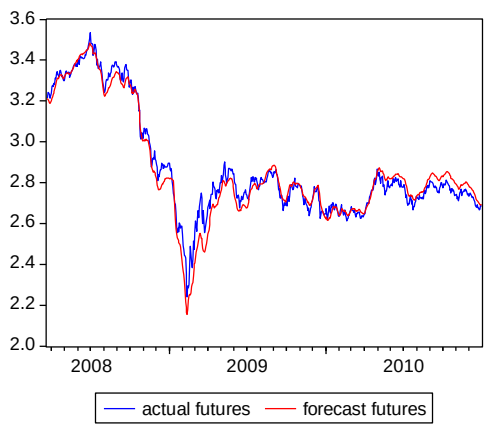


Figure 7.14: Futures forecast (eqn. 7.19)

The second best fit, is displayed in equation 7.20:

$$F_t = 0.608S_t + 0.276F_{t-1} + 0.15F_{t-2} - 0.027gasf_{t-1} + 0.348ma(1) + 2.368\sigma + 0.042 \quad (7.20)$$

[0.000] [0.000] [0.000] [0.047] [0.000] [0.000] [0.173]

$$R^2 = 0.994 \quad DW = 1.704$$

$$\log(\sigma_t^2) = -0.064 + 0.0872|\varepsilon_{t-1}/\sigma_{t-1}| + 0.0533(\varepsilon_{t-1}/\sigma_{t-1}) + 1.0008\log(\sigma_{t-1}^2)$$

[0.007] [0.000] [0.000] [0.000]

The variance in equation (7.20) decreases with time and reaches equilibrium (see Figure 7.15). The forecasting ability of the model is shown in Figure 7.16, and the forecast statistics are: (1) Theil coefficient = 0.011, which is a small increase from previously (0.009), (2) Bias proportion = 0.46, which is a big increase from the previous value (0.046), (3) Variance

proportion = 0.000, (4) Covariance proportion = 0.54, which is a large drop from the value of 0.94 previously.

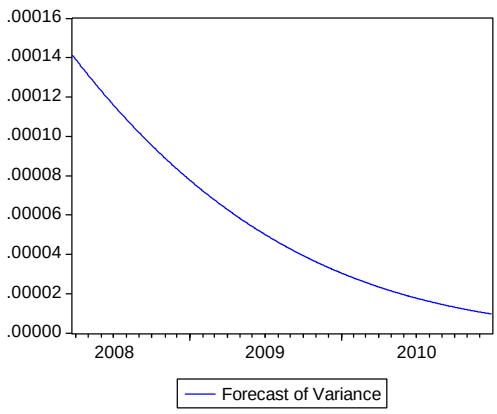


Figure 7.15: Variance of the futures (eqn. 7.20)

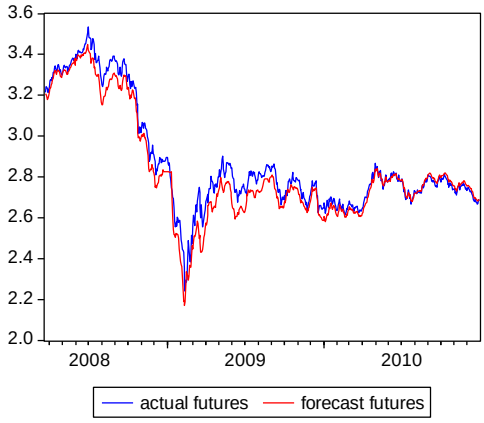


Figure 7.16: Futures forecast (eqn. 7.20)

From table 7.7, the best fit equation involves electricity futures prices with lagged emission futures prices, by using the EGARCH model with standard deviation:

$$F_t = 0.526S_t + 0.445F_{t-1} + 0.106\text{electricity f} + 0.178\text{ma}(1) + 1.953\sigma - 0.316 \quad (7.21)$$

[0.000] [0.000] [0.000] [0.000] [0.000] [0.000]

$$R^2 = 0.994 \quad DW = 1.637$$

$$\log(\sigma_t^2) = -0.102 + 0.1125|\varepsilon_{t-1}/\sigma_{t-1}| + 0.056(\varepsilon_{t-1}/\sigma_{t-1}) + 0.999\log(\sigma_{t-1}^2)$$

[0.000] [0.000] [0.000] [0.000]

