Environmental versus economic performance in the EU ETS from the point of view of policy makers: a statistical analysis based on copulas

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Abstract

The European Union Emissions Trading System (EU ETS) was created with the aim of promoting reductions of greenhouse gas emissions in a cost-effective and economically efficient manner. In line with this objective, when making their decisions, policy makers should consider not only the CO_2 reduction targets but also the influence of these pollution reduction goals on companies' economic performance. This paper analyses the relationship between the economic and environmental performance of a sample of Spanish companies involved in the EU ETS in order to provide more information to the institutions responsible for developing these policies. This relationship is considered from two perspectives: the first examines how a company's production affects the ratio of the level of emissions to allocated allowances (the EA ratio), while the second examines how the EA ratio affects company results. A statistical methodology based on copulas is used, which allows us to analyze the relationship between these variables without requiring the assumptions of joint normality and linearity, thus providing the study with greater flexibility and realism. Our results highlight the existence of three different periods that correspond to Phases I, II and III of the EU ETS. During Phase I (2005-2007), the relationship between the EA ratio and firms' production and profitability was weak and, in the case of production, not significant. In Phase II (2008-2012), the efficiency of the EU ETS was higher, the allocations were better adjusted to firms' activities, and firms with EA values close to 1 were the most productive and profitable. The same trend occurred in Phase III (2013-2015), where a significant reduction of CO_2 emissions levels was observed but with higher EA values, especially in the Energy and Other Manufacturing sectors (including the Food, Textile, Leather, Footwear and Clothing, and Rubber and Paper industries). Therefore, although the environmental policy promulgated by the EU ETS is partially achieving its goal of reducing CO_2 emissions, it is still necessary to encourage green investments in order to decrease the EA levels, which are too high to satisfy the European Union Allowances allocation policy.

Keywords: Copulas; Economic Performance; Environmental Performance; Multivariate Analysis; Dynamic Models

1- Introduction

Climate change is greatly challenging the sustainability of human society. In particular, greenhouse gases (GHG) and carbon emissions are major problems that are attracting substantial worldwide attention (Li et al., 2014; Gallego-Álvarez et al., 2015; Calel and Dechezleprêtre, 2016; Zeng and Chen, 2016; Zeng et al., 2016). Efforts are being made to more accurately evaluate the amount of human-induced emissions (Wang et al., 2016; Zeng et al., 2017 a) and companies are aligning themselves to the international proposal (put forward in the Kyoto protocol) to reduce emissions which is an important aspect of their social responsibility.

The European Union Emissions Trading System (EU ETS) was created with the aim of promoting reductions of GHG emissions in a cost-effective and economically efficient manner (Directive 2003/87/EC). In line with this objective, policy makers should consider not only the CO_2 reduction targets but also the influence of these pollution reduction goals on the economic performance of companies when making their decisions.

Given the importance of achieving a balance between pollution reduction targets and economic growth (European Commission, 2012), an important problem concerns analyzing the link between the environmental and economic performance of companies involved in the EU ETS. These performances are linked in two different ways: revenues and costs. The revenues of energy and industrial companies essentially come from production, and the production level, in turn, determines CO_2 emissions. At the same time, the level of CO_2 emissions influences the cost production function, since companies in the EU ETS must buy European Union Allowances (EUAs) if their CO_2 emissions surpass the limit established, or they can sell EUAs if their CO_2 emissions are below the limit.

Few studies have analyzed the above relationship, so to fill this gap, the objective of this paper is to study Spanish companies that were involved in the EU ETS during the period 2005-2016. Our purpose is twofold: first, we analyze the effect of production on environmental performance on a year-on-year basis by measuring the intensity of the effect of production on CO_2 emissions; second, we examine the effect of environmental performance on profitability in order to study how the behavior of companies with regard to their emissions targets (whether they emit less or more than the established limits) affects company results. In this way, we want to determine whether the costs of meeting the CO_2 emissions limits imposed by the EU ETS have had any effect on company profitability by analyzing whether the EU ETS created a real financial incentive for companies to emit less than they were allocated.

We use a statistical methodology based on copulas (Trivedi and Zimmer, 2005), which allows us to analyze the relationship between these variables without requiring the assumptions of joint normality and linearity (which are not satisfied), thus providing the study with greater flexibility and realism.

Our research may have implications for Spanish policy makers in terms of designing policies oriented toward EU ETS companies. Spanish companies involved in the EU ETS (combustion plants, oil refineries, coke ovens, iron and steel plants 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 of economic development in Spain from 1990 until 2008, when the economic crisis erupted. Therefore, an analysis of these companies is not only important for the companies themselves but also for the whole economy.

The rest of the paper is organized as follows. Section 2 provides a detailed literature review, Section 3 describes the data, Section 4 presents the statistical methodology, and Section 5 shows our results. Finally, Section 6 sets out our conclusions. Three appendices are also included: Appendix A contains the main concepts and mathematical properties related to copulas, while Appendices B and C include some additional figures and tables, respectively.

2. Literature review

EU ETS is the world's largest cap-and-trade program and the most important market-based application of economic principles to the climate problem. In a cap-and-trade system, a constraining quantitative limit is placed on the aggregate emissions of a specified set of plants, and the plants are allowed to trade their implied emission reductions among themselves in order to minimize costs and to limit emissions that would otherwise be produced that are considered "business-as-usual" emissions. Such trading is conducted through the sale and purchase of allowances, which are issued in an amount equal to the aggregate cap. Regulated plants are required to surrender an amount of EU allowances equal to their emissions. Allowances can be acquired either through free allocation or by purchasing through auctions or from others through trading (Ellerman et al., 2016). The European Commission (2009) stated that the quantity of allowances received by each installation should not be higher than the level of CO_2 emissions it was likely to emit in order to create the scarcity needed for trading and, therefore, to ensure a high EUA price. To that aim, it was necessary to determine the quantity of allowances received by each installation for which an accurate emissions estimation was carried out.

The EU ETS is implemented through a multinational framework, namely, the EU, rather than through the action of a single state or national government. The EU ETS was designed in three phases. Phase I came into effect in 2005 as a three-year pilot. This phase covered CO_2 emissions and focused mainly on power generation and energy-intensive manufacturing industries (mineral oil refineries, coke ovens, iron and steel plants, and factories producing cement, glass, lime, bricks, ceramics and pulp and paper). Participation was mandatory for all plants that exceeded 20 MWh of energy use, including conventional power plants. The allowance allocations and the emissions estimations for Phase I (2005-2007) were carried out in 2004 and were based on the level of emissions in prior years. Phase II ran from 2008-2012, in which the coverage of both countries and sectors was expanded. In this phase, the rules changed and banking the permits to posterior phases was permitted. The allowance allocations and the emissions estimations were carried out in 2006 and were based not only on the level of emissions but also on the production levels of prior years. However, a price drop was again noticed that was not due to the system's design; instead, it was the consequence of reduced economic activity and, hence, emissions.

In the first two phases, each member state developed a National Allocation Plan (NAP) stating the total number of allowances to be created and how they would be allocated to affected installations in that state. These NAPs would go into effect unless the commission rejected it because it failed to comply with certain criteria in the ETS Directive. Additionally, there was a lack of agreement on a suitable benchmark, which made it inevitable that the basis for allocation would be historical emissions. One of the negative consequences of this system was the "windfall profits" in the electricity sector due to the free allocation of allowances (at least 95% of the allowances were allocated freely in the first phase and 90% in the second phase), carbon cost pass throughs to electricity prices and the alleged competitive distortions resulting from different member-state rules for allocation (Sijm et al., 2008; Fabra and Reguant, 2014; Fell et al., 2015; Hintermann, 2016). These flaws in the initial years led the European Commission to adopt significant revisions to the EU ETS in late 2008 (Directive 2009/29/EC). The most important revisions were the following: the adoption of a single EU-wide cap that was to decline at 1.74% per annum, the adoption of auctioning as the basic allocation principle for allowances, continued free allocation for industrial facilities according to centrally determined benchmarks during the transition to full auctioning and changes to the offset provisions that further limited their use while expanding the scope for linking with GHG cap-and-trade systems that might be developed in other parts of the world. These agreements are being applied in Phase III, which covers the period 2013-2020, in which more than 12,000 power and industrial plants in 31 countries are taking part in the scheme.

