TESIS DE LA UNIVERSIDAD
DE ZARAGOZA

2015

65

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Economic performance of the EU ETS: three points of view: policy makers, companies and investors

Departamento
Contabilidad y Finanzas

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ISSN 2254-7606

Prensas de la Universidad
Universidad Zaragoza

ISSN 2254-7606

Tesis Doctoral

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2015

Phd Dissertation:

ECONOMIC PERFORMANCE OF THE EU ETS. THREE POINTS OF VIEW: POLICY MAKERS, COMPANIES AND INVESTORS

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AGRADECIMIENTOS

Expresar mi agradecimiento, en primer lugar, a la Diputación General de Aragón y al Ministerio de Educación, Cultura y Deporte por la concesión de las dos becas predoctorales que me han permitido dedicarme a la elaboración de la presente Tesis Doctoral.
A todos los miembros del Departamento de Contabilidad y Finanzas de la Universidad de Zaragoza por el buen trato recibido durante estos cuatros años.
A mis directores de tesis, los profesores Luis Ferruz y Pilar Gargallo, por transmitirme todos sus conocimientos, por su infinita paciencia y por confiar en mi trabajo.
Al profesor Manuel Salvador, por participar tan activamente en esta Tesis, poniendo a nuestra disposición su amplia experiencia en el análisis estadístico de datos.
A los miembros de GIECOFIN, grupo de investigación en economía financiera al que pertenezco, en especial a la profesora Isabel Marco, con la que comencé mi andadura investigadora gracias a una beca de colaboración.
Al profesor Mark Steel por acogerme en la Universidad de Warwick durante cuatro meses, por su amabilidad y su ayuda. Extiendo mi agradecimiento a todos los miembros del Departamento de Estadística de dicha universidad, especialmente a la profesora Jane Hutton, a todos los estudiantes de doctorado y a Sayan Banerjee, mi compañero de fatigas durante esos meses.
A mi amiga Yvonne Craddock por ayudarme a mejorar mi inglés y a mi amigo Quique Barberán por su inestimable ayuda en temas informáticos.
A mis compañeros de la Sala de Becarios 1, por la ración de risas diarias necesarias para mantener la cordura durante todo el proceso. A los que leyeron la tesis antes que yo, gracias por guiarme y ayudarme siempre que lo he necesitado. A los que están aún en el proceso, por escucharme y ser un gran apoyo durante la fase final.
A mis amigos por su apoyo constante durante todo este tiempo.
A mi hermano José Miguel, a mis padres, José Miguel y María Carmen, y a mis yayos, Emiliano, María, Manuel y Pilar, por quererme tanto. Sobran las palabras.

ABSTRACT

To date, the European Union Emissions Trading Scheme (EU ETS) is the largest carbon market in the world. An analysis of the EU ETS is important for three different agents: policy makers, companies, and investors. The thesis comprises three essays, each addressing questions related to the economic performance of the EU ETS from a different point of view (policy makers, companies, and investors).

In the first essay, we analyze the relationship between economic and environmental performance of Spanish companies involved in the EU ETS. The EU ETS was created with the aim of promoting reductions of greenhouse gas emissions in a cost-effective and economically efficient manner. According to this aim, policy makers should take into account not only the CO_2 reduction targets, but also the influence of these pollution goals on company economic performance, when making their decisions.

The aim of the second essay is two-fold. First, both the technical and the environmental efficiency for Spanish energy companies in the EU ETS are measured. Second, it is studied how the level of environmental efficiency influences the number of EUAs a company must buy, or is able to sell. Our research is very valuable for company management as we can determine how the level of environmental efficiency influences and determines the number of EUAs a company must buy, or is able to sell, and, consequently, the expenses and revenues of the company related to those EUAs.

In the third essay, we take the investor point of view. EUAs have become a new asset that attracts investors interest and, given that the energy sector is responsible for the bulk of the CO_2 emissions of the carbon market, our aim here is is to examine how the EU ETS and energy stocks markets interact.

RESUMEN

Un análisis del EU ETS es importante para tres tipos de agentes: instituciones públicas (consideran este mercado como pieza clave de la polı́tica climática de la UE), empresas (deben acudir a este mercado con el fin de cumplir con sus restricciones ambientales) e inversores (ven este mercado como una nueva oportunidad de inversión). Basándonos en las necesidades particulares de cada uno de estos tres grupos de interés, la tesis está integrada por tres capítulos empíricos que tienen como objetivo analizar la performance económica, con vistas a obtener cada uno, implicaciones adaptadas a los necesidades de cada uno de los citados grupos.

El primero, tiene como objetivo analizar la relación existente entre la performance económica y la medioambiental de la totalidad de empresas españolas pertenecientes al EU ETS con el fin de proporcionar más información a las instituciones encargadas de elaborar políticas relacionadas con el EU ETS nacional, teniendo en cuenta la importancia de conseguir un balance entre las metas económicas y medioambientales.

El objetivo del segundo es doble. En primer lugar, calculamos la eficiencia técnica y medioambiental de cada una de las empresas del sector energético español pertenecientes al EU ETS. En segundo lugar, examinamos hasta qué punto la eficiencia medioambiental determina el número de derechos de emisión que una empresa debe comprar o se puede permitir vender, y por tanto, los gastos o ingresos derivados de un bajo o alto grado de eficiencia. Esta investigación es considerablemente relevante para el management empresarial ya que permite conocer hasta qué punto mejoras en la eficiencia medioambiental influyen en el dinero que una empresa debe gastar en el EU ETS.

Para el tercer capítulo empírico, tomamos el punto de vista del inversor. Teniendo en cuenta que la mayor parte de las emisiones del EU ETS proceden del sector energético, nuestro objetivo es analizar la relación existente entre los EUAs y los títulos bursátiles de empresas del sector energético, en concreto empresas del sector del petróleo & gas y de energías limpias.

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Chapter 1

Introduction

The problem of climate change has become a topic of global concern in the scientific, political, and economic spheres. Human activity generates significant emissions of carbon dioxide and other Greenhouse Gases (GHG) that accumulate in the atmosphere and are absorbed by oceans and forests, leading to global warming. The obvious importance of this issue has raised many voices calling for the reduction of the emissions of these poisonous gases. Such a reduction, however, has major repercussions for global economy, and so an analysis of this topic is interesting not only from a scientific point of view, but also from a social sciences perspective.

This extract from the European Commission webpage summarizes the situation: "Environment has become a scarce resource. Since economics is about how to deal with scarce resources, it can often be useful when tackling environmental problems. One way of using economics is to ensure that the costs and the benefits of environmental measures are well balanced. Although it is difficult to estimate costs and benefits, there is an increasing demand that this is done before environmental policy is decided on a European level. With the use of market-based instruments, environmental goals can sometimes be reached more efficiently than with traditional command and control regulations". (European Commission, 2015).

In this context, a relatively new branch of the Economics literature appeared:

Environmental Economics, which studies the relationship between the economy and the environment. Our thesis fits into a sub-field of Environmental Economics: Environmental Finance. This sub-field emerged alongside with the creation of market-based mechanisms to reduce emissions. Environmental Finance focuses on analyzing the new financial environmental markets, where a new type of asset is traded: the right to emit a specific quantity of a certain GHG. These markets are called Emission Trading Schemes (ETS).

Today, there are several such schemes in operation. In addition, the number of this kind of market is likely to increase in the future, as there are already several ETS under consideration in different parts of the world. (See Table 1.1).

To date, the European Union Emissions Trading Scheme (EU ETS) is the largest Emissions Trading Scheme. It limits emissions from 11000 industrial and power installations based in 31 European countries (28 EU countries and the three EEA-EFTA states (Iceland, Liechtenstein and Norway) and covers around 45% of the EU's greenhouse gas emissions. The EU ETS, also known as the carbon market, was launched in 2005 and is defined by the European Commission as the cornerstone of the EU's policy to reduce CO_2 emissions. The market works as follows: at the end of each year[1] each company must hold a number a European Union Allowances (EUA) equal to its level of emissions. Companies that maintain their emissions below the level of their allowances can sell their excess. Those that want, or need, to emit more than what is permitted must buy EUAs. This way, the EUA is considered as a new asset with a daily price determined by supply and demand.

An analysis of the EU ETS is important for three different agents: policy makers, companies and investors.

◇**Policy makers**. The EU ETS was created with the aim of promoting reductions of greenhouse gas emissions in a cost-effective and economically efficient manner.

[1]Auctioning, not free allocation, is now the default method for allocating allowances. In 2013 more than 40% of allowances will be auctioned, and this share will rise progressively each year. (http://ec.europa.eu/clima/policies/ets/index_en.htm)

Table 1.1: **Emission trading schemes around the world**

ETS in force
Canada - Québec Cap-and-Trade System China - Beijing pilot system China - Chongqing pilot system China - Guangdong pilot system China - Hubei pilot system China - Shanghai pilot system China - Shenzhen pilot system China - Tianjin pilot system EU Emissions Trading System (EU ETS) Japan - Saitama Target Setting Emissions Trading System Japan - Tokyo Cap-and-Trade Program Kazakhstan Emissions Trading Scheme (KAZ ETS) Korea Emissions Trading Scheme New Zealand Emissions Trading Scheme (NZ ETS) Swiss ETS USA - California Cap-and-Trade Program USA - Regional Greenhouse Gas Initiative (RGGI)
ETS implementation scheduled
China
ETS under consideration
Brazil Brazil - Rio de Janeiro Brazil - Sao Paulo Canada - Manitoba (WCI) Canada - Ontario (WCI) Chile Japan Mexico Russia Thailand Turkey Ukraine USA - Washington Vietnam

Source: International Carbon Action Partnership (ICAP)

According to this aim, policy makers should take into consideration not only the CO_2 reduction targets, but also the influence of these pollution goals on company economic performance.

◇**Companies**. As explained above, companies involved in the EU ETS must buy or be able to sell EUAs depending on their level of emissions. Therefore, EUAs are either a revenue or a cost for companies involved in the EU ETS. In this way, pollution issues have been directly introduced into company income statements.

◇**Investors**. Market participants such as risk managers and traders have an increasing financial interest in this market, and forecasting the EUA price can facilitate their investment decisions.

The thesis comprises three essays, each addressing question related to the economic performance of the EU ETS from a different point of view (policy makers, companies and investors). Clearly, although each chapter is biased towards being useful for a specific kind of agent, the findings of each chapter have implications for the three kinds of agent in general.

Before presenting the thesis outline in more detail, we provide a brief overview of the EU ETS.

1.1 The EU ETS. An overview

This section is divided into three parts. First, we focus on the Kyoto Protocol, which is the origin of the creation of market-based instruments to combat climate change. Second, we concentrate on the creation of the EU ETS, as a measure taken by the European Commission to help European countries achieve their targets under the Kyoto Protocol. Third, since Spain plays a significant role in our research, we describe how the Spanish Government has adapted to the inclusion of around 1000 Spanish installations into the EU ETS.

1.1.1 The origin of the EU ETS. Kyoto Protocol

Although the second half of the 20^{th} century saw the first global-scale efforts against climate change, as demonstrated by actions such as the creation of the World Meteorological Organization (WMO) in 1950 and the United Nations Environment Programme (UNEP) in 1972, it was not until the end of the 1980s and beginning of the 1990s that the governments of most developed countries began to express their concerns over climate change. Thus, in 1992 the United Nations Convention on Climate Change was adopted, taking effect two years later when 195 countries committed to join forces to reduce global emissions of GHG. Since the Convention only announced a declaration of intent, given its lack of executive power, it is no surprise that a year after it took effect (1994) not one of the participating countries had taken any required measures.

In order to remedy the situation, the Convention established the Kyoto Protocol in 1997, marking the beginning of a new era in which environmental objectives would bring with them the creation of new institutions and mechanisms.

The Kyoto Protocol was adopted in Japan on December 11, 1997 and took effect on February 16, 2005. This document set a goal for 37 industrialized countries (Annex B of the Kyoto Protocol. See Table 1.2) and the European Union: to reduce the group's emissions of greenhouse gases by at least 5%, compared to 1990 levels, during the period 2008-2012.

It was hoped that these countries would achieve this goal by the establishment of policies on a national scale. In addition, with the goal of facilitating compliance with the objective that had been set, the Protocol designed three market mechanisms as additional instruments; those instruments were to play a complementary role, always keeping national strategies in the forefront. These tools are: Emission Trading Scheme (ETS), Clean Development Mechanism (CDM) and Joint Implementation (JI).

Emission Trading Schemes (ETS)

As mentioned above, the Protocol establishes a goal for each country. This objec-

Table 1.2: **Annex B of the Kyoto Protocol**

Party	**Emission limitation**
Australia	108
Austria	92
Belgium	92
Bulgaria	92
Canada	94
Croatia	95
Czech Republic	92
Denmark	92
Estonia	92
European Community	92
Finland	92
France	92
Germany	92
Greece	92
Hungary	94
Iceland	110
Ireland	92
Italy	92
Japan	94
Latvia	92
Liechtenstein	92
Lithuania	92
Luxembourg	92
Monaco	92
Netherlands	92
New Zealand	100
Norway	101
Poland	94
Portugal	92
Romania	92
Russian Federation	100
Slovakia	92
Slovenia	92
Spain	92
Sweden	92
Switzerland	92
Ukraine	100
United Kingdom of Great Britain and Northern Ireland	92
United States of America	93

Note: The second column indicates the quantified emission reduction to be achieved in period 2008-2012. The reduction is expressed as a percentage of the emissions level in the base year (the general rule was 1990). Note that, although United States of America signed the Protocol it did not ratified the treaty.

tive, besides being a percentage of reduction of emissions (in the case of the European Union, 8% with regard to 1990) can also be expressed in the form of a maximum level of emissions permitted. The initial quantity assigned for each country is calculated as follows: the emissions of Greenhouse gases collected in Annex A of the Kyoto Protocol[2]in the base year (1990), multiplied by its objective of emissions reduction, and by five. At the same time, this level of emissions is divided in units that are equal to the right to emit an equivalent metric tonne of carbon dioxide, and termed Assigned Amount Units (AAU).

In this way, if a country has emitted fewer tonnes of carbon than those assigned, it can sell the AAUs that are left to another country that may find itself in the opposite situation, having exceeded its limit. The trade in emissions rights does not affect the total number of rights assigned (or, what is the same, the maximum level of global emissions set for a specific period), it simply acts as a redistribution tool for those rights among countries.

Clean Development Mechanism (CDM)

A Clean Development Mechanism (CDM) can be defined as the investment made by an industrialized country, which has an obligation to reduce its emissions within the framework of the Kyoto Protocol, in a developing country, with the goal of reducing emissions and promoting sustainable development in that country. With a view toward strengthening this mechanism, the Protocol has established that developed countries that carry out this type of project may receive Certified Emission Reductions(CER) that can be used by them to fulfill their objective of emissions reduction.

In this sense, the CDM establishes a mechanism that benefits developed as well as developing countries. The former can use their participation in these projects as accountability to the Kyoto agreement. The latter benefit from the investments in their countries made by the developed countries.

[2]Carbon dioxide ($C0_2$, Methane (CH_4, Nitrous oxide (N_20, Hydrofluorocarbons (HFCs),Perfluorocarbons (PFCs), Sulphur hexafluoride (SF_6))

Joint Implementation (JI)

A project of Joint Implementation consists of the investment made, by one of the 37 countries of the Kyoto Protocol, in another country that is also a signatory. By virtue of this activity, the investor receives Emissions Reduction Units (ERU), which, like the CERs, facilitate compliance with its goal.

Thus, the AAU, CER, ERU have been converted into commodities that can be sold on the carbon market. In this sense, the Kyoto Protocol allows for the creation of these types of markets at the national as well as the regional level, and although they enjoy autonomy with regard to Kyoto, the Protocol does demand that the transactions taking place in these markets are reflected in the register that has been created for such a purpose. Currently, the European Union Emission Trading Scheme (EU ETS), in which 11,000 installations in 31 European countries participate (the 28 Members of the European Union, Norway, Liechtenstein and Iceland) is the largest in terms of its level of operations.

The Kyoto Protocol establishes a first step in the struggle to reduce emissions of GHG and provides the basis for a future agreement that will encompass virtually all the countries of the world. In this sense, although the Protocol expired in 2012, the IPCC, on numerous occasions has expressed the need to negotiate a new accord that will allow continuing on the path to emissions reduction. United Nations negotiations are under way to draw up a new global climate agreement to achieve greater cuts in global emissions. This new agreement is to be finalised by 2015 and implemented from 2020.

1.1.2 Kyoto Protocol. Adaptation to the European Union

Coinciding with the adoption of the United Nations Framework Convention on Climate Change (UNFCCC), 1991 marks the beginning of a series of actions designed within the European Union with the objective of mitigating the effects of climate change.

The first, and most representative of these initiatives was the commissioning of the first community strategy with a view to reducing carbon dioxide emissions and improving energy efficiency. Ten years later, at the turn of the century, there was a significant advance in this field. The European Union published the "Green Paper" , in which the trading of emission rights was presented as the key strategy on which the Union should focus in order to achieve its objectives in relation to the Kyoto Protocol.

In this context, through the Council Decision 2002/358/EC, the European Community endorsed the Kyoto Protocol, committing to reducing its aggregate anthropogenic emissions of greenhouse gases by 8% compared to 1990 levels, in the period between 2008-2012, and thus exercising its rights under Article 4 of the Protocol that allow countries to group themselves with a view towards fulfilling their objectives to reduce emissions jointly. The decision was taken to tackle the general objective for all the Member States, constituting the only example of the practical application of the Article 4. Under the terms of this agreement, each Member State could have a different goal than in principle was established in the Kyoto Protocol. Provided that at the end of the period covered the emissions were on aggregate less than 8% compared to the base year, it could be claimed that the European Union was in a state of compliance.

To contribute to the goal of compliance with this objective there emerged the Directive 2003/87/EC, which fosters the use of more efficient energy technologies. The Directive indicates that the Member States must safeguard its implementation and lay down rules on penalties applicable to possible infringements. As will be explained in Section 1.1.3, in Spain the Directive was incorporated into the domestic via the Law 1/2005 (Ley 1/2005).

Regarding the rights of emission, which is the topic that concerns us, the total amount of rights assigned by the Kyoto Protocol will be shared among the European Union Member States, always keeping in mind that the assignment to each country will depend on the potential of emissions reduction of each one. In addition, there must be an effort to maintain the integrity of the internal market, and to avoid competitive distortions. Similarly, each country will decide the total number of rights that will be assigned for each of the periods, and how many will correspond to the owner of each installation. With the goal of establishing a framework in which these rights of emission could be commercialized, the European market of trading emission rights was created, the European Union Emission Trading Scheme (EU ETS). These instruments can be transferred between persons in the Community and persons in third countries where such rights of emission are recognized. Thus, new assets are created: European Union Allowances (EUA), European Union rights of emission.

The EU ETS is a system of emissions trading on a national scale only (an internal measure of the European Community)and[3]. It became operational in 2005 and its establishment can be divided into three phases. The First Phase covers the period between January, 2005 and December, 2007 and is called the "pilot phase", since it constitutes a test period before having to be accountable to Kyoto. The Second Phase coincides with the compliance phase of the Kyoto Protocol, that is, 2008-2012. The Third Phase began in 2013 and will extend to 2020, since the European Union intends to continue with this market beyond the end date of the Protocol (2012).

The EU ETS works the following way [4] The EUA are offered to the market by the operators of installations, subject to the system of trade in rights of emissions. Thus, as the Directive dictates, it is established that no later than April 30th of each year (2005-2012), the operator of each installation must submit a number of rights, equivalent to the total emissions of that installation during the previous year. For that, it may be necessary to turn to the EU ETS to acquire rights (if it has emitted a volume of emissions greater than the quantity initially assigned). If, on the other hand, the number of rights submitted is less than the emissions, the operator of the installation must pay 40 euros (in the first phase) and 100 euros (in the second phase)

[3]The owners of installations in European Union countries can carry out exchanges (EUA) with owners in the rest of the Member countries. Nevertheless, these units cannot be exchanged internationally, since, at that level, the units of negotiation established by the Kyoto Protocol receive the name AAU (Assigned Amount Unit)

[4]As the sample period consider in the Thesis is manily 2005-2012, for the sake of brevity and in order not to confuse the reader with much information, we focus only in the way the EU ETS work over this period.

for each equivalent tonne of carbon dioxide emitted. In addition to paying the fine, the operator must submit a quantity of rights equivalent to the excess amount of emissions when the corresponding rights of emission are submitted for the following year.

To facilitate the trade in rights of emission, secondary markets exist in Europe. Some examples are: Climex (Holland), the European Energy Exchange (EEX) in Germany, the BlueNext in France, Nord Pool in Norway, Austrian Energy Exchange in Austria, and the European Climate Exchange International Petroleum Exchange (ECX-IPE) in the United Kingdom. Noteworthy among these is SENDECO2, the market of reference for Spain, Italy, and Portugal. This is a secondary market specializing in Small and Medium Enterprises that allows all its participants to exchange EUAs and CERs (RCE, the acronym in Spanish).This body began work in 2004 and enjoys institutional support from the Generalitat de Catalunya, Generalitat Valenciana, Región de Murcia y Fundación Forum Ambiental. Among its shareholders are representatives from the environmental business sector (Ros Roca Group, Grupo Hera y GBI Serveis) and Banco Sabadell.

1.1.3 Adaptation of the European Directive for Spain

As indicated in Annex B of the Kyoto Protocol, Spain has an obligation to reduce its emissions of Greenhouse Gases by 8% compared to the levels of 1990. Nevertheless, as mentioned in Section 1.1.2, the EU set up certain protections. Under the terms of this agreement (Article 4 of the Kyoto Protocol), each Member State can have a goal different from that established, in principle, in the Kyoto Protocol. This is the case of Spain, which is permitted to increase its emissions by no more than 15% compared to the base year (1990).

As a Member State of the EU, Spain forms part of the EU ETS and the need Directive 2003/87/EC was incorporated into domestic law, via the Law 1/2005, regulating the trading of emission rights.(Ley 1/2005)

In Spain, the Commission for coordination of climate change policies was created as the collaborative body between the General Administration of the State and the Autonomous Communities, for the application of the trading of emissions rights, as well as for compliance with international obligations. The National Allocation Plan (NAP)[5] is approved by the Government through Royal Decree and contains the following information: the total number of anticipated rights to be assigned, the corresponding procedures of assignment, the quantity of Certified Reduction Units (CERs)and Emissions Reduction Units (ERUs) which is anticipated to be in compliance with the national objective and the percentage of the assignment for each installation.When distributing the rights of emissions among the various installations, the generation of unjustified imbalances between sectors of activity or installations must be avoided. The technical and economic possibilities of emissions reduction in each sector, as well as predictions regarding the evolution of production, and the measures taken to establish markets of rights, must all be carefully monitored.

The National Allocation Plans have long-term validity (for the First Phase (2005-2007) and the Second Phase (2008-2012)). From 2013, the National Allocation Plans disappear, strictly speaking. Thus, according to the Directive 2009/29/EC, the assignment of rights of emission will take place (by general law) through auctions at the community level.

1.2 Thesis outline. Economic performance of the EU ETS. Three points of view.

The structure of the Thesis is as follows. Following this Introduction, Chapters 2, 3 and 4 consist of three essays, each one analyzing the economic performance of the EU ETS from three different points of view: policy makers (Chapter 2), companies (Chapter 3), and investors (Chapter 4). The three essays are self contained -each introduces the

[5] The NAP is approved by the Government by Royal Decree, pursuant to mandatory reports from the National Council on Climate and from the Commission of coordination of policies on climate change, at least 18 months prior to the beginning of the corresponding period.

topic and presents the relevant prior literature, explains the methodology employed, describes the results, and draws conclusions- and can be read separately.

In Chapter 2, we analyze the relationship between the economic and environmental performance of Spanish companies involved in the EU ETS. When establishing environmental targets, the European Commission states that achieving a balance between emissions restrictions and economic growth is essential. Following this line, the Directive 2003/87/EC states that the objective of the EU ETS is to promote reductions of greenhouse gas emissions in a cost-effective and economically efficient manner.

This conception gained more importance after the onset of the global economic crisis in 2008, and especially for countries such as Spain that were strongly affected. To undertake our research, we select a sample of Spanish installations (almost 90% of the total), whose emissions were traded in the EU ETS during the period 2005-2011.

For each company, we construct an environmental performance indicator that we have called Surplus of Allowances (SA)and which is calculated as the difference between assigned CO_2 emissions and those actually emitted each year, all divided by the allocated units. To measure economic performance we take two different measures: an activity and a profitability ratio. The underlying logic of these two ways of measuring economic performance is explained by the fact that a company's environmental performance in the EU ETS, is both a result and a determinant of economic performance. First, the production level of a company determines its level of CO_2 emissions and, thus, its SA. Second, the SA (which indicates the number of EUAs a company must buy or can sell, in relative terms) is a component of a company cost production and thus, influences its profitability.

Given the lack of normality of the considered variables, we use a statistical methodology based on copulas, which provides a set of models to capture dependence in a broader context than the standard multivariate methodology and thus, gives more realistic results.

The contribution of this research is three-fold. First, we contribute to prior studies that analyze the link between environmental and economic performance. These studies usually take CO_2 emissions as an indicator of environmental performance. Nevertheless, the focus of our research is quite different from prior studies, in that we investigate company emissions by taking into account the constraints imposed by the EU ETS, rather than considering only the company CO_2 emissions. Second, to the best of our knowledge, ours is the first study to cover an entire sample of companies from a country involved in the EU ETS. Normally, such studies focus on a group of important companies from a given country, but in our case, we consider it is important for policy makers to have a complete picture of the situation in the whole country. Third, ours is the first research to examine in depth the link between environmental and economic performance for Spanish companies in the EU ETS.

Chapter 3 focuses on the Spanish energy companies involved in the EU ETS. With our analysis we aim to provide useful results for the management of these energy companies.

Companies involved in the EU ETS are divided into 9 sectors. The first, covers power stations ("Combustion installations with a rated thermal input exceeding 20 MW, mineral oil refineries, and coke ovens"), i.e. the energy sector, and sectors 2 to 9 are industrial sectors, producing iron, steel, cement, glass, lime, bricks, ceramics, and pulp and paper. We focus on the energy sector since, in Spain, emissions from this sector represented 60% of the EU ETS total in the period 2005-2012. In addition, apart from adjusting their emissions to the restrictions imposed by the EU ETS, the energy companies are expected to make an effort to improve efficiency (a 20% energy efficiency improvement by 2020 is expected) according to the "20-20-20" targets (Directive 2012/27/EU). This Directive encourages the more efficient use of energy at all stages of the energy chain.

Our objective in this Chapter is two-fold. First, given that energy companies must increase efficiency, we measure both technical and environmental efficiency of every company in our sample, by estimating a production stochastic frontier model with two outputs: good (production) and bad (emissions). The estimation is carried out with a bayesian methodology. This model provides us with a technical and environmental efficiency value for each company, so we can determine efficiency rankings. This information is important for managers in order to know how well the company is doing compared to its peers. Second, as these firms have CO_2 emissions limits imposed by the EU ETS, we analyze how environmental efficiency influences Surplus of Allowances (SA). To achieve this goal, we use quantile regression techniques which allows us to study how the level of environmental efficiency affects the number of EUAs a company must buy, or is able to sell (SA), and, consequently, the expenses and revenues of the company related to those EUAs.

Our contribution to the literature is two-fold. First, this is the first paper to analyze in depth the environmental and technical efficiency of Spanish energy companies in the EU ETS in the period 2005-2012. Second, we have found no other analysis in the literature that focuses on how environmental efficiency affects the way a company uses EUAs.

In the Chapter 4, we take the investor point of view. EUAs have become a new asset that attracts investor interest and, given that the energy sector is responsible for the bulk of the CO_2 emissions of the carbon market, our aim here is to examine how the EU ETS and energy stocks markets interact. More specifically, we concentrate on the inter-relationship between EUA, stocks of clean energy companies and stocks of oil & gas companies.

With this analysis our aim is three-fold. First, given that the objective of the EU ETS is to encourage investment in clean energy, we analyze whether EUA pricing does, in fact, accomplish this, while discouraging investment in oil and gas stocks. Second, we analyze the inverse effects, that is, how stocks of both kinds influence EUA prices. These prices are the cornerstone of the European climate change policy, and thus knowing what factors affect this price is important in terms of EU ETS efficacy. Third, given that investment in energy markets continues to grow, we study the link between clean energy stocks and oil and gas stocks. This analysis is important for financial risk management of investors in the energy sector, i.e. diversification issues.

We analyze the simultaneous relationships among a set of variables and, given the high frequency of the data, we propose the use of the Vector Autoregressive Regression (VAR).In addition, to model the volatility of the considered variables, we employ a multivariate GARCH structure to estimate co-volatility dynamics. The multivariate GARCH approach is widely used in the financial literature when analyzing time series data.

With this chapter, we contribute to the literature in two ways. First, prior studies have already analyzed the effect of clean energy stocks on EUA prices, but our work examines the effect of EUA on clean energy stocks, as well as but also the effect on oil and gas stocks. Second, although the EUA drivers have been widely studied in the literature, the price evolution of other stocks has not usually been considered to be driving EUA. With this analysis, we aim to fill this gap in the literature.

Finally, in Chapter 5, the key findings of the previous essays are pulled together.

Chapter 2

Environmental versus economic performance in the EU ETS.

First point of view: Policy makers

2.1 Introduction

The European Union Emissions Trading Scheme (EU ETS) was created with the aim of promoting reductions of greenhouse gas emissions in a cost-effective and economically efficient manner (Directive 2003/87/EC). According to this aim, policymakers should take into account not only the CO_2 reduction targets, but also the influence of these pollution goals on company economic performance, when making their decisions.

Given the importance of achieving a balance between pollution reduction targets and economic growth issues (European Commission, 2012), the objective of this Chapter is to analyze the link between environmental and economic performance in Spanish companies involved in the EU ETS during the period 2005-2011. The environmental and the economic performance in companies of the EU ETS are linked in two different ways: revenues and costs. First, revenues of energy and industrial companies come basically from production, and the production level, in turn, determines CO_2 emissions. Second,the level of CO_2 emissions influences the cost production function, since companies in the EU ETS must buy European Union Allowances (EUA)(if its CO_2 emissions surpass the limit) or are able to sell EUAs (if its CO_2 emissions are lower than the limit).

Accordingly, the objective of this Chapter is two-fold. First, to analyze the effect of production on environmental performance. We study this effect on a year-on-year basis with the aim of getting information on how intense is the effect of production on CO_2, and indirectly know whether companies have taken measures in order to reduce its CO_2 in their production process. Second, to examine the effect of environmental performance on profitability in order to discover how the behavior of companies towards its emissions targets (if they emit less or more than the limits) affects company results. With this analysis we seek to discover whether the costs derived from fulfilling CO_2 emissions limits imposed by the EU ETS have any effect on company profitability and, in turn, discover whether the EU ETS created a real financial incentive for companies to emit less than allocated.

For each company, we construct an environmental performance indicator that we have called Surplus of Allowances (SA) and which is calculated as the difference between assigned CO_2 emissions and those actually emitted each year, all divided by the allocated units. When analyzing the link between economic and environmental performance, there is no consesous on the best way to measure environmental performance. Measures of environmental performance used in the literature can be divided into three groups: the behaviour of companies towards environment, e.g., implementation of environmental strategies by the management Molina-Azorín et al., 2008;Yang et al.,2010;Aragón-Correa et al., 2008); the consequences of companies behavior in terms of pollution,e.g. GHG emissions (Clarkson et al., 2011; Iwata and Okada, 2011; Sarkis and Codeiro, 2001;Hart and Ahuja, 1996.) and environmental ratings and scores carried out by organizations independent of companies' management that measure environmental perfomrance taking into consideration both previous perspectives (Elsayed and Paton, 2004). The variable we have selected fits into the second group: companies' pollution. Nevertheless, the focus of our research is quite different from prior studies, in that we investigate companies' emissions by taking into account the constraints imposed by the EU ETS.