Table 7.7 Regressions between the emission futures and electricity

	Energy variable: electricity			
Variables	GARCH	GARCH with standard deviation	EGARCH	EGARCH with standard deviation
$electricity_t$, S_t, S_{t-1}, S_{t-2}	not significant	not significant	not significant	not significant
$electricity_t$, S_t, F_{t-1}	-0.012 [0.000] AIC= -5.2026 SC= -5.1521	-0.009 [0.001] AIC= -5.299! SC= -5.2421!	not significant	not significant
$electricity_{t-1}$, S_t, S_{t-1}, S_{t-2}	not significant	not significant	not significant	not significant
$electricity_{t-1}$, S_t, F_{t-1}	-0.0135 [0.000] AIC= -5.2097 SC= -5.1591	not significant	not significant	not significant
electricityf, S_t, S_{t-1}, S_{t-2}	0.5075 [0.000] AIC= -5.1753 SC= -5.1183	0.413 [0.000] AIC= -5.2687 SC= -5.2054	not significant	0.399 [0.000] AIC= -5.3348! SC= -5.2652!
electricityf, S_t, F_{t-1}	0.2285 [0.02] AIC= -5.3841* SC= -5.3336*	0.111 [0.000] AIC= -5.4492* SC= -5.3923*	0.168 [0.000] AIC= -5.3579* SC= -5.301*	0.106 [0.000] **AIC= -5.5057!*** **SC= -5.4425!***
$electricityf_{t-1}$, S_t, St_{-1}	0.4426 [0.000] AIC= -5.003 SC= -4.9521	0.343 [0.000] AIC= -5.1203 SC= -5.0634	not significant	0.089 [0.000] AIC= -5.3039! SC= -5.2408!
$electricityf_{t-1}$, S_t,, F_{t-1}	0.131 [0.000] AIC= 5.2818 SC= -5.2312	0.081 [0.000] AIC= -5.3939 SC= -5.337	0.13 [0.000] AIC= -5.2614 SC= -5.2045	0.036 [0.047] AIC= -5.4676! SC= -5.4044!

Note: significance levels in brackets, ***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation

The variance in equation (7.21) decreases with time and reaches equilibrium (see Figure 7.17). The forecasting ability of the model is shown in Figure 7.18, and the forecast statistics are the following: The Theil coefficient is reduces again down to 0.008. Similarly, the Bias

proportion is also down to 0.254. There is a slight increase in the Variance proportion (0.002) and the Covariance proportion is increased to 0.744.

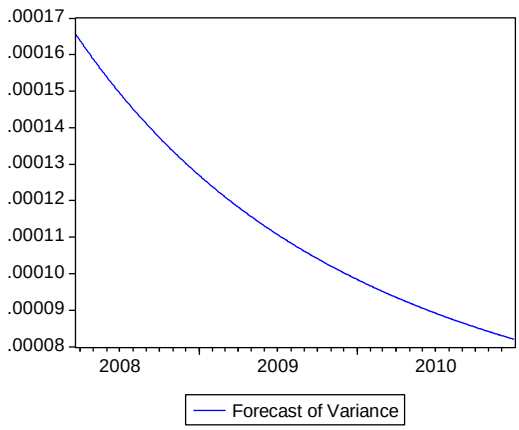


Figure 7.17: Variance of the futures (eqn. 7.21)

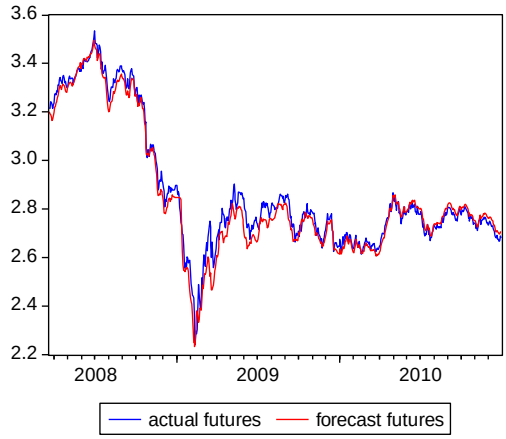


Figure 7.18: Futures forecast (eqn. 7.21)

From table 7.8, the best fit equation involves coal futures prices with lagged emission futures prices, by using the EGARCH model with standard deviation:

$$F_t = 0.536S_t + 0.458F_{t-1} + 0.053coalf + 0.174ma(1) + 2.763\sigma - 0.212 \quad (7.22)$$

$$[0.000] \quad [0.000] \quad [0.000] \quad [0.000] \quad [0.000] \quad [0.000]$$

$$R^2 = 0.994 \ DW = 1.634$$

$$\log(\sigma_t^2) = -0.059 + 0.076|\varepsilon_{t-1}/\sigma_{t-1}| + 0.051(\varepsilon_{t-1}/\sigma_{t-1}) + \log(\sigma_{t-1}^2)$$

$$[0.019] \quad [0.000] \quad [0.000] \quad [0.000]$$

The variance in equation (7.22) decreases with time and reaches equilibrium (see Figure 7.19). Figure 7.20 demonstrates the model's forecasting ability, and the resulting statistics are as follows: (1) Theil coefficient = 0.013, which is a small increase from before, (2) Bias proportion = 0.607 (increased from 0.254), (3) Variance proportion = 0.015 (increased from 0.002) and (4) Covariance proportion = 0.378 (reduced from 0.744).