To evaluate the performance of the EU ETS, studies have analyzed the following topics: emissions reductions, the evolution of allowance prices, and impacts on economic performance, competitiveness and innovation (Laing et al., 2014; Ellerman et al., 2016; Hinterman et al., 2016; Martin et al., 2016; Muûls et al., 2016).

With respect to emissions reductions, research has shown that the EU ETS has driven reduced GHG emissions in the participating companies when measured by aggregate emissions at the sector level (Ellerman and Buchner, 2007, 2008; Ellerman et al., 2010; Anderson and Di Maria, 2011; Egenhofer et al., 2011; Kettner et al., 2015), firm-level emissions (Abrell et al., 2012; Petrick and Wagner, 2014) and plant-level emissions (Klemetsen et al., 2016).

With respect to allowance prices, the EUA price has varied considerably over the first 10 years of the EU ETS. In Phase I, the price was between 5€ and 10€, before it then rose quickly to 25-30€ in late April 2006, at which time several member states reported that their emissions for 2005 were lower than expected. In response, the price fell to a few euro cents because Phase I allowances could not be banked for use in Phase II. As Phase II began, the EUA price reached almost 30€, but it declined by approximately 50% as result of the economic crisis in late 2008. After recovering in early 2009, it experienced a 2-year period of stability until the summer of 2011, when it fell again to approximately 4€ as Phase III began. Since the beginning of 2013, the EUA price has risen steadily, unlike what occurred in Phase I. The EUA price did not fall to zero again because Phase II allowances could be banked for use in Phase III and later years, when the caps would continue to be lowered and prices are therefore expected to be higher (Ellerman et al., 2016; Muûls et al., 2016).

Hintermann et al. (2016) revised the empirical evidence on the influence of different factors on allowance price formation, and the authors find that across all studies, economic activity and growth announcements as well as the oil and gas price positively influence allowance prices; in addition to electricity, fuel and allowance prices are cointegrated, although these relationships differ across markets due to differences in fuel mixes in electricity generation. Additionally, long-term changes in renewable capacity have a negative influence on allowance prices, whereas short-term shocks do not, which can be explained by allowance banking. Even though the EUA price is currently low, the authors suggest tightening the cap because of allowance banking, which should affect the price even today. However, they interpret this lower than expected value as good news because it proves that the EU climate policy was cheaper than expected.

One stream of the literature has focused on the program's possible impact on indicators of economic performance, such as profits, revenues, output, investment and employment. To comply with the EU ETS, regulated firms can undertake costly abatement, thus reducing their profit margins, or they can improve the efficiency of their operations (Laing et al., 2014) or buy EUAs, both of which will also lower their profits. In addition, regulated firms may lose market share to rival firms outside the EU ETS (Martin et al., 2016). In the case of power generation, this competitiveness effect is limited by the institutional and technical aspects of European electricity markets. In industrial firms, however, it may not feasible to pass through the cost of carbon without losing market share. In such cases, the result would be lower levels of production and employment or, alternatively, firms might relocate in order to avoid compliance with the EU ETS policy (carbon leakage), thus moving jobs and carbon emissions to unregulated countries.

The recent empirical literature finds, on average, very little evidence of adverse economic consequences from the EU ETS; thus, carbon leakage may not be a problem that is as important as had been anticipated. However, this broad finding may mask variations in the ability of different participants to pass through the cost of regulations and, consequently, differences in the costs that regulated plants face within the system (Muûls et al., 2016).

Marin et al. (2017) recently analyzed the impact of the EU ETS (Phases I and II) on a larger set of indicators of economic performance (value added, turnover, employment, investment, labor productivity, total factor productivity and markup) based on a large panel of European firms. To evaluate the causal impact of the EU ETS, the authors apply a difference-in-differences approach with pretreatment matching. They find that the EU ETS had a positive impact on the scale-related measures of economic performance (value added, turnover, employment and investment) of treated firms and a negative, but slight, impact on the scale-free measures (productivity and profitability), especially in Phase II. In their view, the Porter Hypothesis[1] (Porter and van der Linde, 1995), the lobbying activity engaged in by EU ETS companies and sectors on European Authorities and the low price of pollution permits in Phases I and II are some possible explanations of the positive effect of the EU ETS in the case of value added, employment and turnover.

Finally, there is also strong evidence that the EU ETS has had a positive effect on the amount of clean technology innovation to stimulate the development of low-carbon technologies, which make it cheaper to reduce carbon emissions. Thus, Calel and Dechezleprêtre (2016) compare patent applications for low-carbon technologies across both EU ETS and non-EU ETS firms, and they find that the EU ETS caused a small but significant increase in low-carbon patenting (8.1% for EU ETS firms versus 0.85% for all low-carbon patents filed with the EPO). Martin et al. (2013) investigate the impact of the EU ETS on clean innovation in processes and products using responses from manager interviews and find that firms in sectors just below the thresholds required for free allocation engage in significantly more innovation than those just above those thresholds, suggesting that the EUA allocation mechanism had an effect on firms' innovation decisions.

Against this background, this paper focuses on analyzing the link between environmental and economic performance in companies involved in the EU ETS. The literature provides different measures of environmental performance, which can be classified into three groups: those that analyze the behavior of companies toward the environment, e.g., the implementation of environmental strategies by management (Aragón-Correa et al., 2008; Molina-Azorín et al., 2009; Yang et al., 2011); those that reflect the consequences of companies' behavior in terms of pollution, e.g., GHG emissions (Hart and Ahuja, 1996; Sarkis and Codeiro, 2001; Clarkson et al., 2011; Iwata and Okada, 2011); and those that provide environmental ratings and scores carried out by organizations independent of companies' management that measure environmental performance by taking both of the previous perspectives into consideration (Elsayed and Paton, 2004).

In this paper, we center our attention on the second group of measures: the pollution produced by companies. Nevertheless, unlike other studies, we investigate

[1] The benefits of environmental management are larger than the costs, and tighter regulatory standards stimulate green innovation.

companies' emissions by taking into account the constraints imposed by the EU ETS. To that aim, we build an environmental performance indicator that is calculated as the total CO_2 emissions emitted each year by each company divided by the allocated units. This ratio, which we call the Emission to Allowances (EA) ratio, may be higher (lower) than 1 that indicates a deficit (surplus) of allowances.

Economic performance is usually measured using financial ratios. Contrary to the lack of consensus on the selection of a proper environmental performance measure, there seems to be agreement that the use of a financial measure has no impact on the results (Horvathova, 2010). For this reason, 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.

With respect to the link between environmental and economic performance, the literature is inconclusive and inconsistent. Some authors have found a positive link (Molina-Azorín et al. 2009, López-Gamero et al. 2009 and Yang et al. 2011), while others have found a neutral (Elsayed and Paton, 2004) or even a negative relationship (Sarkis and Cordeiro 2001). According to Horvathova (2010), this inconsistency is due to the use of inappropriate methodologies, and he provides several suggestions for obtaining more reliable results. He recommends using more advanced econometric analysis, rather than simple correlation coefficients, and accounting for omitted variable biases such as unobserved firm heterogeneity.

Following these recommendations, Segura et al. (2014) analyze the link between environmental and economic performance in Spanish companies involved in the EU ETS during the period 2005-2011 using linear quantile regression techniques. However, their linearity hypothesis might be unrealistic considering the lack of normality of the variables analyzed. In addition, the authors do not consider control variables, which may also bias the results obtained.

To overcome these problems, in this paper, we use a more flexible statistical methodology based on copulas, which provides a set of models to capture dependence in a broader context (Trivedi and Zimmer, 2005). Copulas have been widely and successfully used in finance (Patton, 2006, 2009; Heinen and Valdesogo, 2009; Jondeau and Rockinger, 2006) and in environmental contexts (Denault et al., 2009; Grothe and Schnieders, 2011). In addition, we include as control variables a set of firm characteristics that may influence companies' profitability, and we extend the analyzed period to 2005-2015, which includes part of Phase III. We believe that all of these issues increase the reliability and generality levels in the study.

