CO2 Emissions Allowances

Modeling the Price Dynamics in the EU Emission Trading System

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Authors: **Lucia Duguleana**
Lena Iulia Dumitrache

Advisor: **Hossein Asgharian**

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ABSTRACT

The aim of this paper is to characterize the daily price fundamentals of European Union Allowances (EUAs) traded in the EU Emissions Trading Scheme (ETS) during the period September 2005 - February 2010. We use GARCH model in order to account for changes in volatility. We split our analysis into two periods according to the two phases of the ETS. We disregard the period 02.04.2007 – 11.08.2008, when the trading in the spot market was practically inexistent and the price of EUAs was smaller than 1 Euro. Our findings suggest that weather data does not have a linear influence, while the coldest days, extremely rainy days and extremely windy days have an important impact during the first period. From energy variables, brent is a sustainable factor. Additionally, electricity and coal seem to be substitutes for each other, with electricity having a negative impact on EUAs prices in the first period and coal in the second. We also find that the change in industrial production is not one of the factors that seem to influence the price of emissions allowances.

Proposal for Master Thesis in Finance

TITLE	**$CO2$ Emissions Allowances.** Modeling the Price Dynamics in the EU Emission Trading System
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AUTHORS	Duguleana Lucia Dumitrache Lena Iulia
E-MAIL	lucia.duguleana@gmail.com iuliadumitrache@yahoo.com
ADVISOR	Hossein Asgharian
PROPOSALS THESIS TYPE	Empirical study
PURPOSE	In this paper we analyze the spot price behaviour of carbon dioxide (CO2) emissions allowances of the EU-wide CO2 emissions trading system (EU ETS). This allows an initial understanding of the risks and determining factors of this new commodity. Our study will be of interest to academics in the field of finance, risk management consultants, brokers and traders who buy and sell emissions allowances. To our knowledge no recent study so far has been conducted which includes economic growth, weather index and fuel price as determinants of CO2 emissions allowances prices. We intend to shed light on these matters.
RESEARCH OBJECTIVES	There are several questions which need to be answered in this master thesis: • How do spot prices and prices of derivatives move over time? • How does industrial production (and economic growth) influence the price dynamics of CO2 emissions allowances? • How does weather influence the price dynamics of CO2 emissions allowances? • How do fuel prices influence the price dynamics of CO2 emissions allowances?
METHODOLOGY	In this paper we use multiple regression analysis combined with GARCH modeling in order to determine the spot price dynamics of CO2 emissions allowances.
EMPIRICAL FOUNDATION	For CO2 emissions allowances spot prices we use Point Carbon Spot Index. Datastream database is used to collect industrial production data, energy prices.
KEY REFERENCES	• Eva Benz, Stefan Trück, 2009, *"Modeling the price dynamics of CO2 emission allowances"*, Energy Economics 31, pp. 4-15 • Alberola, Chevallier and Chéze, 2007, "*Price drivers and structural breaks in European carbon prices 2005–2007"*, Energy Policy 36, pp 787–797 • Mansanet-Bataller, Pardo and Valor, 2007, *"CO_2 Prices, Energy and Weather"*, The Energy Journal, Vol. 28, No. 3, pp 73-92

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1. INTRODUCTION

This chapter provides a background for European Union Allowances (EUAs) trading; presents and motivates the choice of research topic and gives delimitations of the thesis purpose. The chapter ends with a description of the audience and a thesis outline.

1.1. Background

Greenhouse gas (GHG) emissions represent the biggest market failure the world has ever seen and are proved to be linked to human activities. All of us produce emissions, people around the world are already suffering from past emissions – through global warming and climate change - and current emissions will potentially have a catastrophic impact in the future for human health, environment and the economy (see Stern, 2007).

As a response to these risks, governments realized that something must be done, with considerable disagreement as to exactly what. The initial form of environmental policy has been a command-and-control type regulation, which meant that companies had to rigorously comply with emissions standards or implement particular technologies (see Benz and Trück, 2009).

But market mechanisms proved to be, as usual, more efficient than centralized systems of decision. In the financial world, pioneering financial products have been developed, specifically to manage such environmental problems, namely CO2 emissions allowances. Initially traded OTC, the market for CO2 emissions allowances has grown in importance since the Kyoto Protocol was enforced in February 2005, requiring that all affected plants in the 170 countries that adhered to the Protocol limit their GHG emissions according to well-specified caps. The ultimate goal is to reduce GHG emissions by 8% compared to the 1990 level by the years 2008-2012. In order to give incentives for the companies to find the least costly and most efficient way to reduce CO_2 emissions, the Kyoto Protocol proposes three market mechanisms: International Emissions Trading (IET), Clean Development Mechanism (CDM) and Joint Implementation (JI).

Through IET the Protocol lays the groundwork for trading human-related emissions permits, primarily carbon dioxide, in organized financial markets.

In an Emission Trading Scheme, the central authority decides on the total level of emissions and each year issues to companies a number of emissions allowances depending on their size and on a decided base-year's actual emissions. These allowances/credits can be traded: when a company can abate CO_2 emissions at a lower cost than the price of a CO_2 credit it will do so, selling the credit on the market and making a profit. Other companies that cannot find a cheap enough way to reduce emissions will buy the credits needed. In effect, the system allows for the seller to be rewarded for reducing emissions with more than it was needed, while the buyer is charged for polluting. At the end of the year the companies have to own a number of allowances equal to their actual emissions. The companies that fail to comply will be sanctioned for exceeding their allowances. On the same principle, IET allows for emissions trading between governments. The other two mechanisms allow for flexibility. While CDM permits industrialized countries to invest in CO_2 emissions reduction projects in developing countries, JI considers industrialized and transition countries to invest in emissions reduction projects in other industrialized and transition countries. In each case, such countries are allocated Certified Emission Reductions (CERs) and Emission Reduction Units (ERUs) respectively. CERs and ERUs are also tradable and able to substitute to a certain level the emissions allowances.

Out of several national and regional emissions markets that have been established, Europe has emerged as the leader in the emissions trading industry, with the EU Emissions Trading Scheme (EU ETS) being the largest market for CO2 emissions allowances worldwide (see Daskalakis, Psychoyios and Markellos, 2009).

In a carbon constrained economy, CO2 emissions allowances are traded with increasing liquidity within the EU ETS and the market is evolving towards maturity, having already experienced a severe economic crisis. These new financial products are innovative, exciting, and have been called by scientists "the link between economics and ethics" (see Stern, 2007). It is for these reasons that we decided to focus our study on pricing the carbon emission permits spot contracts.

1.2. Problem Discussion

EU ETS has been organized in three phases. The first phase is called the trial period and it lasted from 2005 to 2007 while the second one, called Kyoto commitment phase, lasts from 2008 to 2012. A third period has been proposed from 2013 to 2020. There is a very important restriction that separates the first period from the second in essentially two different markets. The EUAs from the first period cannot be banked, i.e. they cannot be stored in order to be used at a later date in the second phase of the EU ETS. In effect the EUAs from the first period have an expiration date. In the same manner companies that have to comply with regulation in the first period cannot borrow credits from a future year in the second period. Borrowing is only possible *during* the phase of EU ETS. This might have an impact on our analysis as we are going to initially consider the whole period and, when doing the analysis, we are going to separate between the two phases.

The current paper proposes a model for pricing of spot EUAs. For the purpose of this paper we are going to consider the emissions trading rights as a commodity and determine their price according to commodity pricing models rather than stock pricing models. As Benz and Trück (2009) discuss, emissions permits have little in common with stocks, for which the demand and the value are based on future profit expectations of the underlying firm. They also determine two main factors influencing the demand and price of permits:

1. Policy and regulatory issues that have a long term impact on prices and consist of NAPs[1] (National Allocation Plans) that set rules and reduction targets and lead to sudden changes in price levels or volatility
2. Market fundamentals that concern the production of CO_2, such as weather data, fuel prices (cost of fossil fuels relative to cost of oil or natural gas), economic growth and unexpected events such as unforeseen problems at a power plant.

The literature discussing the pricing of emissions allowances is rather new and sparse, mostly concerned with environmental economy and policy, despite the growth and importance of the carbon market. Recent literature that addresses empirical evidence deals with one of the

[1] The National Allocation Plan defines the basis on which allocations of free greenhouse gas emission allowances to individual installations covered by the Emissions Trading Scheme will be made.

following three models: equilibrium modeling (see Beltratti, Colla and Cretì, 2009; Chesney and Taschini, 2009), time series modeling (Benz and Trück, 2009; Uhrig-Homburg and Wagner, 2009) and continuous time modeling (Daskalakis, Psychoyios and Markellos, 2009; Uhrig-Homburg and Wagner, 2009). Fundamentals used to be discussed a few years ago (Mansanet-Bataller, Pardo and Valor, 2007; Alberola, Chevallier and Chéze, 2007) but recently have been disregarded. Even though all new articles recognize the influence of the factors presented above, neither explicitly takes them into account in their models. The vast majority of the research is concerned with EU ETS since it is by far the biggest market and the most liquid.

The present research also focuses on the EU ETS market, but it tries to look at it from a different perspective. It brings two major contributions by explicitly accounting for factors such as fuel prices, economic development and it takes into account weather data as a way of explaining the different movements of the price of carbon emission permits, and bringing fundamentals once again into light. The second major contribution regards the period taken into consideration. It extends the previous research through the financial crisis phase and it examines any special characteristics it might have on carbon market. The present paper proposes pricing models for spot contrcts.

We are going to consider data from countries that are both part of EU ETS and Annex1 countries of the Kyoto protocol (see Appendix 1) throughout all the period we take into account. For this purpose we will use the EU25 member states. We are going to consider Norway, Iceland and Liechtenstein that joined the scheme in 2008 and also Bulgaria and Romania which entered the scheme in 2007. In each case we have to adjust the data when new countries join the EU ETS.

1.3. Purpose

The aim of this study is to determine to what extent fuel prices, weather data and economic development influence the price of spot carbon emissions permits. The paper is also intended to establish if there are any important differences between the phases of EU ETS and to account for reasons for such disparities. In essence we intend to establish what the determinants are for each period and whether in different periods we can determine different determinants. Due to changes in regulations we expect that the periods will have different results. At the same time we give some suggestions for further research.

1.4. Delimitations

One delimitation is the fact that, due to lack of data availability, we did not include any kind of weather or industry production data for Lichtenstein, although it adhered to EU ETS IN 2008.

Also, we essentially consider that there are two markets, one for the first trading period, particularly the interval 15.09.2005-30.03.2007 and one for the second trading period, namely 11.08.2008-26.02.2010. The reason, as it will be described in more detail in Chapter 4, is that trading in the spot market was practically inexistent during the period 02.04.2007 – 11.08.2008. This interval is therefore excluded from our regressions.

Additionally, the weather data we included were monthly data extrapolated to a daily basis, while previous research used daily data. However, due to limited availability of daily weather data we were coerced to use monthly data.

1.5. Audience

Our study will be of interest to academics in the field of finance, risk management consultants, brokers and traders who buy and sell emissions allowances. Having a reliable pricing and forecasting model will allow companies, investors and traders to realize effective risk management, investment decisions and trading strategies in the carbon market. The results of our paper will also be of interest to policy makers and for the future organization of the carbon market.

1.6 Thesis Outline

The remainder of the thesis is divided into four chapters. Chapter two gives an overview of the theoretical framework related to carbon emissions allowances. We also consider the methods used for pricing of emissions permits in the framework of EU ETS. Chapter three presents data collection and methodology used in the empirical study. The fourth chapter shows the empirical results following from the methodology presented previously and the findings from the analysis performed. Finally, chapter five consists of conclusions, reflections on the study, and proposes ideas for future research.