Table 7.8 Regressions between the emission futures and coal

	Energy variable: coal			
Variables	GARCH	GARCH with standard deviation	EGARCH	EGARCH with standard deviation
coalf, S_t, S_{t-1}, S_{t-2}	0.152 [0.000] AIC= -4.457* SC= -4.4*	0.164 [0.000] AIC= -5.0273! SC= -4.9641!	not significant	0.097 [0.000] AIC= -4.527 SC= -4.4574
coalf, S_t, F_{t-1}	not significant	0.03 [0.000] AIC= -5.3654* SC= -5.3086*	not significant	0.053 [0.000] **AIC= -5.4949!*** **SC= -5.4317!***
$coalf_{t-1}$, S_t, St_{-1}, S_{t-2}	0.123 [0.000] AIC= -4.4121 SC= -4.3552	0.102 [0.000] AIC= -4.9727! SC= -4.9095!	not significant	0.067 [0.000] AIC= -4.3856 SC= -4.316
$coalf_{t-1}$, S_t,, F_{t-1}	not significant	0.015 [0.000] AIC= -5.3378 SC= -5.2909	not significant	0.027 [0.009] AIC= -5.4728! SC= -5.4096!

Note: significance levels in brackets
***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation

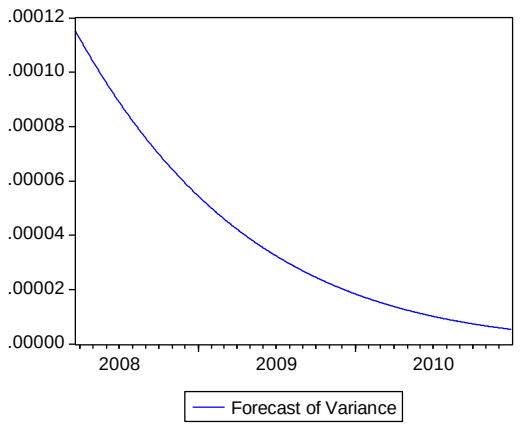


Figure 7.19: Variance of the futures (eqn. 7.22)

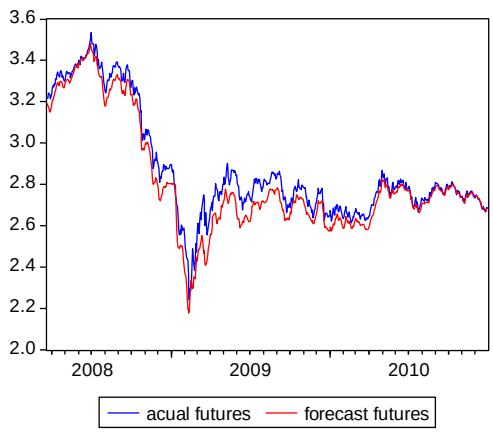


Figure 7.20: Futures forecast (eqn. 7.22)

From the above we may conclude that the introduction of the energy variables, and in particular their futures prices contribute to a good emission futures forecasting, when they get included in the cost-of-carry relationship between the emission spot prices with their futures.

7.5 Forecast the futures using economic indices

Equation 7.17 is further enhanced by adding selected economic indicators as extra predicting variables. Table 7.9 shows the possible regressions, where we interchange the economic variables.

Table 7.9 Regressions between the emission futures and the economic indicators

	Dependent variable: Futures none (1)	**Dependent variable: Futures with standard deviation (2)**
cars	-0.0296 [0.000] AIC=-5.0998 SW=-5.0493	-0.0211 [0.000] AIC= -5.1094! SC=-5.0525!
chemicals	-0.0400 [0.000] AIC= -5.1161!* SC=-5.0655!*	-0.0348 [0.000] AIC= -5.1136 SC=-5.0567
energy	not significant	0.0414 [0.000] AIC= -5.128 SW= -5.0707
industry	-0.0382 [0.000] AIC= -5.1129! SC=-5.0623!	-0.0328 [0.000] AIC= -5.1108 SC=-5.0539
construction	not significant	0.0203 (0.002) AIC= -5.111 SW= -5.054
basic materials	-0.0101 [0.014] AIC= -5.0745 SC=-5.0239	not significant
technology	-0.0058 [0.492] AIC= -5.067 SC=-5.0164	0.0247 [0.007] AIC= -5.106! SW= -5.049!
utilities	0.0344 [0.000] AIC= -5.08271 SC=-5.0322	0.0456 [0.000] **AIC= -5.139!*** **SW= -5.082!***