3. Data

We select a sample of Spanish installations whose emissions were traded under the EU ETS during the period 2005-2016. The list of Spanish installations was obtained from the "*European Union Transaction Log*" web page of the European Commission (http://ec.europa.eu/environment/ets/allocationComplianceMgt.do), which includes all European firms participating in the EU ETS. We focus on the companies in the registry up to July 2016, and we find a total of 1,205 installations corresponding to 920 companies. Due to data unavailability, our sample was reduced to 777 companies (almost 85% of the total) for which we had data on all the variables for at least one year. In addition, we do not consider the year 2016 because data corresponding to the annual accounts of companies for that year were not available at the time of the study. The variables employed in our research were divided into three groups: environmental performance, economic performance and control variables. In the following subsections, we define our variables and provide a descriptive analysis.

3.1. Environmental performance

Environmental performance is measured as the ratio of CO_2 emissions over the allowances and is given by:

$$EA_{i,t} = \frac{E_{i,t}}{A_{i,t}} \quad (1)$$

where $A_{i,t}$ represents the assigned allowances, and $E_{i,t}$ represents the verified emissions of company i in period t.

Data related to the EA ratio were taken from the *European Union Transaction Log* (EUTL), an online database where the accounts of companies and physical people holding these allowances are listed. Each installation held an account in the EUTL 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, thus allowing us to obtain a single assigned (A) and verified (E) emission figure for each firm.

Table 1 shows, for each year, the main statistics for the EA ratio. Three different periods clearly stand out: 2005-2007, 2008-2012 and 2013-2015, corresponding to

Phase I (2005-2007), Phase II (2008-2012) and Phase III (2013-2027) of the EU ETS, respectively.

(Insert Table 1 about here)

In the case of NAP I, as stated in Order PRE/2827/2009, the maximum amount of emissions per year assigned to EU ETS sectors was 182.17 Metric Tonnes of Carbon Dioxide Equivalent (Mt CO_2). As explained by the 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 1, on average, companies had an allowance surplus of 10%, 11% and 8% in 2005, 2006 and 2007, respectively. The difference between the two sets of results occurred because approximately 75% of the companies had a surplus of allowances (EA≤1) 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 NAP II, the maximum level of allowances per year in Spain was 152.25 Mt CO_2 (Order PRE/2827/2009). Because the European Commission 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. Nevertheless, in the period 2008-2012, Spanish companies had an allowances surplus of 10.3% (Spanish Government, 2012).

Although NAP II was more stringent than NAP I, the lower EA ratio levels in the second period (see Table 1) suggest that the deviation from what was expected was more marked than in the first phase. According to data from 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 noted in Royal Decree 1370/2006. During the period 2008-2012, however, emissions were only 25.02% above 1990 levels due to the economic crisis. This reduction of CO_2 emissions from 2008 onward stemming from crisis-related declines in companies' production appears to be the reason why companies, on average, had an allowances surplus of approximately 37% (see Table 1).

However, in Phase III, the mean values of the EA ratio increased significantly, even though the mean level of CO_2 emissions was significantly lower, with a slight rebound in 2015-2016. This result is due to an increase in environmental awareness together with greater control of CO_2 emissions by firms (see Table 1), with a decrease in the averaged assigned allowances (73.97%) from Phase II to Phase III that was greater than the decrease in the level of CO_2 emissions (49.71%), thus causing a significant number of firms (approximately 38%) to have EA ratio values higher than 1.

Finally, it should be noted that the normality of the EA variable is rejected in all periods due to significant positive asymmetry and leptokurtosis. This result arises from the existence of a non-negligible percentage of firms with large EA 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 CO_2 emissions deficit in the period 2005-2008, as mentioned above. This trend was reduced in Phase III (skewness and kurtosis of the EA distribution are significantly lower) as a consequence of the adoption of a single EU-wide cap, with auctions instead of free allocations as the default method for allocating allowances, which reduced the competitive distortions resulting from different member states' allocation rules.

3.2. Economic performance

The EA ratio is linked to economic performance in two ways. First, it can primarily result from a company's level of production, and second, it can directly affect company profitability. To measure profitability, we employ Return on Assets (ROA = Operating income/Assets), which calculates how efficient management is at using its assets to generate earnings. To measure a company's production, we use the Asset Turnover Ratio (ATR = Operating revenue/Assets). The ideal measure would have been the production figure, but we did not have access to these data; thus, we use this activity ratio, which is widely used in the literature, as a proxy of companies' production level.

Table 2 shows the main descriptive statistics for ROA, while Table 3 presents the main descriptive statistics for ATR. Again, three different periods stand out: 2005-2007, 2008-2012 and 2013-2015. On average, companies had a positive ROA during the first period and it was relatively stable. However, the values corresponding to the period 2008-2012 were much lower. The breaking point was in 2008, when the global crisis began. Finally, an increase in profitability is shown from 2013 onward as a result of the recovery in Spanish economic activity.

(Insert Table 2 about here)

With respect to ATR, it should be noted that its mean and median decreased considerably after 2008, with a significant recovery from 2013 onward, where average values of ATR similar to those in 2005-2007 were achieved. This evolution is consistent with that of the Spanish GDP during this period. According to data from the Spanish National Statistics Institute, while the annual growth of GDP in 2005, 2006 and 2007 was approximately 4%, from 2008-2012, this value was approximately -1.3%, and it was 1.6% in 2014-2015.

(Insert Table 3 about here)

Finally, it should be noted that the normality hypothesis is rejected for both variables. In the case of ROA, this result is due to the presence of significant leptokurtosis (and negative asymmetry in the period 2005-2007) caused by a set of firms with higher absolute levels of profitability. In the case of ATR, the result is due to significant leptokurtosis and positive asymmetry, which appear in economic variables with a natural lower limit; in this case, it is related to the productive size of the firm.

3.3. Control variables

To eliminate some possible biases, we include a set of firm characteristics that may influence the link between environmental and economic performance. These characteristics are:

♦ Size of the company, which affects both the level of CO_2 emissions and the economic results. Following Elsayed and Paton (2004) and Clarkson et al. (2011), we measure it with *Log(Assets)*

♦ Risk of the company. Following Waddock and Graves (1997), McWilliams and Siegel (2000) and Elsayed and Paton (2004), we measure company risk using the debt-to-capital ratio, which has the following expression*: Liabilities/Assets*. The higher the ratio is, the more the company uses debt to finance its operations. If its revenues fall, a company with a high ratio might not be able to meet its debt payments, whereas a company with a low ratio financed its operations with equity and thus will be better prepared to face declining revenues.

♦ Sector of the company, which influences both the level of CO_2 emissions and the economic results (Elsayed and Paton, 2004). According to Directive 2003/87/CE, the companies in the EU ETS are divided into 9 sectors. The first comprises 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, respectively. When designing its National Allocation Plans (both NAP I and NAP II), the Spanish Government (2010) divided companies into two large groups: energy companies (sector 1) and industrial companies (sectors 2-9). The allocated quantity for each company was calculated using two different methodologies: one for all companies belonging to industrial sectors and the other for energy companies. In addition to companies' industry, property also plays an important role in environmental performance. For this reason and in order to propose specific policy advice, we divide the companies into four groups: Energy companies, Chemical and Metal Processing companies, Other Manufacturing Industries (food, textile, leather, footwear and clothing, rubber and paper) and Other Sectors (building, transportation and communications and services). This grouping was designed to allow a large enough sample size to carry out a statistical analysis for each year.

Data on economic performance and the control variables were taken from the SABI (*Sistema de Análisis de Balances Ibéricos*), a database maintained by the Bureau Van Dijk that provides 1,250,000 Spanish and 400,000 Portuguese company reports. These reports include, among other information, companies' financial profile, a summary of companies' industrial activities, balance sheets, profit and loss accounts, and financial ratios.

Tables 4 and 5 provide the descriptive statistics for Size and Risk, respectively. An increasing trend in firm size can be observed throughout the period as well as an increase in risk levels during the crisis period (2008-2011), followed by a decrease from 2012-2015 toward similar levels to those from 2005-2007, in the period before the crisis. The normality hypothesis is rejected for both variables, again due to the presence of significant leptokurtosis and positive asymmetry because of the existence of a natural lower limit for both variables and their relation to the economic size of the firm.