The economic performance is usually measured by financial ratios. Contrary to the lack of consensous on the selection of a proper environmental performance measure, as Horvathova (2010) explained, there seems to be no impact of the financial measure on results. To measure economic performance we take two financial ratios widely used in the literature: Asset Turnover Rotation (ATR) to measure company production and Return on Assets (ROA) to measure company profitability.

We can now rewrite our two objectives in terms of the measures employed. Accordingly, we examine the effect of production (ATR) on surplus of allowances (SA) and the influence of SA on profitability (ROA), from 2005 to 2011, on a year-on-year basis for Spanish companies in the EU ETS.

In order to achieve accurate conclusions we need to carry out an appropriate empirical strategy and, thus, we follow the recommendations of Horvathova (2010). This author studied the inconsistency in the literature regarding the link between environmental and economic performance (certain authors such as Molina-Azorín et al. (2008), López-Gamero et al. (2009) and Yang et al. (2011) have found a positive link, whereas others discern a neutral, Elsayed and Paton, (2004) or negative, Sarkis and Cordeiro (2001), relationship) and makes several suggestions in order to obtain reliable results: to use more advanced econometric analysis, rather than simple correlation coefficients, and to account for omitted variable biases such as unobserved firm heterogeneity.

Following Horvathova (2010) recommendations, in this first Chapter, we complete the study presented in Segura et al. (2014), where we assumed that quantiles of economic performance were linear functions of environmental performance, although the lack of normality of both variables could make this hypothesis unrealistic. To solve this problem, a more flexible statistical methodology is now used, namely, copulas. This methodology provides a set of models to capture dependence in a broader context, as Trivedi and Zimmer (2005) show, and it has been widely used in the field of finance (Patton, 2006, 2009; Heinen and Valdesogo, 2008;Jondeau and Rockinger, 2006) and in environmental contexts (Denault et al, 2009; Grothe and Schnieders, 2011). Apart from using a more appropriate methodology, we include a set of firm characteristics that may influence companies' profitability and that were not considered in Segura et al.(2014), which may also bias our results.

Our research has implications for Spanish policy makers in terms of designing policies oriented to help EU ETS companies achieve a balance between environmental restrictions and economic growth. Spanish companies involved in the EU ETS (combustion plants, oil refineries, coke ovens, iron and steel and factories producing cement, glass, lime, bricks, ceramics, and pulp and paper) are strongly connected to the construction industry, which was one of the main pillars economic development in Spain, from the 1990s until 2008, when the economic crisis erupted. Therefore, an analysis of these companies is not only important for these companies themselves but also for the whole economy.

The contribution of this research is three-fold. First, we contribute to prior studies that analyze the link between environmental and economic performance. These studies usually take CO_2 emissions as an indicator of environmental performance. Nevertheless, the focus of our research is quite different from prior studies, in that we investigate company emissions by taking into account the constraints imposed by the EU ETS, rather than considering only the company CO_2 emissions. Second, to the best of our knowledge, ours is the first study to cover an entire sample of companies from a country involved in the EU ETS (almost 90% companies of the total). Normally, such studies focus on a group of important companies from a given country, but in our case, we consider it is important for policy makers to have a complete picture of the situation in the whole country. Third, ours is the first research to examine in depth the link between environmental and economic performance for Spanish companies in the EU

ETS.

The Chapter is organised as follows: Section 2.2 describes the data, Section 2.3 presents the statistical methodology and Section 2.5 shows our results. Finally, Section 2.6 sets out our conclusions.

2.2 Data

We select a sample of Spanish installations whose emissions were traded under the EU ETS during the period 2005-2011. The list of Spanish installations was obtained from the "Registro Nacional de Derechos de Emisión de Gases de Efecto Invernadero (RENADE)", the Spanish national registry, containing all Spanish firms participating in the EU ETS. We focus on those companies in the registry as of July, 2011, making a total of 1,131 installations corresponding to 839 companies. Due to data unavailability, our sample was reduced to 745 companies (almost 90% of the total). The variables employed in our research are divided into three groups: environmental performance, economic performance and control variables. In the following subsections we define our variables and provide a descriptive analysis. The descriptive analysis of the environmental performance variable is more extense than the others due to the importance of this variable in the context of the EU ETS. Furthermore, the same variable will be analyzed in next Chapter so we would like to provide the reader with an exhaustive description from the beginning.

2.2.1 Environmental performance

As stated in the Introduction, environmental performance is measured as a surplus of allowances, using the following expression:

$$SA_{it} = \frac{A_{i,t} - E_{i,t}}{A_{i,t}} \tag{2.1}$$

Table 2.1: **Descriptive statistics of SA**

	YEAR						
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
Observations	533	649	615	626	622	559	559
% firms with SA≥0	75	75	72	80	84	84	84
Minimum	-2.54	-2.71	-1.60	-1.77	-1.66	-3.01	-1.03
Mean	0.08	0.14	0.12	0.20	0.32	0.33	0.38
Median	0.08	0.12	0.12	0.19	0.32	0.32	0.38
Maximum	0.95	0.99	0.99	0.99	0.99	0.99	0.99
Std.deviation	0.26	0.31	0.32	0.33	0.36	0.40	0.40
Skewness	-2.46**	-1.72**	-1.10**	-1.17**	-0.85**	-0.50**	-0.45**
Kurtosis	25.69**	17.51**	8.09**	8.60**	6.03**	12.35**	3.00**
Jarque Bera (p-value)	0	0	0	0	0	0	0

*Note:Statistically different from zero at the ** 5% significance level*

where A_{it} represents the assigned emissions to company i; E_{it} represents the verified emissions of company i in period t. SA may have either a positive or negative sign, in such a way that a positive (negative) sign indicates a surplus (deficit) of allowances. Data related to SA were taken from the Community Independent Transaction Log (CITL), an online database where accounts of companies and physical persons holding these allowances were listed. Each installation held an account in the CITL where the allowance allocation, verified emissions, and compliance status were tracked. The allowances assigned to, and the verified emissions from, installations owned by the same company were aggregated, having, as a consequence, a unique assigned (A) and verified (E) emission figure for each firm.

Table 2.1 shows, for each period, the main statistics for SA. Two different periods stand out: 2005-2007 and 2008-2011, corresponding to Phase I (2005-2007) and Phase II (2008-2012) of the EU ETS.

The European Commission (2009) stated that the quantity of allowances received by each installation must not be higher than the level of CO_2 emissions it is likely to emit, in order to create the scarcity needed for trading and, therefore, to ensure a high EUA price. The allowance allocations and the emissions estimations for Phase I (2005-2007) were carried out in 2004 and for Phase II (2008-2012), in 2006. In this way, the more accurate the emissions estimation, the more appropriate will be allocated quantity, sufficient to ensure a high EUA price.

First, allowances were distributed at the sector level and, second, among installations within each sector. This allocation of allowances was carried out according to the estimated emissions for each sector and, then, for each installation. In the case of NAP I, these predictions were based on the level of emissions in prior years, and in NAP II, not only on the level of emissions but also on the production levels of prior years. As can be observed in Table 2.1, both mean and median have a positive sign over the whole sample period, indicating a surfeit of allowances.

In the case of NAP I, as stated in Order PRE/2827/2009, the maximum number of allowances per year assigned to EU ETS sectors was 182.17 Metric Tonne Carbon Dioxide Equivalent (Mt). As explained in Spanish Government (2007), at the end of Phase I, Spanish companies as a whole had a deficit of 22.49 Mt CO_2. However, as can be observed in Table 2.1, on average, companies had a surplus of 0.08, 0.14 and 0.12 in years 2005, 2006 and 2007, respectively.

The difference between both sets of results is due to the fact that around 75% of the companies had a surplus of allowances during Phase I. Although the country as a whole emitted more than expected, the majority of companies tended to emit less CO_2 than expected.

In the case of NAP II, the maximum level of allowances per year in Spain was 152,250 Mt CO_2 (Order PRE/2827/2009). Following the line of the European Commission, who cut the volume of emission allowances permitted in Phase II to 6.5% below the 2005 level, the Spanish cap for Phase II was more stringent than for Phase I. Specifically, the total Spanish Phase II cap was 16% less than in Phase I. In spite of this, in the period 2008-2010 there was a surplus of 33.23 Mt CO_2 (Spanish Government, 2010).

Despite the fact that NAP II was more stringent than NAP I, the higher SA levels in the second period (See Table 2.1) suggest that the deviation from what was expected was more marked than in the first phase. According to data in the Spain GHG Inventory 1990-2010, during the period 2005-2007, CO_2 emissions were 49.43% above 1990 levels, due to considerable economic and population growth, as was pointed out in Royal Decree 1370/2006. During the period 2008-2010, emissions were only 29.53 above 1990 levels due to the economic crisis. This reduction of CO_2 emissions from 2008 onwards, stemming from crisis-related declines in companies' production, appears to be the reason why companies, on average, had a surplus of around 0.30.

The results of Table 2.1 indicate that normality of the SA variable is rejected in all periods, due to a significant negative asymmetry and leptokurtosis, which tended to decrease from 2008 onwards. This arises from the existence of a low percentage of firms with strong negative SA values, i.e., CO_2 emissions much higher than the allowance allocations, which are responsible for the fact that Spain as a whole had a deficit of CO_2 emissions in period 2005-2008, as mentioned above.

2.2.2 Economic performance

Surplus of allowances is linked to economic performance in two ways: It results primarily from a company's level of production, and it can directly affect company profitability. To measure profitability, we employ the Return on Assets (ROA), which calculates how efficient management is at using its assets to generate earnings. To measure a company's production, we use the Assets Turnover Rotation (ATR). The ideal measure would be the production figure but we do not have access to this data, thus, we use this activity ratio widely used in literature as a proxy of company production level. For a firm $i = 1, ..., N$ in period $t = 1, ..., T_i$ the ROA and ATR ratios are given by the following expressions:

$$ROA_{it} = \frac{Operating\, income_{it}}{Assets_{it}} \tag{2.2}$$

$$ATR_{it} = \frac{Operating\, revenue_{it}}{Assets_{it}} \tag{2.3}$$

Table 2.2: **Descriptive statistics of ROA**

	2005	2006	2007	2008	2009	2010	2011
Minimum	-31.72	-66.77	-120.02	-155.89	-81.4	-59.11	-59.11
Mean	4.86	2.57	4.04	0.17	0.38	0.7	0.7
Median	3.59	2.59	3.65	10.67	0.49	1.51	1.51
Maximum	79.08	58.32	52.64	73.99	100.63	52.24	52.24
Std.deviation	10.57	12.58	14.47	16.53	14.89	11.96	11.96
Skewness	1.38	-0.62	-2.72	-3.21	0.22	-0.41	-0.41
Kurtosis	12.46**	8.12**	26.75**	28.88**	12.19**	7.78**	7.78**
JB (p-value)	0	0	0	0	0	0	0

*Note:Statistically different from zero at the ** 5% significance level*

Table 2.3: **Descriptive statistics of ATR**

	2005	2006	2007	008	2009	2010	2011
Minimum	0.06	0.02	0.06	0.02	0.01	0.01	0.004
Mean	0.98	0.97	0.01	0.96	0.77	0.82	0.77
Median	0.79	0.84	0.86	0.77	0.625	0.63	0.59
Maximum	34.27	12.87	7.24	12.84	3.86	21.53	4.99
Std.deviation	1.56	0.75	0.68	0.86	0.59	1.06	0.69
Skewness	18.66**	7.13**	3.09**	5.77**	1.67**	13.53**	1.99**
Kurtosis	3.95**	10.23**	20.61**	6.51**	6.90**	2.60**	10.01**
JB (p-value)	0	0	0	0	0	0	0

*Note:Statistically different from zero at the ** 5% significance level*

Table 2.2 shows the main descriptive statistics of ROA. Again, two different periods stand out: 2005-2007 and 2008-2011. On average, companies have a positive ROA during the first period and it is relatively stable. Values corresponding to period 2008-2011 are much lower. The break point took place in 2008, when the global crisis began. The data of both phases is heavily skewed to the left (with the sole exception of 2009) and kurtosis is considerably pronounced. This is due to the presence of a set of firms with higher absolute levels of ROA, with very strong negative values.

Table 2.3 presents the main descriptive statistics of ATR. As can be seen, ATR mean and median considerably decreased after 2008, consistent with the evolution of Spanish GDP during this period. According to data from the Spanish National Statistics Institute, while in 2005, 2006 and 2007 the annual growth of GDP was around 4%, in 2008 this fell to 1%, and to -3.7% in 2009 and -0.3% in 2010. The data is skewed to the right and kurtosis is pronounced.

2.2.3 Control variables

We include a set of firm characteristics that may influence the link between environmental and economic performance that were not considered in Segura et al.(2014): size,risk and sector.

◇ Size. Company size, obviously, affects both the levels of CO_2 emissions and economic results. Following Elsayed and Paton (2004) and Clarkson et al (2011), we measure size as $Log(Assets)$.

◇ Risk. Following Waddock and Graves (1997); McWilliams and Siegel (2000) and Elsayed and Paton (2004), we measure company risk with the square root of the debt-to-capital ratio, which has the following expression:

$\frac{Liabilities}{Assets}$

The higher the ratio, the more the company uses debt to finance its operations. If the revenues fall, a company with a high ratio might not be able to meet its debt payments, whereas a company with a low ratio is one that financed its operations with equity and thus will be better prepared to face declining revenues.

◇ Sector. The sector to which a company belongs also influences its level of CO_2 emissions and its economic results (Elsayed and Paton, 2004). According to Directive 2003/87/CE, companies in the EU ETS are divided into 9 sectors. The first comprises

Table 2.4: **Descriptive statistics of SIZE**

	2005	2006	2007	2008	2009	2010	2011
Minimum	12.04	12.56	12.73	12.68	7.87	12.32	12
Mean	16.78	17.12	17.26	17.33	17.32	17.44	16.90
Median	16.49	16.76	16.90	16.96	16.93	17.06	17.00
Maximum	23.07	23.17	23.65	23.97	24.22	24.20	23.00
Std.deviation	1.95	2.01	2.02	2.00	2.05	2.07	1.9
Skewness	0.77**	0.59**	0.55**	0.52**	0.34**	0.46**	0.77**
Kurtosis	3.55**	2.97**	2.85**	2.92**	3.50**	2.93**	3.68**
JB(p-value)	0	0	0	0	0	0	0

*Note:Statistically different from zero at the ** 5% significance level*

power stations ("Combustion installations with a rated thermal input exceeding 20 MW, mineral oil refineries and coke ovens"). Sectors 2 to 9 are industrial sectors producing iron, steel, cement, glass, lime, bricks, ceramics, pulp and paper. We divide our sample into two groups: energy companies (sector 1) and industrial companies (sector 2-9).

Data of economic performance and the control variables were taken from SABI, a database that provides 1,250,000 Spanish and 400,000 Portuguese company reports. These reports include, among other information: company financial profile, summary of company industrial activities, Balance Sheet, Profit and Loss account, and financial ratios.

We, finally, focus on SIZE and RISK descriptive statistics (Table 2.4 and 2.5). In both cases, mean and median are quite stable during the whole sample period. Again the normality hypothesis is rejected for both variables.

Taking into account that the normality of our variables is rejected for all seven years of our sample, these findings suggest that the relationship would not be treated effectively in the normal multivariate context. This is why we choose a copula approach to model the relationship between both variables, which, as Trivedi and Zimmer (2005) point out, is an adequate tool when capturing dependence in a broader context than

Table 2.5: **Descriptive statistics of RISK**

	2005	2006	2007	2008	2009	2010	2011
Minimum	2.25	1.84	2	1.17	1.29	1.25	0.86
Mean	7.18	7.32	7.20	7.29	7.10	7.10	6.70
Median	7.48	7.57	7.41	7.49	7.35	7.29	6.81
Maximum	12.44	14.36	20.31	16.25	21.04	16.88	17.95
Std.deviation	1.83	1.83	2.04	2.09	2.28	2.21	2.28
Skewness	-0.39^{**}	-0.29**	0.46**	-0.10^{**}	0.17**	-0.11^{**}	0.06**
Kurtosis	2.60**	3.26**	6.60**	3.85**	5.33**	3.87**	4.33**
JB(p-value)	0	0	0	0	0	0	0

*Note:Statistically different from zero at the ** 5% significance level*

the multivariate normal.

2.3 Methodology

Given that our statistical methodology is based on the use of copulas, we first provide a brief review of the main concepts and results related to copulas, and then describe the selection and estimation of the model procedure used in this paper. We only consider the bivariate case, which corresponds to our problem. Good introductory texts of copulas are Cherubini et al. (2004) and Nelsen (2006).

2.3.1 Definition

A copula $C : [0,1]^2 \to [0,1]$ is a cumulative distribution of a bi-dimensional random vector on $[0,1]^2$ with uniform marginals:

$$C(u_1, u_2) = P(U_1 \leq u_1, U_2 \leq u_2) \tag{2.4}$$

where U_1 and U_2 are uniformly distributed on $[0,1]$.

The importance of copulas in the modelling of dependence between variables arises from Sklar's Theorem (Sklar, 1959), which provides the theoretical foundation for their application. This theorem states that a bivariate cumulative distribution function $F_{1,2}(x_1, x_2)$ of a random vector (X_1, X_2) with marginals $F_1(x_1)$ and $F_2(x_2)$ can be written as:

$$F_{1,2}(x_1, x_2) = C(F_1(x_1), F_2(x_2) \tag{2.5}$$

where C is a copula. This copula is unique on $Ran(F_1)xRan(F_2)$ which is the cartesian product of the ranges of the marginal cdf $'$s if the marginals $F_1(x_1)$ and $F_2(x_2)$ are continuous and can be obtained from:

$$C(u_1, u_2) = F_{1,2}(F_1^{-1}(u_1), F_2^{-1}(u_2)) \tag{2.6}$$

The converse is also true: given a copula $C : [0, 1]^2 \rightarrow [0, 1]$ and margins $F_1(x_1)$ and $F_2(x_2)$ this defines a bi-dimensional cumulative distribution function $F_{1,2}(x_1, x_2)$

2.3.2 Dependence in Copulas

Correlation is the most familiar measure of dependence between variables. The Pearson coefficient ρ is the covariance divided by the product of the standard deviations and the main advantage of this correlation coefficient is its tractability. There are, however, a number of theoretical shortcomings. A major shortcoming is that correlation is not invariant to monotonic transformations. The linear correlation coefficient expresses the linear dependence between random variables, and when nonlinear transformations are applied to those random variables, linear correlation is not preserved. Thus, the correlation of two return series may differ from the correlation of the squared returns or log returns.

Actually, correlation is a linear measure of dependence, and may not capture important nonlinearities. In those cases, a rank correlation coefficient, such as Kendall's τ or Spearman's ρ_s, is more appropriate. Roughly speaking, these rank correlations measure the degree to which large or small values of one random variable associate with large or small values of another. However, unlike the linear correlation coefficient, they measure the association only in terms of ranks. As a consequence, the rank correlation is preserved under any monotonic transformation. Therefore, Kendall's τ or Spearman's ρ_s are more useful in describing the dependence between random variables, because they are invariant to the choice of marginal distribution.

Kendall's ρ is a measure of concordance between random variables and it is possible to express Kendall's ρ in term of the copula that joins X_1 with X_2:

$$\tau = 4 \int_0^1 \int_0^1 C(u_1, u_2) c(u_1, u_2) du_1 u_2 - 1 \tag{2.7}$$

Kendall's τ is a very useful alternative to the linear correlation coefficient because it does not depend on the marginal distribution of X_1 and X_2. In fact, Kendall's τ only depends on the copula function. As a measure of concordance based on copulas, which means that it is invariant to increasing transformations of its arguments, Kendall's τ can capture nonlinear dependences that are not possible to measure with linear correlation.

Another related, nonlinear measure is the Spearman rank correlation ρ_s. The Spearman rank correlation is especially useful when analyzing data with a number of extreme observations, since it is independent of the levels of the variables, and therefore robust to outliers. Spearman's correlation coefficient could also be expressed solely in terms of the copula function:

$$\rho_s = 12 \int_0^1 \int_0^1 C(u_1, u_2) - u_1 u_2) du_1 u_2 = 12 \int_0^1 \int_0^1 C(u_1, u_2) dC(u_1, u_2) - 3 \tag{2.8}$$

This means that if we know the correct copula, we can recover the Spearman rank correlation.

2.3.3 Quantile regression

In addition to measures of association and dependence properties, classical regression is a statistical tool used to model the relation between a predictor variable X_1 and the response variable X_2. For random variables X_1 and X_2, the regression curve $x_2 = E(X_2|X_1 = x_1)$ specifies the mean value of X_2 for each value of X_1. While this model can address the question "is X_1 important?" it cannot answer an important question: "does X_1 influence differently for different values of X_2?". An alternative to the mean for specifying values of X_2 for each value of X_1 is the quantile, which leads to the notion of Quantile regression.

Definition.- Let X_1 and X_2 be random variables. For x_1 in Ran X_1, let $x_2 = Q_p(x_2|x_1)$ denote a solution to the equation $P(X_2 \leq x_2|X_1 = x_1) = p$ with $p\,\epsilon(0,1)$. Then the graph of $x_2 = Q_p(x_2|x_1)$ is the quantile regression curve of X_2 on X_1.

Quantile regression models the relation between X_1 and specific quantiles of X_2, so it specifies changes in the quantiles of X_2 as a function of X_1. Quantile regression can be used to measure the effect of X_1 not only in the centre of a distribution, but also in the upper and lower tails. In linear regression, the regression coefficient represents the increase in X_2 produced by one unit increase in X_1. The quantile regression parameter estimates the change in a specified quantile of X_2 produced by a one unit change in X_1. This allows comparing how some percentiles of X_2 may be more affected by X_1 than other percentiles. This is reflected in the change in the size of the regression coefficient.

Now suppose that X_1 and X_2 are continuous, with joint distribution function, marginal distribution functions and, respectively, and copula. Then $U_1 = F_1(X_1)$ and $U_2 = F2(X2)$ are uniform (0, 1) random variables with joint distribution function C. We have that:

$$P(X_2 \leq x_2|X_1 = x_1) = P(U_2 \leq F_2(x_2)|U_1 = F_1(x_1)) = \frac{\partial C(u_1, u_2)}{\partial u_1} \tag{2.9}$$

which yields the following algorithm for finding quantile regression curves for continuous random variables. To find the p-quantile regression curve $x_2 = Q_p(x_2|x_1)$ of X_2 on X_1:

1. Fix $X_1 = x_1 \to u_1 = F_1(x_1, \alpha_1)$

2. Set $\frac{\partial C(u_1,u_2)}{\partial u_1} = p$ and solve for the regression curve $x_2 = Q_p(x_2|x_1)$ (of U_2 on U_1). Calculate $Q_p(x_2|x_1) = F_2^{-1}(Q_p(u_2|u_1))$.

2.3.4 Notable Copulas

Researchers use a number of parametric copula specifications. Two of the most frequently used copula families are elliptical and Archimedean, which we briefly review below.

Elliptical

Elliptical copulas are the copulas of elliptically contoured (or elliptical) distributions. The most commonly used elliptical distributions are the multivariate normal and Student-t distributions. The Gaussian copula is obtained from the bivariate normal distribution with correlation matrix, R, and is given by:

$$C_R^{Ga}(u_1, u_2) = \int_{-\infty}^{\phi(u_1)} \int_{-\infty}^{\phi(u_2)} \frac{1}{(2\pi)\sqrt{|\Re|}} exp\{\frac{-u'\Re^{-1}u}{2}\}du \tag{2.10}$$

where $u = (u_1, u_2)$ and $\phi^{-1}(.)$ is the inverse of the cumulative distribution function of the univariate standard normal distribution. The Kendall's τ and Spearman's ρ_s are, respectively expressed as $\tau_{Ga} = \frac{2}{\pi} arcsin\,(\rho)$ and $\rho_{S,Ga} = \frac{6}{\pi} arcsin\,(\frac{\rho}{2})$. The p-quantile regression curve for gaussian copula is given by:

$$x_2 = F_2^{-1}(\phi(\rho(\phi^{-1}(F_1(x_1)) + \sqrt{1-\rho^2}\phi^{-1}(p))) \tag{2.11}$$

where ρ is the Pearson correlation between x_1 and x_2. The normal allows for equal degrees of positive and negative dependence; However it assumes that there is no dependence in the tails of the distribution, which can be unrealistic in some situations as, for instance, in financial markets where financial returns tend to be very dependent in extreme conditions. Therefore, in financial economics, it is often more useful to consider the t-copula, which is obtained from the bivariate t-distribution with η degrees of freedom and correlation matrix, R, and is given by:

$$C_R^{\eta,t}(u_1,u_2) = \int_{-\infty}^{t_\eta^{-1}(u_1)} \int_{-\infty}^{t_\eta^{-1}(u_2)} \frac{\Gamma(\frac{\eta+2}{2})(1+\frac{u' R^{-1} u}{2})^{-\frac{\eta+2}{2}}}{\Gamma(\frac{\eta}{2})(\pi\eta)\sqrt{|R|}} du \tag{2.12}$$

where $t_\eta^{-1}(.)$ denotes the inverse of the cumulative distribution function of the standard univariate Student-t distribution with η degrees of freedom. Note that the Gaussian copula is obtained as a special case of the t-copula when η goes to infinity. The Kendall's τ and Spearman's ρ coincide with those of the Gaussian, i.e. $\tau_{Ga} = \frac{2}{\pi} arcsin\,(\rho)$ and $\rho_{S,Ga} = \frac{6}{\pi} arcsin\,(\frac{\rho}{2})$. The p-quantile regression curve of the Student's-t copula is given by:

$$x_2 = F_2^{-1}(t_\eta(pt_\eta^{-1}(F_1(x_1))) + \sqrt{(1-p^2)(\eta+1)^{-1}(\eta+(t_\eta^{-1}(F_1(x_1)))^2)}t_{\eta+1}^{-1}(p))) \tag{2.13}$$

Unlike the Gaussian copula, the t-copula has symmetric tail dependence which makes it very useful in models of the joint movements of financial returns. The dependence structure in elliptical copulas is determined by the correlation matrix of the variables, which is one of their key advantages since different levels of correlation between their marginal distributions can be specified. However, one of the key disadvantages is that they are restricted to radial symmetry and, with the sole exception of Gaussian and Student t copulas, they do not have closed form expressions. (A general discussion of elliptical distributions can be found in Fang et al., 1990.)

Archimedean

An Archimedean copula is constructed through a generator function φ as

$$C_\varphi(u_1,u_2) = \varphi^{-1}(\varphi(u_1)+\varphi(u_2)) \tag{2.14}$$

where φ^{-1} is the inverse of the generator φ. The generator needs to be a complete monotonic function (see, for example, Nelsen, 2006, Theorem 4.6.2). A generator uniquely (up to a scalar multiple) determines a copula, so the Archimedean representation allows us to reduce the study of a bivariate copula to a single univariate function. The p-quantile regression curve for an Archimedean copula is given by

$$x_2 = F_2^{-1}(\varphi^{-1}[\varphi(\varphi'^{-1}(\frac{1}{p}\varphi'(F_1^{-1}(x_1)))) - \varphi(F_1(x_1))]) \tag{2.15}$$

Archimedean copula find a wide range of applications because of the ease with which they can be constructed, the great variety of families that belong to this class, and the many nice properties possessed by the members of this class. Details of generators for various Archimedean copulas can be found in Nelsen (2006). Three of the more frequently-used families of copulas are Gumbel, Clayton, and Frank, which expressions and generator functions are given in the following table.

Table 2.6: **Nelsen (2006)**

Family	**Parameter space**	**Generator** φ	**Bivariate copula** $C_\varphi(u,v)$
Gumbel	$\alpha \leq 1$	$(-lnt)^\alpha$	$exp(-((-lnu)^\alpha) + ((-lnv)^\alpha)^{(1/\alpha)})$
Frank	$\alpha\ \epsilon(-\infty,\infty)$	$-ln\frac{e^{-\alpha t}-1}{e^{-\alpha}-1}$	$-\frac{1}{\alpha}ln(1+\frac{(e^{-\alpha u}-1)(e^{-\alpha v}-1)}{e^{-\alpha}-1})$
Clayton	$\alpha > 0$	$\frac{1}{\alpha}(t^{-\alpha}-1)$	$max((u^{-\alpha}+v^{-\alpha}-1)^{-\frac{1}{\alpha}},0)$

The Gumbel copula is an asymmetric copula that has non-linear positive dependence throughout the data and exhibits greater dependence in the positive tail than in the negative. The Frank copulas describe situations of symmetric tail independence and are an appropriate option when modelling strong positive or negative dependence throughout the data. Dependence in the tails of the Frank copula tends to be relatively weak compared to the Gaussian copula, with the strongest dependence centred in the middle of the distribution, suggesting that the Frank copula is most appropriate for data that exhibit weak tail dependence (Trivedi and Zimmer, 2005). The Clayton copula is an asymmetric copula describing situations of non-linear positive dependence throughout the data, but, in contrast to the Gumbel copula, exhibits greater dependence in the negative tail than in the positive.

The relationship between the parameter of the Archimedean copulas and the Kendall's τ and Spearman's ρ is summarized in Table 2.7.

Table 2.7: **Association between some Archimedean copulas and the rank correlation measures: Kendall and Spearman**

Copulas	Kendall's tau	Spearman's tau
Clayton	$\tau_{Cl} = \frac{\alpha}{2+\alpha}$	Complicated
Gumbel	$\tau_{Gu} = \frac{\alpha-1}{\alpha}$	No closed form
Frank	$\tau_{Fr} = 1 - \frac{4}{\alpha}\left(1 - \frac{1}{\alpha \int_0^\alpha \frac{1}{e^t-1}} dt\right)$	$\rho_{s,Fr} = 1 - \frac{12}{\alpha}\left(\frac{1}{\alpha}\int_0^\alpha \frac{1}{e^t-1} dt - \frac{2}{\alpha}\int_0^\alpha \frac{t^2}{e^t-1} dt\right)$

2.3.5 Estimation of copulas

Usually, the copula C belongs to a family of copulas indexed by a parameter θ; $C = C(u_1, u_2; \theta)$ and the margins $\{F_i; i = 1, 2\}$ and the corresponding univariate densities $\{f_i; i = 1, 2\}$ are indexed by parameters $\{\alpha_i; i = 1, 2\}$ with $\{F_i = F_i(x_i; \alpha_i), f_i = f_i(x_i; \alpha_i); i = 1, 2\}$. In this case, it is necessary to estimate the values of θ, α_1 and α_2.

If we have data corresponding to a random sample $\{x_1^j, x_2^j; j = 1, ..., n\}$ of (X_1,X_2), the most direct estimation method is the simultaneous estimation of all parameters using the full maximum likelihood (FML). The log-likelihood function is given by:

$$L(\theta, \alpha_1, \alpha_2) = \sum_{j=1}^{n} \log f_{1,2}(x_1^j, x_2^j; \alpha_1, \alpha_2, \theta) \tag{2.16}$$

where the joint density function $f_{1,2}$ is given by:

$$f_{1,2}(x_1, x_2; \alpha_1, \alpha_2, \theta) = c(F_1(x_1; \alpha_1), F_2(x_2; \alpha_2); \theta) f_1(x_1; \alpha_1) f_2(x_2; \alpha_2) \tag{2.17}$$

where $C(u_1, u_2; \theta) = \frac{\delta C(u_1,u_2;\theta)}{\delta_1 \delta_2}$ is the copula density and f_1, f_2 are the density functions of the marginal distributions F_1 and F_2. The full maximum likelihood estimator MLE - $(\hat{x}_1^{MLE}, \hat{x}_2^{MLE}, \hat{\theta}^{MLE})$ of the model parameters (α_1, α_2, θ) corresponds to simultaneous maximization of the log-likelihood L:

$$(\hat{x}_1^{MLE}, \hat{x}_2^{MLE}, \hat{\theta}^{MLE}) = \arg\ max_{\alpha_1,\alpha_2,\theta} L(\alpha_1, \alpha_2, \theta)$$

$$= arg\ max_{\alpha_1,\alpha_2,\theta} \sum_{j=1}^{n} \log c(F_1(x_1^{(j)}; \alpha_1), F_2(x_2^{(j)}; \alpha_2); \theta) + \sum_{i=1}^{2} \sum_{j=1}^{n} \log f_i(x_i^{(j)}; \alpha_i)$$

A second option is a sequential 2-step maximum likelihood method referred to as the method of inference functions for margins, IFM, (Joe, 2001) in which the marginal parameters α_1, α_2 are estimated in the first step, and the dependence parameter θ is estimated in the second step, using the copula after the estimated marginal distributions have been substituted into it. This method exploits the attractive feature of copulas for which the dependence structure is independent of the marginal distributions, in such a way that.

$$L(\theta, \alpha_1, \alpha_2) = L_c(\theta) + L_1(\alpha_1) + L_2(\alpha_2))$$

where

$$L_c(\theta) = \sum_{j=1}^{n} \log c(F_1(x_1^{(j)}; \alpha_1), F_2(x_2^{(j)}; \alpha_2); \theta)$$

is the log-likelihood contribution from dependence structure in data represented by the copula C, and $L_i(\alpha_i = \sum_{j=1}^{n} \log f_i(x_i^{(j)}; \alpha_i)$, $i = 1, 2$ are the log-likelihood contributions from each margin: observe that this is exactly the log-likelihood of the sample under the independence assumption.