oil & gas	not significant	0.0350 [0.000] AIC= -5.123 SW= -5.066
basic materials	-0.0158 [0.002] AIC= -5.0802 SC=-5.0296	not significant
all industrials	-0.0267 [0.000] AIC=-5.0844 SC=-5.0338	not significant
Standard& Poor's	-0.0269 [0.005] AIC= -5.0769 SC=-5.0264	0.0216 (0.044) AIC= -5.102! SW= -5.045!
DAX	-0.0465 [0.000] AIC= -5.1032! SC=-5.0527!	-0.0321 (0.002) AIC= -5.103 SW= -5.046
Ftseurofirst-300	-0.0253 [0.008] AIC= -5.0758 SC=-5.0253	0.0234 (0.000) AIC= -5.102! SW= -5.046!

Note: significance levels in brackets
***** represents the vertical best fit, whereas **!** is for the horizontal best fit representation

We also consider the signs of the estimated coefficients. These are positive if we argue that high production follows high demand and causes an increase in CO_2 emissions and in requesting more emission allowances and results in their prices to rise. From the results presented in table 7.9, we choose the equation that includes the utilities index. The oil & gas and the FTSEurofirst300 indices also provide good results, however their forecasting is weaker than the utilities index equivalent. We reject the chemicals as the coefficient appears to be negative. The estimated resulting equation is presented in 7.23:

$$F_t(T) = 0.198S_{t-1} + 0.798F_{t-1} + 0.046util300 + 0.097ma(1) + 1.383\sigma - 0.335 \quad (7.23)$$

$$[0.000] \quad [0.000] \quad [0.000] \quad [0.014] \quad [0.000] \quad [0.000]$$

$$R^2 = 0.99 \quad DW = 1.99$$

$$\sigma_t^2 = 3.1E-6 + 0.06e_{t-1}^2 + 0.932\sigma_{t-1}^2$$

$$[0.244] \quad [0.000] \quad [0.000]$$

The variance in equation (7.23) increases with time and reaches equilibrium (see Figure 7.21). We can observe the forecasting capacity of the model in Figure 7.22. The forecast statistics show that the Theil coefficient is close to 0 (0.0097), the Bias proportion is reduced to 0.022, the Variance proportion also appears to have a small values (0.017) and the Covariance proportion is close to 1 (0.961). These statistics are close to the ideal values and therefore appear to be rather good.

From the above we can conclude that although carbon futures are found to be weakly connected to economic indicators during the first Kyoto period (Chevallier, 2007), however, this is not the case for the second trading period. This shows that the carbon market has got more stable and has started reacting positively to certain economic indicators.

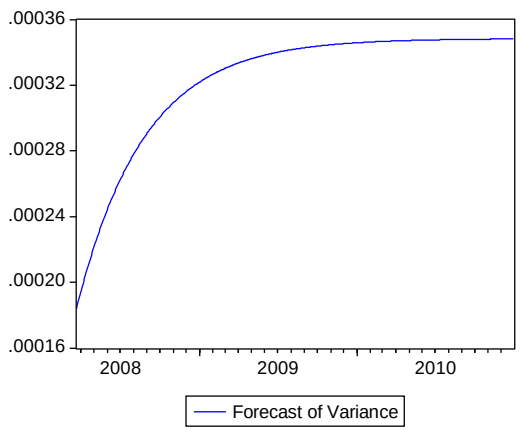


Figure 7.21: Variance of the futures (eqn. 7.23)

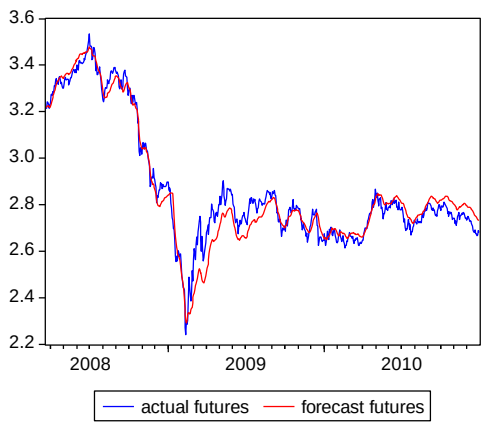


Figure 7.22: Futures forecast (eqn. 7.22)

7.6 Results summary

In this chapter, we have attempted to forecast the prices of the emission spots and their futures by using GARCH(1,1) models and by involving our energy and economic variables. We find agreement with previous research that the emission futures are related to the spots via a cost-of-carry relationship (Daskalakis, 2009) and that by adding the latter to the price forecasting tests we improve the emission spots forecasting.