(Insert Tables 4 and 5 about here)

In Table 6, we show the number of firms corresponding to each group for each year. Additionally, in Appendix C we present the results of a statistical sector comparison study for each variable and each year. The largest sector is "Chemical and Metal Processing Industries," which includes approximately 65% of the firms (see Table 6). The Energy sector has the highest CO_2 emissions, EUAs, EA ratio values and, with the exception of the period 2005-2007, the most profitable companies. The economic crisis affected the Chemical and Metal Processing industries as well as the

Other Sectors (especially the construction sector), which were less profitable, emitted less CO_2, had lower ATR and EA ratio values and higher risk levels. In the years of Phase III and as a consequence of the Spanish economic recovery, the table shows that CO_2 emissions and EUAs have decreased (with a rebound in 2015), while the ATR and EA ratio levels have tended to increase, with average EA ratio values larger than 1, especially in the Energy sector. In addition, the risk levels have decreased significantly, and most sectors experienced an increase in profitability from 2014 onward. The only exception was the Energy sector, which had significantly lower profitability in 2014 due to the suspension, in March of 2012, of pre-award procedures for remuneration and economic incentives provided by the Spanish government for new electricity production facilities powered by renewable energy, cogeneration and waste.

(Insert Table 6 about here)

Because the normality of each variable is rejected for all years of the study, the relationships should not be examined in a normal multivariate context. For this reason, we chose the copula approach to model the relationship between economic and environmental performance. As Trivedi and Zimmer (2005) note, this approach is an adequate tool when capturing dependence in a broader context than the multivariate normal.

4. Methodology

Our objective is to analyse, on the one hand, the effect of production (ATR) on CO_2 emissions (EA) and, on the other hand, the effect of CO_2 emission (EA) on profitability (ROA) controlling for Size, Risk and Sector. To that aim, we determine the quantile regression lines which describe this influence, not only in the central of their joint distribution, but also in other parts (intermediate and tails), which gives a greater level of depth to the study. Due to the non-normality of the above variables, the relationship does not have to be linear. For this reason we set up the problems in terms of copulas which provide greater flexibility to the study. This section describes the methodology used in the paper. First, we set-up the problem and then, we describe the model selection and estimation procedures. In addition, Appendix A includes a brief summary about copulas and their properties as well as mathematical details of the procedures used in the paper.

4.1. Setting up the problem

Let us consider N_t firms observed in period $t \in \{1, \ldots, T\}$.

Let $\{(EA_{i,t}, ROA_{i,t}, ATR_{i,t}, Size_{i,t}, Risk_{i,t}, \mathbf{Sector}_{i,t})'; i=1,\ldots,N_t; t=1,\ldots,T\}$ be the observed data where $EA_{i,t}$ is the CO_2 verifed emissions to Allowances ratio, $ROA_{i,t}$ is the Return on Assets ratios, $ATR_{i,t}$ is the Assets Turnover Rotation ratio, $Size_{i,t}$ is the size, $Risk_{i,t}$ is the risk, and $\mathbf{Sector}_{i,t} = (Sector_{energy,i,t}, Sector_{chemical,i,t}, Sector_{other\text{-}manuf,i,t})'$ is the vector of dummies associated with the sector of company i in period t, where $Sector_{j,i,t} = 1$ if the i-th firm belongs to sector j and 0 otherwise.

Given that the methodology is the same in the two regressions, we only explain in detail the procedure used for obtaining the effect of ATR on EA. The effect of EA on ROA would be determined by applying the same algorithms, exchanging ATR for EA and EA for ROA.

4.2. Quantile regression

In order to analyze the influence of ATR on EA we will estimate the conditional quantiles lines:

$$EA_t = Q_{p,t}(EA_t|ATR_t,Size_t,Risk_t,\mathbf{Sector}_t) \quad \text{with } 0<p<1,\ t=1,\ldots,T \qquad (2)$$

where $Q_{p,t}(x_2|\ \mathbf{x}_1 = (x_1,\ldots, x_k)')$ denotes the p-quantile of the conditional distribution $X_2|\mathbf{X}_1= \mathbf{x}$ in period t.

In this way, and varying the values of parameter t and p, we can study the dynamic effect of ATR on EA for given values of the control variables (Size, Risk, **Sector**), not only in the center of the distribution ($p = 0.5$), but also in the upper ($p \geq 0.9$) and lower ($p \leq 0.1$) tails. Usually it is assumed that (2) is a linear function of the conditioning variables, i.e.

$$Q_{p,t}(EA_t|ATR_t,Size_t,Risk_t,\mathbf{Sector}_t) =$$

$$= \beta_{0,p,t} + \beta_{1,p,t}ATR_t + \beta_{2,p,t}Size_t + \beta_{3,p,t}Risk_t + \boldsymbol{\beta}'_{4,p,t}\ \mathbf{Sector}_t \qquad (3)$$

and $\beta_{1,p,t}$ represents the increase in p-quantile of EA_t produced by one unit increase in ATR_t for given values of (Size, Risk, **Sector**)[2]. However, this linearity hypothesis can

[2] The estimation of $(\beta_{0,p,t},\beta_{1,p,t},\beta_{2,p,t},\beta_{3,p,t}, \boldsymbol{\beta}'_{4,p,t})$ was carried out with function fminsearch of MATLAB R2015 b. This function minimizes the weighted absolute deviations sum $\sum_{i\in N_t}\left(pe^{+}_{i,t} + (1-p)e^{-}_{i,t}\right)$

be overly restrictive and, in order to weaken it, in this paper we will use a methodology based on the use of copulas.

4.3. Quantile regression based on copulas

In order to calculate (2), we will use copulas to model the conditional joint distribution, $F_{1,2}$, of ATR and SA given (Size, Risk, **Sector**) in such a way that:

$$F_{1,2,t}(ATR_t,EA_t|Size_t,Risk_t,\mathbf{Sector}_t) =$$

$$= C_t(F_{1,t}(ATR_t|Size_t,Risk_t,\mathbf{Sector}_t),\ F_{2,t}(EA_t|Size_t,Risk_t,\mathbf{Sector}_t)) \qquad (4)$$

where $F_{1,t}(ATR_t|Size_t,Risk_t,\mathbf{Sector}_t)$ and $F_{2,t}(EA_t|Size_t,Risk_t,\mathbf{Sector}_t)$ are the corresponding marginal distributions and $C_t(u_1,u_2)$ is a copula function which models the dependency relationship between ATR and EA conditional on (Size, Risk, **Sector**) in period t.

Copulas have certain properties that are very useful in the study of dependence. For instance, they can model potentially nonlinear dependence. In addition, they are invariant to strictly increasing transformations of random variables (Schweizer and Wolff, 1981). Thus, the simultaneous movements of ATR_t and EA_t can be captured by copulas, regardless of the scale in which each variable is measured.

From (4) we can also obtain the conditional joint density function given by:

$$f_{1,2,t}(ATR_t,EA_t|Size_t,Risk_t,\mathbf{Sector}_t) =$$

$$= c_t(F_{1,t}(ATR_t|Size_t,Risk_t,\mathbf{Sector}_t),\ F_{2,t}(EA_t|Size_t,Risk_t,\mathbf{Sector}_t))$$

$$f_{1,t}(ATR_t|Size_t,Risk_t,\mathbf{Sector}_t)\ f_{2,t}(EA_t|Size_t,Risk_t,\mathbf{Sector}_t) \qquad (5)$$

where $f_{1,t}(ATR_t|Size_t,Risk_t,\mathbf{Sector}_t)$ and $f_{2,t}(EA_t|Size_t,Risk_t,\mathbf{Sector}_t)$ are the corresponding marginal densities and $c_t(u_1,u_2) = \frac{\partial^2}{\partial u_1 \partial u_2} C_t(u_1,u_2)$. From (5) we obtain the conditional density of $EA_t|ATR_t,Size_t,Risk_t,\mathbf{Sector}_t$ which will be given by:

$$f_{2|1,t}(EA_t|ATR_t,Size_t,Risk_t,\mathbf{Sector}_t) =$$

$$= c_t(F_{1,t}(ATR_t|Size_t,Risk_t,\mathbf{Sector}_t),\ F_{2,t}(EA_t|Size_t,Risk_t,\mathbf{Sector}_t))f_{1,t}(ATR_t|Size_t,Risk_t,\mathbf{Sector}_t) \qquad (6)$$

---

where $e_{i,t} = EA_{i,t} - \beta_{0,p,t} - \beta_{1,p,t}ATR_{i,t} - \beta_{2,p,t}Size_{i,t} - \beta_{3,p,t}Risk_{i,t} - \boldsymbol{\beta}'_{4,p,t}\mathbf{Sector}_{i,t}$ and $e^{+}_{i,t} = \max\{e_{i,t},0\}$, $e^{-}_{i,t} = \max\{-e_{i,t},0\}$.