In the first stage of the inference procedure, the estimators $\hat{\alpha}_i^{IFM}$ of the parameters α_i are estimated from the log-likelihood $L_i(\alpha_i)$ of each margin: $\hat{\alpha}_i^{IFM} = \arg\max_{\alpha_i} L_i(\alpha_i)$. That is, $(\hat{\alpha}_1^{IFM}, \hat{\alpha}_2^{IFM})$ is defined to be the MLE of the model parameters under independence. In the second stage of the procedure, the estimator $\hat{\theta}_i^{IFM}$

of the copula parameter θ_i^{IFM} is computed by maximizing the copula likelihood contribution LC with the marginal parameters α_i replaced by their first-stage estimators $\hat{\alpha}_i^{IFM} : \hat{\theta}_i^{IFM} = \arg\max_{\alpha_i} L_c(\hat{\alpha}_1^{IFM}, \hat{\alpha}_2^{IFM}, \theta)$.

As discussed in Joe (2001), the MLE and IFM estimation procedures are equivalent in the special case of multivariate normal d.f.s that have multivariate Gaussian copulas and univariate normal margins. Naturally, however, this equivalence is not a general rule. Furthermore, and similar to the MLE, the IFM estimator $(\hat{\alpha}_1^{IFM}, \hat{\alpha}_2^{IFM}, \hat{\theta}^{IFM})$ is consistent and asymptotically normal under the usual regularity conditions (see Serfling, 1980) for the bivariate model and for each of its margins. However, estimation of the corresponding covariance matrices is difficult both analytically and numerically, due to the need to compute many derivatives, and jack-knife and related methods may be used in inference (see Joe, 2001).

Efficiency comparisons based on estimation of the asymptotic covariance matrices and Monte-Carlo simulation for different dependence models suggest that the IFM approach to inference provides a highly efficient alternative to the MLE estimation of multivariate model parameters.

This second method IFM has a variant in which a non-parametric method is used to estimate the univariate marginal densities, denoted $\hat{f}_1(x_1)$ and $\hat{f}_2(x_2)$. This is used to compute the empirical distribution functions $\hat{F}_1(x_1)$ and $\hat{F}_2(x_2)$, which may be treated as realizations of uniform random variables U_1 and U_2, respectively. In this case, given, $\hat{u}_{1j} = \hat{F}_1(x_1^{(j)}), \hat{u}_{2j}) = \hat{F}_2(x_2^{(j)}), j = 1, ..., n$, and a copula C, the dependence parameter θ can be estimated as follows:

$$\hat{\theta}^{IFM} = \arg\max_{\theta} \sum_{j=1}^{n} \log c(\hat{u}_{1j}, \hat{u}_{2j}; \theta)$$

2.4 Setting up the problem

Let us consider N firms observed in period $1, ..., T$. Let $\{SA_{i,t}; t \epsilon T_i\}$ be the Surplus of Allowances for the company i in period t, let $\{ROA_{i,t}; t \epsilon T_i\}$ be the Return on Assets ratios for the company i period t, let $\{ATR_{i,t}; t \epsilon T_i\}$ be the Assets Turnover Rotation ratio for the company in period t, $Size_{i,t}$ be the log of assets for the company i in period t, $Risk_{i,t}$ be the risk for the compay i in period t and $Sector_{i,t}$ be the sector of the company i in period t, where $T_i \subseteq \{1, ..., T\}$ is the observation period for company i for i=1,...,N.

Our first objective is to analyze the influence exerted by ATR on SA taking into account the control variables: size, risk and sector. To do so, we estimate the nonlinear p quantile regression that is based on the specification of the copula function that defines the dependency structure between the ATR and SA. $SA_t = Q_p(SA_t|ATR_t, Size_t, Risk_t, Sector_t)$

To obtain the p quantile regression function we need the conditional density function $f_{1,2}(SA_t|ATR_t, Size_t, Risk_t, sector_t)$ which is given by the expression:

$$f_{1,2}(SA_t|ATR_t, Size_t, Risk_t, Sector_t) = \frac{f_{1,2}(ATR_t, SA_t|Size_t, Risk_t, Sector_t)}{f_2(ATR_t|Size_t, Risk_t, Sector_t)} \tag{2.18}$$

In this chapter, we use copulas to obtain the joint distribution functon of ATR and SA given by:

$$\begin{aligned} &F(ATR_t, SA_t|Size_t, Risk_t, Sector_t) = \\ &C(F_1(SA_t|Size_t, Risk_t, Sector_t), (F_2(SA_t|Size_t, Risk_t, Sector_t)) \end{aligned} \tag{2.19}$$

and from this joint distribution, we can obtain the joint density function given by:

$$
\begin{aligned}
&f_{1,2}(ATR_t, SA_t|Size_t, Risk_t, Sector_t) = \\
&c((F_1(SA_t|Size_t, Risk_t, Sector_t), (F_2(SA_t|Size_t, Risk_t, Sector_t))* \\
&* f_1(SA_t|Size_t, Risk_t, Sector_t), f_2(SA_t|Size_t, Risk_t, Sector_t)
\end{aligned} \tag{2.20}
$$

where $c((F_1(SA_t|Size_t, Risk_t, Sector_t), (F_2(SA_t|Size_t, Risk_t, Sector_t))$ is the copula density.

Due to the difficulty of treating a 5-dimensional distribution we use the procedure employed by Patton (2006), which supposes as simplified hypothesis that F_1 and F_2 are built by means of linear regression methods.

So, we suppose that:

$$SA_t = \beta_0^{SA} + \beta_1^{SA} Size_t + \beta_2^{SA} Risk_t + \beta_3^{SA} Sector_t + \varepsilon_t^{SA} \quad with \quad \varepsilon_t^{SA} f_\varepsilon \sim f_{\varepsilon^{SA}}(.) \tag{2.21}$$

therefore,

$$f_1(SA_t|Size_t, Risk_t, Sector_t) = f_{\varepsilon^{SA}}(SA_t - \beta_0^{SA} + \beta_1^{SA} Size_t + \beta_2^{SA} Risk_t + \beta_3^{SA} Sector_t) \tag{2.22}$$

Similarly, we suppose that:

$$ATR_t = \beta_0^{ATR} + \beta_1^{ATR} Size_t + \beta_2^{ATR} Risk_t + \beta_3^{ATR} Sector_t + \varepsilon_t^{ATR} \quad with \quad \varepsilon_t^{ATR} f_\varepsilon \sim f_{\varepsilon^{ATR}}(.) \tag{2.23}$$

therefore,

$$f_1(ATR_t|Size_t, Risk_t, Sector_t) = f_{\varepsilon^{ATR}}(ATR_t - \beta_0^{ATR} + \beta_1^{ATR} Size_t + \beta_2^{ATR} Risk_t + \beta_3^{ATR} Sector_t) \tag{2.24}$$

Our target is to estimate the parameters $\beta_0^{SA}, \beta_1^{SA}, \beta_2^{SA}, \beta_3^{SA}, \beta_0^{ATR}$, $\beta_1^{ATR}, \beta_2^{ATR}, \beta_3^{ATR}$ and the densities $f_{\varepsilon^{SA}}$ and $f_{\varepsilon^{ATR}}$ To carry out all this process, we use the following algorithm:

Step 1.- Estimation of the parameters $\beta_0^{SA}, \beta_1^{SA}, \beta_2^{SA}, \beta_3^{SA}, \beta_0^{ATR}, \beta_1^{ATR}, \beta_2^{ATR}, \beta_3^{ATR}$ by means of a robust regression method (MATLAB robustfit function).

Step 2.- With the previous estimations, we obtain the residuals $\widehat{\epsilon_t^{ATR}}$ and $\widehat{\epsilon_t^{SA}}$ given by the following expressions:

$\widehat{\epsilon_t^{ATR}} = ATR_t - \widehat{\beta_0^{ATR}} + \widehat{\beta_1^{ATR}} Size_t + \widehat{\beta_2^{ATR}} Risk_t + \widehat{\beta_3^{ATR}} Sector_t$

$\widehat{\epsilon_t^{SA}} = SA_t - \widehat{\beta_0^{SA}} + \widehat{\beta_1^{SA}} Size_t + \widehat{\beta_2^{SA}} Risk_t + \widehat{\beta_3^{SA}} Sector_t$

Step 3.- Fit marginal distributions to $\widehat{\epsilon_t^{ATR}}$ and $\widehat{\epsilon_t^{SA}}$ using non-parametric kernel estimators $\widehat{f}_{\epsilon^{ATR}}(\widehat{\epsilon_t^{ATR}})$ and $\widehat{f}_{\epsilon^{SA}}(\widehat{\epsilon_t^{SA}})$

Step 4.- Use the marginal distribution functions $\widehat{F}_{\epsilon^{ATR}}(\widehat{\epsilon_t^{ATR}})$ and $\widehat{F}_{\epsilon^{SA}}(\widehat{\epsilon_t^{SA}})$ to transform $\widehat{\epsilon_t^{ATR}}$ and $\widehat{\epsilon_t^{SA}}$ to U(0,1) distributions, that is to say, $u_1 = \widehat{F}_{\epsilon^{SA}}(\widehat{\epsilon_t^{SA}})$ and $u_2 = \widehat{F}_{\epsilon^{ATR}}(\widehat{\epsilon_t^{ATR}})$

Step 5.- For each family of copula, use the maximum likelihood procedure to fit a copula to u_1 and u_2. If the copula C belongs to a family of copulas indexed by a Θ: $C = C(u_1, u_2; \theta)$ then the maximum likelihood estimator $\widehat{\theta}^{MLE}$ of the parameters θ corresponds to the maximization of the log-likelihood:

$\widehat{\theta}^{MLE} = arg\ max_\theta L(\theta) = arg\ max_\theta \sum_{i=1}^{N} log\ c\left(\widehat{F}_{\epsilon^{SA}}(\widehat{\epsilon_t^{SA}}), \widehat{F}_{\epsilon^{ATR}}(\widehat{\epsilon_t^{ATR}}), \theta\right)$

where $c = \frac{\partial C(u_1,u_2;\theta)}{\partial u_1 \partial u_2}$ is the density of the copula $C(u_1, u_2; \theta)$

Step 6.- Selection of the appropriate copula model using the AIC criterion.

Step 7.- Calculation of the p-quantile regression curve of $\widehat{\epsilon_t^{SA}}$ on $\widehat{\epsilon_t^{ATR}}$ for a certain value of p. In this Chapter we calculate the p-quantile regression curve for p=0.5 (median regression curve). So fixing, $\widehat{\epsilon_t^{SA}} = (\widehat{\epsilon_t^{SA}})^0$ then $u_2 = \widehat{F}_2\left((\widehat{\epsilon_t^{SA}})^0\right)$. We set the equation $\frac{\partial C(u_1,u_2)}{\partial u_1} = 0.5$ and solve for the regression curve $u_1 = Q_p(u_1|u_2)$. Finally, we calculate $SA_t = Q_p(SA_t|ATR_t) = F_1^{-1}(Q_p(u_1|u_2))$.

The second objective of the chapter is to analyze the influence exerted by SA on ROA taking into account the control variables size, risk and sector. We want to determine the p-quantile regression function $ROA_t = Q_p(ROA_t|SA_t, Size_t, Risk_t, Sector_t)$ for p=0.5,that is, the median regression function. We follow the procedure above.

2.5 Empirical results and discussion

In this section we estimate the relationship between economic performance and surplus of allowances from two points of view: production (measured by ATR) versus surplus of allowances and surplus of allowances versus profitability (measured by ROA). Both links are estimated using copulas structures following the procedure described in Section 2.4. Additionally, we present the estimation of both links through two linear regression models for comparative purposes. All calculations were made in MATLAB R2013b. The code written to obtain our results is provided in Appendix A.

2.5.1 The effect of production (ATR) on SA

In this section we focus on the link between ATR and SA using copula structures. In Table 2.8 the linear regression of SA on ATR is presented for comparative purposes.

We first focus on the sign of the link. Table 2.9 shows, for each year, the AIC value for each family of copulas considered in this Chapter. According to this criteria, the Student-t copula was the family selected, with the exception of years 2005 (Frank) and 2006 (Gaussian). These selections are explained by the existence of a significant inverse relationship between ATR and SA (see Table 2.10) that eliminates the Gumbel and Clayton copulas, which assume that this dependence is positive. The Student-t copula is appropriate to model symmetric tail dependence, whereas both Gaussian and Frank copulas are more suitable when the link is stronger in the center of the distribution. The selection of the Student-t copula in most of the years reflects that the strongest effects of the dependency between ATR and SA appeared in both tails of their distribution, where the firms with the highest and lowest production levels are placed.The estimated parameters corresponding to copulas and the linear coefficient regression (Table 2.8) are negative for the whole sample period i.e., the more a company produced, the less SA it had.

Second, we analyze how this relationship changes its shape for different levels of production. In Figures 2.1, 2.2 and 2.3, the regression curves of SA on ATR, according to the selected copula each year, are presented. The negative slope of the curve is consistent with the negative sign of the copula parameter already mentioned above. In general, it appears that the slope is more pronounced for ATR values below 1.5, which indicates that an increase of ATR would have greater effects on SA in the case of companies with lower production levels. According to this, it appears that companies with lower production figures may be more rewarded for controlling their level of emissions, as it would have considerable consequences in emissions terms CO_2, compared to firms with high production figures. This finding will not be obtained if we simply use a linear regression approach.

Third, we look at the evolution of the link through the years of our sample. Table 2.10 also shows the Spearman and Kendall coefficients implied by the selected copulas. As can be seen, the strength of the relationship between SA and ATR is not constant over time and the link between ATR and SA was more intense after the onset of the global economic crisis. The evolution of the intensitity of ATR-SA sheds further light on EU ETS efficiency in fostering green investment in Spanish companies.In this context, we argue that, if the EU ETS had encouraged green investments, although an increase in production would be linked to a decrease in SA, this decrease in SA due to higher levels of production would have been lower each year. Given that the intensity of ATR-SA did not decrease, on the contrary, it increased we can indirectly deduce that companies, in general, did not take any substantive measures to reduce their CO_2 emissions.

Finally, we analyze the effect that control variables have on the link between ATR and SA. As can be seen in Figure 2.1, size negatively influences the link between ATR and SA. In other words, if we consider a set of companies with identical ATR values, the largest company would be the one with less SA. The contrary happens when we look at a firm's level of risk (See Figure 2.2). Considering a group of companies with equal ATR, the riskier have higher SA. Differences due to size and risk tend to reduce following the onset of the crisis. Finally, as can be observed in Figure 2.3, companies in the energy sector had a higher surplus of allowances before year 2008. The inverse situation occurred from 2008 onwards.

Table 2.8: **Linear Regression of SA on ATR**

	2005	2006	2007	2008	2009	2010	2011
Constant	0.11***	0.17***	0.16***	0.26***	0.45***	0.51***	0.56***
ATR	-0.01	-0.02	-0.02	−0.05***	−0.14***	−0.19***	−0.22***
SIZE	−0.03***	−0.03***	−0.02***	−0.05***	−0.06***	−0.06***	−0.09***
RISK	0.01	0.02***	0.02*	0.01	-0.01	-0.01	0.01
SECTOR	0.01	0.05***	0.03***	−0.05***	−0.10***	−0.07***	−0.11***
R^2	0.52	0.37	0.30	0.37	0.36	0.33	0.43

*Note: Statistically different from zero at the *** 1%, ** 5%, * 10% significance levels. Sector is a dummy variable: 1 energy sector, 0 industrial sector*

Table 2.9: **AIC values corresponding to the compared families of copulas (SA-ATR)**

	2005	2006	2007	2008	2009	2010	2011
Gaussian	-0.35	**-10.90**	-3.71	-14.78	-48.13	-55.36	-75.16
Student's-t	0.65	-10.79	**-3.86**	**-29.76**	**-72.90**	**-100.2**	**-106.2**
Clayton	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Frank	**-0.56**	-4.83	-2.30	-19.05	-64.77	-81.76	-99.99
Gumbel	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 2.10: **Parameter estimation of the selected copulas and the Kendall's τ and Spearman's ρ associated with the copulas (SA-ATR)**

	2005	2006	2007	2008	2009	2010	2011
Selected	Frank	Gaussian	Student's-t	Student's-t	Student's-t	Student's-t	Frank
Parameter	-0.34**	-0.14**	-0.09**	-0.19**	-0.35**	-0.41**	-0.97**
Kendall	-0.04**	-0.09**	-0.06**	-0.12**	-0.22**	-0.27**	-0.11**
Spearman	-0.06**	-0.13**	-0.08**	-0.18**	-0.32**	-0.38**	-0.16**

*Note: Statistically different from zero at the ** 5% significance level*

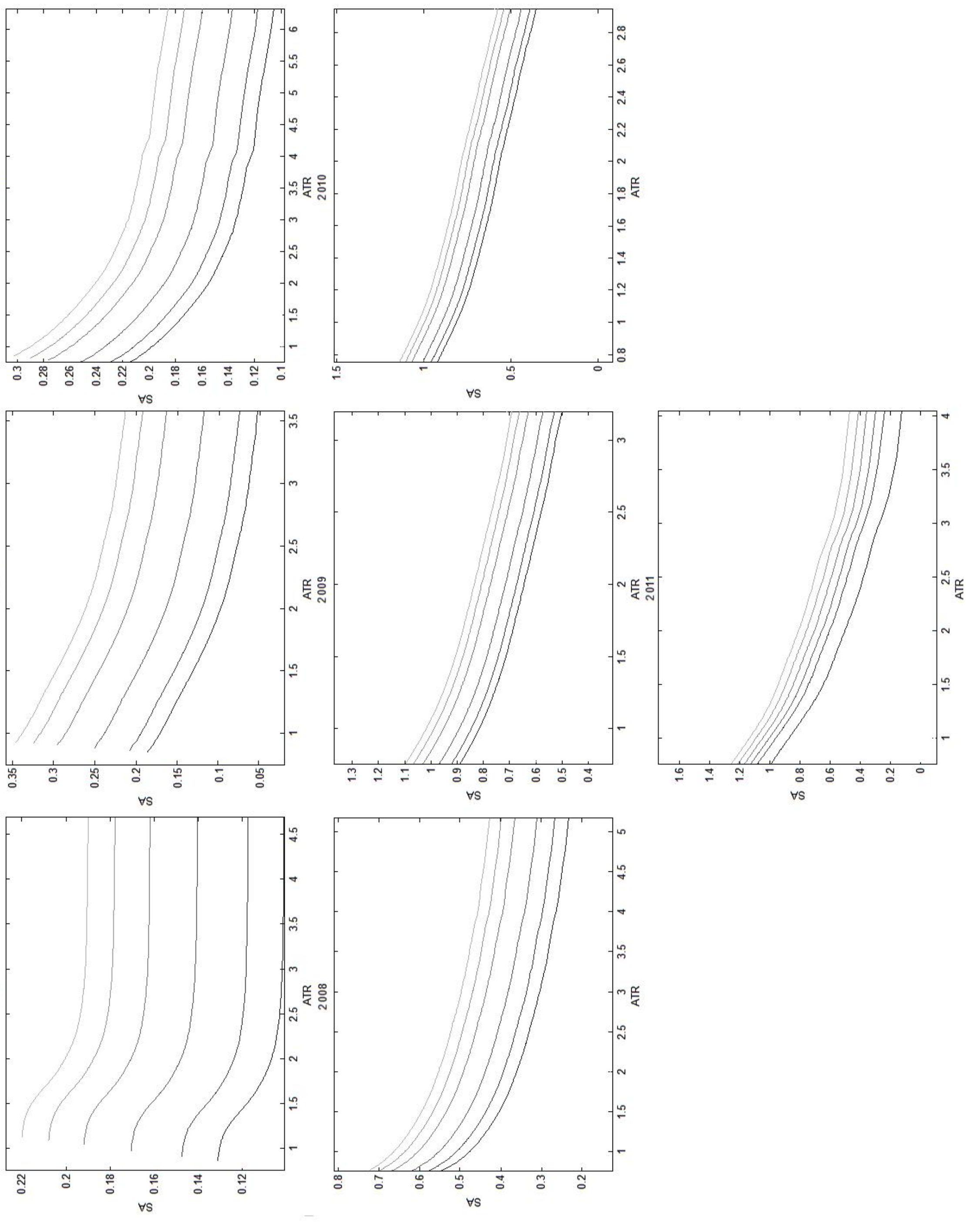

Figure 2.1: **Median regression curves of SA on ATR. Size effect.**

Note: Seven median regression curves of SA on ATR are presented. We draw a median regression curve for a given quantile of the variable size (quantiles 5%, 10%, 25%, 50%, 75%, 90%, 95%). Darker lines correspond to higher quantiles of the variable size.

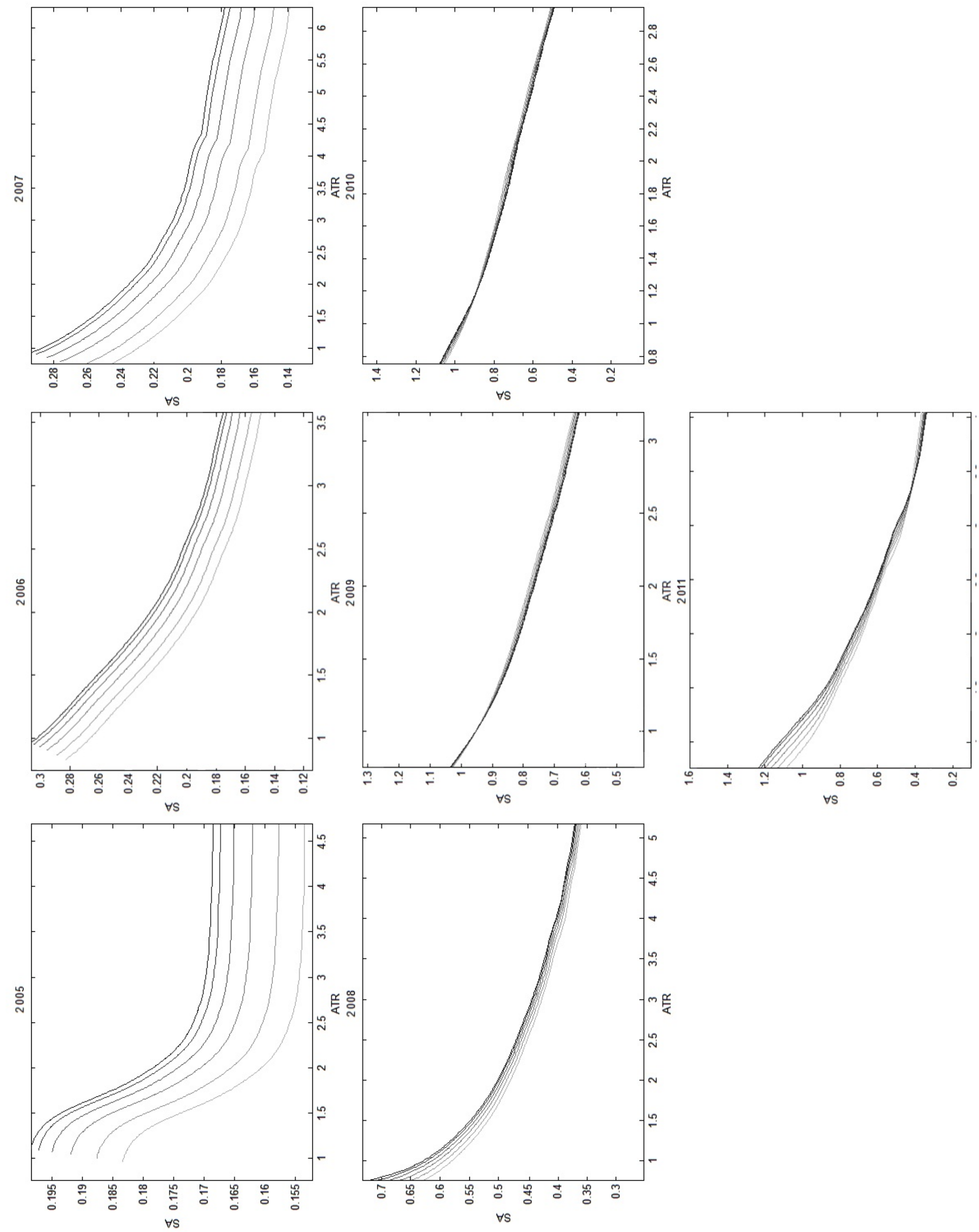

Figure 2.2: **Median regression curves of SA on ATR. Risk effect.**

Note: Seven median regression curves of SA on ATR are presented. We draw a median regression curve for a given quantile of the variable risk (quantiles 5%, 10%, 25%, 50%, 75%, 90%, 95%). Darker lines correspond to higher quantiles of the variable risk.

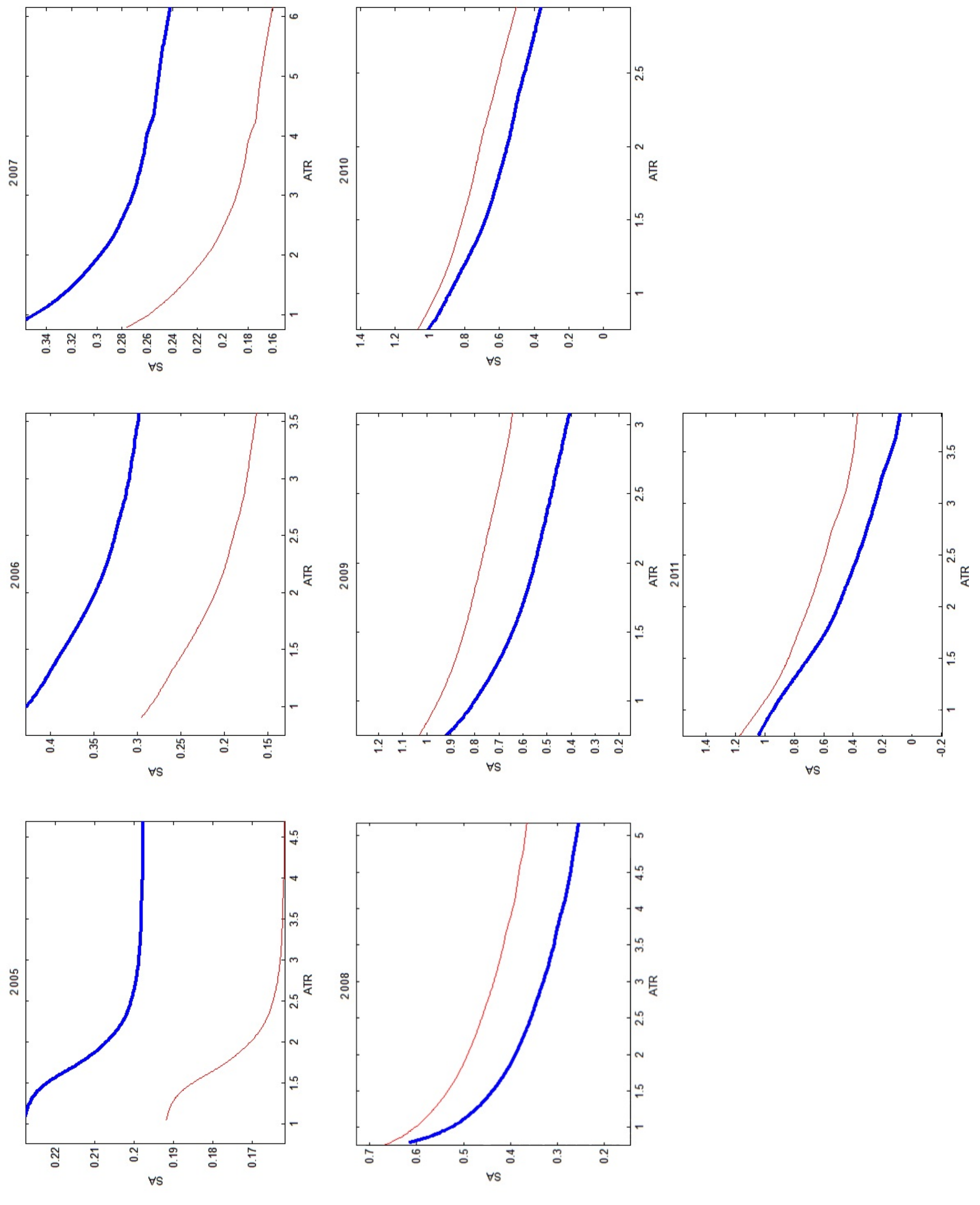

Figure 2.3: **Median regression curves of SA on ATR. Sector.**

Note: We draw two median regression curves. Blue line: energy sector. Red line: industrial sector

2.5.2 The effect of SA on profitability

In this section we concentrate on the impact of SA on ROA. We will follow the structure of the previous section. The linear regression of ROA on SA is presented for comparative purposes in Table 2.11.

First, we focus on the sign of SA-ROA. Table 2.12 shows the AIC values for the five estimated copulas. As can be seen in Table 2.12 , the Frank copula is the family selected for every year, with the sole exception of 2008 (Student's-t copula), which is the most appropriate for data that exhibit weak tail dependence. This reveals that the relationship between SA and ROA is more intense in companies with intermediate levels of ROA and SA. The parameter of the copula is negative, as can be observed in Table 2.13, which is consistent with the sign of the linear coefficient (Table 2.11). This indicates that SA has a negative effect on ROA. The companies that made greater (lower) use, in relative terms, of their allowances tended to be more (less) profitable. In other words, being greener (in terms of more SA) was linked to lower profitability.

Nevertheless, this conclusion could be misleading. As stated in Section 2.2.1, most companies in our sample (75% in 2005-2007) and (84% in 2008-2011) have a positive surplus. The main reason, especially after the economic crisis, is that they produced much less than expected and, consequently, they had lower economic performance figures. Given this, we should limit our attention to companies with low SA, typical of companies that emitted approximately the quantitiy of CO_2 predicted. Looking at these companies, we will be more able to obtain feasible conclusions about whether an improvement in environmental performance (an increase in SA) would lead to better economic performance.

As seen in Figures 2.4, 2.5, 2.6 there is a clear difference between the link for companies with negative SA and those with positive SA. As stated, we focus on companies with negative SA, i.e. those that had to buy EUAs in order to emit more than the quantity of EUAs initially allocated. As can be observed, for these companies, an increase of surplus of allowances, which would imply the purchase of less EUAs in the market, has no effect on their ROA. This finding suggests that EUA prices during the period 2005-2011 were not high enough to create a profitability advantage for those companies that took measures to reduce their CO_2 emissions.

Finally, we turn to the control variables role. As can be observed in Figure 2.4, and in the positive sign of the size parameter in Table 2.11, size positively affects companies' ROA. If we focus on firm risk, the contrary happens; the riskier a company is, the less ROA (see Figure 2.5). With regard to the sector (see Figure 2.6), companies belonging to the energy sector have higher ROA than those from the industrial sector in all the years of our sample, except for 2006 and 2007.