For the emission spot prices forecast, we find that the best fit model is provided when we include the oil and gas spot prices along with variance. However, this model provides poor forecast results. It appears that the emission spot prices are strongly dependent on their own lagged prices and do not react to the energy spot prices. We can also see that the variance is not converging.

By including the various economic indicators separately to the forecast model, we attempt to establish how each economic variable may influence the forecasting results. The best fit here is with the basic resources stock index, using the EGARCH model with standard deviation. The forecasting statistics still seem poor. Also, the variance increases without reaching equilibrium. If we try other combinations between the emission spots and more than one economic indicator simultaneously, the best fit we get involves the basic resources index along with DAX, using a GARCH(1,1) model with standard deviation. Although the forecasting statistics improve, the variance decreases to equilibrium. The forecasted values are still nowhere near the actual values.

For the emission futures price forecast, we found that by adding the emission spot prices, together with the futures prices from the previous day improves the variance (it reaches equilibrium) and also the forecasting statistics. This model provides good forecast in total.

Concerning the futures price forecast with the energy variables, we considered both the spots and the futures prices of the energy variables and we also added lagged values of the energy variables to check how much the emission futures depend on prices of previous days. The best fit models were achieved by including each energy variable separately and in particular we found that their futures prices contribute to a good emission futures forecasting. Therefore:

- Including the oil variable, the best fit model is the one that includes the oil futures along with the EGARCH model and standard deviation and including the emission spots and the lagged futures prices. Here, the variance decreases with time.
- Including the gas variable, we get two fits: one is when we include lagged gas spot prices with lagged emission futures prices, by using the GARCH model with standard deviation, and the other when we include lagged futures gas prices with lagged emission futures prices (previous two days), by using the EGARCH model with standard deviation. The variance converges to equilibrium in both models.
- Including the electricity variable, the best fit model that we get involves electricity futures prices with lagged emission futures prices, by using the EGARCH model with standard deviation. The variance in this case decreases with time and reaches equilibrium.
- Including the coal variable, the best fit equation involves then coal futures prices with lagged emission futures prices, by incorporating the EGARCH model with standard deviation. The variance seems to decrease with time and reach equilibrium.

Considering the futures price forecast with the economic variables, we succeed in forming the best fit models by including the utilities index in the price forecast, along with standard deviation in a simple GARCH(1,1) model. The variance increases with time and reached equilibrium. The oil & gas and the FTSEurofirst300 also provide good price forecasting.

Chapter 8

Conclusions

8.1 Introduction

In this thesis, we have investigated the market of carbon credits and provided a thorough dynamic analysis of the emission spots and futures prices and their relation to the energy sector and economic activity in Europe. We have concentrated our research on the European carbon market, specifically the EU ETS mechanism, as this has been defined by the Kyoto protocol and have dealt with daily data that extends over a period of two years (2008-2010). Our aim has been to forecast the price of the carbon credits (both the spots and their futures) by including energy prices (oil, gas, electricity and coal) and various economic stock indices, representative of the European economy.

The structure of this chapter is as follows:

1. A summary of the literature
2. A summary of the framework of the research methodology followed
3. A summary of the key results
4. Limitations, contribution, implications and proposals for further research

8.2 Literature summary

We provide a thorough literature survey regarding the various theoretical and empirical studies about the carbon market and how this relates to other markets, in particular to the energy markets. There appear to be few statistical models that deal with the price forecasting of the emission credits. This is mainly due to the fact that there is a shortage of available historical data, since the carbon market started in the beginning of 2005. Therefore, we can observe that most statistical models include emission prices from the first commitment period (2005-2007). The research concentrates in:

- The emission prices dynamics. There is a strong relationship between the emission spots with their futures. The market has changed from initial backwardation to contango, where the futures prices appear to have exceeded the spot prices. Overall, there is increasing price volatility with maturity for both the commitment and the pilot trading period.
- The emission prices and their returns exhibit different periods of price behaviour that included price jumps or spikes and also phases of high volatility and heteroscedasticity in the return (Benz and Trück, 2009).
- Emission allowances differ from classical stocks (Benz and Truck, 2006) and a step to specify them is to consider them as a factor of production.
- EUA spot prices are found to react not only to energy prices with forecast errors, but also to unanticipated temperature changes during colder events (Alberola et al., 2008; Mansanet-Bataller et al., 2007).
- The volatility of the historical data, which is high during the first commitment period, mainly due to the over-allocation of emission allowances along with banking prohibition (carbon credits expire at the end of each commitment period). The first commitment period indicates that when the cap is not set below business-as-usual emissions, allowance trading does not necessarily guarantee a carbon price high enough to provide incentives to reduce CO_2 emissions, which resulted to the collapse of the emission allowances prices.
- The relationship between carbon credits and energy prices. In general, the energy prices seem to affect the carbon prices. Further analysis reveals that there is correlation between the emission spots and electricity and a co-integration relationship between the emission spots with natural gas and oil, but not with electricity (Obermayer, 2009). Also, gas and oil appear to have a positive effect on the emission spot prices (Bunn and Fezzi, 2007), whereas coal seems to have a negative effect. Also, energy prices appear to be the most important drivers of carbon prices due to the ability of power generators to switch between their fuel inputs (Kanen, 2006; Christiansen et al., 2005; Bunn and Fezzi, 2007; Convery and Redmond, 2007).
- Policy, regulatory and sociological factors need to be taken into account when considering the emission prices formation, i.e. decisions and announcements

concerning the National Allocation Plans, fairness and equality within the trading participants, abatement costs.

- The carbon price development has to reflect the private economic interests of the participants, to provide them with the incentive to reduce their emissions and at the same time not to result in profits losses. It is argued that energy taxes and especially CO_2 taxes will be an important instrument for decoupling of economic growth and CO_2 emissions (Enevoldsen, Ryelund and Andersen 2007).
- The details of the emission allocation methods are also important, as they may affect the incentives, pricing and efficiency of the trading scheme. If the allocation plan is not based on abatement costs, but on actual or expected emissions then there is distortion between the ETS and the non-ETS sectors. Such an allocation mode would in general lead to a higher amount of allowances being generated and eventually would lead to a collapse of their price (Klepper and Peterson, 2004). Auctioning is found to be the most efficient allocation approach (Matthes et al., 2005). However, in the case of free allocation to new entrants, this can be based on production data defined by load factor (capacity utilisation) benchmarks. The problem of windfall profits arising from exaggerated installation-specific projections can thus be avoided.
- The banning of the transfer of allowances from 2007 to 2008 (last year of phase 1 to first year of phase 2) increases overall compliance costs, since costs savings cannot be traded over time. If banking is prohibited, then the market prices will not reflect the real opportunity costs, which will lead to inefficient abatement measures (Schleigh et al., 2006).
- Certain sectors including power, cement, iron and steel have the potential to profit from free allocation, by adjusting output and pricing (Smale et al, 2006).

8.3 A summary of the framework of the research study

The research methodology can be described as follows:

1. First, all the variables involved in our study are analysed and described, in relation to their logarithmic values and their returns. We display their fundamental statistical properties and we also check for possible correlations between the main variables (emission spots and their futures) and the energy and economic variables.

2. We check for stationarity (or the presence of a unit root) by applying three different unit root tests to the logarithmic levels and the returns of our study variables to overcome the issue of "fake regression" and to determine long-run relationships, i.e. equilibriums among the study variables. The issue of the presence of autocorrelation in the price series is resolved by including a large number of lags while running the above tests.
3. The evidence of stationarity indicates that the study variables can be further analysed to check for causality. The Granger test is used here to establish which variables may "Granger" cause the emission spot and futures prices and vice versa. This is a statistical test that is not based on any established theory, but only on the ability for the best fit equation that predicts the dependent variable.
4. The cointegration methodology is applied for further investigating the relationships between our variables. This explores whether two or more variables "move" together, which shows that there may be a relationship between two or more variables in equilibrium in the long-run. The assumptions for the possible relations among the study variables are considered as follows:
    - Possibility of cointegration between emission spots and the other energy variables and the economic indices. Separate tests are run for those economic indicators that represent each industrial sector, those that reflect the more liquid sectors and finally those that echo the general economic growth in EU.
    - Possibility of cointegration between emission futures and the other energy variables and the economic indices (same distinction is applied here).
    - Possibility of cointegration between the pair of emission spots-futures with the other energy variables and the economic indices, to check whether such an equilibrium, that includes the emission spots and futures at the same time, exists.
5. Considering the results of the cointegration methodology, the analysis was further extended to the error correction methodology. This was done in order to investigate the short-run relationships between specific variables of the study and to test whether the short-run adjustment coefficient appears to indicate the deviation of specific variables from their long-run equilibrium level that is corrected every day.
6. The analysis above creates the initiative to continue with the prediction of the emission spots and futures prices formation. A good price model will lead to a

successful carbon market and therefore to an efficient emission reduction mechanism. The forecast of the emission spot and futures prices is carried on by including various combinations of energy variables and economic indicators. The ARCH-GARCH models and other variations, such as E-GARCH are introduced for running the regressions to decide on the best fit equations.