Using (6), the quantile $Q_{p,t}(EA_t|ATR_t,Size_t,Risk_t,\mathbf{Sector}_t)$ will be calculated by solving the equation:

$$P(EA_t \leq Q_{p,t}(EA_t|ATR_t,Size_t,Risk_t,\mathbf{Sector}_t)|\ ATR_t,Size_t,Risk_t,\mathbf{Sector}_t) =$$

$$= \int_{-\infty}^{Q_{p,t}(EA_t|ATR_t,Size_t,Risk_t,\mathbf{Sector}_t)} f_{2|1,t}\left(y \mid ATR_t,Size_t,Risk_t,\mathbf{Sector}_t\right)dy \ = p \qquad (7)$$

Making the change of variables $u_{1,t} = F_{1,t}(ATR_t \mid Size_t, Risk_t, \mathbf{Sector}_t)$ and $u_{2,t} = F_{2,t}(EA_t \mid Size_t, Risk_t, \mathbf{Sector}_t)$ it follows from (6) and (7) that:

$$P(EA_t \leq Q_{p,t}(EA_t|ATR_t,Size_t,Risk_t,\mathbf{Sector}_t)|\ ATR_t,Size_t,Risk_t,\mathbf{Sector}_t) =$$

$$= \int_{-\infty}^{Q_{p,t}(EA_t|ATR_t,Size_t,Risk_t,\mathbf{Sector}_t)} c_t\left(u_{1,t},u_{2,t}\right)du_{2,t} \ =$$

$$\frac{\partial C_t\left(F_1\left(ATR_t \mid Size_t,Risk_t,\mathbf{Sector}_t\right),F_2\left(Q_{p,t}\left(EA_t \mid ATR_t,Size_t,Risk_t,\mathbf{Sector}_t\right) \mid Size_t,Risk_t,\mathbf{Sector}_t\right)\right)}{\partial u_1}$$

4.4. Estimation procedure

In this section we describe our estimation procedure which is based on Patton (2006). Given that our problem has 5 variables and the size of our sample is not large, we will adopt some simplifying hypotheses which let us increase the reliability of the estimation process.

We will assume that:

$$ATR_t = \beta_{0,t}^{ATR} + \beta_{1,t}^{ATR}Size_t + \beta_{2,t}^{ATR}Risk_t + \boldsymbol{\beta}_{3,t}^{'ATR}\mathbf{Sector}_t + \varepsilon_t^{ATR} \text{ with } \varepsilon_t^{ATR} \sim f_{\varepsilon_t^{ATR}}(\cdot) \qquad (8)$$

$$EA_t = \beta_{0,t}^{EA} + \beta_{1,t}^{EA}Size_t + \beta_{2,t}^{EA}Risk_t + \boldsymbol{\beta}_{3,t}^{'EA}\ \mathbf{Sector}_t + \varepsilon_t^{EA} \text{ with } \varepsilon_t^{SA} \sim f_{\varepsilon_t^{SA}}(\cdot) \qquad (9)$$

Therefore:

$$f_{1,t}(ATR_t|Size_t,Risk_t,\mathbf{Sector}_t) =$$
$$= f_{\varepsilon_t^{ATR}}(ATR_t - \beta_{0,t}^{ATR} - \beta_{1,t}^{ATR}Size_t - \beta_{2,t}^{ATR}Risk_t - \boldsymbol{\beta}_{3,t}^{'ATR}\mathbf{Sector}_t)$$

$$f_{2,t}(EA_t|Size_t,Risk_t,\mathbf{Sector}_t) = f_{\varepsilon_t^{SA}}(EA_t - \beta_{0,t}^{EA} - \beta_{1,t}^{EA}Size_t - \beta_{2,t}^{EA}Risk_t - \boldsymbol{\beta}_{3,t}^{'EA}\ \mathbf{Sector}_t)$$

Additionally, we will assume that the copula function depends on a parameter ϑ in such a way that $C_t(u_1,u_2) = C(u_1,u_2, \vartheta_{M_t}, M_t)$ where ϑ_{M_t} is the vector of parameters of model M_t and $M_t \in \mathbf{M}$ where $\mathbf{M}$ is a set of families of copulas (see Appendix A in which some notable copulas are described).

Our target is to estimate the vector of parameters $\boldsymbol{\beta}_t^{ATR} = \left(\beta_0^{ATR}, \beta_1^{ATR}, \beta_2^{ATR}, \boldsymbol{\beta}_3^{'ATR}\right)'$, $\boldsymbol{\beta}_t^{EA} = \left(\beta_0^{EA}, \beta_1^{EA}, \beta_2^{EA}, \boldsymbol{\beta}_3^{'EA}\right)'$, the distributions $F_{\varepsilon_t^{ATR}}$, $F_{\varepsilon_t^{EA}}$ and θ_t = (ϑ_{M_t}, M_t) for t = 1,…,T. To carry out this process, we use the following algorithm for each t:

4.4.1. Copula model selection and estimation algorithm

Step 1.- We estimate $\boldsymbol{\beta}_t^{ATR}$ and $\boldsymbol{\beta}_t^{EA}$ by means of a robust regression method and using the dataset {($EA_{i,t}$, $ROA_{i,t}$, $ATR_{i,t}$, $Size_{i,t}$, $Risk_{i,t}$, $\mathbf{Sector}_{i,t}$); $i \in N_t$}. We have used the MATLAB function *robustfit*.

Step 2.- With the previous estimations, $\hat{\boldsymbol{\beta}}_t^{ATR}$ and $\hat{\boldsymbol{\beta}}_t^{EA}$, we obtain the residuals $\hat{\varepsilon}_{i,t}^{ATR}$ and $\hat{\varepsilon}_{i,t}^{EA}$ given by the following expressions:

$$\hat{\varepsilon}_{i,t}^{ATR} = ATR_{i,t} - \hat{\beta}_{0,t}^{ATR} - \hat{\beta}_{1,t}^{ATR} Size_{i,t} - \hat{\beta}_{2,t}^{ATR} Risk_{i,t} - \hat{\boldsymbol{\beta}}_{3,t}^{'ATR} \mathbf{Sector}_{i,t} \text{ for } i \in N_t$$

$$\hat{\varepsilon}_{i,t}^{EA} = EA_{i,t} - \hat{\beta}_{0,t}^{EA} - \hat{\beta}_{1,t}^{EA} Size_{i,t} - \hat{\beta}_{2,t}^{EA} Risk_{i,t} - \hat{\boldsymbol{\beta}}_{3,t}^{'EA} \mathbf{Sector}_{i,t} \text{ for } i \in N_t$$

Step 3.- Estimate $F_{\varepsilon_t^{ATR}}$ and $F_{\varepsilon_t^{EA}}$ using non-parametric kernel estimators applied to the residuals data $\left\{\hat{\varepsilon}_{i,t}^{ATR}; i \in N_t\right\}$ and $\left\{\hat{\varepsilon}_{i,t}^{EA}; i \in N_t\right\}$, respectively. We use the MATLAB function *ksdensity* with *function* argument '*cdf*'.

Step 4.- With the previous estimations $\hat{F}_{\varepsilon_t^{ATR}}$ and $\hat{F}_{\varepsilon_t^{SA}}$, calculate $\hat{u}_{1,i,t} = \hat{F}_{\varepsilon_t^{ATR}}\left(\hat{\varepsilon}_{i,t}^{ATR}\right)$ and $\hat{u}_{2,i,t} = \hat{F}_{\varepsilon_t^{EA}}\left(\hat{\varepsilon}_{i,t}^{EA}\right)$ for $i \in N_t$ to transform $\hat{\varepsilon}_{i,t}^{ATR}$ and $\hat{\varepsilon}_{i,t}^{EA}$ to U(0,1) distributions.