2. THEORETICAL BACKGROUND

In this chapter we will describe the theoretical context of CO2 emissions allowances. Previous research will be reviewed and compared through the perspectives of methodology employed and determinants of the prices of CO2 emissions allowances.

2.1 European Union Emissions Trading Scheme

The European Union Emissions Trading Scheme (EU ETS) started in 2005 and it is the largest multinational greenhouse gas (GHG) emissions trading system accounting for 98% of global transactions for 2007 (see Daskalakis, Psychoyios and Markellos, 2009). The EU member states participate in this system in order to reach the binding targets of GHG reduction established through the Kyoto Protocol at the lowest cost possible. EU ETS is in effect an IET system broken down to the company level. EU ETS covers more than 10 000 installations, i.e. refineries, coke ovens, companies form metal, pulp and paper, glass and ceramic industries (see Uhrig-Homburg and Wagner, 2009), that have a heat excess of 20 MW and which are collectively responsible for close to half of the EU's emissions of CO_2 and for 40% of its total greenhouse gas emissions (see Questions and Answers on the Commission's proposal to revise the EU Emissions Trading System, 2008).

Each year, the member states decide upon the so-called national allocation plans (NAPs), which determine their total level of GHG emissions allowances and the number of emissions allowances (EUAs) for each installation. Each allowance gives the holder the right to emit 1 tone of CO_2. The yearly cap is decreasing, putting pressure on companies to reduce their emissions. Companies are free to trade the credits (using spot market or derivatives): the ones that have cheap abatement opportunities will be sellers while companies for which abatement is too costly will buy emissions permits on the market. After a year companies have to submit to the national authorities the EUAs in accordance with their emissions volume. In case a company fails to deliver the appropriate number of permits it has to pay a sanction of 40€/ton of CO_2 (in 2005-

2007) or 100€/ton of CO_2 (in 2008-2012), plus to surrender the missing number of EUAs the following year (see Beltratti, Colla and Cretì, 2009).

EU ETS has been organized in three phases. The annual allocations for the first period were 2270 million permits, 2080 million for the second period (see Beltratti, Colla and Cretì, 2009) and for 2013 to 2020 as follows:

Table 2.1: EU wide emissions cap

Year	Mil t CO2
2013	1,974
2014	1,937
2015	1,901
2016	1,865
2017	1,829
2018	1,792
2019	1,756
2020	1,720

Source: Questions and Answers on the Commission's proposal to revise the EU Emissions Trading System (2008).

These figures need to be adjusted as they do not take into account the inclusion of aviation (an industry which will be included in the EU ETS from 2011 onwards), nor of emissions from Norway, Iceland and Liechtenstein. A linear factor of 1.74% (applicable to the previous number of permits) was used to determine the cap in the third phase and will continue to be applied after the end of this trading period (see Questions and Answers on the Commission's proposal to revise the EU Emissions Trading System 2008).

2.2. Literature Review and Existing Models

In spite of the fact that the carbon market is increasing in size and importance, relevant academic research is rather sparse and almost entirely concentrated on the EU ETS market, since they are without a doubt the most liquid.

The first paper that deals with emissions trading belongs to Dales (1968), who defines them as market-based instruments created to efficiently reduce GHG emissions. By setting an emissions cap applied to an entire industry, country, or a set of countries, companies that want to emit more (fewer) emissions than covered by their allowances can buy (sell) EUAs. According to market theory, companies will adjust their buying and selling behavior in accordance to their marginal abatement costs (see Klepper and Peterson, 2006; de Brauw, 2006). If marginal abatement costs exceed the price of CO2 emissions allowances, companies will buy additional EUAs; if they are lower, it is beneficial to sell allowances.

Consequently, emissions allowances are seen as an efficient market-based instrument of environmental policy encouraged by many economists and politicians. This opinion is based on the assumption of a perfect market and rational behavior of all market players. However, this assumption does not hold in practice and leads to serious market failures. To illustrate this, it was clear that large companies with significant market power were favored when national allocation plans where distributed, especially electricity producing companies (see Gilbert et al., 2004). This leaves room for information asymmetry as the dominant companies, which are also main emitters, have better information of the total scarcity of allowances.

Although CO2 emissions allowances have been traded in the EU ETS for a considerable period of time, the literature has not presented yet any conclusive results with respect to the most appropriate pricing method. Benz and Trück (2009) analyze the short-term OTC spot price behavior of CO2 permits employing both an AR-GARCH and a Markov–switching model to capture the heteroskedastic behavior of the return time series. In contrast, Paolella and Taschini (2008) use a new, innovative GARCH-type structure to analyze the intrinsic heteroskedastic dynamics in the returns of SO2 in the U.S. and of CO2 emissions permits in the EU ETS. They find that models based on the analysis of fundamentals yield implausible results due to the increased market complexity.

Chesney and Taschini (2008) constructed an endogenous model for describing the emissions allowances spot price dynamics, which accounts for the prospective presence of asymmetric information in the market. Seifert et al. (2008) developed a theoretical stochastic equilibrium model with the purpose of incorporating the most important stylized features of EU ETS in the CO2 emissions allowances price dynamics. Their analysis showed that spot prices must always be positive and bounded by the penalty cost plus the cost of having to deliver any lacking allowances. Regarding volatility, they argued that a steep increase will occur towards the end of the trading period. This requires the use of models with conditional variance, in order to capture whether the market is in a period of high or low volatility.

Mansanet-Bataller et al. (2007) study the relevance of energy prices and weather variables on the determination of CO2 emissions allowances spot prices by performing multivariate linear regressions using the least squares method. The results show that energy sources are the prime factors determining CO2 allowances price levels, and that only extreme temperatures influence them. Alberola, Chevallier and Chèze (2007) employ similar multivariate regressions but, compared to previous literature, find two structural breaks in phase I (April 2006 and October 2006) due to the disclosure of emissions and the announcement of new allocations for phase II, respectively. Also in contrast to previous literature, they find that prices react to unanticipated weather events and show the nonlinearity of the relationship between temperatures and carbon price changes.

The methodology employed in our paper combines multivariate regressions used in Mansanet-Bataller et al. (2007) with a GARCH-type structure similar to the one used by Benz and Trück (2009) to capture the heteroskedastic behavior of the spot returns time series.

2.3. Price Determinants of CO2 Emissions Allowances

Browsing through previous research, we find that various models give different answers to the question of what factors influence CO2 allowances price levels, as they focus on different aspects of the effects of emissions trading on the economy.

So far, the most comprehensive reference on this subject has been Springer (2003), who gathered results from 25 models of the market for tradable GHG emissions permits. Among the factors that influence the long-term CO2 emissions allowances price levels, the author considers climate factors (temperature and climatic conditions), energy factors (price level of energy sources and energy substitutability possibilities) and microeconomic and macroeconomic factors (characteristics of the energy sector, GDP growth, emissions growth, and emissions targets).

Similarly, Benz and Trück (2009) categorize the main driving factors of CO2 allowances prices into policy and regulatory issues and market fundamentals that concern the production of CO2.

The former have a long term impact on prices and consist of NAPs that set rules and reduction targets and lead to sudden changes in price levels or volatility. The latter refer to weather data, energy prices, economic growth and unexpected (environmental) events[2].

Mansanet-Bataller et al. (2007) and Alberola, Chevallier and Chèze (2007) are the only papers where the influence of weather variables and energy prices on the determination of CO2 spot prices is analyzed by performing multivariate linear regressions. In the former, Mansanet-Bataller et al. (2007) have considered the supply of EUAs and factors that affect European CO2 production such as weather variables (temperature and rainfall) and energy-related variables (oil, gas, and coal price levels and fuel switching from coal to gas) in order to explain the main determinants of carbon price levels. Their methodology is similar to that followed in studies of determinants of other weather dependent variables such as the price level of electricity (Longstaff and Wang, 2004; Stevenson et al, 2006), the price level of gas (Bopp, 2000) and the price level of orange juice futures contracts (Roll, 1984; Boudoukh et al, 2007). The results show that the energy sources are the main factors in the determination of CO2 price levels, and that only extreme temperatures influence them. The findings of Alberola, Chevallier and Chèze (2007) extend, among other contributions, the results of Mansanet-Bataller et al. (2007) by emphasizing that carbon price changes react not only to energy prices with forecast errors, but also to unanticipated temperatures changes during colder events.

We noticed that the factors found in theoretical models are generally consistent with market agents' perceptions. Firstly, Point Carbon[3] and Powernext consider weather, macroeconomic and microeconomic factors as being the main determinants of CO2 emissions allowances price levels. Secondly, energy factors such as the price level of oil, natural gas and electricity, as well as temperature and rainfall are quoted in most of the *"Weekly summary of emissions market"* published by Enervia[4]. Finally, the European Climate Exchange jointly with the Chicago Climate Exchange and Point Carbon, in their report entitled *"What determines the price of carbon in the European* Union?" by Christiansen and Arvanitakis (2004), argue that the way to

[2] E.g. power plant breakdowns (nuclear-, coal-fired- or hydroelectric power plants) where more emission intensive power stations have to be set up or unexpected environmental disasters (forest fire, earthquakes, etc.) shock the demand and supply side of CO2 allowances.
[3] See http://www.pointcarbon.com, www.powemext.fr and http://www.carbonriskmanagement.com.
[4] http://www.enervia.com/

forecast trends in price levels is to assess three fundamental aspects: policy and regulatory issues, market fundamentals and technical analyses. In the role of fundamentals they consider both the supply of allowances and the demand for allowances, which are in turn a function of CO2 production levels (Mansanet-Bataller et al., 2007).

In contrast with the before mentioned literature, Paolella and Taschini (2008) found that commodity prices do not generally exhibit trends over long periods. Even though steep rises are observed during short periods for specific events, such as the weather or political conditions, commodity prices tend to revert to normal levels in the long run. The resulting properties of commodity prices are a consequence of the general behavior of mean-reversion combined with spikes in prices caused by shocks in the supply/demand balance.

The table 2.2 summarizes the most important literature in the field of CO2 emissions allowances price dynamics.

Table 2.2: Literature review on CO2 emissions allowances:

Methodology employed	Study	Sample	Price determinants	Key findings
GARCH-type	Paolella and Taschini (2008)	Spot daily prices from Powernext (25.06.2005-3.11.2006)	Prices are mean-reverting, with short-term influences caused by: -weather conditions -political conditions	-The fundamentals analysis based on few market components overlooks the complexity of the variables that come into play -The spot-forward parity approach is, in the current market conditions, inadequate.
- AR-GARCH - Regime-switching model	Benz and Trück (2009)	OTC Spot daily prices from Spectron (03.01.2005-29.12.2006)	-Policy and regulatory issues (NAPs changes) -Market fundamentals (weather, fuel prices, economic growth)	-Analysis of short-term price behaviour of EUAs -Superior performance of models with conditional variance explained by the relationship between allowance prices, regulatory factors and fundamental variables
Stochastic two-factor equilibrium model(GBM with jumps)	Daskalakis et al. (2009)	-Spot daily prices from Powernext and NordPool (25.10.2005-28.12.2007) -Futures daily prices from ECX and NordPool for Dec 2006- 2009 contracts	-Negative correlation with equity market returns -Changes in public policy -Variations in emitter marginal pollution control costs	-The prohibition of banking of emissions allowances between distinct phases of the EU ETS has significant implications in terms of futures pricing. - Valid framework for the pricing and hedging of intra-phase and inter-phase futures and options on futures - Emissions allowance spot prices are likely to be characterized by jumps and nonstationarity and are better approximated by a GBM augmented by jumps.
Stochastic equilibrium model (GBM)	Chesney and Taschini (2009)	Phase I emissions permits spot prices	-The future probability of a shortfall in permits -The penalty that will be paid in the event of a shortfall -The discount rate	-Using dynamic optimization, this paper generates endogenously the price dynamics of emissions permits under asymmetric information, allowing inter-temporal banking and borrowing. - Derived a closed-form pricing formula for European-style options