8.4 A summary of the key results

We summarise the major findings of the research as follows:

1. The emission spot prices are found to be:
    a. strongly correlated with those of their futures, the coal, gas and the electricity futures and also with the energy and the utilities sectors indices
    b. weakly correlated with oil spots and oil futures, the gas and the electricity spot prices correlation and also with the oil & gas sector and the FTSEurofirst300 stock prices

    The emission futures are found to be:
    a. strongly correlated with oil, coal, gas and electricity futures and the utilities index
    b. weakly correlated with oil, gas and electricity spots and the energy sector
2. All of the study variables are found to be non-stationary in their logarithmic levels and stationary in their first differences (returns). Therefore, we can say that they are integrated of order 1.
3. The emission spots are found to Granger cause the emission futures, the gas spots and their futures, the futures of electricity, oil and coal, and also the indices of the energy and the oil & gas indices. The emission spots do not Granger cause the electricity and oil spots, and also all the economic indices apart from the energy and the oil & gas ones.
4. The variables that Granger cause the emission spots are the emission futures, the gas futures and the coal futures.
5. The emission futures Granger cause the electricity futures. They do not Granger cause the gas spots and their futures, the electricity spots, the oil spots and their futures, and none of the economic indicators.

6. The variables that Granger cause the emission futures are the gas spots and their futures, the electricity futures, the oil spots, the coal futures and also the energy and oil & gas indices.
7. The emission spots are cointegrated with:
    a. The emission futures in a long-run relationship. In the short-run, the short-term adjustment coefficient appears to be significant.
    b. the energy spots in a long-rum relationship. In the short-run, gas spots influence negatively the emission spots, whereas the electricity spots have a positive effect upon them. Oil is found to be non significant.
    c. the economic variables that represent the 300 most active European companies in a long-run relationship. In the short-run, the emission spot prices are positively influenced by the industrials index.
    d. the economic variables that represent the general European in the long-run with the emission spots. In the short-run, the emission spots negatively influenced by the Standard & Poor's index.
8. The emission futures are cointegrated with:
    a. the energy prices in a long-run relationship. In the short-run, oil and gas seem to have a negative effect and the electricity has a positive effect upon the emission futures in the short-term. Also, the short-term adjustment coefficient appears to be significant.
    b. the economic variables that represent each separate industrial sector in a long-run relationship. In the short-run, the basic resources index is found to have a negative influence upon the emission futures. Also, the automobiles and technology indices appear to be significant and positively influencing the emission futures, whilst the basic resources index is significant and negatively influences the emission futures.
    c. the economic variables that represent the 300 most active European companies in a long-run relationship. In the short-run, the oil & gas index has a negative influence upon the futures prices. The emission futures are influenced positively the basic materials sector and negatively from the industrials and the utilities sectors.

d. the economic variables that represent the general European economy in the long-run with the emission spots. In the short-run, the FtSEurofirst300 index has a negative effect upon the emission futures prices. The DAX index is significant and positively connected with the emissions spots.

9. The pair of spots-futures is cointegrated with:

   a. the energy spots in a long-run relationship. In the short-run, the emission futures are negatively influenced by the electricity spots and positively influenced by the emission spots. The oil and gas spots affect the futures in a negative manner, whereas the electricity spots seem to affect the futures in a positive way.

   b. the energy futures prices in a long-run relationship. In the short-run, oil, gas and electricity futures influence the emissions futures positively and significantly. In contrast, the coal futures influence the emissions futures negatively and significantly.

   c. the economic variables that represent each separate industrial sector in a long-run relationship. In the short-run, the emission futures are influenced positively from emissions spots and the technology index and negatively from the industrial and the construction sectors.

   d. the economic variables that represent the 300 most active European companies in a long-run relationship. In the short-run, the oil & gas sector affects the emission futures in a negative manner.

   e. the economic variables that represent the general European economy in a long-run relationship. In the short-run, the emission futures are influenced negatively by the Standard&Poors index, and they are influenced negatively by the FTSEurofirst300 index.

10. For the emission spot prices forecast, the best fit model is the one with the oil and gas spot prices, using the GARCH(1,1) along with variance (energy variables) and the one with the basic resources stock index, using the EGARCH model with standard deviation (economic variables). Both models provide poor forecast results.