Step 5.- For each $M \in \mathbf{M}$, use the maximum likelihood procedure to estimate ϑ_{M_t} from $\left\{\left(\hat{u}_{1,i,t}, \hat{u}_{2,i,t}\right); i \in N_t\right\}$. This estimator will be given by:

$$\hat{\vartheta}_M = \arg\max_{\vartheta_M} \ell\left(\vartheta_M; \left\{\left(\hat{u}_{1,i,t}, \hat{u}_{2,i,t}\right); i \in N_t\right\}, M\right) = \arg\max_{\vartheta_M} \sum_{i \in N_t} \log\left(c\left(\hat{u}_{1,i,t}, \hat{u}_{2,i,t}, M, \vartheta_M\right)\right)$$

Step 6.- Select model M_t using the AIC criterion in such a way that

$$M_t = \arg\min_{M \in \mathbf{M}} AIC(M) = \arg\min_{M \in \mathbf{M}} \left\{-2\,\ell\left(\hat{\vartheta}_{M_t}; \left\{\left(\hat{u}_{1,i,t}, \hat{u}_{2,i,t}\right); i \in N_t\right\}, M\right) + \dim(\vartheta_M)\right\}$$

Once we have estimated and selected the best copula we use the following algorithm to calculate the p-quantile regression curves of EA on ATR for a given value of $0 \leq p \leq 1$ and t.

4.4.2. Quantile regression line estimation algorithm

1. Calculate, for i=1,…, N_t, $\hat{u}_{i,1,t} = F_{\varepsilon_t^{ATR}}\left(\hat{\varepsilon}_{i,t}^{ATR}\right)$ with

$$\hat{\varepsilon}_{i,t}^{ATR} = ATR_{i,t} - \hat{\beta}_{0,t}^{ATR} - \hat{\beta}_{1,t}^{ATR} Size_{i,t} - \hat{\beta}_{2,t}^{ATR} Risk_{i,t} - \hat{\boldsymbol{\beta}}_{3,t}^{'ATR} \mathbf{Sector}_{i,t}$$

2. Solve in $u_{2,t}$ the equation $\dfrac{\partial C\left(\hat{u}_{i,1,t}, u_{2,t}, \hat{\vartheta}_{M_t}, M_t\right)}{\partial u_{1,t}} = p$
3. Calculate

$$\hat{Q}_{p,t}(EA_{i,t}|ATR_{i,t}, Size_{i,t}, Risk_{i,t}, Sector_{i,t}) = \hat{\beta}_{0,t}^{EA} + \hat{\beta}_{1,t}^{EA} Size_{i,t} + \hat{\beta}_{2,t}^{EA} Risk_{i,t} + \hat{\boldsymbol{\beta}}_{3,t}^{'EA} \mathbf{Sector}_{i,t} + \hat{u}_{i,2,t}$$

where $\hat{u}_{i,2,t}$ is the solution obtain in step 2.

We have used 5 different families of copulas (Gaussian, Student's t, Clayton, Frank and Gumbel) that are widely used in the literature to capture different types of dependences between two variables, both in central areas and in the tails of the joint distribution (see Appendix A for details). Finally, once the best copula has been selected, we calculate the p-quantile regression curve of ε_t^{EA} on ε_t^{ATR} for a set of values of p using the algorithm 4.4.2. Additionally, and in order to analyze the goodness of fit to data of the selected model, we have compared the values of the Spearman's ρ correlation coefficients of the observations $\left\{\left(ATR_{i,t}, EA_{i,t}\right); i \in N_t\right\}$ with those estimated using the selected copula and the estimated model (8)-(9) (see algorithm A.5.1 in Appendix A), respectively.

5. Empirical results and discussion

In this section, we estimate the relationship between economic and environmental performance from two perspectives: production versus the EA ratio and the EA ratio versus profitability. Both links are estimated using copula structures following the procedure described in Section 4. Additionally, we present the estimation of both links through two linear regression models for comparative purposes. All calculations were conducted in MATLAB R2015b.

5.1 The effect of production ATR on EA

Table 7 shows the results obtained from a robust linear regression of the EA ratio on ATR, while Tables 8 and 9 show the results obtained from applying the estimation procedure described in sub-section 4.4. Concretely, Table 8 shows, for each year, the AIC value for each family of copulas considered in this paper. Table 9 shows for each year the observed Pearson and Spearman's ρ correlations as well as the results of the test of the goodness of fit of the model to the data. Finally, Figure 1 displays, for each year, the quantile regression lines (2) of the EA ratio on ATR calculated from the selected copulas using algorithm 4.4.2, together with the linear quantile regression functions (3) and the linear regression for five quantiles, 2.5%, 25%, 50%, 75% and 97.5%. The individual data correspond to companies within the largest sector, "Chemical and Metal Processing industries," with average characteristics for the control variables Size and Risk.

(Insert Tables 7, 8 and 9 about here)

The results show that the strength of the relationship between the EA ratio and ATR was not constant over time, as it was not significant in Phase I, it was more intense and increasing after the onset of the global economic crisis in Phase II, and it lost some importance in Phase III (see the observed Spearman's ρ values in Table 9). In the period 2005-2007, there was an economic boom with high production and CO_2 emissions levels (Tables 1 and 3). Given that NAP I was not very stringent, with allocations that exceeded the projected emissions, the average levels of the EA ratio were less than 1 (Table 1). Figure 1 and Table 9 show that firms tended to adjust their emissions to their allocations independently of their production levels: all the regression lines are essentially horizontal, and the observed Spearman's ρ values are not significant.

From 2008 to 2012, the situation changed: the economic crisis caused a decrease in production (Table 3), and NAP II was more stringent, simple and transparent than NAP I. That is, the use of allowances by companies was more in accordance with their production levels, with a significant increase in the percentage of firms with EA≤1 (Table 1). The observed Spearman's ρ values corresponding to the selected copulas (Table 9) and the regression coefficients of ATR in the linear regression (Table 7) increased significantly and achieved their largest values at the end of Phase II. Clayton, Frank and t copulas were selected in this period (Tables 8 and 9) because the link between these variables tends to be stronger in the center of the distribution and, in the case of a Clayton copula, also in the left tail (Figure B1 in Appendix B). The relationship between the EA ratio and ATR was non-linear, given that the Spearman's ρ values were significantly greater than the Pearson correlation coefficients (Table 9), with the effect of production on the EA ratio being approximately linearly increasing in the central areas of the EA distribution (quantiles 25% to 75%) but essentially horizontal in both tails (quantiles 2.5% and 97.5%), mainly for high production levels ($ATR \geq 2$, see Figure 1).

(Insert Figure 1 about here)

From 2013 to 2015, the relationship between the EA ratio and ATR continued to be significantly positive but with smaller observed values of Spearman's ρ. Student's t is the selected copula (see Tables 8 and 9) because the degree of dependency between ATR and the EA ratio tends to be similar in all areas of their joint distribution (see Figure B1 in Appendix B). The influence of ATR on the EA ratio was essentially linear for all the quantiles with the only exception for quantile 97.5, where a U-shaped curve is shown with a minimum around ATR = 1 in 2013 and 2014 and an increasing relationship for higher values of ATR (Figure 1). Given that in Phase III the number of EUAs decreased significantly (Table 1), some disagreement between the EUA determination policy and CO_2 emissions practices is revealed: CO_2 emissions display a non-negligible trend to be greater than allowances, especially in the Energy sector (Table C1 in Appendix C).

Finally, we can say that the goodness of fit of the selected model to the data is adequate: most of the p-values described in Appendix A (section A.5) are greater than 0.05. Only in 2007 is there a small discrepancy that is significant at the 5% level but not at 1%, and the observed Spearman's ρ values are not significant.

5.1.1. The effects of the control variables

To analyze the effect of the control variables on the link between ATR and the EA ratio, Figure 2 (Figure 3) displays the median (p=0.5) regression curves of the EA ratio on ATR for Chemical and Metal Processing firms as well as quantiles 2.5%, 25%, 50%, 75% and 97.5% of Size (Risk) while maintaining Risk (Size) at its average values. Size did not have a significant effect during Phase I on the link between ATR and the EA ratio, but it had a positive influenced in Phases II and III (the lines become more separated). Small firms had EA values significant lower than large firms; this result seems to reflect, indirectly, that the impact of the crisis (Phase II) was less severe in large companies than in small. These differences continued in Phase III due to the stricter CO_2 emissions policy under the EU ETS, which made small firms tend to adjust their CO_2 emissions to their productive needs. The effect of Risk was not significant for most periods, with only a slight positive influence in the period 2012-2015, when riskier installations tended to have higher EA values, although the differences were small and not very significant.