Stochastic equilibrium model	Seifert et al. (2006)	Phase I emissions permits spot prices	-Time left until the end of the trading period	- Spot price processes incorporating Brownian motion better fit the CO_2 price data compared to mean reversion models. - Discounted spot prices are martingales - The volatility increases when coming closer to the end of the trading period while at the same time it reaches zero when spot prices are close to the price bounds. - It would be advantageous for the further development of trading in the CO_2 emissions market if the regulators enabled a smoother transition between trading periods.
Cost-of-carry relation	Uhrig-Homburg and Wagner (2009)	-Spot daily prices from Powernext (24.06.2005-15.11.2006) -Futures daily prices from ECX for Dec 2006 and 2007 contracts	-Futures contracts lead the price discovery process of CO_2 emissions allowances	- Spot and futures prices are linked by the cost-of-carry approach within the first trading period. - After initial divergence, spot prices equal discounted futures prices for futures maturing within the trial period. - It is not recommended to link spot and second period futures prices via some convenience yield approach.
Multivariate linear regression	Mansanet-Bataller et al. (2007)	OTC Forward daily price changes from ECX during 2005	-Weather (extreme temperatures) - Energy sources - Supply versus demand of emissions allowances	-Some rationality of pricing behaviour is found - The most important variables in the determination of CO_2 price changes are the Brent and natural gas price changes. - Extremely hot and cold days in Germany have a positive influence on CO_2 price levels. - Neither the price level of the most intensive emission source (coal) nor the switching effect between gas and coal price changes affect CO_2 price changes.
Multivariate regression	Alberola, Chevallier and Chèze (2007)	Spot daily EUAs price changes (01.07.2005-30.04.2007)	-Policy issues -Energy prices -Temperature events -Economic activity	- EUAs spot prices react not only to energy prices with forecast errors, but also to unanticipated temperatures changes during colder events. - Two structural breaks occurred in phase I (April 2006 and October 2006) due to the disclosure of emissions and the announcement of new allocations for phase II, respectively.

3. METHODOLOGY

This chapter describes the methodology used in order to perform the empirical study. The data collection process, the hypotheses, the computation of variables and the regression construction are presented further.

3.1. Research Approach

There are two general research approaches: deductive and inductive. The deductive approach develops a theory and designs the research to test the previously-mentioned theory; the inductive approach develops theories as a result of data analysis (Saunders, Lewis, Thornhill, 2003).

The primary purpose of this thesis is to determine how factors such as oil, coal, gas and electricity prices, weather data and economic development influence the price of carbon emissions permits. The theories regarding these factors already exist and we intend to test them and bring amendments if necessary. As a consequence a deductive approach will be employed.

In order to perform our analysis quantitative data is mainly used. The quantitative information is used to objectively test the hypothesis and perform descriptive statistics. In order to reach our goals related to the impact of weather data we will be using qualitative information in form of extremely high/low temperatures or extremely rainy/dry weather accounted for through dummy variables.

3.2. Data Collection

All the data employed is secondary data. The database DataStream is used to download spot carbon, oil, gas, coal and electricity prices. The temperature and rainfall indices, as well as industrial production index are gathered from monthly reports created by BlueNext exchange.

The temperature index is the average of BlueNext weather indices – France, Germany, UK and Spain – weighted by the allowances allocated to each country. The BlueNext temperature indices are defined on the basis of average temperatures, weighted by the population of the representative regions making up each country.

The rainfall index is the average of precipitation indices for Lyon, Oslo, Turin, Vienna and Madrid, weighted by the hydroelectric share in each country's electric power mix.

Wind speed data were downloaded from Weather Underground[5]. The wind speed index is the wind speed in each country's capital weighted by the share of the country's number of wind turbines at the end of the preceding year in the total number of wind turbines in Europe in that year. We only take into consideration countries that have a clear policy of developing the wind energy sector.

We use for spot prices data the Point Carbon Spot Index from 15.09.2005 to 26.02.2010.

Industrial production is gathered for the EU25[6] up to January 2007, when Romania and Bulgaria joined the EU ETS. For the period January 2007- December 2007 we use EU27 and starting January 2008 we will also include Norway and Iceland[7].

The sample periods are explained by the EU-ETS phases and availability of data. There is available data before 2005, starting as early as 2003 when trading with EUAs began, in form of futures prices of a not yet traded underlying that could complete our spot series (see Benz and Trück, 2009). However since the volume was very small and bid-ask spreads quite large we consider the inconsistency to be too large and disrupting for our analysis and, as a consequence, we disregard the pre-2005 period.

One particular problem that we are concerned about regarding the data sample is selection bias. We try to avoid this problem by always taking into account all the countries that participate in the EU ETS. We consider the weather indices to be representative as they include countries both from north, centre and south of Europe and have been used by other authors also.

[5] http://www.wunderground.com/history/
[6] The countries were members of both EU-ETS and Kyoto Protocol – Annex 1 Countries in Kyoto Protocol – See appendix 1
[7] They joined the carbon trading scheme in 2008, once the second period started along with Liechtenstein which we disregard due to lack of data.

3.3. Criticism of Data Sources

The secondary data used (price of EUAs, price of energy, oil, coal, gas) is gathered from DataStream, which is an established database. The validity of this source can be proven by the fact that it is common for researchers to use this source to collect information for their empirical studies. BlueNext and Weather Underground are used for obtaining weather data. As important and established international sources for a wide range of information, we consider them trustworthy.

3.4. Hypotheses regarding the determinants of EUAs prices

3.4.1. Weather Data

The weather has an impact on CO_2 emissions allowances, whether there are very high or very low temperatures, very rainy, windy or very dry periods, it is supposed to affect the energy consumption. This, in turn, will lead to an increase or decrease in CO_2 emissions, on which a scarcity condition is imposed.

We first determine a set of hypotheses which will lead to expected signs for each of the coefficients in our regression.

Hypothesis 1: Extremely low temperatures lead to an increase in the price of CO_2 emissions allowances. Cold weather increases energy consumption and CO_2 emissions for power and heat generation. This leads to an increase in the demand side for CO_2 allowances and hence to an increase in the price of EUAs. (see Mansanet-Bataller, Pardo and Valor, 2007)

Hypothesis 2: Extremely high temperatures lead to an increase in the price of CO_2 emissions allowances. It is expected that very high temperatures will lead to an increase in energy consumption due to use of air conditioning and by the same rationale as above to an increase in the price of EUAs. We expect that the effect will not be as large as in the case of extremely cold weather, as industrial activity won't need the same increase in power generation as in the case of cold weather. (see Mansanet-Bataller, Pardo and Valor, 2007)

Hypothesis 3: Extremely rainy weather leads to a decrease in the price of CO_2 emissions allowances. Rainfall will affect the share of power generation of non-CO_2 sources. High precipitation level will increase the possibility of producing hydroelectricity and will make it possible to switch the energy production to non intensive emission sources (see Mansanet-Bataller, Pardo and Valor, 2007)

Hypothesis 4: Extremely dry weather leads to an increase in the price of CO_2 emissions allowances. This can be explained considering flip side of the rationale above. (see Mansanet-Bataller, Pardo and Valor, 2007)

Hypothesis 5: Extremely windy weather leads to a decrease in the price of CO_2 emissions allowances. Wind speed will affect the share of power generation of non-CO_2 sources. High wind-speed level will increase the possibility of producing wind energy and will make it possible to switch the energy production to non intensive emission sources (see Mansanet-Bataller, Pardo and Valor, 2007)

Hypothesis 6: Extremely little wind leads to an increase in the price of CO_2 emissions allowances. This can be explained considering flip side of the rationale above.

3.4.2. Energy Data

As previous studies have determined, high (low) energy prices contribute to high (low) CO_2 emissions allowances prices (see Kanen, 2006; Alberola, Chevallier and Chéze, 2007). The prices of energy sources as input prices to produce the electricity are also important.

Hypothesis 7: Switching cost from coal to gas has a positive impact on EUAs. The difference between the price of gas and the price of coal is considered to represent the abatement cost to reduce CO_2[8]. The higher this difference, the fewer sources will change to using gas and as a consequence there will be higher CO_2 emissions and the price of EUAs will increase.

Hypothesis 8: Clean dark spread has a positive impact on EUAs. The clean dark spread represents the theoretical profit of a electricity producer based on frying coal and is calculated as

[8] By burning gas instead of coal Europe can reduce CO_2 emissions.

the difference between the price of electricity and the price of coal, corrected with the price of CO_2 emissions. As long as using gas is more expensive than coal we expect a positive correlation between the clean dark spread and the price of EUAs (see Alberola, Chevallier and Chéze, 2007).

Hypothesis 9: Clean spark spread has a negative impact on EUAs. The clean spark spread represents the theoretical profit of a electricity producer based on frying gas and is calculated as the difference between the price of electricity and the price of gas, corrected with the price of CO_2 emissions. As long as using gas is more expensive than coal we expect a negative correlation between the clean spark spread and the price of EUAs because producers will prefer using coal (see Alberola, Chevallier and Chéze, 2007).

We also intend to see the separate influence of changes in the price of oil, coal, gas and electricity on the carbon emissions allowances returns.

3.4.3. Macroeconomic Data

Hypothesis 10: It is expected that an increase in industrial production will lead to higher EUAs prices. Economic development leads to higher CO_2 emissions and to an increase in the demand side for CO_2 allowances and hence to an increase in the price of EUAs.

3.5. Computation of Variables

3.5.1. Weather Variables

In order to account for extreme weather events we are going to create two dummy variables for each weather characteristic. We first transform the monthly weather data in daily data by considering the same value for the ten or eleven days in the middle of the month. The days in the last part of the month and the first part of the following month will be given a value equal to the average between the two monthly values. We take the distribution of the values for each factor and we determine the 10% and 90% quintiles, as the lowest temperature/ driest weather/least windy and the highest temperature/ most rainy/ most windy weather.

Further we are going to construct a set of dummy variables. For all days that are at least as cold as the lowest quintile for the temperature series we give the dummy variable *Temp-* the value of 1 and 0 otherwise. For all days that are at least as hot as the highest quintile for the temperature series we give the dummy variable *Temp+* the value of 1 and 0 otherwise. For all days that are at least as dry as the lowest quintile for the rainfall series we give the dummy variable *Rain-* the value of 1 and 0 otherwise. For all days that are at least as rainy as the highest quintile for the rainfall series we give the dummy variable *Rain+* the value of 1 and 0 otherwise. For all days that are at least as windless as the lowest quintile for the wind speed series we give the dummy variable *Wind-* the value of 1 and 0 otherwise. For all days that are at least as windy as the highest quintile for the wind speed series we give the dummy variable *Wind+* the value of 1 and 0 otherwise. Thus we have six dummy variables which we expect to behave as presented in table 3.1

Table 3.1: Weather influences

Temp- will have a positive impact on EUAs prices
Temp+ will have a positive impact on EUAs prices
Rain- will have a positive impact on EUAs prices
Rain+ will have a negative impact on EUAs prices
Wind- will have a positive impact on EUAs prices
Wind+ will have a negative impact on EUAs prices

3.5.2. Energy Variables

We calculate the cost of CO_2 abatement as the difference between the cost of gas and the cost of coal for obtaining the same amount of energy. We use this variable as the *Switch* variable in our regression to account for the cost of switching to a new, less pollutant technology.