Table 2.11: **Linear Regression of ROA on SA**

	2005	2006	2007	2008	2009	2010	2011
Constant	0.04***	0.03***	0.043***	0.01***	0.04***	0.04***	0.04***
SA	−0.02**	-0.02	−0.03***	−0.03***	−0.10***	−0.07***	−0.08***
SIZE	0.01***	0.02***	0.02***	0.02***	-0.00	0.01	0.01
RISK	−0.03***	−0.04***	−0.05***	−0.03***	−0.03***	−0.02***	−0.01***
SECTOR	−0.01*	−0.01***	−0.01***	0.01*	0.02***	0.02***	0.02***
R^2	0.54	0.65	0.86	0.74	0.69	0.69	0.54

*Note: Statistically different from zero at the *** 1%, ** 5%, * 10% significance levels. Sector is a dummy variable: 1 energy sector, 0 industrial sector*

Table 2.12: **AIC values corresponding to the compared families of copulas (ROA-SA)**

	2005	2006	2007	2008	2009	2010	2011
Gaussian	-9.33	-2.35	-11.38	-16.03	-113.5	-62.18	-47.16
Student's-t	-8.33	-2.18	-10.38	**-24.50**	-113.97	-62.40	-46.16
Clayton	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Frank	**-11.21**	**-2.85**	**-13.19**	-21.72	**-126.9**	**-72.64**	**-54.67**
Gumbel	1.00	1.00	1.00	1	1.00	1.00	1.00

Table 2.13: **Parameter estimation of the selected copulas and the Kendall's τ and Spearman's ρ associated with the copulas (ROA-SA)**

	2005	2006	2007	2008	2009	2010	2011
Selected	Frank	Frank	Frank	Student's-t	Frank	Frank	Frank
Parameter	-0.97^{**}	-0.50^{**}	-0.95^{**}	-0.19^{**}	-30.05^{**}	-23.79^{**}	-26.45^{**}
Kendall	-0.11**	-0.05**	-0.10**	-0.12**	-0.31**	-0.25**	-0.27**
Spearman	-0.16**	-0.08**	-0.16**	-0.18**	-0.45**	-0.37**	-0.40**

*Note: Statistically different from zero at the ** 5% significance levels*

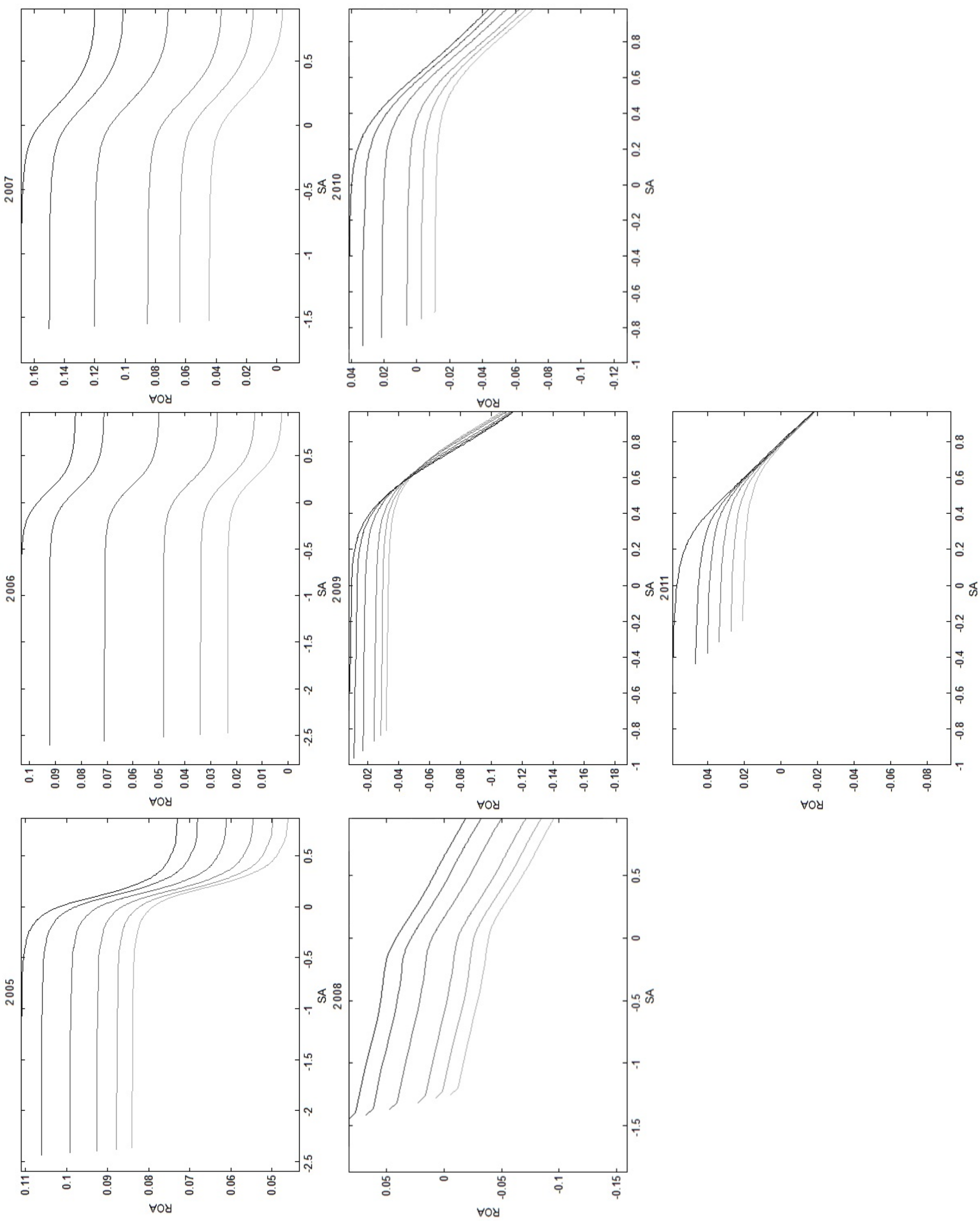

Figure 2.4: **Median regression curves of ROA on SA. Size effects**

Note: Seven median regression curves of ROA on SA are presented. We draw a median regression curve for a given quantile of the variable size (quantiles 5%, 10%, 25%, 50%, 75%, 90%, 95%). Darker lines correspond to higher quantiles of the variable size.

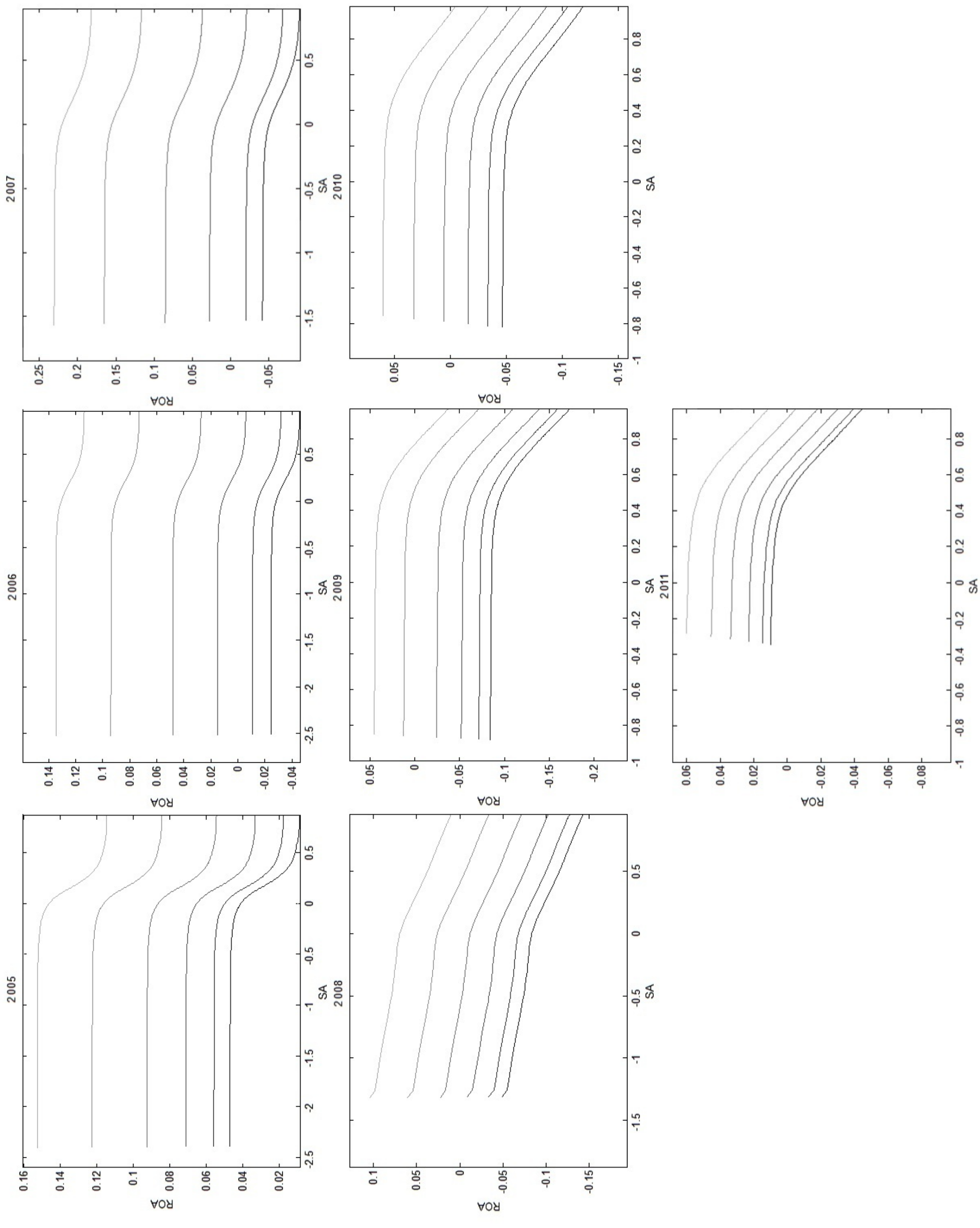

Figure 2.5: **Median regression curves of ROA on SA. Risk effect.. Risk effects**

Note: Seven median regression curves of ROA on SA are presented. We draw a median regression curve for a given quantile of the variable risk (quantiles 5%, 10%, 25%, 50%, 75%, 90%, 95%). Darker lines correspond to higher quantiles of the variable risk.

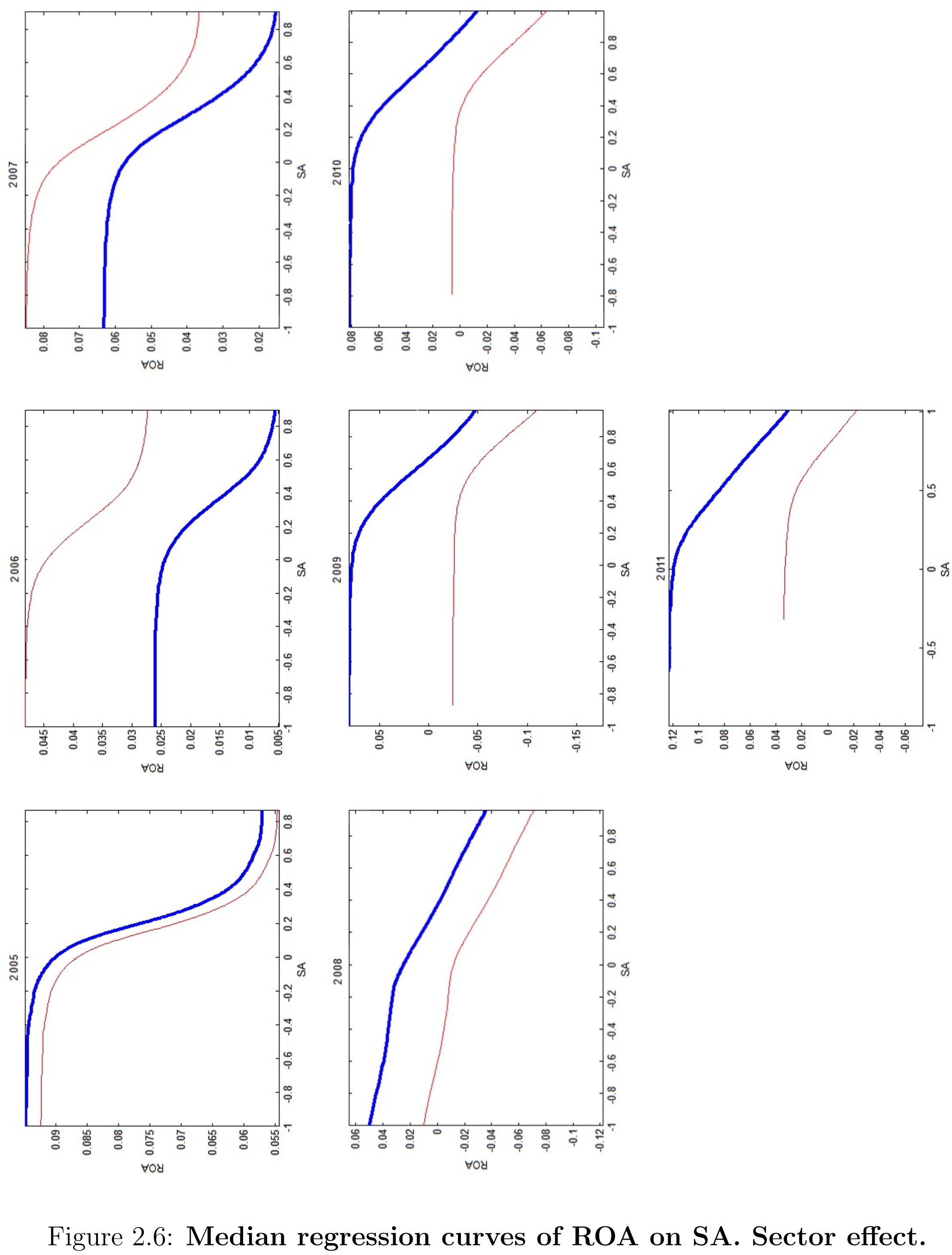

Figure 2.6: **Median regression curves of ROA on SA. Sector effect.**

Note: We draw two median regression curves. Blue line: energy sector. Red line: industrial sector

2.6 Conclusions

To the best of our knowledge this is the first research to examine in depth the relationship between economic performance and environmental performance for Spanish companies in the EU ETS during period 2005-2011.

To measure environmental performance, instead of considering just the CO_2 companies' emissions as most of researchs do when measuring companies' environmental performance, we take the difference between assigned CO_2 emissions and those actually emitted each year (surplus of allowances). This way, we can analyze how the CO_2 emission constraints imposed by the EU ETS affects economic performance.

In analyzing this link between surplus of allowances and economic performance we take two different points of view: how the companies' production level affects a company surplus of allowances and the impact of surplus allowances on companis' profitability. This two different points of view provides us with two main findings.

On the one hand, the evolution of the intensitity of the link between production and surplus of allowances sheds further light on EU ETS efficiency in fostering green investment in Spanish companies. In this context, we argue that if the EU ETS had encouraged green investments, although an increase in production would be linked to a decrease in SA, this decrease in surplus of allowances due to higher levels of production would have been lower each year. Given that the intensity did not decrease, on the contrary, it increased we can indirectly deduce that companies, in general, did not take any measures in order to reduce their CO_2 emissions.

On the other hand, an increase of surplus of allowances, which would imply to buy less EUAs in the market, has no effect in companies' ROA. This finding suggests that EUAs price during period 2005-2011 was not high enough to create a profitability advantage for those companies that take measure to reduce their CO_2 emissions.

Chapter 3

Technical and environmental efficiency. Does it pay to be environmentally efficient?

Second point of view: Companies.

3.1 Introduction

In March, 2007, the EU stablished three binding targets related to climate and energy, known as the "20-20-20" targets. These goals set three key objectives for 2020: a 20% reduction in EU GHG emissions from 1990 levels, a 20% improvement in the EU's energy efficiency and increasing the share of EU energy consumption produced from renewable resources to 20%.(Directive 2012/27/EU).

One of the main measures to achieve the emissions reduction target was the creation of the EU ETS. As explained in the Introduction of this thesis, the EU ETS works as follows. European Union Allowances (EUA) are allocated at not charge (only in period 2005-2012, which is also our sample period), among all participating companies at the beginning of each year. At the end of each year, each company must hold a number of EUAs equal to its level of emissions. Companies that maintain their emissions below the level of their allowances can sell their excess and, thus, obtain revenue. Those that want to emit more than permitted must buy EUAs and, thus bear cost. Given the above, EUAs are either a revenue or a cost for companies involved in the EU ETS. In this way, pollution issues have been directly introduced in company income statements. As a consequence, the difference between allocated units and actual emissions, which determines the number of EUAs to buy or sell, is a key issue for company management.

Apart from adjusting their emissions to the restrictions imposed by the EU ETS, power stations (companies involved in the EU ETS are divided by the European Commission into two main groups: power stations and industrial plants) are expected to make an effort to improve efficiency, according to the 20% efficiency target mentioned above, which encourages the more efficient use of energy at all stages of the energy chain, from production to final consumption. (Directive 2012/27/EU).

In this research, we focus on the Spanish energy companies integrating the EU ETS with two objectives in mind. First, given that these companies aim to increase efficiency in the context of the climate and energy package, we measure both their technical and their environmental efficiency. Second, as these firms have CO_2 emissions limits imposed by the EU ETS, we calculate to what extent environmental efficiency determines the way a company can achieve its emissions goals. In this context, our research is very valuable for company management as we can determine how the level of environmental efficiency influences and determines the number of EUAs a company must buy, or is able to sell, and, consequently, the expenses and revenues of the company related to those EUAs.

To achieve our first objective of measuring technical and environmental efficiency we estimate a production stochastic frontier with two outputs: good (production) and bad (emissions) proposed by Fernandez et al. (2002). This model provides the estimation of both environmental and technical efficiency for each company in our sample. We use Bayesian methods to estimate the model, which are a good option when estimating models with latent variables, as is our case (technical and environmental efficiency are latent variables in our model). We then focus on our second objective, to estimate the effect of environmental efficiency on the number of EUAs companies must buy or can sell. To achieve our goal, we use quantile regression techniques that, allow us to study the relationship in depth by analysing behavior not only in the centre but also in the intermediate and tail areas of the distribution (Koenker and Hallock, 2001).

Efficiency issues have already been tackled in the context of the EU ETS with the objective of analyzing how the EU ETS influences company and country environmental efficiency. Examples of studies in the literature that analyze how the EU ETS affects environmental efficiency at the country level are Wu et al. (2014) and Jaraite and Di Maria (2012). The former, focuses on the production of desirable and undesirable outputs in the agricultural European sector, while the latter, examines the productive and environmental efficiency of fossil-fuel public power plants. Both studies conclude that carbon pricing leads to an increase in environmental efficiency. In addition, the study of the energy sector in the context of emissions markets is wide spread in the literature not only in the EU ETS context (see Schmidt et al. (2012)) but also in other carbon markets, such as the US (see Thuthill (2008) and Cuesta et al. (2009)).

Our contribution to the literature is two-fold. First, this is the first paper to analyze in depth the environmental and technical efficiency of Spanish energy companies in the EU ETS, in the period 2005-2012. Second, we have found no other analysis in the literature that focuses on how environmental efficiency affects the way a company uses EUAs.

In addition to the implications for company management, our research has implications for policy makers. In Spain, emissions from the energy sector represented 60% of the total in period 2005-2012 and is the one that makes the most physical investments in Spain, and in the process generates over 50,000 direct jobs and 400,000 indirect jobs (UNESA, 2015). Taking into account the dependence of the whole economy on this sector, an increase in the costs of power stations increases the costs of companies in all sectors.

The structure of the paper is as follows: Section 3.2 provides a brief explanation of the EU ETS allocation system, Section 3.3 focuses on the first objective of this research, Section 3.4 works on the second objective, and Section 3.5 presents the conclusions of our work.

3.2 The energy sector in Spain

Given that the difference between allocated EUAs and actual emissions of the energy sector is an important variable in our research, we consider it quite useful to provide the reader with a brief review on how EUAs were allocated during period 2005-2012, and the particular situation of the energy sector in this context.

The European Union Emissions Trading Scheme (EU ETS) was launched in 2005 and its implementation was planned in three phases: Phase I in 2005-2007, Phase II in 2008-2012, and Phase III beginning in 2013 and extending to 2020.

In 2005-2012, companies in the EU ETS received, free, a quantity of EUAs at the beginning of each year. Each country had its owns distribution plan among the companies involved, known as the National Allocation Plan (NAP).There were two NAPs: NAP I for period 2005-2007 and NAP II for 2008-2012 and each country had its own rules when configuring its NAPs. In the case of Spain, the calculation of each company's allowances was carried out according to a given company's previous emissions and production levels. NAP I was designed in 2004 and each allocation was calculated according to the emissions levels prevailing during period 1990-2001. First, emissions annual average growth for period 1990-2001 was calculated. Second, this annual growth was applied to emissions in year 2001, to determine emissions in 2006. Third, potential reduction of emissions for 2006 was subtracted from the predicted emissions figure. Finally, taking into account emissions for 2006, emissions for 2005 and 2007 were determined. NAP II was drawn in 2006 and EUAs distribution was carried out following an emissions/production criteria using data from 2001-2005.First, the emissions intensity ratio was calculated: emissions 2005/production 2005 (adjusted by a potential reduction factor). Second, estimated production for year 2010 was calculated by multiplying annual average production growth for period 2001-2005 and production in 2005.

For period 2013-2020, a single, EU-wide cap on emissions applies replacing the previous system of national caps, and auctions not free allocation, is now the default method for allocating allowances. Nevertheless, the transition from one allocation system to the other is carried out gradually. In 2013 more than 40% of allowances were auctioned, and this share will rise progressively each year. Those industries that have a large share of international trading, and whose international competitors do not have a climate-change policy restriction, would be at a disadvantage (an additional cost) because of the EU ETS.

This situation is known as *carbon leakage*. To help sectors and sub-sectors with *carbon leakage* risk, the European Commission gives the affected companies a larger share of free allowances than the rest. In this context, the European Commission considers the risk of carbon leakage for the energy sector is not significant. From 2013 onwards, power stations receive a smaller proportion of free allowances than the industrial sectors. Thus, the study of the drivers of the Surplus of Allowances, which indicates the number of EUAs a company buys or sells in relative terms, is of some importance for the energy sector, as it has an additional cost, linked to EUAs, in comparison to the industrial sector.

3.3 Analysis of the technical and environmental efficiency

3.3.1 Setting up the problem

Our first objective is to measure the technical and environmental performance of Spanish energy companies in the EU ETS. To achieve our goal, we use the production stochastic frontier model proposed by Fernández et al., (2002). This model is appropriate for production processes that yield both good outputs and undesirable ones. We consider one good output (the electricity produced by power stations) and one undesirable output(CO_2 emissions released during the electricity generating process).

In this model, the best-practice technology for turning inputs into outputs is given by the following relationship:

$$f(y, b, x) = 0 \tag{3.1}$$

where y denotes the quantity of electricity produced, b represents the CO_2 emissions and x is the vector of inputs needed to obtain these outputs. In this paper we consider three different inputs: labour, capital and supplies.

The maximum good output obtained with the available x inputs is given by the function $h_y(x)$ known as the production frontier.

$$y = h_y(x) \tag{3.2}$$

The minimum quantity of bad output necessary to obtain a certain amount of good output is given by the function $h_b(y)$ known as the environmental frontier.

$$b = h_b(y) \tag{3.3}$$

For a firm producing (y,b) with inputs x, we can now define:

$$u_y \equiv y/h_y(x) \tag{3.4}$$

$$u_b \equiv h_b(y)/b \tag{3.5}$$

$$0 \leq (\tau_y, \tau_b) \leq 1 \tag{3.6}$$

where u_y denotes the technical efficiency and u_b the environmental efficiency.

3.3.2 The model

We have data from an unbalanced panel of $i = 1, ..., N_i$ firms, where the i^{th} firm has been observed for $t = 1, ..., T_i$ time periods. The i^{th} firm in the t^{th} period produces good output $y_{i,t}$ and bad output $b_{i,t}$. $x_{i,t}$ is the vector of inputs used by the i^{th} firm in the t^{th} period. For both the production and the environmental frontier, we consider a Cobb-Douglas specification, i.e. it contains an intercept and is linear in the logs of the inputs. We include another variable affecting both frontiers: a year indicator variable. The equations of the model are given by:

$$y_{i,t} = x^{'}_{i,t}\beta - z_i + \varepsilon^y_{i,t} \quad with \quad \varepsilon^y_{i,t} \sim N(0, \sigma^2_y) \tag{3.7}$$

where y_{it} is $log(Production_{i,t})$

$x^{'}_{it} = (1, log(Labour_{i,t}), log(Capital_{i,t}), log(Supplies_{i,t}), I_{2005}, I_{2006}, I_{2007}, I_{2008}, I_{2009}, I_{2010}, I_{2011}, I_{2012})$

$x^{'}_{i,t}\beta$ defines the maximum level of production for a given quantity of inputs. We impose regularity conditions on β except for the intercept and β of the year indicator. Economically we are assuming that the maximum production obtained by a firm increases (decreases) when inputs increase (decrease). Any (negative)deviation from this maximum level of production is labelled as *technical inefficiency*: z_i . The stochastic element of the model is introduced through $\varepsilon^y_{i,t}$. We assume ε^y_{it} distribution to be Normal.

$$b_{i,t} = y'_{i,t}\delta + \upsilon_i + \varepsilon^b_{i,t} \quad with \quad \varepsilon^b_{i,t} \sim N(0, \sigma^2_b) \tag{3.8}$$

where $b_{it} = log(Emissions_{it})$ $y'_{i,t} = (1, log(Production_{it}), I_{2005}, I_{2006}, I_{2007}, I_{2008}, I_{2009}, I_{2010}, I_{2011}, I_{2012})$ $y'_{i,t}\delta$ defines the minimum level of CO_2 emissions for a given level of energy production, similar to the regularity condition imposed on β in equation 3.7. δ is restricted to be non-negative (except for the intercept and δ of the year indicator). In this way, we are assuming that an increase in the production level will never imply a reduction in the amount of CO_2 emissions. Any (positive) deviation from this minimum level of emissions is considered as *environmental inefficiency*: υ_i. The stochastic element of the model is introduced through ε^b_{it}, which captures the usual measurement error and model imperfections. We assume ε^b_{it} distribution to be Normal

The connection between inefficiencies (z_i and υ_i) in the equations 3.7 and 3.8 and efficiencies in 3.4 and 3.6 is carried out as follows. As dependent variables in 3.7 and 3.8 have been transformed to logarithms, technical efficiency u_y for the i^{th} firm is defined as $u_y = exp(-z_i)$ and environmental efficiency u_b for the i^{th} firm is defined as $u_b = exp(-\upsilon_i)$. Similarly to Fernández et al. (2002),in this paper we assume that z_i and υ_i for each company are constant over time. In that study, the authors consider that other firm-specific characteristics may affect the inefficiencies distributions. In our paper, we consider company size as the inefficiencies distributions unique explanatory variable.

$$\begin{pmatrix} z_i \\ \upsilon_i \end{pmatrix} \sim TN_{2,R^+xR^+}\left(\begin{pmatrix} \mu^z_i \\ \mu^\upsilon_i \end{pmatrix}, \Omega\right) \tag{3.9}$$

where TN denotes the Truncated Normal and:

$$\begin{pmatrix} \mu^z_i \\ \mu^\upsilon_i \end{pmatrix} = \begin{pmatrix} \phi' \\ \psi' \end{pmatrix} g_i \tag{3.10}$$

where g_i is a matrix of dimension dx1, with d being the number of categorical possible values of the size variable. We divide companies in our sample in four groups: g_i^1, g_i^2, g_i^3, g_i^4 that go from the smallest companies to the larggest ones. To simplify the notation we make this transformation: $G_i = g_i^{'} \otimes I_2$ and $\gamma = \begin{pmatrix} \phi \\ \psi \end{pmatrix}$ So, expression 3.10 can now be written as:

$$\begin{pmatrix} \mu_i^z \\ \mu_i^v \end{pmatrix} = G_i\gamma \tag{3.11}$$

Finally, we also denote:
$\tau_y = \frac{1}{\sigma_y^2}\tau_b = \frac{1}{\sigma_b^2}$ and $E_i = \begin{pmatrix} z_i \\ v_i \end{pmatrix}$

The estimation of the parameters presented above will be carried out following a bayesian approach. (see Appendix B.2).

3.3.3 Data

According to Directive 2003/87/EC companies in the EU ETS are divided into 9 sectors. The first covers power stations (”Combustion installations with a rated thermal input exceeding 20 MW, mineral oil refineries and coke ovens”). Sectors 2 to 9 are industrial sectors producing iron, steel, cement, glass, lime, bricks, ceramics, and pulp and paper.

Each member of the EU ETS had a national registry where all participating companies were listed until 2012. ”Registro Nacional de Derechos de Emisión (RENADE)” was the Spanish EU ETS national registry. According to the RENADE , there were 355 companies belonging to the energy sector that had been part of the EU ETS in any year from 2005 to 2012. Thirty of these companies provided no data on CO_2 emissions and allocations so we had to discard them. Then, our initial sample was reduced to

Table 3.1: **Data availability. Years**

Year	companies
2005	64
2006	163
2007	183
2008	212
2009	227
2010	235
2011	205
2012	209
TOTAL	1498

325 companies, and from these, we selected those that had available information on our variables of interest, for at least one of the years between 2005 and 2012. Thus, our final sample was reduced to N=267 in T=8, in total 1498 observations. Table 3.1 presents the number of companies that have available all the data needed to undertake our research in every year of our sample.

To estimate the technical and environmental frontier we used the following data.

Good output: Sales in millions of euros.

Bad output: Emissions in tonnes of CO_2.

Inputs: Personnel expenses in millions of euros (Labour), Amortisation of assets in millions of euros (Capital), Supplies in millions of euros (Supplies) (In energy companies "supplies", usually aggregates three kinds of costs: energy purchases, fuels consumption and transport expenses. We found only the "supplies" figure, the share of each cost was not available in the database we used for this research)

Other variables affecting the frontiers: Dummy time variable. Years: 2005,2006,2007, 2008,2009,2010,2011,2012

Explanatory variables affecting the inefficiency distribution: Company size (asset size). First, the average of the asset value for 2005-2012, for each company, was calculated. Companies were divided into four groups corresponding to the four quartiles of the size distribution (Q1.Small companies, Q2.Small-medium commpanies, Q3.Medium-big companies, Q4.Big companies). This classification remains constant for the whole period.

Data on sales, personnel expenses, amortisation of assets, supplies and size were taken from SABI, a database that provides 1,250,000 Spanish and 400,000 Portuguese company reports. These reports include, among other information: company financial profiles, summary of company industrial activities, Balance Sheets, Profit and Loss accounts, and financial ratios.

Data of CO_2 emissions were taken from the Community Independent Transaction Log (CITL) for the years 2005-2011, and from the European Union Transaction Log (EUTL).From 2005 to June 2012, every national registry was linked to the Community Independent Transaction Log (CITL). According to Directive 2009/29/EC, the CITL, together with the national registries, was replaced by a unique European Registry: the European Union Transaction Log (EUTL), activated in June 2012. Since we concentrate on the period 2005-2012, and we began to collect data in 2011, when EUTL had not yet been activated, we took our data from RENADE and CITL for the period 2005-2011 and from EUTL for year 2012.

Descriptive statistics

Tables B.1, B.2, B.3, B.4, B.5, present the main statistics of the variables used in our work. As can be observed in Table B.1, the sales mean decreased gradually from year 2005 to 2009, when sales reached the minimum for the period. This decline followed the onset of the economic crisis. From 2010 onwards, sales began to increase until 2012. This pattern is the same as that of labour costs (see Table B.2), amortisation (see Table B.3)and supplies (see Table B.4).All of these variables are heavily skewed to the right and kurtosis is considerably pronounced, arising from the existence of a low percentage of firms with strong positive values.