(Insert Figures 2 and 3 about here)

Figure 4 displays the median regression curves of the EA ratio on ATR for firms with average Size and Risk values in Energy (blue line), Chemical and Metal Processing (magenta line), Other Manufacturing (green line) and the Rest of the Sectors (red line). The figure shows that companies in the Energy sector had the highest EA values from 2008 onward, followed by the Other Manufacturing sectors. These differences tended to be larger in Phase III, with EA values much higher than 1 for firms with ATR$\geq$2. This result highlights the need to adapt allowance allocation policies to different sectors, especially for companies in the Energy sector, which, even though they significantly reduced their CO_2 emissions levels (Table C1 in Appendix C), have had the highest EA values due to their higher productive needs.

(Insert Figure 4 about here)

5.2 The effect of the EA ratio on ROA

Table 10 presents the results of a robust linear regression of ROA on the EA ratio, while Tables 11 and 12 show the results of applying the estimation procedure described in sub-section 4.4. Finally, Figure 5 displays, for each year, the quantile regression lines (2) of ROA on the EA ratio calculated from the selected copulas using algorithm 4.4.2, together with the linear quantile regression functions (3) and the linear regression for the 2.5%, 25%, 50%, 75% and 97.5% quantiles of companies in the Chemical and Metal Processing Industries sector with average characteristics of Size and Risk.

(Insert Tables 10, 11, 12 and Figure 5 about here)

The tables show that ROA and the EA ratio are positively related (note that the Spearman's ρ values in Table 12 are significantly positive) in all the analyzed periods. This relation is linear in the central parts of their joint distribution (quantiles 25%, 50%

and 75%), with very similar estimated linear regression, quantile linear regression, and quantile regression lines based on copulas (Figure 5). The main differences correspond to the tails of the distribution (quantiles 2.5% and 97.5%), where a non-linear relationship is displayed such that for values of EA≥0.5, the influence of the EA ratio on ROA is not significant or is even non-increasing (quantile 2.5% in 2005, 2008, 2010, see Figure 5). Therefore, firms that emitted more CO2 than expected did not have a significant increase in profits, especially during Phases II and III. This result explains the selection of a Frank copula (Table 10), with more intense dependence between both variables in the central part of their joint distribution (see also Figure B.2 in Appendix B).

The strength of this relation tended to be larger in Phase II and reached its maximum in 2012, when the value of Spearman ρ was equal to 0.3325 (Table 12). The minimum value of these coefficients in 2014 was due to some firms that had high EA and low ROA values (EA≥1.5 and ROA ≤-20%, see Figure B2 in Appendix B). Finally, the model showed acceptable goodness of fit: all the p-values explained in Appendix A.5 are higher than 0.10 (see Table 12).

5.2.1. The effects of the control variables

Finally, we analyze the effect of the control variables on the link between the EA ratio and ROA. Figure 6 (Figure 7) displays the median (p=0.5) regression curves of ROA on the EA ratio for Chemical and Metal Processing firms as well as quantiles 2.5%, 25%, 50%, 75% and 97.5% of Size (Risk) while maintaining Risk (Size) at its average values. The results show that in general, Size positively affected companies' ROA, while Risk negatively affected it, with the only exception being 2009, when large firms (mainly from the Chemical and Metal Processing and Other Manufacturing sectors) with higher EA values tended to have lower profit levels than other firms.

(Insert Figures 6 and 7 about here)

Figure 8 shows the median regression curves of ROA on the EA ratio corresponding to firms with average size and risk characteristics within the four sectors considered in this study. The figure shows that in Phase I, companies in the Chemical and Metal Processing sector tended to have higher profitability than firms in the other sectors (see Table 10 as well). This trend was inverted during Phase II, when firms in the Energy sector were the most profitable and those in the Chemical and Metal

Processing Industries sector were less profitable. Finally, in Phase III, a decrease in the profitability of companies in the Energy sector in 2013-2014 is observed, which was due to the suspension, in March of 2012, of pre-award procedures for remuneration and economic incentives provided by the Spanish government for new electricity production facilities from renewable energy, cogeneration and waste. However, in 2015, an increase in the profitability of firms in this sector is observed (see Figure 8 and Table C1 in Appendix C), likely due to the recovery of economic activity in Spain, which significantly increased these firms' level of CO_2 emissions and their EA values.

(Insert Figure 8 about here)

5.3. Discussion of results

The results from Sections 5.1 and 5.2 highlight that the EUA allowance concession policies have shown increasing effectiveness across Phases I, II and III. During Phase I (2005-2007), NAP I was not very stringent, too complex and not sufficiently transparent, and the allocations exceeded the projected emissions; as a result, production and profitability were not significantly related to the allowances use. In Phase II (2008-2012), which was more stringent, simpler and transparent, firms' CO_2 emission levels were conditioned by the economic crisis: firms' production levels decreased significantly, and most emitted less CO_2 than they were assigned. However, firms with high EA values tended to be the most profitable, and this effect was greater in large, less risky and energy firms. In contrast, companies that had to buy EUAs in order to emit more CO_2 than they were initially allocated (and that therefore had EA values greater than 1) did not achieve a significant increase in profits. Finally, in Phase III (2013-2015), a significant reduction of CO_2 emissions was observed, and it was accompanied by a significant increase in the firms' productivity and profitability. This increase was positively related to their EA levels, but with a decreasing influence for EA values greater than 1. However, the average EA values were greater than 1 for a significant proportion of companies (approximately 38%), mainly those in the Energy, Other Manufacturing and Other sectors (see Table C1 in Appendix C) due to the decrease in EUAs during this phase. These results suggest that EU ETS policy in Phase III was effective in Spain. CO_2 emissions have been reduced, thus indicating that firms' environmental awareness has increased and, even though the EA values were greater than 1 for a significant proportion of firms, the impact on productivity and profitability has not been negative, likely due to Spain's economic recovery. However, some firms (mainly in the Energy sector) should adapt their CO_2 emissions to their allocated allowances because the impact on profitability has decreasing returns.

6. Conclusions

In this paper, we have examined the relationship between economic performance and environmental performance for Spanish companies in the EU ETS during the period 2005-2015. Unlike previous studies, we have used the EA ratio of emitted (E) to assigned (A) CO_2 emissions. In this way, we can analyze how the constraints on CO_2 emissions imposed by the EU ETS have affected economic performance.

We have carried out a dynamic study using quantile regression based on copulas, which increases the flexibility of our study and allows us to capture non-linear relationships between the variables and dependencies in different parts of their joint distribution. Additionally, we have included a set of firm characteristics as control variables in order to avoid omitted variable biases.

Our results highlight the existence of three different periods, which correspond to Phases I, II and III of the EU ETS. During Phase I (2005-2007), the relationship of the EA ratio to firms' production was not significant, and its relationship with the firms' profitability was weak. This was due to the not very stringent, too complex and not sufficiently transparent character of NAP I, which barely affected firms' use of allowances, as the allocations exceeded their CO_2 emissions. In Phase II (2008-2012), the efficiency of the EUAs was higher, as NAP II was more stringent, simpler and transparent, which increased the intensity of the direct link between the EA ratio and firm's production and profitability. In this period, the allocations were more appropriate for the firms' activities, and firms with EA values close to 1 were the most productive and profitable. Additionally, firms with high EA values did not experience a significant increase in their profits. The same trend was observed in Phase III (2013-2015), where a significant reduction of CO_2 emissions levels was also observed, but with higher EA values, especially in the Energy and Other Manufacturing sectors (Food, Textile, Leather, Footwear and Clothing, Rubber and Paper industries), whose average levels were greater than 1.

These results shed further light on the efficiency of the EU ETS in fostering green investment by Spanish companies. Although a significant reduction in CO_2 emission levels was produced in Phase III, an increase in EA values due to a decrease in

EUAs was also observed. Therefore, even though the environmental policy implemented through the EU ETS is partially achieving a reduction in CO_2 emissions, it also needs to encourage green investment, especially in the Energy sector, in order to decrease firms' EA levels, which are still too high to fully satisfy the EUA allocation policy. Furthermore, policy makers should pay more attention to firms with high production levels, which tend to have higher EA values without significantly increasing their profits, especially in the Energy and Other Manufacturing sectors.