Switch = Gas price/unit of electricity - Coal price/unit of electricity

In order to calculate the dark spread and the spark spread we need to consider the fuel efficiency factors[9] and energy conversion factors[10]. In the case of gas the fuel efficiency factor is 49.13% and the energy conversion factor is 0.2929 and in the case of coal 35% and 7.1 respectively. We compute the dark spread and spark spread as below:

[9] The factor represents how much energy is obtained from 1 unit of fuel.
[10] The factor converts 1 unit of fuel into 1 unit of energy (million British thermal units in megawatt/hour for example)

DS = Electricity price – (Coal price / 7.1/ 0.35)

SS = Electricity price – (Gas price / 0.2929/ 0.4913)

We then calculate the clean dark spread and the clean spark spread by accounting for the price of CO_2. We have to consider the emission intensity factor[11] for each source of power. In the case of coal this factor is 0.96 tCO_2/MWh and in the case of gas 0.411 tCO_2/MWh.

CDS = *DS* – (Carbon price*0.96)

CSS = *SS* – (Carbon price*0.411)

We expect energy variables to influence the price of emissions allowances in the following way:

Table 3.2: Energy influences

Switch will have a positive impact on EU prices
CDS will have a positive impact on EUAs prices
CSS will have a negative impact on EUAs prices

3.5.3. Macroeconomic Variables

There is one big difference between the macroeconomic data and other variables we use. While energy prices, carbon prices and weather data are with daily frequency, the macroeconomic data is available only monthly. In order to account for changes in industrial production we are going to use a dummy variable. For each month that the European industrial production increased the value of the dummy *EUprod* will be 1, while for each month the average industrial production decreases the value of the *EUprod* will be -1. We expect this variable to have a positive coefficient.

3.6. Constructing the Regression

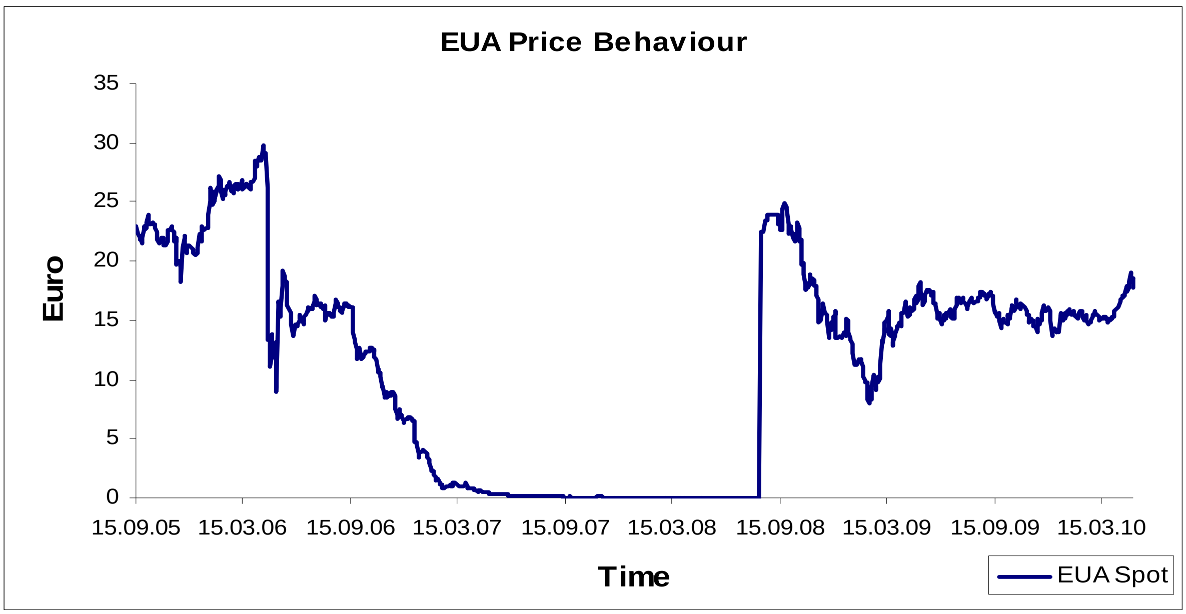
In order to determine which variables have an impact on the price of carbon emissions allowances, we are going to construct a set of multiple regressions. Our dependent variable, the first log difference of EUAs prices, R_t, is split into two periods 15.09.2005-30.03.2007 and 11.08.2008-26.02.2010. For each period we are going to use multiple specifications estimated by GARCH method. We disregard the period 02.04.2007 – 11.08.2008 when the trading in the spot

[11] The factor represents the quantity of CO2 that will be emitted as a result of burning coal or gas

market was practically inexistent and the price of EUAs was smaller than 1 Euro (see Figure 3.1).

Our explanatory variables are energy variables, industrial production dummy variable, weather variables, weather dummies and the lagged return on EUAs (as it proved to be significant in previous studies). For each energy variable we calculate the return on the price series as we consider that the changes in the prices of emissions allowances are due to changes in the prices of energy variables. In contrast with Alberola, Chevallier and Chèze (2007) we consider that changes in the clean dark and clean spark spreads and changes in the switching cost, rather than the simple price series, influence the changes in EUAs prices.

Figure 3.1: Price Behavior of EUAs



Source of data: Point Carbon Spot Index

As a consequence to our approach, we also dispose of non-stationarity by using either log returns, where possible, or normal returns, where the series contains negative values.

We begin by checking for existence of multicolinearity between the independent variables. We consider only the energy variables, as the dummy variables cannot be multicolinear due to the way they were constructed.

We construct the correlations between the returns on energy variables separate for each period. For the first period we have the following result:

Table 3.3: Correlations between independent variables in the first period

	RCoal	RBrent	RGas	RElectricity	RCES	RCDS	RSwitch
RCoal	1						
RBrent	0.005706	1					
RGas	0.021021	0.253615	1				
RElectricity	0.009205	0.009867	-0.006840	1			
RCSS	0.050222	0.030755	-0.070140	0.15334248	1		
RCDS	0.010425	-0.041910	-0.005560	0.19383856	0.24247838	1	
RSwitch	-0.180410	0.217520	0.907052	0.00253517	-0.08600617	-0.024729	1

The only correlation that might impose problems is the one between the return on switching cost and RGas. In case both variables turn out to be significant, we have to control for the high correlation between the two.

For the second period we have the following results:

Table 3.4: Correlations between independent variables in the second period

	RCoal	RBrent	RGas	RElectricity	RCSS	RCDS	RSwitch
RCoal	1						
RBrent	-0.055080	1					
RGas	0.103099	0.143415	1				
RElectricity	-0.041980	0.022779	0.129165	1			
RCSS	0.011241	0.028949	-0.016510	0.243979	1		
RCDS	0.016692	0.012691	-0.000880	0.012195	-0.00371897	1	
RSwitch	0.144460	-0.004650	0.016120	-0.041320	-0.01103893	-0.0006684	1

In this case we are not concerned with any correlation between the returns on energy variables, as all the correlations are low.

The **first specification** we are going to use includes weather data, extreme weather events, returns on composed energy variables and macroeconomic data.

$$R_t = \alpha_0 + \alpha_1 * L(R_t) + \alpha_2 * \text{Temperature} + \alpha_3 * \text{Temp}_- + \alpha_4 * \text{Temp}_+ + \alpha_5 * \text{Rainfall} + \alpha_6 * \text{Rain}_- + \alpha_7 * \text{Rain}_+ + \alpha_8 * \text{Wind-speed} + \alpha_9 * \text{Wind}_- + \alpha_{10} * \text{Wind}_+ + \alpha_{11} * \text{RSwitch} + \alpha_{12} * \text{RCDS} + \alpha_{13} * \text{RCSS} + \alpha_{14} * \text{EUprod} + U_t;$$

Where L is the lag operator, U_t is the error term and each of the α coefficients has the following expected sign:

Table 3.5: Expected sign of coefficients in the first specification

Coefficient	α_0	α_1	α_3	α_4	α_5	α_6	α_7	α_8	α_9	α_{10}	α_{11}	α_{12}	α_{13}	α_{14}
Expected sign	+	+	+	+	-	+	-	-	+	-	+	+	-	+

In the **second specification**, we are only going to include weather data, the returns on basic energy data: prices of coal, gas, electricity and oil, and the macroeconomic dummy variable.

$$R_t = \alpha_0 + \alpha_1 {*} L(R_t) + \alpha_2 {*} Temperature + \alpha_3 {*} Temp_- + \alpha_4 {*} Temp_+ + \alpha_5 {*} Rainfall + \alpha_6 {*} Rain_- + \alpha_7 {*} Rain_+ + \alpha_8 {*} Wind\text{-}speed + \alpha_9 {*} Wind_- + \alpha_{10} {*} Wind_+ + \alpha_{11} {*} RCoal + \alpha_{12} {*} RBrent + \alpha_{13} {*} RGas + \alpha_{14} {*} RElectricity + \alpha_{15} {*} EUprod + U_t;$$
where

Table 3.6: Expected sign of coefficients in the second specification

Coefficient	α_0	α_1	α_3	α_4	α_5	α_6	α_7	α_8	α_9	α_{10}	α_{11}	α_{12}	α_{13}	α_{14}	α_{15}
Expected sign	+	+	+	+	-	+	-	-	+	-	-	+	+	+	+

As Kanen (2006) showed, energy prices should have, in general, a positive impact on the price of carbon emissions allowances. However, previous empirical studies have shown that not all the variables are significant (see Mansanet-Bataller, Pardo and Valor, 2007; Alberola, Chevallier and Chéze, 2007) and, moreover, different studies have reached different conclusions. We are going to provide further evidence on this issue.

As a **third specification** we are going to consider all the returns on energy variables:

$$R_t = \alpha_0 + \alpha_1 {*} L(R_t) + \alpha_2 {*} Temperature + \alpha_3 {*} Temp_- + \alpha_4 {*} Temp_+ + \alpha_5 {*} Rainfall + \alpha_6 {*} Rain_- + \alpha_7 {*} Rain_+ + \alpha_8 {*} Wind\text{-}speed + \alpha_9 {*} Wind_- + \alpha_{10} {*} Wind_+ + \alpha_{11} {*} RCoal + \alpha_{12} {*} RBrent + \alpha_{13} {*} RGas + \alpha_{14} {*} RElectricity + \alpha_{15} {*} RSwitch + \alpha_{16} {*} RCDS + \alpha_{17} {*} RCSS + \alpha_{18} {*} EUprod + U_t;$$
where

Table 3.7: Expected sign of coefficients in the third specification

Coefficient	α_0	α_1	α_3	α_4	α_5	α_6	α_7	α_8	α_9	α_{10}	α_{11}	α_{12}	α_{13}	α_{14}	α_{15}	α_{16}	α_{17}	α_{18}
Expected sign	+	+	+	+	-	+	-	-	+	-	-	+	+	+	+	+	-	+

In each case we are going to construct a second regression to include lagged energy data, as previous studies have shown significant influences when data is lagged (Alberola, Chevallier and Chèze, 2007). We check for ARCH effects and, in case such effects exist, we are also going to estimate a second equation for the variance. As we will see, the most appropriate model will be a GARCH (1,1) specification.

$U_t = \varepsilon_t * \sigma_t$; $\sigma_t^2 = a_0 + a_1 * U_{t-1}^2 + a_2 * \sigma_{t-1}^2$

In each case we check for autocorrelation in the residual series. We observe that there is no case of autocorrelation.

4. EMPIRICAL FINDINGS AND ANALYSIS

This chapter presents the empirical results from the study performed. A description of the data and the evolution of the CO2 Emissions Allowances price are presented first. Afterwards, the models we consider to best suit the data are evaluated. A regression analysis is used to verify our initial hypothesis regarding the determinants of EUAs prices.