11. For the emission futures price forecast, we can see that by adding the emission spot prices, together with the futures prices from the previous day improves the forecasting

results, however, the resulting forecast values do not form a good interpretation of the actual prices.

12. Concerning the futures price forecast with the energy variables, we consider both the spots and the futures prices of the energy variables and the lagged values of the energy variables. The best fit models here greatly improve the forecasting results and are those with:
    a. the oil futures along with the EGARCH model and standard deviation and including the emission spots and the lagged futures prices
    b. the lagged gas spot prices with lagged emission futures prices, by using the GARCH model with standard deviation
    c. the lagged futures gas prices with lagged emission futures prices (previous two days), by using the EGARCH model with standard deviation
    d. the electricity futures prices with lagged emission futures prices, by using the EGARCH model with standard deviation
    e. the coal futures prices with lagged emission futures prices, by incorporating the EGARCH model with standard deviation
13. Considering the futures price forecast with the economic variables, the best fit models are those with the utilities index in the price forecast, along with standard deviation in a simple GARCH(1,1) model. FTSEurofirst300 also provides good price forecasting.

From the above we can conclude that there is a strong and long term relationship between the emission spots and the emission futures, which is reflected on the price formation of the latter. This confirms that the carbon market becomes more stable and more efficient with time. There is also a strong relationship between the emission spot and futures prices with some of the energy and economic variables involved in the study, in particular the oil, gas, and electricity futures and also the utilities and the FTSEurofirst300 indices. This is evident in the improved forecasting attempts of the emission futures prices.

8.5 Limitations

The limitations of the thesis can be summarised as follows:

- The data used corresponds to the second commitment period (2008-2012) of the EU ETS trading market. However, to check the efficiency of the market and the ability of

the emission allowances to correspond to the general economic trends we need to use the emission spot and futures prices from the beginning of the market. This is not possible as there are structural breaks between the well-defined trading periods. Also, the high volatility of the emission spot prices during the first commitment period do allow efficient market analysis.

- There appears to be some discrepancy to the reference area of the study variables. The emission spot prices and their futures, although they are traded in EEX (based in Leipzig, Germany), they represent the carbon market, where the main participants are either EU member or are companies that trade mainly in the EU area. The energy variables are also traded in the EEX market, though these reflect the fuel prices in the area of Germany. Usually energy prices that are represented in a country-level or a more broad geographical area level exist in monthly rather than daily form. Had we chosen to use monthly data for the energy variables, then we would have not only had to convert our emission allowances daily data, but this would also have a negative impact on the quality of our sample. It would reduce the number of the observations dramatically and therefore it would alter the significance and the validity of the results. Also, the economic indicators reflect not only the area of Germany, but the relative economic activity that each one represents in Europe. So, not all the variables refer to the same geographical area.
- The co-integration test between the pair of the emission spots-futures with the energy variables shows that the emission spots are non-significant in the short-term. From literature, we would expect that the daily changes in the emission spot prices would reflect to their derivatives. However, our results may indicate that the emission spots and their futures do not have a simultaneous cointegrating relationship with the energy spots. A separate relationship between the energy spots and their futures seems to exist otherwise.

8.6 Contribution of the thesis

This thesis contributes to the research field by further enhancing the understanding of the trading of the carbon credits in the EU ETS mechanism, as this has been defined by the Kyoto protocol. It demonstrates the various statistic properties of the carbon credits (both the

spot and the futures prices) and proves their relation to other important energy and economic indicators. It also offers suggestions for ways of taking advantage of such relationships to form efficient emission prices forecasting, with economic potential for the market participants.

8.7 Implications

According to the major findings of this thesis, we can argue that the carbon market seems to have matured during the second commitment trading period of the Kyoto protocol and has started responding to other markets. However, it is difficult to predict the efficiency and the impact that such a market may have on a socio-economic and most importantly on an environmental level. This remains to be seen, especially on the third commitment period that is due to start in a few years time (2013-2020).

8.8 Proposals for further research

As more historical data becomes available, especially as the market enters the next commitment period, further findings can be obtained about its effectiveness. Since the carbon credits are initially accommodated depending on the NAPs of each European country member, policy and other regulatory issues can be incorporated into futures price forecasting models (e.g. as exogenous variables).

Moreover, as the emission futures contracts are issued on a monthly or quarterly or annually basis, a possible comparison of different expiring futures contracts can be investigated in relation with their impact on the spot prices and their price forecasting.

The parameters estimated in the models of this thesis are assumed to be constant over the period of study. However, these parameters may be changing over time. Thus, the use of Kalman filters (Kalman, 1960) can provide a more dynamic pricing modelling. The nature and cause of the dynamic movement of the emission variables can thus be examined in an effective way.

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