We now turn to the descriptive statistics for emissions. Similarly to the distribution of the rest of our variables, the distribution of emissions is highly skewed to the right in every year of our sample. Again, it seems that a small group of companies have a greater level of emissions. As seen in Table B.5, the mean of emissions was much higher in 2005, in comparison with the rest of the period. The EU ETS was created in 2005 and, from that year, companies were incorporated on a gradual basis. As 2005 is the first year, the number of companies involved in this market was significantly lower than in the rest of the sample. It appears that companies with higher emissions entered in the EU ETS in the first year. Although the number of companies in the EU ETS significantly increased in 2006, as those with much higher emissions had already been incorporated in the EU ETS the year before, the mean of emissions from 2006 onwards was significantly lower with respect to year 2005. To avoid biased results, we estimate two different stochastic frontier models: one for the years of our sample, and the other for the sample period: 2006 to 2012.

3.3.4 Empirical results and discussion

In this section we present the results of the Bayesian estimation of the technical and environmental frontiers, based on a Markov chain of 100,000 drawings after discarding the first 10,000. All calculations were made in MATLAB R2013b. The code written to obtain our results is provided in Appendix B.3.

According to the exploratory analysis carried out in the previous section, we consider that year 2005 may bias our results because the number of companies with available data that year was very low (See Table 3.1) so we estimate two different models: one including year 2005 and another without it. Furthermore, we consider two different models: one with a categorical year variable and another with a general intercept. Matching both criteria we estimate the following four models.

◇Model 1. Categorical year variable and T= 2005,...2012.

◇Model 2. Categorical year variable and T= 2006,...2012.

◇Model 3. No Categorical year variable and T= 2005,...2012.

◇Model 4. No Categorical year variable and T= 2006,...2012.

As seen in Table 3.2 and Table 3.3, there is no great difference between Model 1 and Model 2 and between Model 3 (see Table 3.4) and Model 4 (see Table 3.5) so we can consider either Model 1 or Model 3, both of which include the entire sample period without being concerned about any potential 2005 bias effect. Regarding the categorical time variable, it appears irrelevant to introduce a year variable in the technical frontier (no significant difference between the intercept in Model 3 and the categorical variable in Model 1), although it does seem that the categorical time variable is somewhat significant in the case of the environmental frontier, therefore, we finally select Model 1, which includes the dummy time variable, to carry out the analysis of the technical and environmental frontier.

Since our model has a log-log specification, the βs (in the case of the technical frontier) and the δ (in the case of the environmental frontier) are interpreted as elasticities. Each β represents the percentage a company's sales increases when the correspondent input increases 1%. As we have seen, all βs have a positive sign due to the regularity condition we imposed when formulating the model, i.e. an increase in sales could not be achieved without a decrease in one or more of the inputs. The supplies-sales elasticity is considerably higher than the other elasticies, which is consistent with the fact that the supplies usually is the line of the Profit and Loss Statement most representative in this kind of company. δ is also positive due to the regularity condition imposed, which defined that an increase in electricity production could never be obtained without an increase in CO_2 emissions, δ is aproximmately 0.25, i.e. when electricity production increases by 1% , CO_2 emissions go up by 0.25%.

The Returns to Scale (RTS) in the technical frontier is the rate of increase in electricity production relative to the associated increase in labour, capital and supplies. RTS in the environmental frontier has the same value as δ because we only consider one output in our analysis. The RTS technical is 0.7322 (the median), i.e. an increase of 1% in all the inputs is translated into a 0.7322 % increase in electricity production.

The RTS-environmental is 0.2494, i.e. an increase of 1% in electricity production is translated into a 0.2494% increase in CO_2. As we have seen, the RTS bad outputs is considerably lower. This figure should be taken into consideration by energy company managenment when making decisions on increasing their production levels. More specifically, they could evaluate the trade-off between the increase in revenues due to the increase in sales (1%) and the increase in costs (buy more EUAs) because of the additional CO_2 emissions (0.25%).

Regarding the effect of time on the frontiers, note that the difference among the years is more significant in the environmental frontier, as we explained earlier. Note that δ_5 is lower than previous δs, indicating that emissions began to decrease progressively from 2008 on, which is consistent with the beginning of the crisis in 2008.

The stochastic Bayesian estimation provides us with both technical and environmental estimated inefficiency values for each company in our sample.

Regarding company size, large companies appear to be more efficient in technical (ϕ) terms. The contrary happens when we look at the environmental frontier (ψ), small companies appear to be more efficient than large ones. Nevertheless, differences resulting from size are greater in the technical frontier than in the environmental one.

In the context of the "20-20-20" climate & energy targets ((Directive 2012/27/EU) this result shed more light on how the size affects how well companies do. It appears that big companies are better at achieving the 20% energy efficiency improvement target (technical efficiency) and small ones are more likely to achieve their environmental targets in the EU ETS context. This suggests that managers of large companies should focus more on policies to improve their environmental inefficiencies, whereas small companies should pay more attention to their technical efficiency.

Table 3.2: **MODEL 1**

TECHNICAL FRONTIER			
	2.5	Median	97.5
β_1 (Labor)	0.0684	0.1007	0.1284
β_2 (Capital)	0.1236	0.1570	0.1905
β_3 (Supplies)	0.4520	0.4755	0.5008
RTS (Good output)	0.6932	0.7322	0.7708
β_4 (Year 2005)	20.0938	20.3365	20.6252
β_5 (Year 2006)	20.1509	20.3809	20.6656
β_6 (Year 2007)	20.1482	20.3754	20.6745
β_7 (Year 2008)	20.1754	20.4025	20.6918
β_8 (Year 2009)	20.1585	20.3866	20.6882
β_9 (Year 2010)	20.2100	20.4438	20.7276
β_{10}(Year 2011)	20.2625	20.4872	20.7787
β_{11}(Year 2012)	20.2489	20.4766	20.7757
ϕ_1 (Q1. SMALL COMPANIES)	2.6927	3.0026	3.3460
ϕ_2 (Q2 SMALL-MEDIUM COMPANIES)	2.4248	2.7000	3.0235
ϕ_3 (Q3 MEDIUM-BIG COMPANIES)	2.1086	2.3605	2.6879
ϕ_4 (Q4 BIG COMPANIES)	1.4019	1.6879	2.0073
δ_1 (Sales)	0.1903	0.2494	0.3029
ENVIRONMENTAL FRONTIER			
RTS (Bad output)	0.1903	0.2494	0.3029
δ_2 (Year 2005)	0.1660	1.024	2.1161
δ_3 (Year 2006)	0.1710	1.0233	2.1182
δ_4 (Year 2007)	0.2264	1.09401	2.1937
δ_5 (Year 2008)	0.0926	0.9394	2.0764
δ_6 (Year 2009)	0.0668	0.9135	2.0460
δ_7 (Year 2010)	0.0502	0.8895	2.055
δ_8(Year 2011)	0.0005	0.7234	1.8686
δ_9(Year 2012)	0.0040	0.7745	1.8848
ψ_1 (Q1. SMALL COMPANIES)	3.3104	4.0099	4.6311
ψ_2 (Q2.SMALL-MEDIUM COMPANIES)	3.5253	4.1185	4.6630
ψ_3 (Q3 MEDIUM-BIG COMPANIES)	3.8767	4.5163	5.0337
ψ_4 (Q4 BIG COMPANIES)	4.2069	4.8786	5.4021
VARIANCE OF THE MODEL			
τ_y	0.2513	0.2617	0.2725
τ_b	0.4949	0.5159	0.5381

Table 3.3: **MODEL 2**

TECHNICAL FRONTIER			
	2.5	Median	97.5
β_1 (Labor)	0.0632	0.0942	0.1253
β_2 (Capital)	0.1279	0.1601	0.1935
β_3 (Supplies)	0.4479	0.4740	0.4999
RTS (Good output)	0.6878	0.7278	0.7673
β_4 (Year 2005)			
β_5 (Year 2006)	20.1279	20.3663	20.6873
β_6 (Year 2007)	20.1297	20.3590	20.6758
β_7 (Year 2008)	20.1587	20.3846	20.6904
β_8 (Year 2009)	20.1408	20.3726	20.6835
β_9 (Year 2010)	20.1960	20.4212	20.7282
β_{10}(Year 2011)	20.2423	20.4694	20.7784
β_{11}(Year 2012)	20.2312	20.4535	20.7554
ϕ_1 (Q1)	2.7001	3.0102	3.3571
ϕ_2 (Q2)	2.4147	2.6984	3.0201
ϕ_3 (Q3)	2.0902	2.3542	2.6840
ϕ_4 (Q4)	1.3893	1.6746	2.0156
ENVIRONMENTAL FRONTIER			
δ_1 (Sales)(RTS Bad output)	0.1926	0.2445	0.2983
δ_2 (Year 2005)			
δ_3 (Year 2006)	0.2084	1.0144	2.0592
δ_4 (Year 2007)	0.2691	1.0658	2.1394
δ_5 (Year 2008)	0.1285	0.9323	2.0169
δ_6 (Year 2009)	0.1006	0.8919	1.9535
δ_7 (Year 2010)	0.0863	0.8664	1.9548
δ_8(Year 2011)	0.0036	0.7077	1.7853
δ_9(Year 2012)	0.0136	0.7611	1.8153
ψ_1 (Q1)	3.4544	4.1037	4.7583
ψ_2 (Q2)	3.6420	4.2312	4.7407
ψ_3 (Q3)	4.0038	4.6418	5.2462
ψ_4 (Q4)	4.2755	5.0083	5.5725
VARIANCE OF THE MODEL			
τ_y	0.2545	0.2650	0.2750
τ_b	0.4873	0.5090	0.5307

Table 3.4: **MODEL 3**

TECHNICAL FRONTIER			
	2.5	Median	97.5
β_0 (Intercept)	20.2690	20.4924	20.7697
β_1 (Labor)	0.0708	0.1021	0.1344
β_2 (Capital)	0.1168	0.1475	0.1801
β_3 (Supplies)	0.4609	0.4853	0.5102
RTS (Good output)	0.6994	0.7340	0.7746
ϕ_1 (Q1)	2.7594	3.0558	3.3893
ϕ_2 (Q2)	2.4808	2.7566	3.0878
ϕ_3 (Q3)	2.1599	2.4458	2.7878
ϕ_4 (Q4)	1.4885	1.7699	2.0993
ENVIRONMENTAL FRONTIER			
δ_0 (Intercept)	0.0411	0.9762	2.1746
δ_1 (Sales)(RTS bad output)	0.1693	0.2295	0.2778
ψ_1 (Q1)	3.6357	4.2596	4.9093
ψ_2 (Q2)	3.8406	4.3832	4.9065
ψ_3 (Q3)	4.3228	4.8885	5.4750
ψ_4 (Q4)	4.7031	5.2190	5.7974
VARIANCE OF THE MODEL			
τ_y	0.2546	0.2653	0.2776
τ_b	0.5045	0.5248	0.5462

Table 3.5: **MODEL 4**

TECHNICAL FRONTIER			
	2.5	Median	97.5
β_0 (Intercept)	20.2215	20.4710	20.7908
β_1 (Labor)	0.0617	0.0918	0.1243
β_2 (Capital)	0.1172	0.1533	0.1846
β_3 (Supplies)	0.4609	0.4853	0.5102
RTS (Good output)	0.6858	0.7253	0.7646
ϕ_1 (Q1)	2.7492	3.0720	3.4204
ϕ_2 (Q2)	2.4746	2.7543	3.0994
ϕ_3 (Q3)	2.1448	2.4256	2.7624
ϕ_4 (Q4)	1.4513	1.7401	2.0876
ENVIRONMENTAL FRONTIER			
δ_0 (Intercept)	0	0.7041	1.9258
δ_1 (Sales) (RTS Bad output)	0.1668	0.2302	0.2687
ψ_1 (Q1)	3.8333	4.4758	5.1385
ψ_2 (Q2)	4.0134	4.6168	5.1320
ψ_3 (Q3)	4.5384	5.0688	5.6543
ψ_4 (Q4)	4.9657	5.4629	5.9945
VARIANCE OF THE MODEL			
τ_y	0.2575	0.2678	0.2793
τ_b	0.4950	0.5155	0.5377

Finally, we focus our attention on those companies that account for the lion's share of total emissions. As seen in the exploratory analysis, emissions are heavily skewed to the right. The reason for this is that there is a small group of firms with extremely high emissions compared to the other firms. As seen in Table 3.6, only four of our sample of 267 companies (1.5% of our sample) are responsible for over 50% of total emissions in almost every year. We refer to this set of companies as: "the Big 4". As seen in Table 3.6, these companies are also important in terms of sales, capital and supplies. In 2012, they account for 16% of sales, almost 30% of the total capital of the sector and 20% of supplies. Note that the importance of The Big 4 has growth since the beginning of the period.

Table 3.7: **Technical and environmental inefficiencies of Big 4**

Company	z	Ranking (- to +)	v	Ranking (- to +)
Big 4. Company 1	1.4541	20	10.4829	267
Big 4. Company 2	1.2473	10	9.2195	261
Big 4. Company 3	1.5382	26	9.9832	266
Big 4. Company 4	2.0174	74	9.5709	264

Table 3.6: **The Big 4**

	2005	2006	2007	2008	2009	2010	2011	2012
Emissions	0.54	0.52	0.52	0.50	0.42	0.36	0.51	0.51
Sales	0.07	0.07	0.06	0.09	0.08	0.12	0.14	0.16
Labour	0.06	0.06	0.06	0.05	0.07	0.07	0.07	0.07
Capital	0.20	0.19	0.17	0.18	0.22	0.25	0.25	0.29
Supplies	0.09	0.10	0.07	0.11	0.09	0.15	0.17	0.20

Note: The percentage of "The Big 4" out of the total sample

Given this, it is worthwhile focusing on companies with higher emissions, as a great part of the global amount of emissions of Spanish energy firms in the EU ETS is due to the environmental behaviour of these few firms. In Table 3.7 is presented the technical (z) and environmental inefficiency (v) obtained in our model for each of The big 4. Furthermore, we ranked all companies in our sample, from less to more inefficient, and provide the place of each of these four companies in our ranking. As can be seen, they are well-positioned in terms of technical efficiency but are at the bottom of the environmental ranking.

3.4 Does it pay to be environmentally efficient?

3.4.1 Setting up the problem

The stochastic Bayesian estimation provides us with both technical and environmental estimated inefficiency values for each company in our sample. This information is quite valuable to carry out new analysis that may shed further light for companies involved in the EU ETS.

More specifically, we use the environmental inefficiency values to achieve our second objective: to calculate how environmental efficiency affects the quantity of EUAs a company has to buy or has the possibility to sell.

When distributing EUAs among companies in the EU ETS, the European Commission (2009) stated that the allowance allocated to a company should not exceed the amount of CO_2 it was expected to emit, a restriction intended to stimulate a company's efforts to control its emissions. Basically, we consider that, in addition to environmental efficiency, there is another variable that may have an influence on whether or not a company has emitted more or less than its allocation, and that is the company's production levels. Thus, we also take production levels into account.

To analyze the effect of both environmental efficiency and production levels in the difference between allocated EUAs and final CO_2 emissions, we employ quantile regression techniques.

3.4.2 Methodology/quantile regression

In this section, we briefly describe the quantile regression technique. This technique was already used in Chapter 2, where we estimate the nonlinear p quantile regression that is based on the specification of the copula function that defines the dependency structure between the variables of interest. In this case, as we want to analyze the simultaneous effect of two variables on the dependent variables, we would have to estimate a multivariate copula (in Chapter 2 we considered a bivariate copula). As the implementation of this procedure is considerably complex, in this Chapter we decided to estimate a linear quantile regression. The estimation of the non-linear quantile regression through a multivariate copula will be done in future work.

Here, we provide the reader with a revision of the quantile regression technique in a linear context. This methodology allows us to study the effect of environmental efficiency and production on the difference between allocated EUAs and final CO_2

emissions, not only in the centre of the distribution but also in the intermediate and tail areas (Koenker and Hallock, 2001). This technique is appropiate when the normality assumption is rejected for the variables employed, as in our case and as will be shown in the following section.

Let $(\boldsymbol{x_{i,t}}, y_{i,t}); i = 1, ..., N_i; t = 1, ..., T$ be the data set where $y_{i,t}$ is the dependent variable (difference between allocated EUAs and final CO_2 emissions) and $\boldsymbol{x_{i,t}} = (x_{i,t,1}, ..., x_{i,t,k})$ is the $(kx1)$ vector of independent variables (production and environmental efficiency)

We consider linear quantile regression models that assume that

$$Quantile_{\theta}(y_{i,t}|\mathbf{x_{i,t}}) = \mathbf{x}'_{\mathbf{i,t}}\beta_{\theta} \tag{3.4.1}$$

where $Quantile_{\theta}(y_{it}|\mathbf{x_{it}})$ denotes the θ $(0 < \theta < 1)$ quantile of the conditional distribution $(y_{it}|\mathbf{x_{it}})$ and $\boldsymbol{\beta_{\theta}} = (\beta_{\theta,j}; j = 1, ..., k)$ is the $(kx1)$ vector of parameters that quantifies the impact of the independent variables on the θ quantile of $y_{i,t}$. The value of $\boldsymbol{\beta_{\theta}}$ is obtained by minimizing

$$min_{\beta}\frac{1}{n}\sum_{i,t;y_{i,t}\geq x'_{i,t}\beta}\Theta|y_{i,t} - x'_{i,t}\beta| + \sum_{i,t;y_{it}<x'_{i,t}\beta}(1-\Theta)|y_{i,t} - x'_{i,t}\beta| \tag{3.4.2}$$

3.4.3 Data

To measure the number of EUAs to buy/sell, we take the environmental indicator constructed in Chapter 2, SA, which measures the difference between allocated EUAs and actual CO_2 emissions in relative terms.

Surplus of Allowances

$$SA_{i,t} = \frac{A_{i,t} - E_{i,t}}{A_{i,t}} \tag{3.4.1}$$

where A_{it} is the number of allowances for company i to be used to justify CO_2 emissions in year t, E_{it} is the quantity of CO_2 emitted by company i during period t.

Assets Turnover Rotation (ATR)

To measure company production,as we did in Chapter 2, we select the Assets Turnover Ratio (ATR)

$$ATR_{i,t} = \frac{Operating\, revenue_{i,t}}{Assets_{i,t}} \tag{3.4.2}$$

Data for ATR is taken from SABI. Data for CO_2 emissions and CO_2 allocations are taken from the Community Independent Transacation Log (CITL).

Environmental efficiency

The environmental efficiency of each company is taken from the bayesian estimation of the environmental frontier model. In fact, in the previous section, we obtained company inefficiency (v), which we will take into account when interpreting our results.

Descriptive statistics

In table B.6 a descriptive analysis of SA is shown. As can be seen, the mean is positive for every year of the period, indicating that companies emitted less than allocated. Note that, from 2008 on, the SA mean increased considerably. This could be explained by the reduction of emissions due to the reduction of production levels caused by the onset of the economic crisis in 2008. Nevertheless, a small group of companies have lower SA than the rest, as the negative sign of the skewness coefficient indicates. The Jarque-Bera normality test is rejected.

Table B.7 presents the descriptive analysis of ATR. As can be seen, ATR is heavily skewed to the right and kurtosis is considerably pronounced. This arises from the existence of a low percentage of firms with strong positive values. Similarly to the SA variable, the normality test is rejected.

3.4.4 Empirical results and discussion

In this section, we present the results of the estimation of the quantile regression, where SA is the dependent variable and environmental inefficiency and ATR are the explanatory variables. All the calculations were done using the package R with the quantreg library (for more information see Koenker, 2006). Although we have a unique inefficiency measure for each company that works as an average for the whole period, we have SA data for each firm in each period. Therefore, the evolution in time of the link between SA and v is also presented in this research.

As can be seen in Table 3.8, the effects of both environmental inefficiency and production are negative.

Table 3.8: **Quantile regression coefficients**

		0.05	**0.25**	**0.50**	**0.75**	**0.95**	**lineal**
2005	β_v	-0.038	-0.035***	-0.051***	-0.060*	-0.115***	-0.054***
	β_{ATR}	0.012*	0.006	0.004***	0.000	-0.006	0.004
2006	β_v	-0.028	-0.054***	-0.059***	-0.070***	-0.051***	-0.036
	β_{ATR}	-0.089	-0.015	-0.022***	-0.043	-0.069	-0.003
2007	β_v	-0.028	-0.054***	-0.059***	-0.070***	-0.051***	-0.095***
	β_{ATR}	-0.089	-0.015	-0.022***	-0.043	-0.069	-0.014
2008	β_v	-0.028	-0.054***	-0.059***	-0.0697***	-0.051***	-0.036
	β_{ATR}	-0.090	-0.015	-0.022***	-0.043	-0.069	-0.003
2009	β_v	-0.028	-0.054***	-0.059***	-0.070***	-0.051***	-0.036
	β_{ATR}	-0.090	-0.015	-0.022***	-0.043	-0.069	-0.003
2010	β_v	-0.082	-0.133***	-0.141***	-0.132***	-0.090***	-0.119***
	β_{ATR}	0.038	0.001	-0.024	0.005	-0.014	0.006
2011	β_v	-0.015	-0.137***	-0.127***	-0.109***	-0.070***	-0.095***
	β_{ATR}	0.199	-0.019	-0.074***	-0.092***	-0.125**	-0.014
2012	β_v	-0.047	-0.006	-0.033^{***}	-0.058^{***}	-0.019	-0.053^{***}
	β_{ATR}	-0.340	-0.029	-0.052	-0.025	-0.026	-0.061

*Note: Statistically different from zero at the *** 1%, ** 5%, * 10% significance levels*

The negative effect of inefficiency shows that the more inefficient a company is, the less SA it has. In other words, the more inefficient a company, the more EUAs it must buy (more expenses). This result suggests that being more environmentally inefficient has a negative financial consequence.

The negative impact of production indicates that an increase in electricity production is linked to a decrease in SA, and consequently to the purchase of more EUAs.

As mentioned in the descriptive analysis (section 3.4.3), SA is considerably skewed and presents a pronounced kurtosis. For this reason, a lineal regression approach would lead us to misleading conclusions, and so, we use a quantile regression that examines the effect of v and ATR, not only in the central part of the SA distribution, but also in different quantiles of the distribution.

As can be observed in Table 3.8 , the effect of inefficiency is statistically significant in all quantiles of SA, except the lowest. Figure 3.1 and 3.2 show the evolution of the effect of inefficiency on SA for each quantile of SA (quantile 0.05 is not drawn as the effect of v on SA is not statistically significant). As we have seen, from 2005 to 2009, the impact of inefficiency is lower in quantile 0.5 of SA. That is, a decrease in environmental inefficiency, according to our results, would be less rewarded in terms of buying fewer EUAs by companies with median SA. From 2009 to 2011, the effect of v increased (in absolute terms) in all quantiles of SA. In this period, the effect was similar in all quantiles except for quantile 0.95. This reflects that companies with very high SA would have fewer incentives than other companies to improve their environmental efficiency.

The effect of ATR (Table 3.8) is only statistically significant in companies with median SA. As observed in Figure 3.3and 3.4, the impact of ATR is greater in companies with high (quantile 0.95) and medium-high (quantile 0.75).

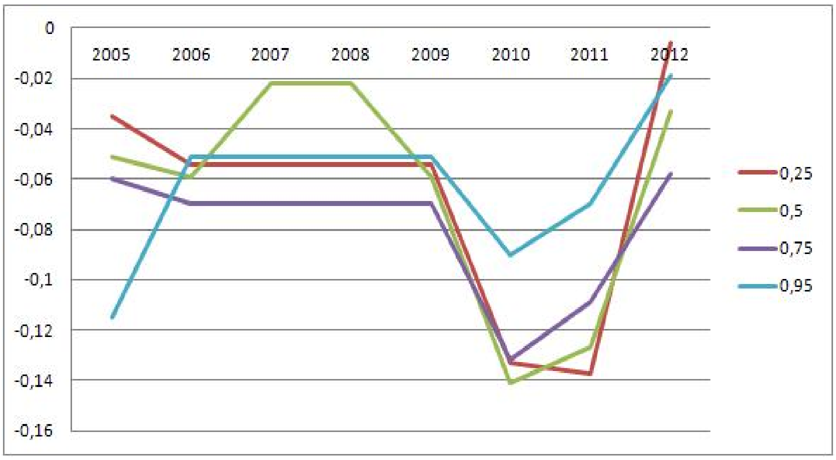

Figure 3.1: **Evolution of inefficiency effect (β_v in Table 3.8). Quantiles**

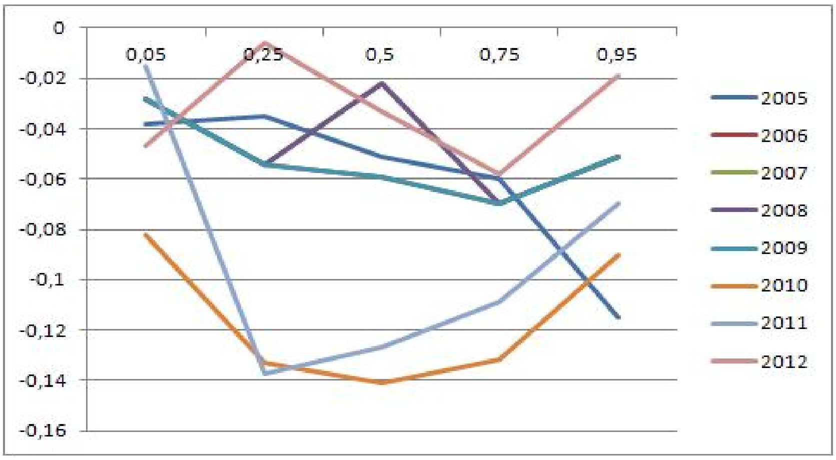

Figure 3.2: **Evolution of inefficiency effect (β_v in Table 3.8). Years**

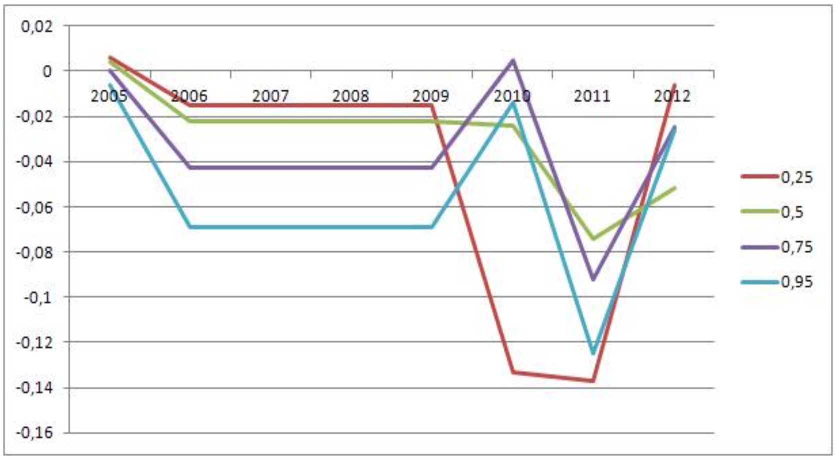

Figure 3.3: **Evolution of production effect (β_{ATR} in Table 3.8). Quantiles**

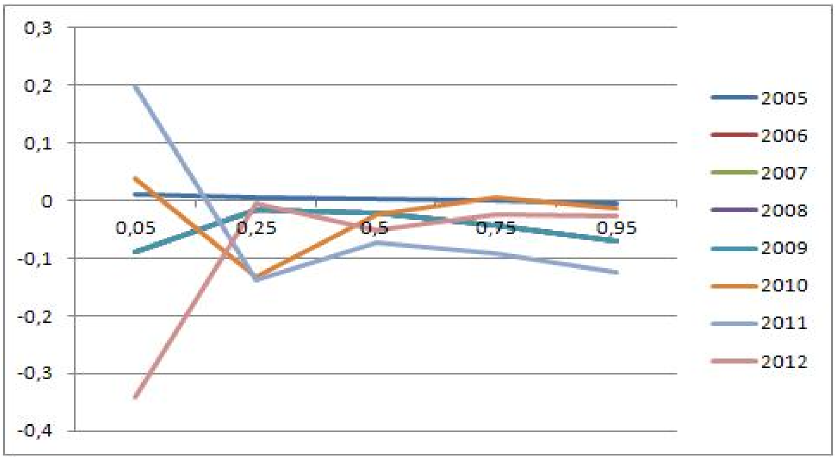

Figure 3.4: **Evolution of production effect (β_{ATR} in Table 3.8). Years**

3.5 Conclusions

Companies in the energy sector play an important role in achieving the targets of the European Union 2020 energy and climate package: they must improve their efficiency and have CO_2 limitations under the EU ETS. Thus, our research has two targets. To measure the technical and environmental efficiency of the companies, and, to calculate to what extent environmental efficiency determines the difference between allocated EUAs and final CO_2 emissions.

The results of our research are important for managent of companies in order to help them make decisions related to improvements in efficiency, and also in terms of improving its CO_2 emissions levels relative to the targets under the EU ETS. In addition, these results are important for policy makers, since the whole economy depends on the energy sector, i.e an increase in the costs of power stations increases the costs of companies in all sectors.

Regarding our first objective we obtain two main findings. First, large companies are more efficient in technical terms, whereas small companies are more efficient in terms of environmental efficiency, which suggests that managers of large companies should pay more attention to their environmental inefficiencies as they are doing worse, whereas small ones should focus more on policies to improve their technical efficiency. Second, the four firms responsible for over 50% of total emissions in the EU ETS ("the Big 4") are well-positioned in terms of technical efficiency, but are at the bottom of the environmental ranking. This finding is very important for policymakers. Since these companies represent more than half of the emissions of the EU ETS, and have very poor environmental scores relative to the other companies, governemnt should pay more attention to these companies individually, in order to discover the causes of this negative environmental behaviour as their CO_2 emissions considerably influence the way the energy sector.

Regarding our second objective, we obtain a relevant finding: there is a negative effect of inefficiency on the surplus of allowances. That is, the more inefficient a company, the more EUAs it must buy (more expenses). This result suggests that being more environmentally inefficient has negative financial consequences.

Chapter 4

Is there any link between the EU ETS and energy stock markets?

Third point of view: Investors.

4.1 Introduction

Today, climate change is a crucial concern and the reduction of CO_2 emissions has become an important issue for most of the governments of the world. Investors are more and more aware of this issue. In this context, it is important to study whether environmental policies influence the behavior of investors. To address this question, we focus on European climate change policy and, more specifically on the European Union Emissions Trading Scheme (EU ETS).

The energy sector is responsible for the bulk of the CO_2 emissions of the carbon market and, thus, the evolution of energy markets has influenced the EU ETS situation and vice-versa. This is in line with Diaz-Rainey et al (2011), who concluded that the financial risks of investing in energy and environmental markets also influence the goals of environmental policies. Likewise, Oberndorfer (2009a) studied the link between EUAs and the stock performance of electricity firms and found that that EU ETS has an impact on financial (stock) markets and therefore has economic consequences, affecting the value of the corporations covered. In addition, energy markets are also strongly connected to financial markets, as concluded Wen et al. (2012), Nazlioglu et al. (2015), among others.

The objective of this paper is to discover how the EU ETS and the investment in energy sector stocks are linked. More specifically, we concentrate on the interrelationship between EUA, stocks of clean energy companies stocks and stocks of oil and gas companies. With this analysis our aim is three-fold.

First, given that the objective of the EU ETS is to encourage investment in clean energy, we analyze whether EUA prices does, in fact, do this, while discouraging investment in oil and gas stocks. When analyzing the capacity of the EU ETS to trigger clean investment, most of the literature focus on the investments made by companies to reduce emissions (Calel and Dechezleprêtre, 2014; Rogge et al, 2011; Sandoff and Schaad, 2009.) Although we pursue the same aim, we study the issue from another perspective which has been less thoroughly explored: the perspective of the investors in energy stocks. Kumar et al. (2012) is an example of this branch of the literature. We contribute to the discussion by analyzing not only the effect of EUA on clean energy stocks but also the effect on oil and gas stocks which, to the best of our knowledge, has not yet been studied.