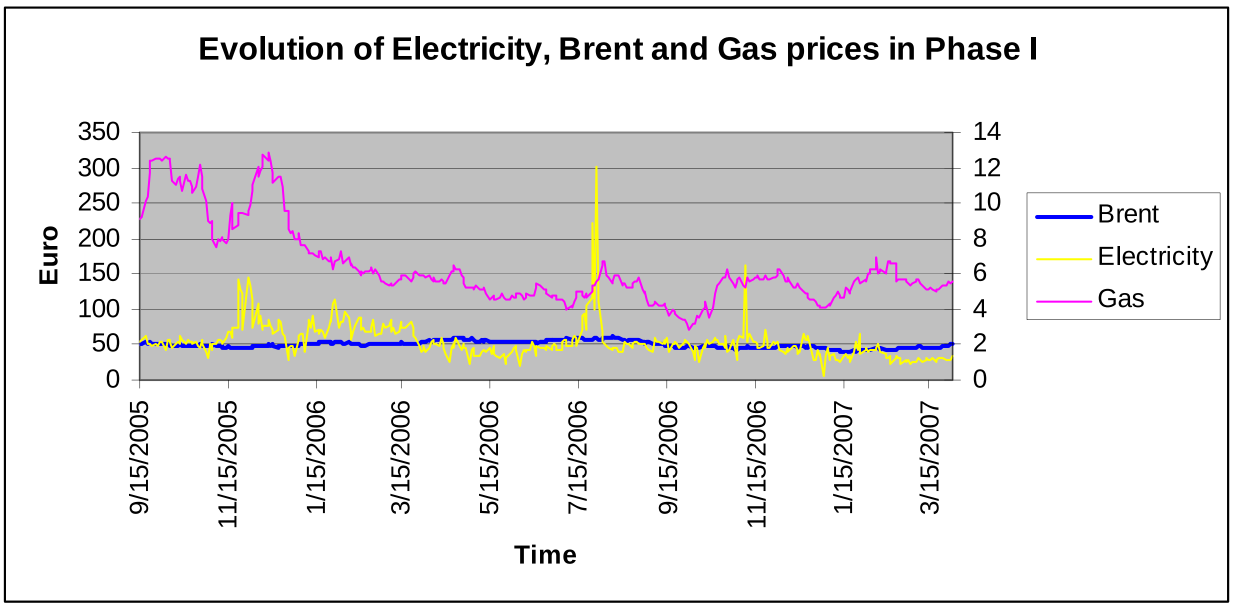
4.1. Evolution of EUAs Prices

Our final sample consists of 807 daily observations, which represent EUAs prices. It can be seen from the plot of the EUAs prices over time (Figure 3.1) that trading in the spot market was practically inexistent during the period 02.04.2007 – 11.08.2008. This interval is excluded from our regressions and delimits between the two main periods in our data set: the first period is 15.09.2005-30.03.2007 (402 observations) and is the sample that corresponds to the trial period (2005-2007), and the second interval is 11.08.2008-26.02.2010 (405 observations) and is the sample representative for the Kyoto commitment period (2008-2012).

New trading markets normally need a "trial period" to achieve real price discovery. As seen in Fig. 3.1, the EUA price pattern experienced strong price fluctuations during the first two years. Starting with the 15th on September 2005, EUAs prices fluctuated during the following four months in the range of 20–25 EUR, then rose to 30 EUR until the end of April. On the last week of April 2006 prices collapsed when operators disclosed 2005 verified emissions data and realized the scheme was oversupplied. That is, disclosures by the Netherlands, Czech Republic, France, and Spain revealing long positions in allowances caused drastic changes in the market's expectations and the sharp price break. On the 15^{th} of May 2006 the European Commission confirmed that verified emissions were about 80 million tons, or 4%, lower than yearly allocations, which made things even more straightforward.

After this significant adjustment by 54% in four days, EUAs prices moved in the range of 15 to 20 EUR until October 2006, when the European Commission announced more restricted allocations for Phase II NAPs. This overlapped with a downturn over the last months in the prices of oil and natural gas, which took the price of electricity with them (see Figure 4.1). From this date, the EU ETS is sending two price signals responding to different dynamics. Phase I prices are declining towards zero, as it can be seen in Figure 3.1., whereas Phase II Futures prices are increasing to 20 EUR. On April 2007 verified emissions were again below the 2006 yearly allocation, and the Phase I Spot price never recovers after this date. This is due to the fact that emissions allowances are not bankable from one Phase to the next, and companies already had in their portfolios more emissions allowances than they needed for compliance with the EU standards for 2007, the last year of Phase I.

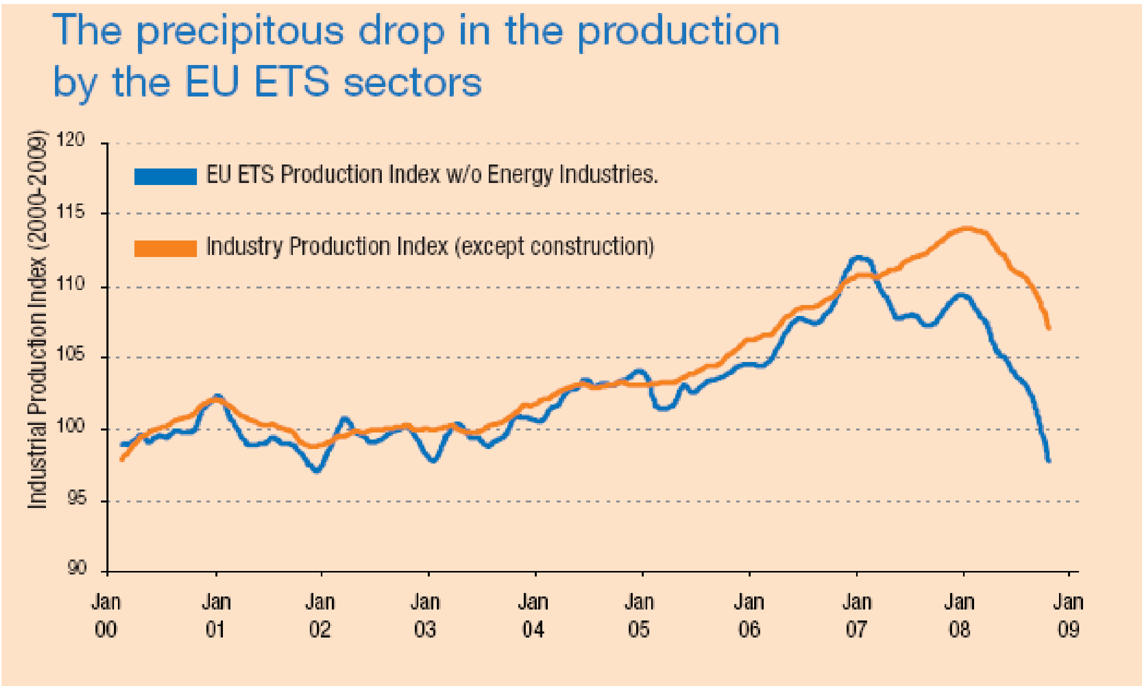
Figure 4.1.



Source of data: Datastream

The second phase of the European Union Emissions Trading Scheme (EU ETS) began in the second half of 2008, at a price equal to the Futures Price Dec 08 of 22.5 EUR. The downward EUA price trend that followed lasted until March 2009 (see Figure 3.1) and reflects the rapid deterioration of the economic situation, which massively reduced the industry's need for allowances (see Figure 4.2). The EUA price downturn took place in spite of the European temperature indicator being almost 3°C below its ten-year average in winter 2009. Such an anomaly would normally boost demand for electricity and heat, which in turn tends to increase the price of CO_2. However, this factor was more than offset by the economy's plunge into the most severe recession of the postwar era. More so, what added to the EUA price decline was the fact that companies started using all possible means of raising cash, including the sale of their CO2 allowances.

Figure 4.2.



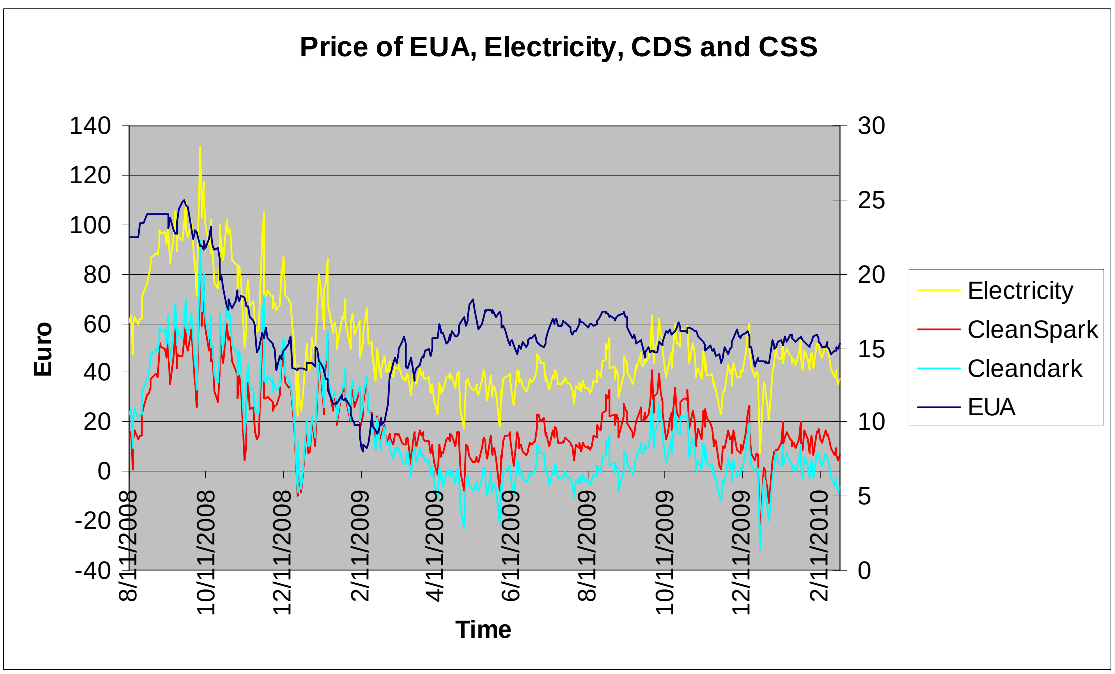
Source: Tendances Carbone

For the first time since its launching in 2005, the EU ETS recorded an overall deficit of allowances in 2008, which can be explained to a great extent by the reduction in the volumes allocated by Member States to installations. To ensure their compliance, installations that were short of allowances used two mechanisms as alternatives to buying allowances on the market in 2008: borrowing from their 2009 allocations - an option that is available only until 2011, the year before the end of phase II - and importing credits issued for CDM or JI[12] projects on condition that the number of imported credits does not exceed the limit set by each Member State[13]. This deficit on the supply side boosted up the price of EUAs in March 2009, after reaching its lowest point in Phase II in February at the 8EUR level. But this was not the only reason for the turnaround.

[12] See section 1.1. of this paper for details on CDM and JI;
[13] http://www.bluenext.fr/TendancesCarbone/TCN.36_05.2009_En.pdf

Growing confidence in a possible economic recovery has caused an improvement in equity and commodity markets worldwide. Crude oil, further supported by OPEC's production cut of 4.2 m barrels per day, has risen nearly 40% from the low reached in December 2008. On the other hand, prices of coal, electricity and gas have remained low. In April 2009, coal and electricity recovered slightly, while gas continued its plunge due to high supply and low demand. Though clean spark spread and clean dark spread have both declined, with prices of gas going down substantially more than those of coal, clean spark spread was greater than clean dark spread for the first time since September 2008, providing an incentive to switch from coal to gas (see Figure 4.3). Under these conditions, carbon recovered remarkably in the month of April, rising 74% from the historical low set in February 2009.

Figure 4.3.



Source: Datastream

Starting with May 2009 and onwards the industrial production index for Europe stabilized and the industrial confidence indicator started to improve, backed by a strong increase in production expectations. The drop in gas prices and the rise in coal prices continued, leaving the CO2 switch price on the decline. It fell from 11.60 EUR/t in May 2009 to 1.98 EUR/t in August 2009. This would, under normal circumstances, provide an incentive for power producers to switch from coal to gas which is less carbon intensive, which would imply a decline in the price of CO2 emissions allowances. However, the carbon price exhibited the opposite trend during the aforementioned period, which could mean that the slack capacity left for coal to gas switching has been more or less exhausted.

The eagerly-expected UN Climate Change Conference held in December 2009 in Copenhagen left a general feeling that international climate negotiations, which failed to yield the expected results, were going nowhere. The only concrete commitment regarded the amount of financing the developed countries must provide to the developing countries over the period 2010-2012 in order to help them reduce their emissions and "adapt" to the effects of climate change. The amount is 30 billion dollars in 2010-2012, to be raised to 100 billion dollars a year by 2020.

In the first few months of 2010 the prices of electricity rose less than those of coal and natural gas, narrowing the difference between clean dark and clean spark spreads. CO2 switch price remained below CO2 market price, providing an incentive for power producers to switch from coal to gas. CO2 price broke out of its trading range and rose to €15.8 in February 2010.

Ultimately, the effectiveness of the EU-ETS will be judged by the extent to which it achieves environmental objectives at the lowest cost. In doing so, the price must continue to be allowed to respond to fundamentals, while also sending price signals to the market that give the industry an incentive to reduce emissions. In the next part of this paper we will empirically test the impact of these fundamentals on CO2 prices.

4.2. Descriptive Statistics

In order to have an overview of the differences in underlying characteristics among the EUA price and the prices of energy-related variables, which will facilitate giving a more accurate interpretation of the empirical findings, a section on descriptive statistics is provided before the results.

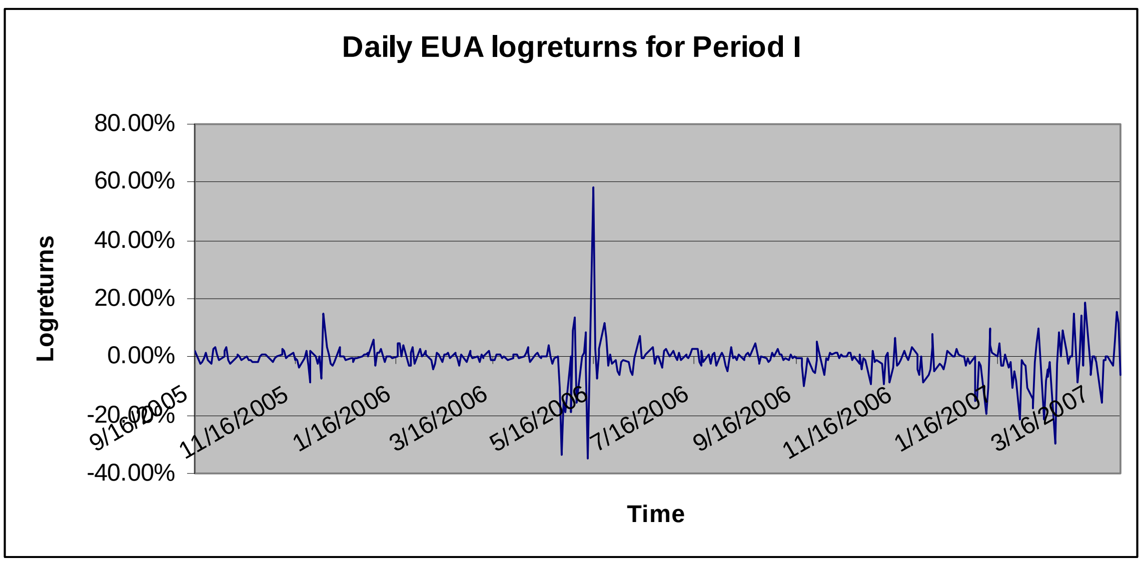
A summary statistics for the EUA prices, logreturns and returns on the energy-related variables in the first period (15.09.2005-30.03.2007) is presented in Table 4.1 below:

Table 4.1: Descriptive statistics for Period I

Period I	Mean	Median	Max	Min	Std. dev.	Skew.	Kurt.	N
EUA	15.682	16.050	29.750	0.780	8.271	-0.312	-0.982	402
R_t	-0.007	-0.001	0.584	-0.346	0.062	0.796	25.674	401
RBrent	0.000	0.000	0.056	-0.055	0.018	-0.207	0.040	401
RGas	-0.001	0.000	0.172	-0.163	0.048	0.120	1.642	401
RCoal	0.001	0.000	0.216	-0.064	0.018	7.954	91.101	401
RSwitch	0.002	0.000	0.643	-0.447	0.107	1.315	8.704	401
RElectricity	-0.001	0.001	1.736	-1.830	0.271	-0.100	10.964	401
RCDS	0.356	-0.048	109.047	-42.134	7.193	10.241	152.579	401
RCSS	0.137	-0.087	32.996	-30.278	4.518	2.383	31.996	401

The EUA price time series exhibits heteroskedasticity and volatility clustering. The spot market under scrutiny is characterized by a very high historical volatility, as estimated by the standard deviation of daily returns, which exceeds 100% (has the level of 8.271). When the first external verified reports regarding each EU member state's actual emissions during the previous compliance year came out in April 2006, prices soared up to their maximum level of nearly 30 euros and the logreturns also exhibit a clearly increased volatility (see Figure 4.4).

Figure 4.4.



Source: Datastream

The minimum level of the logreturns time series is also within that small period surrounding the announcements of the results for 2005. The skewness parameter for the EUA logreturns is 0.796 and the kurtosis parameter is equal to 25.647. This suggests a leptokurtic distribution with positively skewed returns. Due to asymmetry, excess kurtosis and heavy tails, we conclude that the data does not fit the normal distribution. Brent and electricity returns time series are left-skewed during Period I, while the other energy-related time series are right-skewed, also suggesting a different distribution than the normal.

Table 5.2 presents a summary statistics for the EUA prices, logreturns and returns on the energy-related variables in the second period (11.08.2008-26.02.2010).

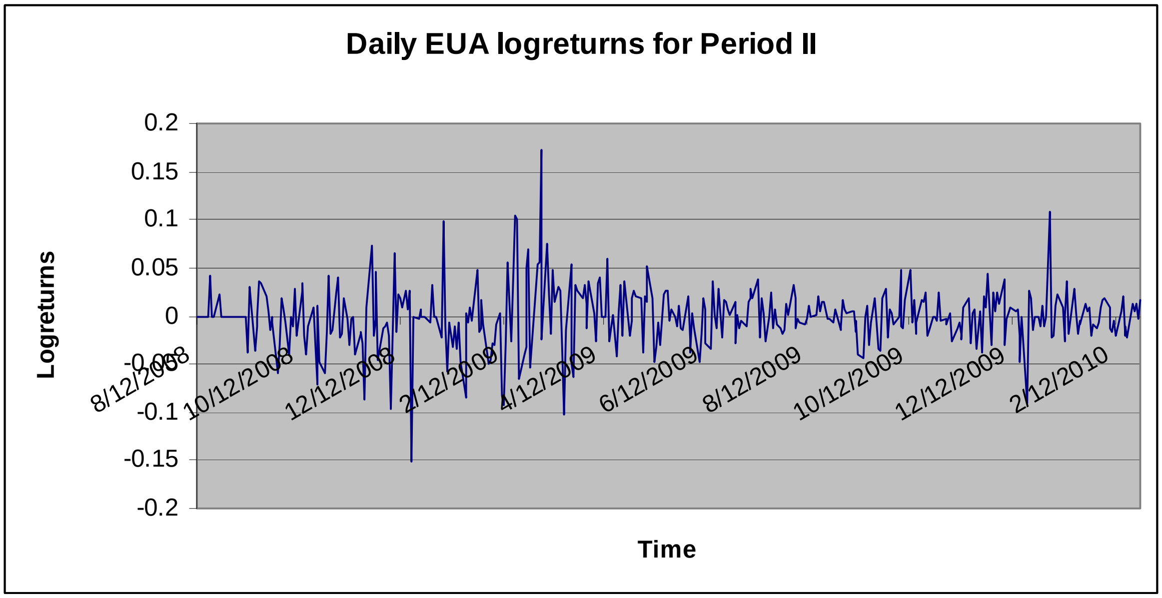
Table 4.2: Descriptive statistics for Period II

Period II	Mean	Median	Max	Min	Std. dev.	Skew.	Kurt.	N
EUA	16.189	15.660	24.950	8.000	3.305	0.704	1.047	405
R_t	-0.001	0.000	0.172	-0.151	0.031	0.165	4.789	404
RBrent	-0.001	0.000	0.157	-0.114	0.029	0.246	2.919	404
RGas	-0.001	0.000	0.250	-0.241	0.049	0.471	4.962	404
RCoal	0.001	0.000	0.221	-0.091	0.019	4.843	51.823	404
RSwitch	-0.065	0.000	14.051	-55.508	3.047	-14.832	275.164	404
RElectricity	-0.001	-0.007	1.608	-1.556	0.196	0.389	22.070	404
RCDS	-3.413	-0.043	99.739	-1514.79	75.676	-19.859	397.679	404
RCSS	0.125	-0.024	60.932	-63.653	4.982	0.080	126.406	404

It is interesting to see that, similar to the first period, not only does the data show volatility clustering, but both maximum positive and negative logreturns could be observed during the same period, namely in April 2009 (see figure 4.5). This is when the EU ETS announced the actual emissions for 2008 and its first overall deficit of allowances.

Just like in the first period, the EUA price time series is characterized by high volatility, as the standard deviation has a value of 3.305. The maximum EUA price is higher in the first period than in the second one, and that is also when the minimum price is the lowest. The skewness parameter for the EUA logreturns is 0.165 and the kurtosis parameter is equal to 4.789, which suggests a leptokurtic distribution with positively skewed returns, just like in the first period. Unlike in period I, brent and electricity returns time series are right-skewed, while the returns on switch costs and clean dark spread are left-skewed.

Figure 4.5.



Source: Datastream

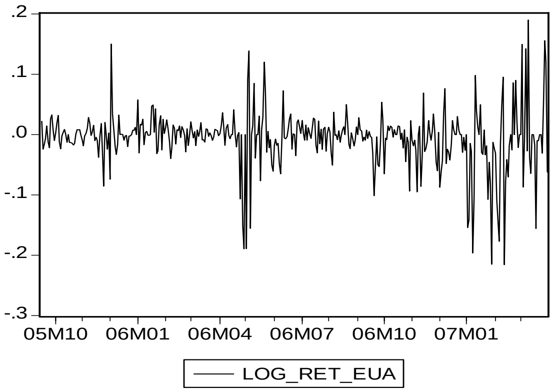
Although analyzing the similarities between the variables' underlying characteristics is useful, running the actual regressions and interpreting the results will give us more information.

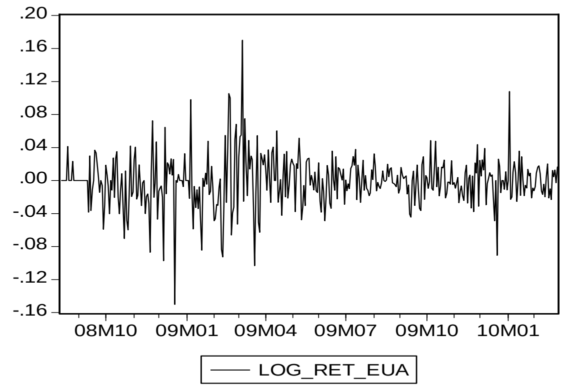
4.3. Regression analysis

4.3.1. Fitting the Model

We firs begin our analysis by looking at the returns on EUA prices. The series looks stationary in both periods taken under consideration and exhibits volatility clustering. We are going to exclude from the first period some dates where the series exhibits abnormal movements: 26.04.2006, 12.05.2006, 15.05.2006. 19.02.2007. We argue that these extreme movements are due to different announcements made by regulators. "On April 25, 2006, first disclosures by the Netherlands, Czech Republic, France, and Spain revealing long positions and caused a sharp price break. On May 15, 2006 the EC confirmed verified emissions were about 80 million tons or 4% lower than yearly allocation, this leading to a sharp decrease in the price of allowances." (Alberola, Chevallier and Chéze, 2007). Each year in February there is the announcement regarding the number of emissions for the next year. The next figure shows the movements of the log return EUA price series during the two periods:

Figure 4.6.