Second, we analyze the inverse effects, that is, how stocks of both kinds influence EUA prices. These prices are the cornerstone of the European climate change policy, and thus knowing what factors affect this price is relevant in terms of EU ETS efficacy. The main difference between EUAs and a traditional stock is that there are two different agents interested in this asset: companies that have binding CO_2 targets under the EU ETS and speculators who seek financial gain. Therefore, when analyzing the drivers of EUA we must take into account that price formation is determined not only by companies that participate in the EU ETS, but also by speculators. The EUA drivers have been widely studied in the literature (Alberola et al. (2013), Aatola et al. (2013)

and Lutz et al (2013)) Despite this, the price evolution of other stocks has not usually been considered to be EUA drivers. With this analysis, we aim to fill a gap in the literature.

Third, given that investment in energy markets is encreasing day by day, we study the link between clean energy stocks and oil and gas stocks. We find papers in the literature that analyze the interaction between clean stocks and high-tech stocks (e.g. Sadorsky, 2012 or Kumar et al., 2012), but the distinction between "clean" and "dirty" energy stocks has only been studied by Wen et al. (2012) in the context of China.

We analyze the simultaneous relationships among a set of variables and given the high frequency of the data we propose the use of the Vector Autoregressive Regression (VAR). We also include a set of control variables in the model. The VAR methodology provides not only results of the relationship among the endogenous variables of interest (EUA, clean energy stocks, oil and gas producers stocks) but also the effect of each exogenous variable on each of the endogenous variables. In addition, to modelize the volatility of the considered variables we employ a multivariate GARCH structure which estimates co-volatility dynamics. The multivariate GARCH approach is widely used in financial literature when analyzing time series data. The study period runs from May 2009 to Dicember 2013. We begin our sample period in May 2009 because it was from then when EUA prices began a period of stability after EUA prices sink in January 2009.

The rest of the chapter is organized as follows. Section 4.2 explains the main market fundamentals, Section 4.3 describes the data, Section 4.4 presents the methodology and Section 4.5, our results and, finally, Section 4.6 contains our conclusions.

4.2 Market fundamentals

The objective of this research is to analyze the inter-relationship between EUA, stocks of clean energy companies stocks and stocks of oil and gas companies. In addition, we take into account a set of control variables that also influence each of the previous variables. In Section 4.2.1 we describe the expected sign of the interrelations among our endogenous variables (main variables): EUA, clean energy stocks and oil-gas stocks. In Section 4.2.2 we focus on the expected effect of control variables on each of our main variables.

4.2.1 Main variables

The objective of the EU ETS is to create a stimulous to reduce CO_2 by switching from dirty to clean energy. With this in mind, an increase in EUA price should encourage (discourage) investment in clean energy stocks (oil and gas stocks) and, obtaining the impact of EUA on clean (dirty) energy investment will be positive (negative).

Analyzing this issue authors have focused only on the impact of EUA on clean energy investment but have not considered the discouraging effect that EUA could create regarding investment in dirty energy. Kumar et al. (2012) found the effect of EUA on clean investment was not significant in 2005-2008. We examine a later sample period 2009-2013, taking into account that the first years of functioning of the EU ETS were a pilot period, so we may obtain a different result from Kumar el al. (2012).

The inverse relationship, i.e. the impact of clean stocks and dirty stocks on EUA also has important policy implications. As we have said, EUA is an asset bought not only by companies involved in the EU ETS but also by speculators. In this context, the movements of clean and oil-gas stocks influence investment decisions in EUA. When prices of oil-gas stocks go up investors may predict an increase in CO_2 emissions, which, in turn leads to an increase in EUA prices. The inverse effect apply to movements in clean energy stocks prices, therefore, we assume a positive (negative) impact of oil-gas stocks (clean energy stocks) on EUA prices.

Finally, we focus on the relationship between clean and dirty stocks, following Wen et al. (2012), who studied this link for the Chinese context and concluded that there is an assymetric effect that good news about new energy stock returns causes fossil fuel returns to fall on the following day whereas good news about fossil fuel stock returns leads to a rise in new energy returns on the subsequent trading day.

Table 4.1 summarizes the expected impacts between the main variables.

Table 4.1: **Expected inter-relationships between main variables**

	EUA (t)	**Clean energy stocks (t)**	**Oil&gas stocks (t)**
EUA (t-1)		+	-
Clean energy stocks (t-1)	-		-
Oil&gas stocks (t-1)	+	+	

4.2.2 Control variables

Our exogenous variables are selected according to the existing literature. Variables affecting EUAs and energy market stocks are usually divided into two main groups: energy prices (Oil, gas and coal prices) and the economic condition of the companies in the industrial sector.

Effects of energy prices.

We begin with the effects of energy prices on EUA. According to the existing literature, oil prices are the most relevant energy price in terms of influence, as remarked in Aatola et al. (2013). Other authors such as, Reboredo (2013) and Hammoudeh et al. (2014), also studied the connection between EUA and oil price and both of them found a positive relationship. The effect of natural gas on EUA price is not conclusive in the previous literture. In this regard, some authors found a positive link between natural gas prices and EUA (see Aatola et al., 2013) whilst others, such as Hammoudeh et al. (2014) found a negative link. Regarding coal price effect a positive impact is expected because when the price of crude oil (or natural gas) increases, economic agents turn to cheaper sources of energy (such as coal), as explained in Hammoudeh et al. (2014) which in turn lead to an increase in CO_2 which pushes EUA price up.

We now focus on the effect of energy prices on clean energy stocks. Positive shocks on pollutant energy prices should create an incentive to invest in clean energy. Thus, we expect there to be a positive impact of fuel, gas and coal prices on clean energy stock as concluded in works by Henriques and Sadorsky (2008), Henriques and Sadorsky (2010), Broadstock et al. (2012), Sadorsky (2012a) and Apergis and Payne (2014) concluded.

Regarding oil and gas companies, an increase in oil and gas prices may be seen by investors as an impulse to invest in these companies. Certain investors will be more interested in oil and gas stocks because they may predict that an increase in the price will be translated in an increase in those companies profits (Lanza et al., 2004 and Scholtens and Yurtesever, 2012). According to this, we expect a positive effect of energy price on oil& gas stocks price.

Effects of economic condition of the companies in the industrial sector. To measure the economic condition of a company, we use an industrial stock index, which varies depending on the expectations of investors of the future economic status of companies. A positive expectation of the economic results of a company is linked to a forecast of an increase in the profits of a firm. Speaking of industrial companies an increase in profits usually goes hand-in-hand with an increase in a firm's production capacity, which leads to an increase in energy consumption (increase in the price of stocks of oil and gas and clean energy companies). This, in turn leads to increased demand for emission allowances, and a rise in their price (Chevallier (2011)).

Table 4.2 summarizes the expected impacts of control variables on the main variables.

Table 4.2: **Expected effect of control variables**

	EUA (t)	**Clean energy stocks (t)**	**Oil&gas stocks (t)**
Coal (t-1)	+	+	+
Gas (t-1)	+/-	+	+
Oil (t-1)	+	+	+
Industrial stocks (t-1)	+	+	+

4.3 Data

Our dataset consists of time-series of the daily prices of four commodities: the European Union Allowances (EUA),coal, gas and oil, and the daily closing prices of three stock indeces: clean energy stock index, oil& gas stock index and industrial stock index. The study period runs from May 2009 to December 2013, resulting in 1164 observations. We began our sample period in May 2009 because it was from then when EUA prices began a period of stability after EUA prices sink in January 2009. EUA, oil (barrel of brent), gas and coal daily prices were obtained from $SENDECO_2$, the European bourse for European Unit Allowances (EUA) and Carbon Credits (CERs) specialized for Small and Medium companies.

To represent the evolution of clean energy stocks, we select the clean energy stock index from S&P and Dow Jones Indexes. It is the S&P Global Clean Energy Index [1], which provides liquid and tradable exposure to 30 companies from around the world involved in clean energy related businesses. This data are taken from the official website of the S&P Dow Jones Indices (http://ca.spindices.com/indices/equity/sp-global-clean-energy-index).

With respect to the oil and gas sector, we take the STOXX Oil and Gas European

[1] For the sake of brevity,we will also refer to this variable as "CLEAN" in some parts of the research

Index [2], which is integrated by 25 european companies producing oil and gas. The data are taken from the official website of the STOXX Indices (http://www.stoxx.com/indices/index_information.html?symbol=SXEP). To measure industrial economic conditions we select the STOXX European Industrial Index [3], comprising stocks of 256 european industrial companies. This data was taken from the official website of the STOXX Indices (http://www.stoxx.com/indices/). No companies are included in more than one index.

In this research, all the variables are expressed in euros. The prices which were originally expressed in dollars, as it is the case of oil, gas, coal and the S&P Global Clean Energy Index are converted into euros using the closing spot rates of the euro to dollar exchange rate provided by $SENDECO_2$.

Time series plots of the data are shown in Figures 4.1, 4.2 and 4.3.

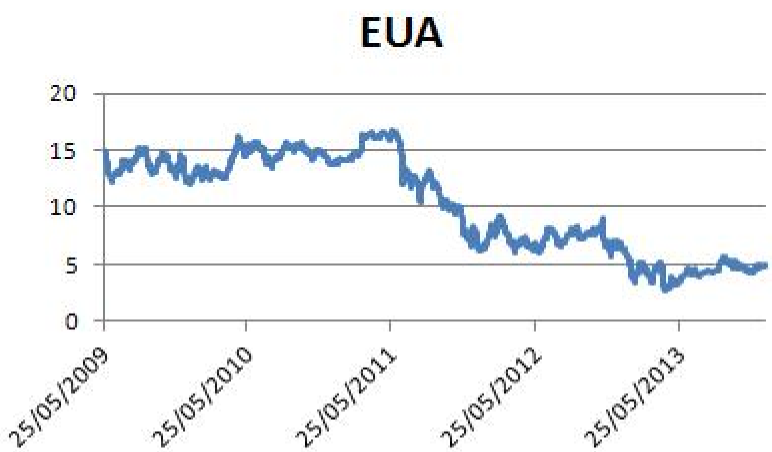

Figure 4.1: **Evolution of EUA price**

As seen in Figure 4.1, EUA prices were quite stable from May 2009 until May 2011. A steep drop followed, after which, a period of price stability occurred. Figure 4.2 illustrates that both coal and oil show a steady path during the study period, whereas gas price was quite volatile. As can be observed in Figure 4.3,both the STOXX oil& gas index and the STOXX industril index have very similiar time series

[2]For the sake of brevity,we will also refer to this variable as "OG" in some parts of the research
[3]For the sake of brevity,we will also refer to this variable as "IND" in some parts of the research

plots. The STOXX oil& gas presents a stable evolution and the STOXX industrial index presents a slightly positive trend during the whole study period. However, the S&P Clean Energy Index was on a downward trend from April 2011 until April 2012, after which, daily closing prices remained quite stable until the end of the study period.

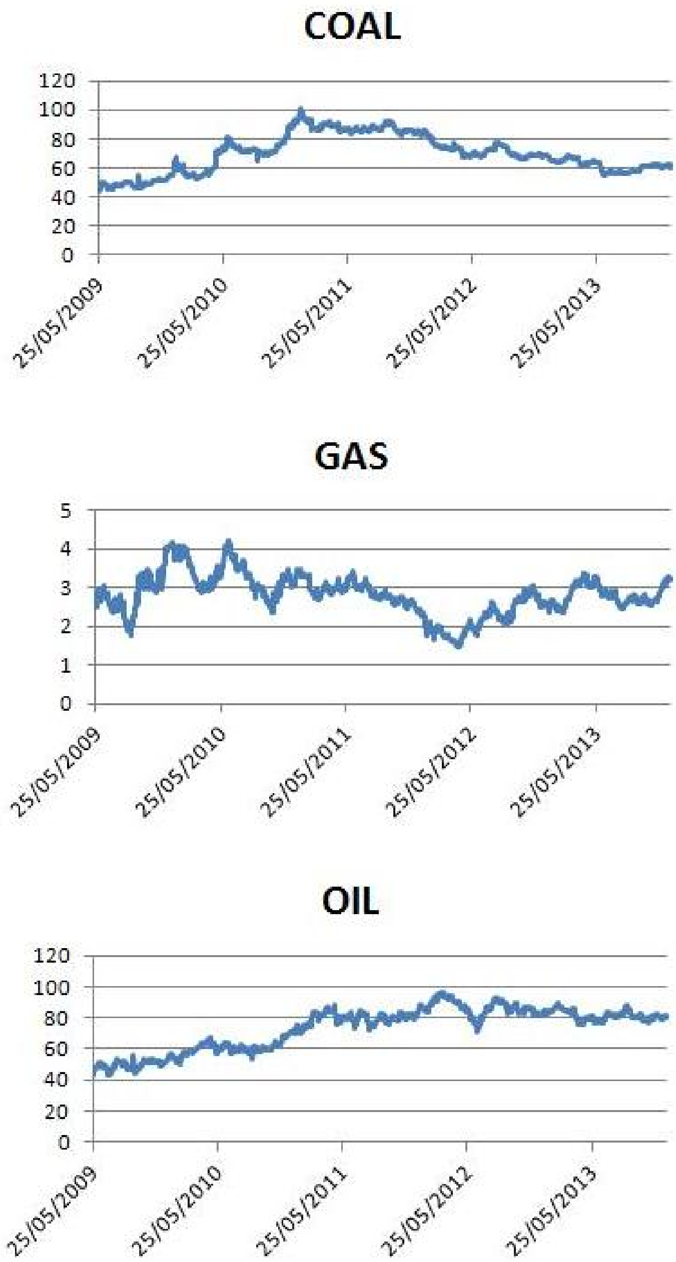

Figure 4.2: **Evolution of energy commodities price**

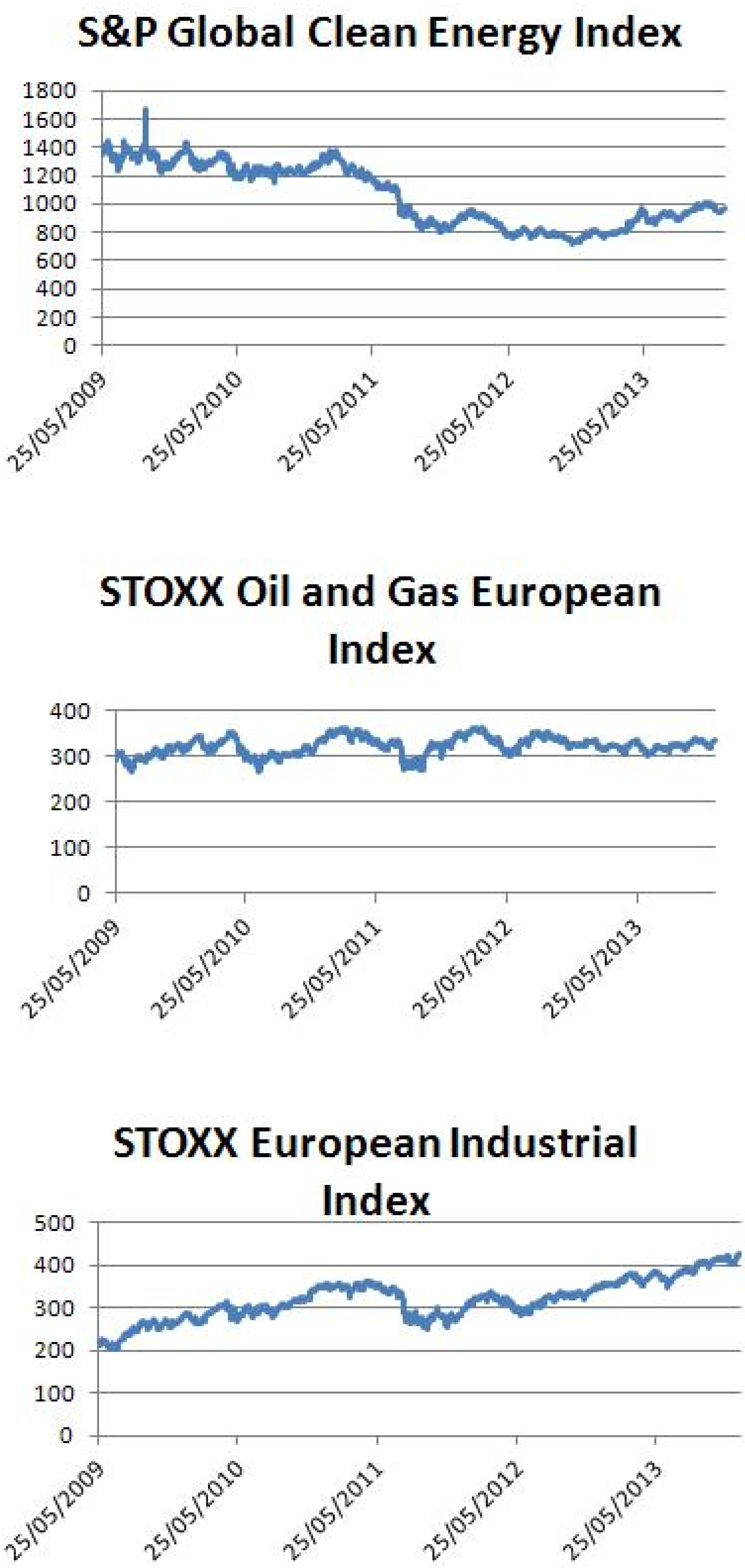

Figure 4.3: **Evolution of stock indeces price**

For each data series, continuously compounded daily returns (r_t) are calculated as $ln(p_t/p_{t-1})$ where p_t is the daily closing price[4]. In order to distinguish between main and control variables we denote the main variables as r_t and control variables as x_t. The summary statistics for the returns are shown in Table 4.3. All the variables exhibit returns around zero and positive on average, except for r_{EUA} and r_{clean} which present average negative returns. The distributions of all the selected variables exhibit pronounced kurtosis and the normality hypothesis is rejected for all time series (see Jarque-Bera).

Table 4.3: **Exploratory analysis** (r_t)

	r_{EUA}	r_{CLEAN}	r_{OG}	x_{COAL}	x_{GAS}	x_{OIL}	x_{IND}
Mean	-0.0009	-0.0003	0.0001	0.0003	0.0002	0.0005	0.0005
Median	0.0000	0.0003	0.0003	0.0000	0.0000	0.0006	0.0007
Maximum	0.2158	0.1732	0.0481	0.1643	0.2451	0.1827	0.0683
Minimum	-0.4225	-0.1797	-0.0542	-0.1623	-0.1290	-0.1941	-0.0658
Std. Dev.	0.0339	0.0148	0.0122	0.0159	0.0310	0.0190	0.0133
Skewness	-1.3949**	-0.2551**	-0.2236**	0.8313**	0.7692**	-0.2178**	-0.1976**
Kurtosis	27.6444**	39.453**	4.4342**	33.096**	8.7246**	20.887**	5.1904**
Jarque-Bera	29704.87	64185.28	109.0036	43876.46	1696.929	15459.98	239.2594
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1159	1159	1159	1159	1159	1159	1159

*Note: Statistically different from zero at the ** 5% level*

Time series graphs of the returns show how volatility has changed across time (Figures 4.4, 4.5 and 4.6). As can be observed, all the returns series exhibit the volatility clustering property: "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes." (Mandelbrot, 1963).

In general, it seems that all the series were more volatile before year 2012 except for EUA. As seen in Figure 4.4, the highest volatility of r_{EUA} is seen in the first six

[4]After testing the augmented dickey fuller is demonstrated that all the series have to be differentiated once

months of year 2013, where the volatility clustering property is shown. This effect might be linked to the uncertainty generated by the beginning of the third Phase of the EU ETS in January 2013.

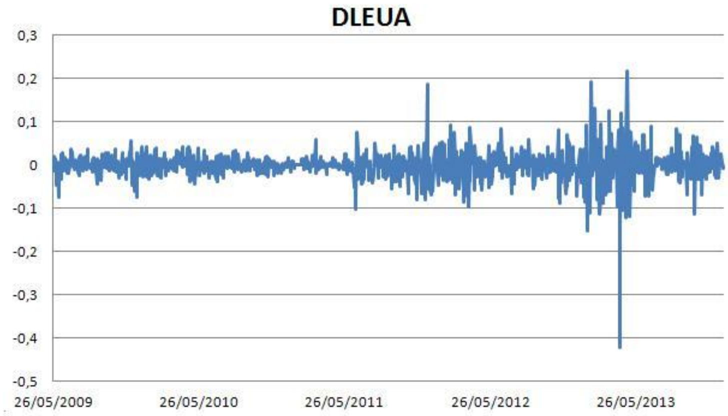

Figure 4.4: **Evolution of** r_{EUA}

As seen in Figure 4.5, r_{OG} and x_{IND} follow the same pattern and are more volatile than r_{CLEAN}. Nevertheless, r_{clean} shows two spikes: the first one in summer of 2009 and the second one (less pronounced than the first one) in summer of 2010.

Figure 4.6 shows the evolution of the returns of energy commodities. Note that, the volatility of x_{GAS} series seems more volatile than the other ones but it is important to take into account the presence of atypicial returns in both x_{OIL} and x_{COAL}.

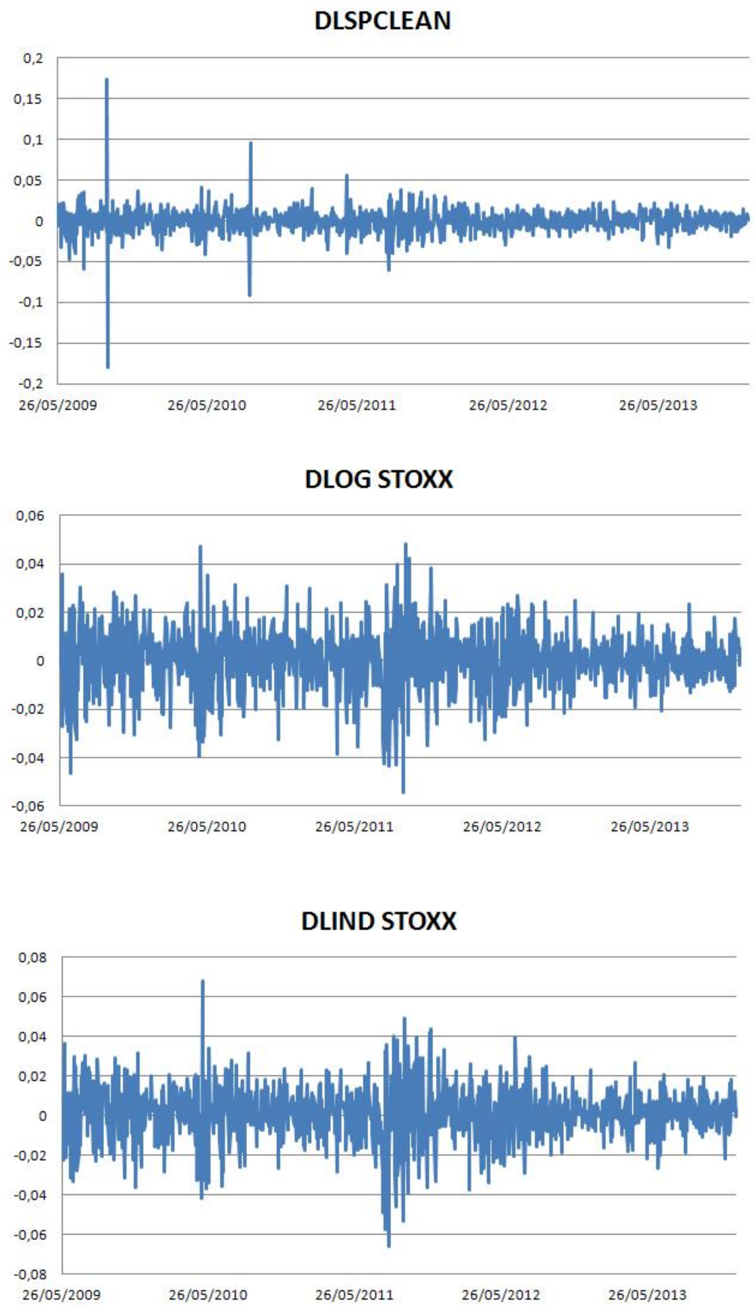

Figure 4.5: **Evolution of stock indeces returns**

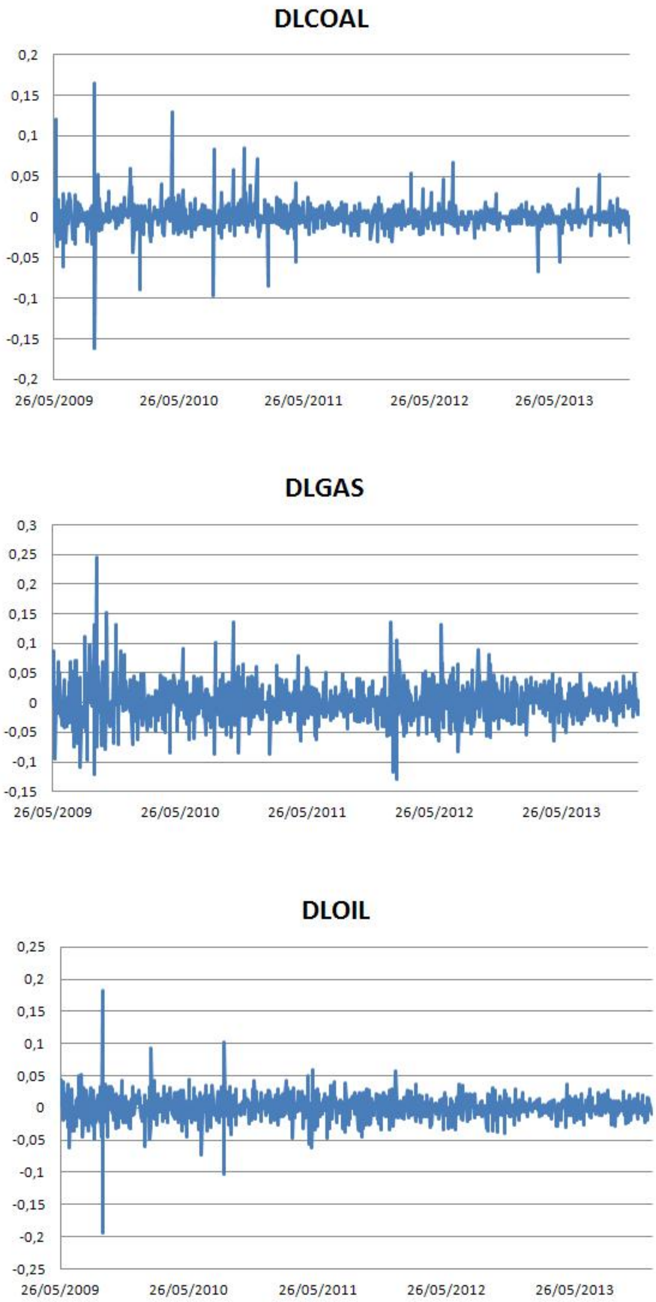

Figure 4.6: **Evolution of energy commodities returns**

4.4 Methodolody

4.4.1 Setting up the problem

The objective of this research is to analyze the interelationship between the main variables and the effect of several control variables on each of the main variables. The Vector Autoregressive Regression (VAR) methodology provides an adequate framework to analyze the simultaneous relationship between a set of variables (main variables) and, also, the impact of control variables on the main ones. In addition, given the existence of volatility clustering in our data (see Section 4.3) we employ a multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH)(Bollerslev, 1986) to modelize the variance of the model. This methodology has been widely used in literature when analysing high-frequency time series in financial markets.

4.4.2 The VAR-GARCH model

Firstly, the VAR (w) model is estimated using the expression 4.4.1.

$$r_{i,t} = c_i + \sum_{i=1}^{3} \sum_{s=1}^{w} \Phi_{i,t-s} r_{i,t-s} + \sum_{j=1}^{4} \beta_m x_{m,t} + \epsilon_{i,t} \tag{4.4.1}$$

where r_{it} is the serie of daily returns corresponding to the the main variable i with $i =_{EUA,CLEAN\ ,OG}$

c_i is the constant of the regression with $i =_{EUA,CLEAN\ ,OG}$

$x_{m,t}$ is the serie of daily returns corresponding to the control variable m, with $m =_{COAL,GAS\ ,OIL\ ,IND}$

$\Phi_{i,t-s}$ is the autoregressive coefficient which determines the influence of the main variable i in period $t-s$, on r_{it}, with $i =_{EUA,CLEAN\ ,OG}$ and $s = 1, ...w$

$\beta_{m,t}$ is the regression coefficient which determine the influence of the control variable m in period t on r_{it}, with $m =_{COAL,GAS\ ,OIL\ ,IND}$

We estimate a multivariate Generalized AutoRegressive Conditional Heteroskedasticity (GARCH)model to modelize the variance of the model. We consider three different GARCH structures: Constant Conditional Correlation(CCC), Diagonal BEKK (Baba et al. (1991)), (Engle and Kroner, 1995) and Diagonal VECH (Bollerslev et al. 1988))

$\epsilon_{EUA,t}, \epsilon_{CLEAN,t}, \epsilon_{OG,t})^{'}$ follow a multivariate GARCH (p,n) process given by:

$\epsilon_t | I_{t-1} \sim N_n(0, \Sigma_t)$

For a VAR system with k=1,...n being the number of dependent variables in the VAR system. p is the length of he ARCH process and n is the order of the GARCH part.

CCC:

$$\Sigma_t = M_k + \sum_{i=1}^{q} A_{ik}\epsilon_{t-i,k}\epsilon^{'}_{t-i,k} + \sum_{i=1}^{p} B_{ik}\Sigma_{k,t-i} \tag{4.4.2}$$

Diagonal BEKK:

$$\Sigma_t = M + \sum_{i=1}^{q} A_i\epsilon_{t-i}\epsilon^{'}_{t-i}A_i + \sum_{i=1}^{p} B_i\Sigma_{t-i}B_i \tag{4.4.3}$$

where M is a scalar, A_i and B_i are diagonal matrices.

Diagonal VECH:

$$\Sigma_t = M + A_1\epsilon_{t-1}\epsilon^{'}_{t-1} + \sum_{i=2}^{q} A_i\epsilon_{t-i}\epsilon^{'}_{t-i} \sum_{i=1}^{p} +B_i\Sigma_{t-i} \tag{4.4.4}$$

where M is a scalar, A_1 is a rank one matrix, A_i and B_i are diagonal matrices. d.

4.5 Empirical results and discussion

According to the Akaike (1974) criterion, we select the model that better fits with the data. In the mean part we estimate a VAR model with two lengths (VAR(2)) (see Table C.1) and a GARCH(2,1) Diagonal VECH in the variance part (see Table C.2). The estimation of the mean equation of the model is presented in Table 4.4 and the variance equation is shown in Table 4.5.

We have divided this section into two subsections. In the first one, we concentrate on the analysis of the interelatioship between the main variables. In the second one, we focus on the effect of control variables on the main variables. All calculations were made in Eviews 7.0.

4.5.1 How do EUAs and energy stocks interact?

As can be seen in Table 4.4, the impact of r_{eua} on r_{clean} is positive and statistically significant,i.e. an increase in EUA prices encourages investment in clean energy companies. The effect of r_{eua} on r_{og} is negative, i.e. an increase in EUA prices discourages investment in oil and gas companies. With this, we indirectly prove that the EU ETS has been efficient not only in spurring clean investment but also in discouraging investment in dirty energy companies. Nevertheless, as can be seen in Table 4.4, clean investment is greater than the dirty disinvestment effect. These significant effects indicate that investors pay attention to European climate change policy when making their investment decisions in the energy sector.

Regarding the inverse effects we find that, as expected in Section 4.2, r_{clean} negatively impacts r_{eua} but r_{og} does not significantly influence r_{eua}. With these results we can deduce that agents speculating with EUAs take into consideration the evolution of clean energy stocks, but they do not see oil and gas stocks as a relevant factor. This fact should be taken into account by policymakers when forecasting EUA prices.

Finally, we concentrate on the relationship between r_{clean} and r_{og}. As can be observed, a rise in r_{og} encourages r_{clean}, as we expected in Section 4.2. whereas, the impact of r_{clean} on r_{og} does not appear to have any influence. Investors in clean companies take into consideration oil and gas company prices in their invesment decision process but when investing in fossil fuel stocks do not consider clean stocks.