First period Second period

Source of data: Datastream

We test for stationarity by performing a unit root test (see results in Appendix 2). In both cases we can reject the null hypothesis that a unit root exists. As a consequence, our series are stationary and we can continue to perform the regressions.

We first perform the regression using the ordinary least squares technique and check for existence of ARCH-effects. The results for the first specification in the first period are presented in Appendix 3. Both F test and Chi-Square are very significant, yielding the same results and suggesting the presence of ARCH effects. We obtain similar results for all the other regressions.

We further try to determine the best GARCH model for our regressions. We start with a parsimonious model of GARCH(1,1), as previous studies have shown that this is the one of the best models in the case of emissions allowances. We test for higher orders of GARCH(p, q). As it turns out, the coefficients for higher orders of GARCH and ARCH terms are insignificant. We also test for a simple ARCH(p) model vs. GARCH(1,1). According to the Schwarz Information Criteria, GARCH(1,1) yields a better performance in all the cases considered.

4.2.2. Regression Results – First Period

The following table presents the results from the **first specification**. As it can be seen, the only significant coefficients at a p-value lower than 10% are: the lagged return on prices of EUA, $Temp_{-}$, $Rain_{+}$, $Wind_{+}$, and the return on switching cost (see Table 4.3.).

Table 4.3: Results from first specification first period

	Coefficient	Std. Error	Prob.	Expected sign
α0	0.030585	0.02241	0.1723	
L(Rt)	0.195582	0.05943	0.0010	+
Temperature	-0.000376	0.00046	0.4170	
Temp-	0.024430	0.01344	0.0690	+
Temp+	-0.000295	0.00728	0.9676	+
Rainfall	-0.000172	0.00020	0.3893	-
Rain-	0.008296	0.01234	0.5016	+
Rain+	-0.020281	0.01203	0.0919	-
Wind Speed	-0.001768	0.00194	0.3617	-
Wind-	0.004414	0.00732	0.5466	+
Wind+	-0.039029	0.00958	0.0000	-
RSwitch	0.034193	0.01330	0.0101	+
RCDS	-0.000435	0.00032	0.1721	+
RCSS	0.000311	0.00035	0.3742	-
EUprod	0.001029	0.00188	0.5840	+

α_0 has a positive value. It is, however, statistically insignificant.

The results for the weather coefficients mostly confirm our expectations regarding the signs of these coefficients. The Temperature (for which we didn't establish an expected sign) has a negative impact, whereas Rainfall and Wind-speed have a negative impact, as expected. However, these coefficients are highly insignificant, leading us to the conclusion that weather data does not have a linear impact on EUA price, but we should rather expect extreme events to influence it. This finding is similar to Alberola, Chevallier and Chéze (2007) and Mansanet-Bataller, Pardo and Valor (2007).

Extremely low temperatures, extremely rainy days and extremely windy days seem to have a significant influence. As expected, low temperatures lead to an increase in the price of CO_2, while high amounts of rain and high wind speed lead to a decrease in the price of CO_2. $Temp_+$, $Rain_-$ and $Wind_-$ don't have a significant influence. As Alberola, Chevallier and Chéze (2007) have also shown, extremely hot weather does not have an impact on allowance price changes.

The return on switching cost is the only composed energy variable that has an influence on the price of EUA. As expected, the higher the switching cost the more use of coal and, as a consequence, the higher the prices for CO_2 emissions rights are.

The industry production dummy is insignificant. This might be due to the fact that the monthly data available for this independent variable cannot be properly accounted for to determine daily movements for the price of CO_2 allowances.

In three cases the expected sign differs from our empirical findings. However, we do not pay too much attention to this issue as the coefficients are insignificant and the results sensitive to the period, variables and model chosen. The signs for clean dark spread and clean spark spreads are opposite than expected. Towards the end of the difference between clean dark and clean spark spreads has narrowed so even if the return on clean dark spread increases, companies might still find it more profitable to use gas and, as a consequence, the signs of the spreads have changed.

We also try to see if the lagged energy data has an influence on our dependent variable. We use the same specification and we lag the composed energy data one period. The results turn out to be completely insignificant and the regression variables do not explain at all the log-return of EUA.

The **second specification** brings further evidence on the important variables that influence the price of allowances. The weather conditions remain significant, as in the first case, with $Temp_{-}$, $Rain_{+}$ and $Wind_{+}$ being significant at least at a 10% level (see Table 4.4. below).

Table 4.4: Results from second specification first period

	Coefficient	Std. Error	Prob.	Expected sign
α0	0.028430	0.023598	0.2283	
L(Rt)	0.204348	0.057082	0.0003	+
Temperature	-0.000297	0.000468	0.5262	
Temp-	0.029045	0.015279	0.0573	+
Temp+	-0.001932	0.006914	0.7799	+
Rainfall	-0.000148	0.000184	0.4223	-
Rain-	0.011278	0.010312	0.2741	+
Rain+	-0.024716	0.013977	0.0770	-
Wind Speed	-0.001722	0.002090	0.4100	-
Wind-	0.005236	0.007301	0.4733	+
Wind+	-0.038577	0.009990	0.0001	-
RCoal	-0.047082	0.106096	0.6572	-
RBrent	0.209028	0.057454	0.0003	+
RGas	0.048940	0.031254	0.1174	+
RElectricity	-0.009494	0.004723	0.0444	+
EUprod	0.001034	0.001825	0.5710	+

From the energy variables considered, the return on prices of brent and electricity are statistically significant. Brent has a positive impact, as expected, while electricity has a negative impact.

We can argue that when the price of electricity increases, the population tends to use less electricity and as a consequence less CO_2 is emitted in order to fulfill the lower demand for electricity. Our results partially resemble those of previous studies. Alberola, Chevallier and Chéze (2007) find a positive impact for brent and also positive for electricity (the sign of the coefficient being in contrast to our results).

We also perform a regression using the lagged energy data. As in the previous case, the coefficients for the lagged data turn out to be completely insignificant.

In the **third specification** we include all energy data. Results are presented in Table 4.5.

Temperature variables seem to have a steady impact among all the specifications. Again $Temp_{-}$, $Rain_{+}$ and $Wind_{+}$ are significant in explaining the movements of the CO_2 emissions allowances.

Table 4.5: Results from third specification first period

	Coefficient	Std. Error	Prob.	Expected sign
α0	0.028173	0.023853	0.2376	
L(Rt)	0.206843	0.057605	0.0003	+
Temperature	-0.000279	0.000466	0.5494	
Temp-	0.029483	0.015236	0.0530	+
Temp+	-0.002159	0.006860	0.7530	+
Rainfall	-0.000141	0.000188	0.4542	-
Rain-	0.010296	0.010564	0.3298	+
Rain+	-0.025035	0.013944	0.0726	-
Wind Speed	-0.001713	0.002105	0.4158	-
Wind-	0.004785	0.007274	0.5106	+
Wind+	-0.038638	0.009982	0.0001	-
RCoal	-0.063597	0.118408	0.5912	-
RBrent	0.202946	0.060522	0.0008	+
RGas	0.094794	0.083358	0.2555	+
RElectricity	-0.009026	0.005113	0.0775	+
RSwitch	-0.024715	0.043247	0.5677	+
RCDS	-0.000183	0.000402	0.6488	+
RCSS	0.000090	0.000353	0.7993	-
EUprod	0.000822	0.001817	0.6510	+

RBrent and RElectricity also keep their significance and sign, while the return on switching cost becomes insignificant. We are not concerned with the multi-colinearity between RGas and RSwitch as both independent variables are insignificant. Including lagged energy data worsens the results. It can be observed that all the composed energy variables have the opposite sign as those expected and are insignificant.

This can be due to the fact that market participants might not see these measures important or consider to be accounted for through other variables such as electricity or brent. Another issue that can lead to distortions in the results might be the fact that the market is still not fully developed and market participants are not used to trading CO_2 allowances, and especially regulators still tackle the problem related to the number of allowances issued to each company.

As a variant of the last specification we are trying to find a parsimonious equivalent by successively eliminating from the regressions the most insignificant variable until all the coefficients are significant at 10% level (see Table 4.6.).

Table 4.6: Results from parsimonious model in the first period

	Coefficient	Std. Error	Prob.
α0	-0.000266	0.001501	0.8595
L(Rt)	0.208151	0.057278	0.0003
Temp-	0.007338	0.002992	0.0142
Wind+	-0.045698	0.005097	0.0000
RBrent	0.234909	0.051684	0.0000
RElectricity	-0.010535	0.004626	0.0228

We end up with five explanatory variables with more powerful coefficients. All coefficients except α_0 keep their signs. α_0 is insignificant, however we keep the coefficient to control for any distortions in inferences. (we keep the coefficient in order to have a distribution for the residuals as close to a normal distribution as possible).

In contrast to previous studies and in contrast to our expectations the models seem to explain little of the dependent variable.

Table 4.7: Comparison measures for the models

	Equation 1	Equation 2	Equation 3	Equation 3b
R Square	0.070873	0.093453	0.091925	0.093378
Adjusted R Square	0.029525	0.050624	0.041476	0.074829
AIC	-3.849472	-3.885101	-3.872481	-3.912159
SIC	-3.669856	-3.695506	-3.652951	-3.822351

We can notice that the parsimonious model performs slightly better (see table 4.7.) than the other models according to the Adjusted R Square and the information criteria used (Akaike and Schwarz). However the models perform worse than the models proposed by Alberola, Chevallier and Chéze (2007) and Mansanet-Bataller, Pardo and Valor (2007), despite the similarities. We consider that the differences are due to the fact that the weather data we included were monthly data extrapolated to a daily basis, while previous research used daily data. However, due to limited availability of daily weather data we were coerced to use monthly data.

4.2.3 Regression Results – Second Period

The three specifications are replicated for the second period. For the **first specification** it can be observed that none of the coefficients are significant (see table 4.8.). Moreover, α_0 turns negative and Wind-speed positive, contradicting our expectations.

Table 4.8: Results from first specification second period

	Coefficient	Std. Error	Prob.	Expected sign
α0	-0.008934	0.031344	0.7756	
L(Rt)	0.061100	0.060105	0.3094	+
Temperature	0.000145	0.000484	0.7648	
Temp-	0.003396	0.009308	0.7152	+
Temp+	0.002599	0.006306	0.6802	+
Rainfal	-0.000073	0.000173	0.6736	-
Rain-	0.002128	0.006695	0.7506	+
Rain+	-0.009807	0.006904	0.1555	-
Wind Speed	0.000961	0.002619	0.7137	-
Wind-	0.003328	0.005688	0.5585	+
Wind+	-0.005581	0.007573	0.4612	-
RSwitch	0.000091	0.001009	0.9280	+
RCDS	-0.000023	0.000205	0.9094	+
RCSS	0.000037	0.000744	0.9599	-
EUprod	0.001204	0.001729	0.4863	+

No weather data seem to influence the price of CO_2 in this case.

We further look at the **second specification** to determine some factors that can be considered determinants of the price of emissions allowances (see Table 4.9.). In this case the lagged return on EUA prices becomes significant at 10% level. Also, coal and brent emerge as determinants of the allowances' price. Coal has a negative impact as the higher the price of coal the less coal companies will use, trying to replace it with other energy source and, as a result, the lower level of emissions will lead to a lower price for CO_2 allowances. The negative impact of coal has also been found by Alberola, Chevallier and Chéze (2007) when computing the regression for their whole period. Mansanet-Bataller, Pardo and Valor (2007) found that lagged coal returns negatively influences the dependent variable; however the coefficient in their case was insignificant.