Nevertheless, it is clear that there is a link between both assets. As can be seen in the variance equation (see Table 4.5) there is a statistically significant interrelation

Table 4.4: **Mean equation**

	Dependent: r_{eua}		Dependent: r_{clean}		Dependent: r_{og}	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
C	0.000157	0.7469	-0.000735	0.0054	-0.000323	0.0787
$r_{eua}(-1)$	0.104773	0.0002	0.016009	0.0043	0.008608	0.1049
$r_{eua}(-2)$	-0.028366	0.3669	-0.008212	0.1728	-0.008526	0.0758
$r_{clean}(-1)$	-0.100327	0.0090	-0.204195	0.0000	-4.85E-05	0.9980
$r_{clean}(-2)$	-0.141956	0.0036	-0.010824	0.6862	-0.022392	0.2433
$r_{og}(-1)$	-0.028485	0.5622	0.229779	0.0000	-0.012634	0.5510
$r_{og}(-2)$	0.075108	0.1219	0.049799	0.0652	0.030309	0.1202
x_{coal}	-0.033265	0.4087	0.140039	0.0000	-0.010740	0.4183
x_{gas}	0.014208	0.2243	0.035722	0.0000	0.007976	0.2289
x_{oil}	0.005397	0.8621	0.089036	0.0000	0.050985	0.0000
x_{ind}	0.269036	0.0000	0.567059	0.0000	0.750886	0.0000
Adj. R squared	0.037211		0.476442		0.693640	

between r_{clean} and r_{og} series indicating that oil and gas stocks and clean energy returns move in the same direction so the simultaneous investment in clean energy and oil and gas stocks does not appear to be a good option in terms of diversification.

4.5.2 The effect of non-renewable energy and industrial activity on EUAs and energy stocks

With respect to r_{eua}, it can be seen that only the Industrial Stoxx Index has a significant positive influence, i.e. the higher the industrial prices, the higher the r_{eua}. It is clear that evolution of EUA prices is determined uniquely by the evolution of industrial results.

Taking this into account, and bearing in mind that the rest of the variables do not have a significant effect and that the adjusted R^2 value is so low, we can deduce that market fundamentals do not really produce EUA price movements. It appears that the EUA price is determined by company demand and supply according to their environmental targets under the EU ETS. Decisions of speculators, who look at

Table 4.5: **Variance equation**

	Coefficient	p-value
M	-2.72E-08	0.5224
A1(1,1)	0.111799	0.0000
A1(1,2)	0.097305	0.0000
A1(1,3)	0.120877	0.0000
A1(2,2)	0.084690	0.0000
A1(2,3)	0.105206	0.0000
A1(3,3)	0.130692	0.0000
A2(1,1)	0.018785	0.4384
A2(2,2)	-0.090067	0.0000
A2(3,3)	-0.110869	0.0000
B1(1,1)	0.896224	0.0000
B1(2,2)	1.005990	0.0000
B1(3,3)	0.980580	0.0000

Note: See expression 4.4.4

market fundamentals when making an investment decision, do not have an important participation in EUA pricing and it seems that the profile of the buyer is a company that emits CO_2 and buys CO_2 allowances for legal purposes and, consequently, the quantity of emissions allowances it buys is related to the level of production, but nothing else.

The contrary happens when we focus on the r_{clean} equation. All the exogenous variables considered are statistically significant. The effect of oil, gas and coal is positive and statistically significant as we assumed in Section 4.2. When prices of polluter energies go up, investors see an opportunity to invest in clean energy as it is an alternative source of energy. Furthermore, it is clear that, as expected, the evolution of the price of industrial company stocks is highly correlated to the stocks of clean energy.

In the case of the r_{og} equation, only x_{ind} and x_{oil} have a significant impact. This is consistent with Oberndorfer (2009b) that concluded that stock market participants primarily use the oil price as the main indicator of energy price developments as a whole. As expected in Section 4.2 of this paper, both have a positive effect; when oil prices rise, investors will be more interested in stocks of oil and gas because they may predict that an increase in the price will be translated into an increase in company profits, and if stocks of industrial companies go up, investors will see an increase in industrial production which, in turn, leads to an increase in energy consumption.

According to these results, it appears that those agents trading in clean energy stocks have a different profile from those investing in oil and gas stocks. In the first case, investors take into account a considerable number of factors before making the decision to invest, whereas investors in oil and gas stocks appear only to be concerned with variables strongly related to those stocks, such as the oil price and the level of industrial activity. From our point of view, this is explained by the fact that investing in clean energy is seen by investors as a riskier investment as said in Sadorsky (2012b) in comparison with oil and gas industries, which are more consolidated and traditional.

4.6 Conclusions

The objective of this chapter is to discover how the EU ETS and investment in stocks of the energy sector are linked. More specifically, we concentrate on the interrelationship between EUA, clean energy company stocks and oil and gas company stocks. We do this in a multivariate GARCH framework. From our empirical results, we obtain three main conclusions.

First, EUA prices are an incentive for the demand for stocks of clean, alternative energy companies, and for disinvestment in oil and gas companies. This is a positive signal with regard to climate change policy, and, more specifically the role of EU ETS. With this result, we indirectly confirm that the EU ETS has been useful in encouraging investment in clean energy, and that clean energy markets are sensitive to European policies on climate change. This, in turn, suggests that such policies have credibility in the market.

Second, from our results we conclude that the profile of the investor is different for each of the assets considered. It appears that EUA price is determined by company demand and supply, according to the environmental targets under the EU ETS. The decisions of speculators, who look at market fundamentals when making an investment decision, do not have a significant participation in EUA pricing.Investors in clean energy consider a range before making a decision of investing, whereas investors in oil and gas stocks seem to only be concerned with the variables strongly related to those stocks, such as the oil price and industrial activity. From our point of view, this is explained by the fact that investing in clean energy is seen by investors as being riskier, in comparison with the oil and gas industries which are more consolidated and traditional.

Third, we conclude that oil and gas stocks and clean energy returns move in the same direction, so there does not appear to be much scope for diversification. In conclusion, according to our results, simultaneous investment in clean energy and oil and gas stocks does not strike us as a viable option in terms of diversification.

Chapter 5

Conclusions

This thesis has collected three essays, each analyzing the economic performance of the EU ETS from a different perspective (policy makers, companies and investors). In this Section, the key findings of all the three essays are summarized.

The first essay (Chapter 2) aimed to provide policy makers with important results regarding the link between environmental and economic performance in the context of Spain. When undertaking this analysis we took into account that company's environmental performance in the EU ETS, is both a result and a determinant of economic performance.

First, the production level of a company determines its level of CO_2 emissions and, thus, its SA. We found that this link was negative for all the years in the period 2005-2011, i.e. an increase in production is translated into a reduction in the surplus of allowances and vice-versa. Furthermore, this link increases its intensity through the years. This finding sheds further light on EU ETS efficiency in fostering green investment in Spanish companies. In this context, we argue that if the EU ETS had encouraged green investments, although an increase in production would be linked to a decrease in SA, this decrease in surplus of allowances due to higher levels of production would have been lower each year. Given that the intensity did not decrease, on the contrary, it increased we can indirectly deduce that companies, in general, did not take any measures in order to reduce their CO_2 emissions. Second, the SA (which indicates the number of EUAs a company must buy or can sell, in relative terms) is a component of a company cost production and thus, influences its profitability (measured by ROA). An increase of surplus of allowances, which would imply to buy less EUAs in the market, has no effect in companies' ROA. These finding suggests that EUAs price during period 2005-2011 was not high enough to create a profitability advantage for those companies that take measure to reduce their CO_2 emissions.

In the second essay (Chapter 3) we focused our attention on Spanish energy companies involved in the EU ETS. The results of this essay are important for managent of companies in order to help them make decisions related to improvements in efficiency, and also in terms of improving its CO_2 emissions levels relative to the targets under the EU ETS. In addition, these results are important for policy makers, since the whole economy depends on the energy sector, i.e an increase in the costs of power stations increases the costs of companies in all sectors.

Companies in the energy sector play an important role in achieving the targets of the European Union "2020 energy and climate package": they must improve their efficiency and have CO_2 limitations under the EU ETS. Thus, our research has two targets. To measure the technical and environmental efficiency of the companies, and, to calculate to what extent environmental efficiency determines the difference between allocated EUAs and final CO_2 emissions.

Regarding our first objective we obtain two main findings. First, large companies are more efficient in technical terms, whereas small companies are more efficient in terms of environmental efficiency, which suggests that managers of large companies should pay more attention to their environmental inefficiencies as they are doing worse than small ones, whereas small companies should focus more on policies to improve their technical efficiency. Second, the four companies responsible for over 50% of total emissions in the EU ETS ("the Big 4") are well-positioned in terms of technical efficiency, but are at the bottom of the environmental ranking. This finding is very important for policymakers. Since these companies represent more than half of the emissions of the EU ETS, and have very poor environmental scores relative to the other companies, governemnt should pay more attention to these companies individually, in order to discover the causes of this negative environmental behaviour as their CO_2 emissions considerably influence the way the energy sector.

Regarding our second objective, we obtain a relevant finding: there is a negative effect of inefficiency on the surplus of allowances. That is, the more inefficient a company, the more EUAs it must buy (more expenses). This result suggests that being more environmentally inefficient has negative financial consequences.

The objective of the third essay (Chapter 4) was to discover how the EU ETS and investment in stocks of the energy sector are linked. More specifically, we concentrate on the interrelationship between EUA, clean energy company stocks and oil and gas company stocks. From our empirical results, we obtain three main conclusions.

First, EUA prices are an incentive for the demand for stocks of clean, alternative energy companies, and for disinvestment in oil and gas companies. This is a positive signal with regard to climate change policy, and, more specifically the role of EU ETS. With this result, we indirectly confirm that the EU ETS has been useful in encouraging investment in clean energy, and that clean energy markets are sensitive to European policies on climate change. This, in turn, suggests that such policies have credibility in the market.

Second, from our results we conclude that the profile of the investor is different for each of the assets considered. It appears that EUA price is determined by company demand and supply, according to the environmental targets under the EU ETS. The decisions of speculators, who look at market fundamentals when making an investment decision, do not have a significant participation in EUA pricing. Investors in clean energy consider a range before making a decision of investing, whereas investors in oil and gas stocks seem to only be concerned with the variables strongly related to those stocks, such as the oil price and industrial activity. From our point of view, this is explained by the fact that investing in clean energy is seen by investors as being riskier, in comparison with the oil and gas industries which are more consolidated and traditional.

Third, we conclude that oil and gas stocks and clean energy returns move in the same direction, so there does not appear to be much scope for diversification. In conclusion, according to our results, simultaneous investment in clean energy and oil and gas stocks does not strike us as a viable option in terms of diversification.

Conclusiones

Esta tesis incluye tres ensayos, cada uno de los cuales analiza la performance económica del EU ETS desde tres puntos de vista diferentes: instituciones públicas (consideran este mercado como pieza clave de la política climática de la UE), empresas (deben acudir a este mercado con el fin de cumplir con sus restricciones ambientales) e inversores (ven este mercado como una nueva oportunidad de inversión).

El primer ensayo (Capítulo 2) tiene como objetivo proveer a las instituciones encargadas de velar por el buen funcionamiento del EU ETS, de resultados importantes en cuanto a la relación entre performance medioambiental y performance económica, en el ámbito español. Al emprender este análisis, tuvimos en cuenta que la performance medioambiental de las empresas del EU ETS es tanto un resultado como un determinante de su performance económica y, en este sentido, se han obtenido dos importantes conclusiones.

En primer lugar, el nivel de producción de una compañía determina su nivel de emisiones de CO_2 y, así, su grado de cumplimiento de su límite de emisiones (medido en este capítulo mediante el ratio SA, superávit de derechos de emisión). Los resultados de nuestra investigación muestran que esta influencia es negativa para todos los años del período 2005-2011, es decir, un aumento de la producción se traduce en una reducción del superávit de derechos de emisión de CO_2. Además, este efecto aumenta su intensidad a lo largo de los años. Este resultado es relevante en cuanto a valorar cómo de eficiente ha sido el EU ETS a la hora de potenciar la inversión en energías limpias por parte de las empresas españolas. En este contexto, sostenemos que si se hubieran promovido las inversiones verdes, aunque un aumento de la producción se relacionara con una disminución en su superávit de derechos, esta disminución, debido a niveles más altos de producción habría sido más baja cada año. Considerando que la intensidad no disminuyó si no que, por el contrario, aumentó, podemos deducir indirectamente que las compañías, en general, no tomaron ninguna medida a fin de reducir sus emisiones de CO_2.

En segundo lugar, partimos de la base que el número de EUAs que una compañía debe comprar o puede vender en términos relativos, es un componente más del coste de producción de la compañía y que, por tanto, influye en los resultados económicos empresariales. Al analizar el efecto del SA sobre la rentabilidad hemos descubierto que un aumento en el SA, lo que implicaría comprar menos EUAs en el mercado, no tiene un efecto significativo en la rentabilidad empresarial. Este resultado sugiere que el precio EUAs durante el período 2005-2011 no era bastante alto para crear una ventaja en costes para aquellas compañías que tomaran medidas para reducir su CO_2.

Los resultados del segundo ensayo (Capítulo 3) tienen especial relevancia para la gerencia de las compañías del sector energético a fin de ayudarles a tomar decisiones relacionadas con mejoras de la eficacia y también en términos de adecuación de su CO_2 con relación a los objetivos bajo el EU ETS. Por otra parte, los resultados obtenidos son importantes en el contexto de diseño de políticas económicas y medioambientales, ya que la economía entera depende del sector energético y, por tanto, un aumento de los gastos de las centrales eléctricas repercute en un aumento de los gastos de las empresas en todos los sectores. Las empresas del sector energético desempeñan un papel importante en el logro de los objetivos medioambientales 2020 de la Unión Europea: deben mejorar su eficacia y controlar sus emisiones de CO_2 bajo el EU ETS. Así, nuestra investigación tiene dos objetivos: medir la eficacia técnica y ambiental de las compañías y descubrir hasta qué punto la eficacia medioambiental determina el número de EUAs que una empresa debe comprar en el mercado o se puede permitir vender y de esta manera conocer hasta qué punto la eficiencia medioambiental permite un ahorro de costes relacionados con la buena performance medioambiental.

En cuanto al primero de estos objetivos, obtenemos dos conclusiones principales. En primer lugar, que las empresas grandes son más eficientes en términos técnicos, mientras que las pequeñas lo son en términos de eficacia medioambiental, lo que sugiere que los gerentes de grandes empresas deberían de prestar más atención a sus ineficiencias ambientales, aspecto en el que son peores que las de menor tamaño, mientras que las pequeñas empresas se deberían concentrar más en políticas de mejora de eficacia técnica. En segundo lugar, las cuatro compañías responsables de más de 50 % de las emisiones totales en la UE ETS ("las 4 Grandes"), si bien están bien posicionadas en lo que se refiere a la eficacia técnica, están, por otra parte, a la cola de la clasificación ambiental. Esta constatación debería ser muy importante para políticos, ya que estas compañías representan más de la mitad de las emisiones de la UE ETS y tienen resultados de eficiencia medioambiental muy pobres con relación a las otras compañías. El órgano encargado de diseñar debería prestar más atención a estas compañías individualmente, a fin de descubrir las causas de este comportamiento ambiental negativo.

En cuanto al segundo objetivo, se ha obtenido un resultado relevante: hay un efecto negativo del nivel de ineficiencia en el superávit de derechos de emisión. Esto es, cuanto más ineficiente es una compañia, más EUAs debe comprar, sugiriendo de manera análoga que mayores niveles de eficiencia suponen un ahorro en costes para la empresa.

El objetivo del tercer ensayo (Capítulo 4) era descubrir cómo se vinculan la inversión en el EU ETS y la inversión en acciones del sector energético. En concreto, nos concentramos en la interrelación entre la EUA, las acciones de compañías de energía limpia y de petróleo y gas. De nuestro estudio se obtienen tres conclusiones principales.

En primer lugar, nuestros resultados sugieren que los precios de los EUA son un incentivo, por una parte, para la demanda de acciones de empresas de energía limpia, y por otra, para la desinversión en empresas de petróleo y gas. Esta es una señal positiva con respecto a la política de cambio climático, y más concretamente del papel del EU ETS. Con este resultado, indirectamente confirmamos que el EU ETS ha sido útil para fomentar la inversión en energías limpias, y que los mercados de energía limpia son sensibles a las políticas europeas en materia de cambio climático. Esto, a su vez, sugiere que esas políticas tienen credibilidad en el mercado.

En segundo lugar, a partir de nuestros resultados se podría concluir que el perfil del inversor es diferente para cada uno de los tres activos considerados. Así parece que el precio de los EUA viene determinado en mayor medida por la demanda de la empresas que deben acudir al mercado para rendir cuentas de sus emisiones, mientras que las decisiones de inversión de aquellos que acuden a este mercado con el único fin de obtener una rentabilidad, no tienen una participación significativa en el proceso de formación del precio del EUA. Por otra parte, nuestros resultados sugieren que los inversores en energía limpia tienen en cuenta un número relavante de factores antes de tomar una decisión de inversión, mientras que los inversores en empresas del sector del petróleo y gas parecen solo preocuparse de las variables fuertemente relacionadas con esas acciones, tales como el precio del petróleo y la actividad industrial. Desde nuestro punto de vista, esto se explica por el hecho de que la inversión en energía limpia es visto por los inversores como de mayor riesgo, en comparación con las industrias de petróleo y gas, sectores más tradicionales y consolidados.

En tercer lugar, llegamos a la conclusión de que los precios de las acciones de las empresas del sector petróleo y gas y las de energía limpia se mueven en la misma dirección. Por lo tanto, no parece haber mucho margen para la diversificación en una cartera formada por dichas acciones.

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Appendix A

Appendix for the second chapter

Copula estimation

```
nombresYXZ = strvcat('SA','ATR','SIZE','RISK','SECTOR');
nombresXZ = nombresYXZ(2:end,:);
nombresZ = nombresYXZ(3:end,:);
nombresXZ1 = strvcat('Cte',nombresXZ);
nombresZ1 = strvcat('Cte',nombresZ);
n = length(X);
nsim = 1000;
indicesn = 1:nsim;
nfigura = 1;
Z = (Z-ones(n,1)*mean(Z))./(ones(n,1)*sqrt(var(Z)));
[betaYXZ,stats_YXZ] = robustfit([X,Z],Y);
strcat('Variable dependiente',char(1),nombresYXZ(1,:))
strcat('Variable',char(1),'Coeficiente',char(1),'Standard Error',char(1),
   'pvalue');
aux = [];
for i=1:size(betaYXZ)
    aux = strvcat(aux,strcat(nombresXZ1(i,:),char(1),num2str(betaYXZ(i)),
       char(1),num2str(stats_YXZ.se(i)),char(1),num2str(stats_YXZ.p(i))))
       ;
```

```
end
aux
strcat('R2',char(1),num2str(1-(stats_YXZ.robust_s^2)/var(Y)))
[betaYZ,stats_YZ] = robustfit(Z,Y);
strcat('Variable dependiente',char(1),nombresYXZ(1,:))
strcat('Variable',char(1),'Coeficiente',char(1),'Standard Error',char(1),
    'pvalue');
aux = [];
for i=1:size(betaYZ)
     aux = strvcat(aux,strcat(nombresZ1(i,:),char(1),num2str(betaYZ(i)),
         char(1),num2str(stats_YZ.se(i)),char(1),num2str(stats_YZ.p(i))));
end
aux
strcat('R2',char(1),num2str(1-(stats_YZ.robust_s^2)/var(Y)))
res_YZ = Y - [ones(n,1),Z]*betaYZ;

[betaXZ,stats_XZ] = robustfit(Z,X);
strcat('Variable dependiente',char(1),nombresYXZ(2,:))
strcat('Variable',char(1),'Coeficiente',char(1),'Standard Error',char(1),
    'pvalue');
aux = [];
for i=1:size(betaXZ)
     aux = strvcat(aux,strcat(nombresZ1(i,:),char(1),num2str(betaXZ(i)),
         char(1),num2str(stats_XZ.se(i)),char(1),num2str(stats_XZ.p(i))));
end
aux
strcat('R2',char(1),num2str(1-(stats_XZ.robust_s^2)/var(X)))
res_XZ = X - [ones(n,1),Z]*betaXZ;
figure(nfigura);
nfigura = nfigura+1;
h0 = scatterhist(res_XZ,res_YZ);
set(get(gca,'Children'),'Marker','*');
xlabel(strcat('Residuos regresion',char(1),etiquetaX));
```

```
ylabel(strcat('Residuos regresion',char(1),etiquetaY,char(1)));
v = ksdensity(res_YZ,res_YZ,'function','cdf');
u = ksdensity(res_XZ,res_XZ,'function','cdf');
figure(nfigura);
nfigura = nfigura+1;
scatterhist(u,v);
xlim([0 1]);
ylim([0 1]);
set(get(gca,'Children'),'Marker','*');
xlabel('u');
ylabel('v')
%
%
Rho_gaussian = copulafit('Gaussian',[u v]);
AIC_gaussian = -2*sum(log(copulapdf('Gaussian',[u v],Rho_gaussian)))+1;
[Rho_t,nu_t] = copulafit('t',[u v],'Method','ApproximateML');
AIC_t = -2*sum(log(copulapdf('t',[u v],Rho_t,nu_t)))+2;
alfa_Clayton = copulafit('Clayton',[u v]);
AIC_Clayton = -2*sum(log(copulapdf('Clayton',[u v],alfa_Clayton)))+1;
alfa_Frank = copulafit('Frank',[u v]);
AIC_Frank = -2*sum(log(copulapdf('Frank',[u v],alfa_Frank)))+1;
alfa_Gumbel = copulafit('Gumbel',[u v]);
AIC_Gumbel = -2*sum(log(copulapdf('Gumbel',[u v],alfa_Gumbel)))+1;
%
%
aux = strcat('Gaussian',char(1),num2str(AIC_gaussian));
aux = strvcat(aux,strcat('t',char(1),num2str(AIC_t)));
aux = strvcat(aux,strcat('Clayton',char(1),num2str(AIC_Clayton)));
aux = strvcat(aux,strcat('Frank',char(1),num2str(AIC_Frank)));
aux = strvcat(aux,strcat('Gumbel',char(1),num2str(AIC_Gumbel)));
aux
AIC_optimo = min([AIC_gaussian;AIC_t;AIC_Clayton;AIC_Frank;AIC_Gumbel]);
if AIC_optimo==AIC_gaussian
```

```
strcat('Copula optima:','Gaussiana')
Rho_gaussian = copulafit('Gaussian',[u v])
Tau_Copula = copulastat('Gaussian',Rho_gaussian);
[Tau_Kendall,pvalor] = corr(res_YZ,res_XZ,'type','Kendall');
strcat('Tau de Kendall:',num2str(Tau_Kendall),char(1),'pvalor:',
   num2str(pvalor))
strcat('Tau de Kendall de la copula:',num2str(Tau_Copula(1,2)))
Rho_Copula = copulastat('Gaussian',Rho_gaussian,'type','Spearman');
[Rho_Spearman,pvalor] = corr(res_YZ,res_XZ,'type','Spearman');
strcat('Rho de Spearman:',num2str(Rho_Spearman),char(1),'pvalor:',
   num2str(pvalor))
strcat('Rho de Spearman de la copula:',num2str(Rho_Copula(1,2)))
figure(nfigura);
nfigura = nfigura+1;
w = copularnd('Gaussian',Rho_gaussian,nsim);
scatterhist(w(:,1),w(:,2));
xlim([0 1]);
ylim([0 1]);
set(get(gca,'Children'),'Marker','*');
xlabel('u copula');
ylabel('v copula');
figure(nfigura);
nfigura = nfigura+1;
y1 = ksdensity(res_YZ,w(:,2),'function','icdf');
x1 = ksdensity(res_XZ,w(:,1),'function','icdf');
[Rho_Pearson,pvalor] = corr(res_YZ,res_XZ);
strcat('Correlacion de Pearson:',num2str(Rho_Pearson),char(1),'pvalor
   :',num2str(pvalor))
indices = indicesn(~isnan(x1)&~isnan(y1));
Rho_Copula = corr(x1(indices),y1(indices));
strcat('Correlacion de Pearson de la copula:',num2str(Rho_Copula))
h = scatterhist(x1,y1);
xmin = min(min(res_XZ),min(x1));
```

```
    xmax = max(max(res_XZ),max(x1));
    ymin = min(min(res_YZ),min(y1));
    ymax = max(max(res_YZ),max(y1));
    set(get(gca,'Children'),'Marker','*');
    xlabel(strcat(etiquetaX,char(1),'copula'));
    ylabel(strcat(etiquetaY,char(1),'copula'));
    set(h(1),'Xlim',[xmin xmax]); set(h(2),'Xlim',[xmin xmax]);
    set(h0(1),'Xlim',[xmin xmax]); set(h0(2),'Xlim',[xmin xmax]);
    intervalo = [ymin ymax];intervaloXY = get(h(1),'Ylim'); set(h(1),'
       Ylim',intervalo);
    intervaloY = get(h(3),'Ylim');set(h(3),'Ylim',[intervaloY(1)+
       intervalo(1)-intervaloXY(1) intervaloY(1)+intervalo(2)-intervaloXY
       (1)]);
    intervaloXY = get(h0(1),'Ylim'); set(h0(1),'Ylim',intervalo);
    intervaloY = get(h0(3),'Ylim');set(h0(3),'Ylim',[intervaloY(1)+
       intervalo(1)-intervaloXY(1) intervaloY(1)+intervalo(2)-intervaloXY
       (1)]);
    regresion_cuantil(X,Y,Z,nombresZ,'Gaussian',nfigura,[0.75, xmax],[
       ymin,ymax],etiquetaX,etiquetaY);
end
if AIC_optimo==AIC_t
    strcat('Copula optima:','t de Student')
    [Rho_t,nu_t,nu_ci] = copulafit('t',[u v])
    Tau_Copula = copulastat('t',Rho_t,nu_t);
    [Tau_Kendall,pvalor] = corr(res_YZ,res_XZ,'type','Kendall');
    strcat('Tau de Kendall:',num2str(Tau_Kendall),char(1),'pvalor:',
       num2str(pvalor))
    strcat('Tau de Kendall de la copula:',num2str(Tau_Copula(1,2)))
    Rho_Copula = copulastat('t',Rho_t,nu_t,'type','Spearman');
    [Rho_Spearman,pvalor] = corr(res_YZ,res_XZ,'type','Spearman');
    strcat('Rho de Spearman:',num2str(Rho_Spearman),char(1),'pvalor:',
       num2str(pvalor))
    strcat('Rho de Spearman de la copula:',num2str(Rho_Copula(1,2)))
```

```
figure(nfigura);
nfigura = nfigura+1;
w = copularnd('t',Rho_t,nu_t,nsim);
scatterhist(w(:,1),w(:,2));
xlim([0 1]);
ylim([0 1]);
set(get(gca,'Children'),'Marker','*');
xlabel('u copula');
ylabel('v copula');
figure(nfigura);
nfigura = nfigura+1;
x1 = ksdensity(res_XZ,w(:,1),'function','icdf');
y1 = ksdensity(res_YZ,w(:,2),'function','icdf');
[Rho_Pearson,pvalor] = corr(res_YZ,res_XZ);
strcat('Correlacion de Pearson:',num2str(Rho_Pearson),char(1),'pvalor
    :',num2str(pvalor))
 indices = indicesn(~isnan(x1)&~isnan(y1));
Rho_Copula = corr(x1(indices),y1(indices));
strcat('Correlacion de Pearson de la copula:',num2str(Rho_Copula))
h = scatterhist(x1,y1);
xmin = min(min(res_XZ),min(x1));
xmax = max(max(res_XZ),max(x1));
ymin = min(min(res_YZ),min(y1));
ymax = max(max(res_YZ),max(y1));
set(get(gca,'Children'),'Marker','*');
xlabel(strcat(etiquetaX,char(1),'copula'));
ylabel(strcat(etiquetaY,char(1),'copula'));
set(h(1),'Xlim',[xmin xmax]); set(h(2),'Xlim',[xmin xmax]);
set(h0(1),'Xlim',[xmin xmax]); set(h0(2),'Xlim',[xmin xmax]);
intervalo = [ymin ymax];intervaloXY = get(h(1),'Ylim'); set(h(1),'
    Ylim',intervalo);
intervaloY = get(h(3),'Ylim');set(h(3),'Ylim',[intervaloY(1)+
    intervalo(1)-intervaloXY(1) intervaloY(1)+intervalo(2)-intervaloXY
```

```
        (1)]);
    intervaloXY = get(h0(1),'Ylim'); set(h0(1),'Ylim',intervalo);
    intervaloY = get(h0(3),'Ylim');set(h0(3),'Ylim',[intervaloY(1)+
        intervalo(1)-intervaloXY(1) intervaloY(1)+intervalo(2)-intervaloXY
        (1)]);
    regresion_cuantil(X,Y,Z,nombresZ,'t',nfigura,[0.75, xmax],[ymin,ymax
        ],etiquetaX,etiquetaY);
end
if AIC_optimo==AIC_Clayton
    strcat('Copula optima:','Clayton')
    [alfa_Clayton,alfa_ci] = copulafit('Clayton',[u v])
    Tau_Copula = copulastat('Clayton',alfa_Clayton);
    [Tau_Kendall,pvalor] = corr(res_YZ,res_XZ,'type','Kendall');
    strcat('Tau de Kendall:',num2str(Tau_Kendall),char(1),'pvalor:',
        num2str(pvalor))
    strcat('Tau de Kendall de la copula:',num2str(Tau_Copula))
    Rho_Copula = copulastat('Clayton',alfa_Clayton,'type','Spearman');
    [Rho_Spearman,pvalor] = corr(res_YZ,res_XZ,'type','Spearman');
    strcat('Rho de Spearman:',num2str(Rho_Spearman),char(1),'pvalor:',
        num2str(pvalor))
    strcat('Rho de Spearman de la copula:',num2str(Rho_Copula))
    figure(nfigura);
    nfigura = nfigura+1;
    w = copularnd('Clayton',alfa_Clayton,nsim);
    scatterhist(w(:,1),w(:,2));
    xlim([0 1]);
    ylim([0 1]);
    set(get(gca,'Children'),'Marker','*');
    xlabel('u copula');
    ylabel('v copula');
    figure(nfigura);
    nfigura = nfigura+1;
    x1 = ksdensity(res_XZ,w(:,1),'function','icdf');
```

```
    y1 = ksdensity(res_YZ,w(:,2),'function','icdf');
    [Rho_Pearson,pvalor] = corr(res_YZ,res_XZ);
    strcat('Correlacion de Pearson:',num2str(Rho_Pearson),char(1),'pvalor
        :',num2str(pvalor))
    indices = indicesn(~isnan(x1)&~isnan(y1));
    Rho_Copula = corr(x1(indices),y1(indices));
    strcat('Correlacion de Pearson de la copula:',num2str(Rho_Copula))
    h = scatterhist(x1,y1);
    xmin = min(min(res_XZ),min(x1));
    xmax = max(max(res_XZ),max(x1));
    ymin = min(min(res_YZ),min(y1));
    ymax = max(max(res_YZ),max(y1));
    set(get(gca,'Children'),'Marker','*');
    xlabel(strcat(etiquetaX,char(1),'copula'));
    ylabel(strcat(etiquetaY,char(1),'copula'));
    set(h(1),'Xlim',[xmin xmax]); set(h(2),'Xlim',[xmin xmax]);
    set(h0(1),'Xlim',[xmin xmax]); set(h0(2),'Xlim',[xmin xmax]);
    intervalo = [ymin ymax];intervaloXY = get(h(1),'Ylim'); set(h(1),'
        Ylim',intervalo);
    intervaloY = get(h(3),'Ylim');set(h(3),'Ylim',[intervaloY(1)+
        intervalo(1)-intervaloXY(1) intervaloY(1)+intervalo(2)-intervaloXY
        (1)]);
    intervaloXY = get(h0(1),'Ylim'); set(h0(1),'Ylim',intervalo);
    intervaloY = get(h0(3),'Ylim');set(h0(3),'Ylim',[intervaloY(1)+
        intervalo(1)-intervaloXY(1) intervaloY(1)+intervalo(2)-intervaloXY
        (1)]);
    regresion_cuantil(X,Y,Z,nombresZ,'Clatyon',nfigura,[0.75, xmax],[ymin
        ,ymax],etiquetaX,etiquetaY);
end
if AIC_optimo==AIC_Frank
    strcat('Copula optima:','Frank')
    [alfa_Frank,alfa_ci] = copulafit('Frank',[u v])
    Tau_Copula = copulastat('Frank',alfa_Frank);
```

```
[Tau_Kendall,pvalor] = corr(res_YZ,res_XZ,'type','Kendall');
strcat('Tau de Kendall:',num2str(Tau_Kendall),char(1),'pvalor:',
   num2str(pvalor))
strcat('Tau de Kendall de la copula:',num2str(Tau_Copula))
Rho_Copula = copulastat('Frank',alfa_Frank,'type','Spearman');
[Rho_Spearman,pvalor] = corr(res_YZ,res_XZ,'type','Spearman');
strcat('Rho de Spearman:',num2str(Rho_Spearman),char(1),'pvalor:',
   num2str(pvalor))
strcat('Rho de Spearman de la copula:',num2str(Rho_Copula))
figure(nfigura);
nfigura = nfigura+1;
w = copularnd('Frank',alfa_Frank,nsim);
scatterhist(w(:,1),w(:,2));
xlim([0 1]);
ylim([0 1]);
set(get(gca,'Children'),'Marker','*');
xlabel('u copula');
ylabel('v copula');
figure(nfigura);
nfigura = nfigura+1;
y1 = ksdensity(res_YZ,w(:,2),'function','icdf');
x1 = ksdensity(res_XZ,w(:,1),'function','icdf');
[Rho_Pearson,pvalor] = corr(res_YZ,res_XZ);
strcat('Correlacion de Pearson:',num2str(Rho_Pearson),char(1),'pvalor
   :',num2str(pvalor))
indices = indicesn(~isnan(x1)&~isnan(y1));
Rho_Copula = corr(x1(indices),y1(indices));
strcat('Correlacion de Pearson de la copula:',num2str(Rho_Copula))
h = scatterhist(x1,y1);
xmin = min(min(res_XZ),min(x1));
xmax = max(max(res_XZ),max(x1));
ymin = min(min(res_YZ),min(y1));
ymax = max(max(res_YZ),max(y1));
```

```
    set(get(gca,'Children'),'Marker','*');
    xlabel(strcat(etiquetaX,char(1),'copula'));
    ylabel(strcat(etiquetaY,char(1),'copula'));
    set(h(1),'Xlim',[xmin xmax]); set(h(2),'Xlim',[xmin xmax]);
    set(h0(1),'Xlim',[xmin xmax]); set(h0(2),'Xlim',[xmin xmax]);
    intervalo = [ymin ymax];intervaloXY = get(h(1),'Ylim'); set(h(1),'
        Ylim',intervalo);
    intervaloY = get(h(3),'Ylim');set(h(3),'Ylim',[intervaloY(1)+
        intervalo(1)-intervaloXY(1) intervaloY(1)+intervalo(2)-intervaloXY
        (1)]);
    intervaloXY = get(h0(1),'Ylim'); set(h0(1),'Ylim',intervalo);
    intervaloY = get(h0(3),'Ylim');set(h0(3),'Ylim',[intervaloY(1)+
        intervalo(1)-intervaloXY(1) intervaloY(1)+intervalo(2)-intervaloXY
        (1)]);
    regresion_cuantil(X,Y,Z,nombresZ,'Frank',nfigura,[0.75, xmax],[ymin,
        ymax],etiquetaX,etiquetaY);
end
if AIC_optimo==AIC_Gumbel
    strcat('Copula optima:','Gumbel')
    [alfa_Gumbel,alfa_ci] = copulafit('Gumbel',[u v])
    Tau_Copula = copulastat('Gumbel',alfa_Gumbel);
    [Tau_Kendall,pvalor] = corr(res_YZ,res_XZ,'type','Kendall');
    strcat('Tau de Kendall:',num2str(Tau_Kendall),char(1),'pvalor:',
        num2str(pvalor))
    strcat('Tau de Kendall de la copula:',num2str(Tau_Copula))
    Rho_Copula = copulastat('Gumbel',alfa_Gumbel,'type','Spearman');
    [Rho_Spearman,pvalor] = corr(res_YZ,res_XZ,'type','Spearman');
    strcat('Rho de Spearman:',num2str(Rho_Spearman),char(1),'pvalor:',
        num2str(pvalor))
    strcat('Rho de Spearman de la copula:',num2str(Rho_Copula))
    figure(nfigura);
    nfigura = nfigura+1;
    w = copularnd('Gumbel',alfa_Gumbel,nsim);
```

```
scatterhist(w(:,1),w(:,2));
xlim([0 1]);
ylim([0 1]);
set(get(gca,'Children'),'Marker','*');
xlabel('u copula');
ylabel('v copula');
figure(nfigura);
nfigura = nfigura+1;
y1 = ksdensity(res_YZ,w(:,2),'function','icdf');
x1 = ksdensity(res_XZ,w(:,1),'function','icdf');
[Rho_Pearson,pvalor] = corr(res_YZ,res_XZ);
strcat('Correlacion de Pearson:',num2str(Rho_Pearson),char(1),'pvalor
    :',num2str(pvalor))
indices = indicesn(~isnan(x1)&~isnan(y1));
Rho_Copula = corr(x1(indices),y1(indices));
strcat('Correlacion de Pearson de la copula:',num2str(Rho_Copula))
h = scatterhist(x1,y1);
xmin = min(min(res_XZ),min(x1));
xmax = max(max(res_XZ),max(x1));
ymin = min(min(res_YZ),min(y1));
ymax = max(max(res_YZ),max(y1));
set(get(gca,'Children'),'Marker','*');
xlabel(strcat(etiquetaX,char(1),'copula'));
ylabel(strcat(etiquetaY,char(1),'copula'));
set(h(1),'Xlim',[xmin xmax]); set(h(2),'Xlim',[xmin xmax]);
set(h0(1),'Xlim',[xmin xmax]); set(h0(2),'Xlim',[xmin xmax]);
intervalo = [ymin ymax];intervaloXY = get(h(1),'Ylim'); set(h(1),'
    Ylim',intervalo);
intervaloY = get(h(3),'Ylim');set(h(3),'Ylim',[intervaloY(1)+
    intervalo(1)-intervaloXY(1) intervaloY(1)+intervalo(2)-intervaloXY
    (1)]);
intervaloXY = get(h0(1),'Ylim'); set(h0(1),'Ylim',intervalo);
```

```
    intervaloY = get(h0(3),'Ylim');set(h0(3),'Ylim',[intervaloY(1)+
        intervalo(1)−intervaloXY(1) intervaloY(1)+intervalo(2)−intervaloXY
        (1)]);
    regresion_cuantil(X,Y,Z,nombresZ,'Gumbel',nfigura,[0.75, xmax],[ymin,
        ymax],etiquetaX,etiquetaY);
end
```