Table 4.9: Results from second specification second period

	Coefficient	Std. Error	Prob.	Expected sign
α0	-0.027487	0.027655	0.3203	
L(Rt)	0.093370	0.055632	0.0933	+
Temperature	0.000503	0.000428	0.2399	
Temp-	0.006689	0.007382	0.3649	+
Temp+	-0.001627	0.005532	0.7687	+
Rainfal	-0.000098	0.000158	0.5346	-
Rain-	0.002992	0.006112	0.6244	+
Rain+	-0.009059	0.006455	0.1605	-
Wind Speed	0.002276	0.002341	0.3310	-
Wind-	0.005928	0.005071	0.2424	+
Wind+	-0.007193	0.007305	0.3248	-
RCoal	-0.133668	0.071224	0.0606	-
RBrent	0.355601	0.041682	0.0000	+
RGas	-0.015296	0.025692	0.5516	+
RElectricity	0.007834	0.006069	0.1967	+
EUprod	0.000432	0.001631	0.7912	+

In our case lagged energy data has no influence on the prices of CO_2 allowances. This might be a consequence of the different choice of data. While we took under consideration spot energy prices, Mansanet-Bataller, Pardo and Valor (2007) considered the price of futures contracts.

For the **third specification** the only significant coefficients are the ones for log-return on EUA prices, coal and brent (see Table 4.10.). Brent again emerges as a highly significant determinant. The positive coefficient, as expected, is similar to previous studies.

Weather data do not have any influence on the price of emissions credits, nor do composed energy data such as switching cost and clean spreads.

The industrial production dummy is highly insignificant, showing no relationship between the constructed dummy and the changes in the price of allowances.

Table 4.10: Results from third specification second period

	Coefficient	Std. Error	Prob.	Expected sign
α0	-0.031785	0.027849	0.2537	
L(Rt)	0.091983	0.055580	0.0979	+
Temperature	0.000583	0.000428	0.1728	
Temp-	0.008202	0.007507	0.2746	+
Temp+	-0.001869	0.005550	0.7363	+
Rainfal	-0.000100	0.000162	0.5395	-
Rain-	0.002869	0.006162	0.6415	+
Rain+	-0.009137	0.006469	0.1579	-
Wind Speed	0.002549	0.002380	0.2842	-
Wind-	0.006093	0.005095	0.2317	+
Wind+	-0.007118	0.007383	0.3350	-
RCoal	-0.136240	0.075380	0.0707	-
RBrent	0.359238	0.041268	0.0000	+
RGas	-0.015043	0.025643	0.5575	+
RElectricity	0.008339	0.006568	0.2042	+
RSwitch	0.000304	0.000557	0.5858	+
RCDS	-0.000025	0.000173	0.8845	+
RCSS	-0.000194	0.000428	0.6504	-
EUprod	0.000398	0.001615	0.8052	+

We also construct for this period the variant of the last specification. We are trying to find a parsimonious equivalent by successively eliminating from the regressions the most insignificant variable until all the coefficients are significant at a 10% level (see Table 4.11).

Table 4.11: Results from parsimonious model in the second period

	Coefficient	Std. Error	Prob.
α0	-0.000635	0.001133	0.5752
L(Rt)	0.101660	0.053926	0.0594
RCoal	-0.150722	0.071556	0.0352
RBrent	0.348256	0.039604	0.0000

We end up only with the significant coefficients in the third specification. All coefficients keep their expected signs. α_0 is insignificant, however we keep the coefficient to control for any distortions in inferences (we keep the coefficient in order to have a distribution for the residuals as close to a normal distribution as possible).

Table 4.12: Comparison measures for the models

	Equation 1	Equation 2	Equation 3	Equation 3b
R Square	0.01026	0.113568	0.115882	0.115091
Adjusted R Square	-0.033442	0.072016	0.067151	0.101683
AIC	-4.288063	-4.419704	-4.411851	-4.456357
SIC	-4.10945	-4.231169	-4.193546	-4.386897

As before, the parsimonious model performs slightly better than the other models according to the Adjusted R Square and the information criteria used (Akaike and Schwarz - see Table 4.12.). The results are somewhat better than in the first period; however our models underperform when compared to similar models from previous research. Nevertheless, previous research besides having slightly different approaches they also consider price movements only up to the end of the first compliance period, i.e. do not contain the second period on which we performed our empirical study.

4.2.4. Differences between the Two Periods

We expected that in the second period the market would be more mature, participants more acquainted to the market, regulators better informed and prices more closely linked to the fundamental price determinants. The question being: which are these price determinants?

It appears that weather data is important only during the first considered period. This might be a consequence of the fact that market participants are less interested in weather conditions, as they seem to cancel out over a certain period of time (temperatures over one month can be very different in Stockholm from, for example, Madrid). At the same time, another reason might be the fact that during the first period, on average, the values for weather data were more extreme than in the second period, thus having a larger impact during the first period.

The returns on composed energy data do not have an important influence on the prices of EUA, with the exception of switching cost in the first specification of the first period. However, when included with all the other energy data, the return on switching cost looses importance. Row energy data on the other hand influences emissions allowances prices, with brent being a steady, highly significant factor during both periods.

The lagged return on CO_2 allowances prices has also a stable and significant influence over both periods, which was expected, as it encompasses all the past information relevant for the current prices.

The changes in industrial production do not influence in any way the prices of CO_2. We previously stated that one of the reasons is the difficulty to transform the monthly industrial production information in a variable on a daily basis. Another reason that can lead to the insignificance of the explanatory variable is that not all sectors included in the industrial production index are part of the EU ETS market. Specific information for EU ETS sector is very hard to find, especially for the first compliance period. Additionally, changes in the production of this sector are not correlated with changes in the industrial production in general.

5. CONCLUSIONS AND PROPOSALS FOR FURTHER RESEARCH

Based on the results from the previous sections, this chapter offers concluding remarks and discusses the possibilities for further research.

The aim of this study is to determine to what extent fuel prices, whether data and economic development influence the price of spot carbon emissions permits. Moreover we intend to see which the main determinants of EUA prices are in different periods and why there might be differences between the periods.

We determined that weather data has some form of nonlinear influence on price changes of CO_2 in the first period. However, the coldest days lead to an increase in price changes during the first period. At the same time, extremely rainy days and extremely windy days lead to a decrease in the same dependent variable. The second period has shown no influence from weather variables. We consider this a consequence of the fact that the first period had weather events that were more extreme than those in the second period. We propose that further research should be made on this issue with daily data, rather than extrapolated monthly data on a daily basis.

The energy variables seem to influence the price changes of EUA, with brent being a sustainable factor. In the first period electricity is statistically significant and has a negative influence. Surprisingly, in the second period, coal substitutes electricity as a significant factor. It would be interesting to determine if the price of coal can be a substitute for electricity prices on a longer term, especially that power plants using coal are expected to switch to gas to abate CO_2 emissions. Therefore we would expect that the price of gas, rather than coal will substitute electricity price.

The return on composed energy variables (switching cost, CDS, CSS) does not influence the dependent variable, exception being the switching cost in the first specification for period one. We consider that the effect of this variable is partially substituted by brent and coal in the third specification of the second period.

Industrial production is not one of the factors that seem to influence the price of emissions allowances. Further research is needed to determine weather the production of EU ETS sector is the proper factor. However, data is scarce and gathering observations for a longer time series might impose problems.

The lagged return on EUA is also a steady and significant factor during both periods and all specifications.

An interesting issue for further study would be to check whether the factors that we mentioned will keep being important for further periods, especially taking into consideration the regulatory changes that will take place: switching to one Europe-wide cap instead on National Allocation Plans, auctioning of allowances instead of allocation, introducing more sectors in the scheme (aluminium and ammonia producers) and new gases (nitrous oxide and perfluorocarbons)[14].

[14] : Questions and Answers on the Commission's proposal to revise the EU Emissions Trading System (2008)

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Appendix 1: Kyoto Protocol - Annex 1 Countries

AUSTRALIA
AUSTRIA
BELARUS
BELGIUM
BULGARIA
CANADA
CROATIA
CZECH REPUBLIC
DENMARK
ESTONIA
FINLAND
FRANCE
GERMANY
GREECE
HUNGARY
ICELAND
IRELAND
ITALY
JAPAN
LATVIA
LIECHTENSTEIN
LITHUANIA
LUXEMBOURG
MONACO
NETHERLANDS
NEW ZEALAND
NORWAY
POLAND
PORTUGAL
ROMANIA
RUSSIAN FEDERATION
SLOVAKIA
SLOVENIA
SPAIN
SWEDEN
SWITZERLAND
TURKEY
UKRAINE
UNITED KINGDOM OF GREAT BRITAIN AND NORTHERN IRELAND
UNITED STATES OF AMERICA

Appendix 2 - Unit Root Tests

First period:

Null Hypothesis: LOG_RET_EUA has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=16)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-16.87562	0.0000
Test critical values:	1% level	-3.446484	
	5% level	-2.868547	
	10% level	-2.570568	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LOG_RET_EUA)
Method: Least Squares
Date: 05/25/10 Time: 15:58
Sample (adjusted): 9/19/2005 3/30/2007
Included observations: 400 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG_RET_EUA(-1)	-0.835478	0.049508	-16.87562	0.0000
C	-0.005276	0.002364	-2.231801	0.0262

R-squared	0.417094	Mean dependent var	-0.000210
Adjusted R-squared	0.415630	S.D. dependent var	0.061353
S.E. of regression	0.046901	Akaike info criterion	-3.276574
Sum squared resid	0.875477	Schwarz criterion	-3.256616
Log likelihood	657.3147	F-statistic	284.7864
Durbin-Watson stat	1.987581	Prob(F-statistic)	0.000000

Second period

Null Hypothesis: LOG_RET_EUA has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=17)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-18.53448	0.0000
Test critical values:	1% level	-3.446362	
	5% level	-2.868493	
	10% level	-2.570539	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LOG_RET_EUA)
Method: Least Squares
Date: 05/25/10 Time: 16:03
Sample (adjusted): 8/13/2008 2/26/2010
Included observations: 403 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG_RET_EUA(-1)	-0.923206	0.049810	-18.53448	0.0000
C	-0.000890	0.001535	-0.579989	0.5622

R-squared	0.461403	Mean dependent var	4.10E-05
Adjusted R-squared	0.460060	S.D. dependent var	0.041916
S.E. of regression	0.030800	Akaike info criterion	-4.117623
Sum squared resid	0.380416	Schwarz criterion	-4.097777
Log likelihood	831.7010	F-statistic	343.5270
Durbin-Watson stat	1.990946	Prob(F-statistic)	0.000000

Appendix 3: ARCH test – First Specification for the First Period

ARCH Test:

F-statistic	21.09520	Prob. F(1,397)	0.000006
Obs*R-squared	20.13174	Prob. Chi-Square(1)	0.000007

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/25/10 Time: 16:20
Sample (adjusted): 9/20/2005 3/30/2007
Included observations: 399 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001589	0.000287	5.530877	0.0000
RESID^2(-1)	0.224713	0.048926	4.592951	0.0000

R-squared	0.050455	Mean dependent var	0.002046
Adjusted R-squared	0.048064	S.D. dependent var	0.005519
S.E. of regression	0.005385	Akaike info criterion	-7.605323
Sum squared resid	0.011513	Schwarz criterion	-7.585328
Log likelihood	1519.262	F-statistic	21.09520
Durbin-Watson stat	2.097745	Prob(F-statistic)	0.000006