Quantile regression curve estimation

```
function yred = regresion_cuantil(x0,y0,z,nombresz,familia,nfigura,xlim1,
    ylim1,etiquetaX,etiquetaY,contador)
n = size(x0,1);
colores = zeros(7,3);
incr = (0.8−0.1)/6;
tonos = 0.1:incr:0.8;
for i=1:7
    colores(i,:) = tonos(8−i);
end
p = [0.025 0.5 0.975];
if size(z,1)>0
    zcuantiles = zeros(7,size(z,2));
    for i=1:size(z,2)
        zcuantiles(:,i) = prctile(z(:,i),[5 10 25 50 75 90 95]);
    end
end
if size(z,1)>0
    [betaYZ,~,y,~] = regress(y0,[ones(n,1),z]);
    [betaXZ,~,x,~] = regress(x0,[ones(n,1),z]);
else
    x = x0;
    y = y0;
end
u = ksdensity(x,x,'function','cdf');
```

```
[ured,indices] = sort(u);
% if size(z,1)>0
%    zred = [ones(n,1),z(indices,:)];
% end
v = ksdensity(y,y,'function','cdf');
%
% Estimacion de la copula
%
switch familia
    case 'Gaussian'
        Rho = copulafit('Gaussian',[u v]);
        parametro = Rho(1,2);
    case 't'
        [Rho_t,nu_t] = copulafit('t',[u v],'Method','ApproximateML');
        parametro = [Rho_t(1,2),nu_t];
    otherwise
        parametro = copulafit(familia,[u v]);
end
%
%
vred = zeros(length(ured),length(p));
for j=1:length(p)
    for i=1:length(ured)
        vred(i,j) = regresion_cuantil_copula(familia,parametro,ured(i),p(
            j));
    end
end
%
%
xred = ksdensity(x,ured,'function','icdf');
% xred = x0;
yred = zeros(length(ured),2*length(p));
for j=1:length(p)
```

```
    yred(:,j) = ksdensity(y,vred(:,j),'function','icdf');
end
%
%
if size(z,1)>0
         zmediana = [1,median(z)];
     xred = zmediana*betaXZ+xred;
     for j=1:length(p)
         yred(:,j) = zmediana*betaYZ+yred(:,j);
     end
     [xred,indices] = sort(xred);
     yred = yred(indices,:);
end
%
%
if size(z,1)>0
    for i=1:size(z,2)
        figure(nfigura);
        nfigura = nfigura+1;
        plot(x0,y0,'w*');
        xlim(xlim1);
        ylim(ylim1);
        xlabel(etiquetaX);
        ylabel(etiquetaY);
        zaux = ones(size(zcuantiles,1),1)*median(z);
        zaux(:,i) = zcuantiles(:,i);
        zaux = [ones(size(zcuantiles,1),1),zaux];
        ymin = Inf;
        ymax = -Inf;
        for j=1: size(zcuantiles,1)
            xred1 = zaux(j,:)*betaXZ+xred;
            yred1 = zaux(j,:)*betaYZ+yred(:,2);
            [xred1,indices] = sort(xred1);
```

```
        yred1 = yred1(indices,:);
        line(xred1,yred1,'LineStyle','-','Color',colores(j,:));
        ymin = min(ymin,min(yred1));
        ymax = max(ymax,max(yred1));
    end
    xlim(xlim1);
    ylim([ymin ymax]);
    title(nombresz(i,:));
end
```

Appendix B

Appendix for the third chapter

B.1 Descriptive analysis

Table B.1: **Descriptive statistics of Sales (millions of euros)**

	mean	median	skewness	kurtosis	JB (p-value)*
2005	346.21	37.22	4.13**	21.37**	0.00
2006	325.76	28.30	4.27**	22.7**1	0.00
2007	330.10	27.32	4.22**	22.27**	0.00
2008	314.44	21.12	4.32**	23.21**	0.00
2009	304.25	16.93	4.41**	24.16**	0.00
2010	307.29	16.94	4.38**	23.86**	0.00
2011	320.33	23.07	4.28**	22.84**	0.00
2012	335.03	26.23	4.17**	21.73**	0.00

*Note: Statistically different from zero at the ** 5% significance level. JB: Jarque-Bera.*

Table B.2: **Descriptive statistics of Labour (millions of euros)**

	mean	median	skewness	kurtosis	JB (p-value)
2005	33.75	5.017	3.48**	15.51**	0.00
2006	32.87	4.38	3.53**	15.93**	0.00
2007	32.56	3.77	3.53**	15.98**	0.00
2008	31.78	3.35	3.55**	16.13**	0.00
2009	30.01	2.87	3.69**	17.30**	0.00
2010	29.72	2.75	3.69**	17.23**	0.00
2011	30.65	2.94	3.63**	16.73**	0.00
2012	31.58	2.95	3.55**	16.08**	0.00

*Note: Statistically different from zero at the ** 5% significance level. JB: Jarque-Bera.*

Table B.3: **Descriptive statistics of Amortisation (millions of euros**

	mean	median	skewness	kurtosis	JB (p-value)
2005	17.39	1.79	4.81**	30.90**	0.00
2006	16.68	1.47	4.92**	32.16**	0.00
2007	16.98	1.47	4.86**	31.44**	0.00
2008	15.89	1.32	5.09**	34.09**	0.00
2009	15.68	1.25	5.05**	33.84**	0.00
2010	16.00	1.32	4.99**	33.03**	0.00
2011	16.62	1.38	4.88**	31.74**	0.00
2012	16.98	1.38	4.81**	30.81**	0.00

*Note:Statistically different from zero at the ** 5% significance level. JB: Jarque-Bera.*

Table B.4: **Descriptive statistics of Supplies(millions of euros)**

	mean	median	skewness	kurtosis	JB (p-value)
2005	312.10	39.44	4.04**	20.56**	0.00
2006	285.52	34.08	4.23**	22.20**	0.00
2007	223.39	13.47	4.83**	28.64**	0.00
2008	213.70	78.53	4.92**	29.70**	0.00
2009	208.37	72.77	5.00**	30.57**	0.00
2010	208.49	71.15	5.00**	30.57**	0.00
2011	220.54	10.97	4.85**	28.83**	0.00
2012	229.75	12.11	4.73**	27.52**	0.00

*Note:Statistically different from zero at the ** 5% significance level. JB: Jarque-Bera.*

Table B.5: **Descriptive statistics of Emissions (thousands of Tonnes of CO_2)**

	mean	median	skewness	kurtosis	JB (p-value)
2005	814.72	60.53	7.01**	59.73**	0.00
2006	466.94	21.43	9.34**	10.45**	0.00
2007	456.50	19.18	9.42**	10.61**	0.00
2008	414.33	34.34	9.89**	11.69**	0.00
2009	403.98	31.02	10.02**	11.98**	0.00
2010	398.48	29.24	10.09**	12.15**	0.00
2011	419.77	32.91	9.97**	11.62**	0.00
2012	424.44	30.44	9.75**	11.36**	0.00

*Note: JB: Jarque-Bera. Statistically different from zero at the ** 5% significance level*

Table B.6: **Descriptive statistics of SA**

	mean	median	skewness	kurtosis	JB (p-value)
2005	0.11	0.10	-0.35**	6.86**	0.00
2006	0.08	0.20	-8.86**	88.33**	0.00
2007	0.033	0.17	-9.32**	98.30**	0.00
2008	0.10	0.10	-1.19**	6.6**1	0.00
2009	0.16	0.13	-1.17**	7.92**	0.00
2010	0.18	0.17	-0.80**	5.73**	0.00
2011	0.17	0.17	-1.20**	7.36**	0.00
2012	0.1451	0.1652	-3.9308**	29.9846**	0.00

*Note:Statistically different from zero at the ** 5% significance level. JB: Jarque-Bera.*

Table B.7: **Descriptive statistics of ATR**

ATR	mean	median	skewness	kurtosis	JB (p-value)
2005	1.20	0.67	9.06**	85.54**	0.00
2006	1.06	0.84	6.99**	73.52**	0.00
2007	1.10	0.89	2.88**	17.42**	0.00
2008	1.10	0.91	6.54**	68.82**	0.00
2009	1.04	0.86	8.51**	103.25**	0.00
2010	1.12	0.88	10.91**	146.99**	0.00
2011	1.16	1.01	1.41****	6.14**	0.00
2012	1.11	0.91	1.15	4.43**	0.00

*Note: Statistically different from zero at the ** 5% significance level. JB: Jarque-Bera.*

B.2 Bayesian estimation

B.2.1 Prior distribution of Θ

Given that we use a Bayesian approach, it is necessary to describe the prior distribution of the parameters of the model.

Let $\Theta = (\beta, \delta, \gamma, \tau_y, \tau_b, \Omega^{-1})$ be the parameters of the model. Their prior distributions are the following:

$\diamondsuit$ Prior of β and δ:

$$\begin{pmatrix} \beta \\ \delta \end{pmatrix} \sim TN_{10,R^+\times R^+}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} H_0^\beta & 0 \\ 0 & h_0^\delta \end{pmatrix}\right) \tag{B.2.1}$$

where TN denotes the Truncated Normal distribution,$H_0 = 0.0001I_{10}$ and $R^+ \times R^+$ is the region where the regularity conditions on (β, δ) are met.

$\diamondsuit$ Prior of γ:

$$\gamma \sim N_6\left(0, \Omega \otimes V\right) \tag{B.2.2}$$

where $\otimes$ denotes the kronecker product and $V = c\begin{pmatrix} a - \frac{2}{3} & 0 \\ 0 & I_2 \end{pmatrix}$, with a=3, d=4, c=1. This values are taken from Fernández et al. (2002).

$\diamondsuit$ Prior of Ω:

$$\Omega^{-1} \sim Wishart_3(\upsilon_0, S_0) \tag{B.2.3}$$

where $S_0 = 0.65I_3$ and $\nu_0 = 6$.This values are taken from Fernández et al. (2002).

$\diamondsuit$ Prior of (τ_y, τ_b):

$$\tau_y \sim \Gamma\left(\frac{n_y}{2}, \frac{n_y S_y^2}{2}\right), \tau_b \sim \Gamma\left(\frac{n_b}{2}, \frac{n_b S_b^2}{2}\right) \tag{B.2.4}$$

$\begin{pmatrix} \beta \\ \delta \end{pmatrix}$, $(\tau_y, \tau_b)'$ and $(\gamma, \Omega^{-1})'$ are assumed to be independent.

B.2.2 Posterior distribution of Θ

$$P\,(\Theta\,|\,Data) \propto L\,(\Theta\,|\,Data) \cdot P\,(\Theta) \propto L\,(\Theta\,|\,Data) \cdot\, [\beta]\,[\delta]\,[\tau_y]\,[\tau_b]\,[\,\gamma\,|\,\Omega^{-1}\,] \propto$$

$$\propto \prod_{i=1}^{N}\prod_{t=1}^{T_i} (\tau_y)^{\frac{1}{2}} \cdot exp\,\{\,-\frac{\tau_y}{2} \cdot (y_{it} \,-\, \chi'_{it}\,\beta \,+\, z_i)^2\} \cdot \prod_{i=1}^{N}\prod_{t=1}^{T_i} (\tau_b)^{\frac{1}{2}} \cdot exp\,\{\,-\frac{\tau_b}{2} \cdot (b_{it} \,-\, y_{it}\delta -\, \upsilon_i)^2\} \cdot$$

$$\cdot \prod_{i=1}^{N} \frac{1}{C\,(G_i\,\gamma\,\Omega^{-1})}\,|\Omega|^{-\frac{1}{2}} \,\cdot\, exp\{-\frac{1}{2}\,(E_i \,-\, G_i\gamma)'\,\Omega^{-1}\,(E_i \,-\, G_i\gamma)\} \,\cdot\, I_{\mathbb{R}^+\times\mathbb{R}^+}\,(\,E_i\,) \,\cdot$$

$$\cdot\, exp\{-\frac{1}{2}\beta'\left(H_{o\beta}^{-1}\beta\right)\} \,\cdot\, I_{\mathbb{R}^+\times\mathbb{R}^+}\,(\beta) \,\cdot\, exp\{-\frac{1}{2}\,\frac{\delta^2}{h_o^\sigma}\} \,\cdot\, I_{\mathbb{R}^+}\,(\delta) \,\cdot\, \tau^{\frac{n_y}{2}-1} \,\cdot\, exp\{-\frac{\tau_y}{2}\left(n_y\,S_y^2\right)\}$$

$$I_{[0,+\infty}\,(\tau_y) \cdot \tau_b^{\frac{n_b}{2}-1} \cdot exp\{-\frac{\tau_b}{2}\,n_b S_b^2\} \cdot I_{[0,+\infty}\,(\tau_b) \cdot |\Omega|^{-\frac{4}{2}} \cdot exp\{-\frac{1}{2}\,\gamma'\left(\Omega^{-1}\,\otimes\,V^{-1}\right)\gamma\} \cdot I_{\mathbb{R}^+\times\mathbb{R}^+}\,(\,\gamma\,) \,\cdot$$
$$|\Omega|^{-1*\frac{n_o-2-1}{2}} \,\cdot\, exp\{-\frac{1}{2}\,trace\,\left(S_o\Omega^{-1}\right)\} \,\cdot\, I_D\left(\Omega^{-1}\right)$$

As this distribution is not analytically tractable we employ MCMC methods, more specifically, the Gibbs sampling. To do so, we need the full conditionals of our parameters.

B.2.3 Full conditionals

$$\Diamond\tau_y|Data,\, \Theta - \{\tau_y\} \sim Gamma\,(A,\,B)$$
$$A \,=\, \frac{ny + \sum_{i=1}^{N} T_i}{2} \quad B \,=\, \frac{n_y S_y^2 + \sum_{i=1}^{N}\sum_{t=1}^{T_i}\left(y_{i,t} - x'_{i,t}\beta + z_i\right)^2}{2} \tag{B.2.1}$$

$$\diamondsuit\tau_b|Data,\,\Theta-\{\tau_b\}\sim Gamma\,(C,\,D)$$
$$C\,=\,\frac{n_b+\sum_{i=1}^{N}T_i}{2}\quad D\,=\,\frac{n_bS_b^2+\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left(b_{it}-y_{it}\delta-\upsilon_i\right)^2}{2} \tag{B.2.2}$$

$$\diamondsuit\beta|Data,\,\Theta-\{\beta\}\sim TN_{\forall x\in\mathbb{R}^+}\,(MEAN,\,VAR)$$
$$VAR\,=\,\left[\left(H_{\mathrm{o}}^{\beta}\right)^{-1}+\tau_y\left(\sum_{i=1}^{N}\sum_{t=1}^{T_i}x_{it}x_{it}'\right)\right]^{-1}MEAN\,=\,VAR\,\cdot\,\tau_y\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left(y_{it}+z_i\right)x_{i,t} \tag{B.2.3}$$

$$\diamondsuit\delta|Data,\,\Theta-\{\delta\}\quad\sim\quad TN_{\mathbb{R}^+x\mathbb{R}^+}\,(MEAN,\,VAR)$$
$$VAR\,=\,\left[\frac{1}{h_o^{\delta}}+\tau_b\sum_{i=1}^{N}\sum_{t=1}^{T_i}y_{it}\right];MEAN\,=\,VAR\,\cdot\,\tau_b\sum_{i=1}^{N}\sum_{t=1}^{T_i}y_{it}\left(b_{it}-\upsilon_i\right) \tag{B.2.4}$$

$$\diamondsuit\gamma|Data,\,\{\gamma\}\sim\frac{1}{\prod_{i=1}^{N}C\left(G_i\gamma,\,\Omega^{-1}\right)}\,\cdot\,N\left(MEAN\,,\,VAR\right)$$
$$MEAN\,=\,VAR\,\cdot\,\sum_{i=1}^{N}G_i'\Omega^{-1}E_iVAR\,=\,\left(\Omega^{-1}\otimes V^{-1}+\sum_{i=1}^{N}G_i'\Omega^{-1}G_i\right)^{-1} \tag{B.2.5}$$

$$\diamondsuit E_i|Data,\,\Theta\ \sim TN_{2,\mathbb{R}^+x\mathbb{R}^+}\ (A,\,B)$$
$$A\,=\,B\,\cdot\,\left(\Omega^{-1}G_i\gamma+\begin{pmatrix}\tau_y\left(\sum_{t=1}^{T_i}x_{i,t}'\beta-\sum_{t=1}^{T_i}y_{i,t}\right)\\ \tau_b\left(\sum_{t=1}^{T_i}b_{i,t}-\delta\sum_{t=1}^{T_i}y_{i,t}\right)\end{pmatrix}\right) \tag{B.2.6}$$

$$
\begin{aligned}
&\Diamond\Omega^{-1}|Data,\, \Theta - \{\Omega^{-1}\} \propto \frac{1}{\prod_{t=1}^{N} C\left(G_i \gamma_1 \Omega^{-1}\right)} \\
&\cdot \left[|\Omega^{-1}| \frac{N + U_o + 1}{2} \cdot \exp\left(-\frac{1}{2} tr \left(\sum_{i=1}^{N} \left(E_i - G_i\gamma\right)\left(E_i - G_i\gamma\right)' + tr\left(\gamma' V^{-1}\gamma\right)\gamma\gamma' + S_o \right) \Omega^{-1} \right) \right]
\end{aligned} \tag{B.2.7}
$$

B.3 Matlab Code.

Bayesian stochastic production frontier estimation

```
%
%
N = size(y,1);
T = size(y,2);
p = size(x,3);
p1 = size(xb,3);
d = size(G,2)/2;
nsim = 100000;
% Distribucion a priori
Hbeta = 0.0001*eye(p);
Hdelta = 0.0001*eye(p1);
ny = 1;
sy = 1;
nb = 1;
sb = 1;
nu0 = 6;
S0 = diag(0.65*ones(2,1));
c = 1;
a = 3;
V = (1/c)*diag([1/(a-(d-1)/3);ones(d-1,1)]);
% Creacion de variables de salida e iniciacion del algoritmo
betas = zeros(p,nsim);
deltas = zeros(p1,nsim);
gammas = zeros(2*d,nsim);
z = zeros(N,nsim);
v = zeros(N,nsim);
Omegas = zeros(2,2,nsim);
tausy = (1/sy)*ones(nsim,1);
tausb = (1/sb)*ones(nsim,1);
```

```
for i=1:nsim
    Omegas(:,:,i) = S0;
end
%
%
for it =2:nsim
    if rem(it,50)==0
        it
    end
    %
    %
    MED = zeros(p,1);
    VAR = Hbeta;
    for i=1:N
        indices = Ti{i};
        for j=1:length(indices)
            t = indices(j);
            MED = MED + (y(i,t)+z(i,it-1))*reshape(x(i,t,:),p,1);
            VAR = VAR + tausy(it-1)*reshape(x(i,t,:),p,1)*reshape(x(i,t
                ,:),p,1)';
        end
    end
    VAR = inv(VAR);
    MED = tausy(it-1)*VAR*MED;
    betas(:,it) = TNormal(MED,VAR);
    % disp(strvcat('Betas:',num2str(betas(:,it)')))
    %
    %
    MED = zeros(p1,1);
    VAR = Hdelta;
    for i=1:N
        indices = Ti{i};
        for j=1:length(indices)
```

```
            t = indices(j);
            MED = MED + (b(i,t)-v(i,it-1))*reshape(xb(i,t,:),p1,1);
            VAR = VAR + tausb(it-1)*reshape(xb(i,t,:),p1,1)*reshape(xb(i,
                t,:),p1,1)';
        end
    end
    VAR = inv(VAR);
    MED = tausb(it-1)*VAR*MED;
    deltas(:,it) = TNormal(MED,VAR);
    % disp(strcat('Delta:',num2str(deltas(:,it)')))
    %
    %
    for i=1:N
        indices = Ti{i};
        VAR = reshape(Omegas(:,:,it-1),2,2)+length(indices)*diag([tausy(
            it-1) tausb(it-1)]);
        VAR = inv(VAR);
        MED = reshape(Omegas(:,:,it-1),2,2)*reshape(G(:,:,i),2,2*d)*
            gammas(:,it-1);
        for j=1:length(indices)
            t = indices(j);
            MED = MED + [tausy(it-1)*(reshape(x(i,t,:),1,p)*betas(:,it)-y
                (i,t));tausb(it-1)*(b(i,t)-reshape(xb(i,t,:),1,p1)*deltas
                (:,it))];
        end
        MED = VAR*MED;
        aux = TNormal(MED,VAR);
        z(i,it) = aux(1);
        v(i,it) = aux(2);
    end
    % disp(strvcat('z:',num2str(z(:,it)')))
    % disp(strvcat('v:',num2str(v(:,it)')))
    %
```

```
%
n = ny;
df = ny*sy;
for i=1:N
    indices = Ti{i};
    n = n + length(indices);
    for j=1:length(indices)
        t = indices(j);
        df = df + (y(i,t)-reshape(x(i,t,:),1,p)*betas(:,it)+z(i,it))
            ^2;
    end
end
tausy(it) = gamrnd(0.5*n,2/df);
% disp(strcat('tauy:',num2str(tausy(it))))
%
%
n = nb;
df = nb*sb;
for i=1:N
    indices = Ti{i};
    n = n + length(indices);
    for j=1:length(indices)
        t = indices(j);
        df = df + (b(i,t)-reshape(xb(i,t,:),1,p1)*deltas(:,it)-v(i,it
            ))^2;
    end
end
tausb(it) = gamrnd(0.5*n,2/df);
% disp(strcat('taub:',num2str(tausb(it))))
%
%
MED = zeros(2*d,1);
VAR = kron(reshape(Omegas(:,:,it-1),2,2),V);
```

```
for i=1:N
    MED = MED + reshape(G(:,:,i),2,2*d)'*reshape(Omegas(:,:,it-1)
        ,2,2)*[z(i,it);v(i,it)];
    VAR = VAR + reshape(G(:,:,i),2,2*d)'*reshape(Omegas(:,:,it-1)
        ,2,2)*reshape(G(:,:,i),2,2*d);
end
VAR = inv(VAR);
MED = VAR*MED;
VAR = 0.5*(VAR+VAR');
gamma_estrella = mvnrnd(MED,VAR)';
K = 0;
Sigma = inv(reshape(Omegas(:,:,it-1),2,2));
Sigma = 0.5*(Sigma+Sigma');
for i=1:N
    mu = reshape(G(:,:,i),2,2*d)*gammas(:,it-1);
    mu_estrella = reshape(G(:,:,i),2,2*d)*gamma_estrella;
    K = log(ProbNormC1(mu_estrella,Sigma))-log(ProbNormC1(mu,Sigma));
end
u = unifrnd(0,1);
if u<exp(K)
    gammas(:,it) = gamma_estrella;
else
    gammas(:,it) = gammas(:,it-1);
end
% disp(strvcat('Gammas:',num2str(reshape(gammas(:,it),d,2)')))
%
%
n = N+nu0-2;
phi = gammas(1:d,it);
psi = gammas((d+1):end,it);
S = nu0*S0 + [phi'*V*phi,phi'*V*psi;phi'*V*psi,psi'*V*psi];
for i=1:N
    aux = [z(i,it);v(i,it)]-reshape(G(:,:,i),2,2*d)*gammas(:,it);
```

```
        S = S + aux*aux';
    end
    S = inv(S);
    S = 0.5*(S+S');
    Omega_estrella = wishrnd(S,n);
    Sigma_estrella = inv(Omega_estrella);
    Sigma_estrella = 0.5*(Sigma_estrella + Sigma_estrella');
    Sigma= inv(reshape(Omegas(:,:,it-1),2,2));
    Sigma = 0.5*(Sigma+Sigma');
    K = 0;
    for i=1:N
        mu = reshape(G(:,:,i),2,2*d)*gammas(:,it);
        K = log(ProbNormC1(mu,Sigma_estrella))-log(ProbNormC1(mu,Sigma));
    end
    u = unifrnd(0,1);
    if u<exp(K)
        Omegas(:,:,it) = Omega_estrella;
    else
        Omegas(:,:,it) = Omegas(:,:,it-1);
    end
    % disp(strvcat('Omega:',num2str(reshape(Omegas(:,:,it),2,2))))
end
clear it i aux S u Omega_estrella Sigma_estrella Sigma gamma_estrella;
clear phi psi K mu mu_estrella n MED VAR df t;
clear N T S0 V a c d hdelta HBeta indices j nb nsim nu0;
clear ny p sb sy p1;
```

Appendix C

Appendix for the fourth chapter

C.1 Appendix

Table C.1: **VAR lag length selection. Akaike criteria**

VAR selection. Akaike criteria									
Lag	0	1	2	3	4	5	6	7	8
AIC	-17.3	-17.4	**-17.4**	-17.4	-17.4	-17.4	-17.4	-17.4	-17.3

Table C.2: **GARCH selection. Akaike criteria**

	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)
D.VECH	-18.07052	-18.07551	**-18.12053**	-18.02853
CCC	-18.07400	-18.07451	-18.08692	-18.08392
BEKK	-17.99557	-18.01967	-18.00677	-17.70