It would be interesting to obtain additional information about other relevant variables, such as the prices of EUAs, carbon, alternative fuel, and other green investments (Zeng et al., 2017 b) in order to provide more precise and forceful conclusions about the relationship between environmental and economic performance.

In this paper, we analyzed each year separately. Alternatively, a dynamic panel approach could have been used. This panel would have to be unbalanced with many short series, given that firms in different phases are different (only a few firms have data available for all years), and they could be analyzed using more sophisticated tools (for instance, Bayesian and dynamic copulas tools). Finally, it would be also necessary to analyze the impact of the EU ETS policy on the production, cost and environmental efficiencies of firms (see Meng et al., 2016 for a recent review on this topic). Some of these lines of research are included in our current work agenda, and the results will be presented elsewhere.

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Appendix A

Given that our statistical methodology is based on the use of copulas, in this Appendix, we provide a brief review of the main concepts and mathematical properties related to copulas. We only consider the bivariate case, which corresponds to our problem. Good introductory texts about copulas are Cherubini et al. (2004) and Nelsen (2006).

A.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:

$$C(u_1, u_2) = P(U_1 \leq u_1, U_2 \leq u_2)$$

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

Copulas are flexible alternatives to correlation which can capture dependence throughout the entire distribution of several variables. The importance of copulas in the modeling of dependence between variables arises from Sklars Theorem (Sklar, 1959) which provides the theoretical foundation for their application. This theorem states that a bivariate cumulative distribution function $F_{12}(x_1, x_2)$ of a random vector (X_1, X_2) with marginals $F_1(x_1)$ and $F_2(x_2)$ can be written as:

$$F_{12}(x_1, x_2) = C(F_1(x_1), F_2(x_2))$$

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

$$C(u_1, u_2) = F_{12}\left(F_1^{-1}(u_1), F_2^{-1}(u_2)\right)$$

The converse is also true: a copula $C:[0, 1]^2 \to [0, 1]$ and $F_1(x_1)$ and $F_2(x_2)$ define a bi-dimensional cumulative distribution function $F_{12}(x_1, x_2)$.

Using a copula, we can construct a bivariate distribution by specifying marginal univariate distributions and provide a correlation structure between two variables. Sometimes it is convenient to differentiate and use a corresponding "canonical" density version

$$f_{12}(x_1, x_2) = c(F_1(x_1), F_2(x_2)).f_1(x_1).f_2(x_2)$$

where $c(F_1(x_1), F_2(x_2))$ is the copula density. We obtain that the density $f_{12}(x_1, x_2)$ has been expressed as the product of the copula density and the univariate marginal densities. So, we can say that the copula has all the information about the dependence structure.

A.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. One of the most important of these 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 these cases, a rank correlation coefficient, such as 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 Spearman's ρ_S is more useful in describing the dependence between random variables because they are invariant to the choice of marginal distribution.

The Spearman rank correlation is especially useful when analysing data with a number of extreme observations because 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:

$$\rho_S = 12\int_0^1\int_0^1 \left(C(u_1,u_2) - u_1u_2\right)du_1du_2 = 12\int_0^1\int_0^1 C(u_1,u_2)dC(u_1,u_2) - 3$$

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

A.3. Notable Copulas

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

A.3.1. 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:

$$C_R^{Ga}\left(u_1,u_2\right)=\int_{-\infty}^{\phi(u_1)}\int_{-\infty}^{\phi(u_2)}\frac{1}{\left(2\pi\right)\sqrt{|\mathbf{R}|}}\exp\left(\frac{-\mathbf{u}'\mathbf{R}^{-1}\mathbf{u}}{2}\right)d\mathbf{u}$$

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

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

where ρ is the Pearson correlation between x_1 and x_2. The normal copula 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 such 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:

$$C_R^{t_\eta}\left(u_1,u_2\right)=\int_{-\infty}^{t_\eta^{-1}(u_1)}\int_{-\infty}^{t_\eta^{-1}(u_2)}\frac{\Gamma\left(\frac{\eta+2}{2}\right)\left(1+\frac{\mathbf{u}'\mathbf{R}^{-1}\mathbf{u}}{2}\right)^{-\frac{\eta+2}{2}}}{\Gamma\left(\frac{\eta}{2}\right)\pi\eta\sqrt{|\mathbf{R}|}}d\mathbf{u}$$

where $t_\eta^{-1}(\cdot)$ 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. Spearman's ρ_S coincide with that of the Gaussian, i.e. $\rho_{S,t_\eta}=\frac{6}{\pi}\arcsin\left(\frac{\rho}{2}\right)$.The p-quantile regression curve of the Student's-t copula is given by:

$$x_2=F_2^{-1}\left(t_\eta\left(\rho t_\eta^{-1}\left(F_1\left(x_1\right)\right)\right)+\sqrt{\left(1-\rho^2\right)\left(\eta+1\right)^2\left(\eta+\left(t_\eta^{-1}\left(F_1\left(x_1\right)\right)\right)^2\right)}t_{\eta+1}^{-1}\left(p\right)\right)$$

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 their 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)

A.3.2. Archimedean

An Archimedean copula is constructed through a generator function φ as

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

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

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

Archimedean copulas 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, whose expressions and generator functions are given in Table A.1.

Table A.1: Archimedean copula characteristics. Nelsen (2006)

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

Gumbel copulas are asymmetric copulas that have non-linear positive dependence throughout the data and exhibit greater dependence in the positive tail than in the negative. Frank copulas describe situations of symmetric tail independence and are an appropriate option when modeling strong positive or negative dependence throughout the data. Dependence in the tails of the Frank copulas tends to be relatively weak compared to the Gaussian copulas, with the strongest dependence centered in the middle of the distribution, suggesting that Frank copulas are most appropriate for data that exhibit weak tail dependence (Trivedi and Zimmer, 2005). Clayton copulas are asymmetric copulas describing situations of non-linear positive dependence throughout the data, but, in contrast to the Gumbel copulas, they exhibit greater dependence in the negative tail than in the positive. The relationship between the parameter of the Archimedean copulas and Spearman's ρ_S is summarized in Table A.2.

Table A.2: Association between some Archimedean copulas and the Spearman rank correlation

Copulas	Spearman's ρ_s
Gumbel	No closed form
Frank	$\rho_{s,Fr} = 1 - \frac{12}{\alpha}\left(\frac{1}{\alpha}\int_0^{\alpha}\frac{1}{e^t-1}dt - \frac{2}{\alpha}\int_0^{\alpha}\frac{t^2}{e^t-1}dt\right)$
Clayton	No closed form

A.4. Estimation of copulas

Usually, copula C belongs to a family of copulas indexed by a parameter θ: $C = C(u_1, u_2; \theta)$ and the marginals $\{F_i;\ i=1,2\}$ 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 $\left\{\left(x_1^{(j)}, x_2^{(j)}\right); j = 1,\ldots,n\right\}$ 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:

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

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

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

where $c(u_1, u_2; \theta) = \frac{\partial C(u_1, u_2; \theta)}{\partial u_1 \partial u_2}$ 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 – $\left(\hat{\alpha}_1^{MLE}, \hat{\alpha}_2^{MLE}, \hat{\theta}^{MLE}\right)$ of the model parameters $(\alpha_1, \alpha_2, \theta)$ corresponds to the simultaneous maximization of the log-likelihood L:

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

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

A second option is a sequential 2-step maximum likelihood method referred to as the method of inference functions for marginals (Joe, 2001) (IFM) 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 in which the dependence structure is independent of the marginal distributions, in such a way that

$$L(\theta, \alpha_1, \alpha_2) = \underbrace{L_C(\theta)}_{\text{dependence}} + \underbrace{\left(L_1(\alpha_1) + L_2(\alpha_2)\right)}_{\text{m arg inals}}$$

where $L_C(\theta) = \sum_{j=1}^{n} \log c\left(F_1\left(x_1^{(j)};\alpha_1\right), F_2\left(x_2^{(j)};\alpha_2\right);\theta\right)$ is the log-likelihood contribution from the dependence structure in data represented by copula C, and $L_i(\alpha_i) = \sum_{j=1}^{n} \log f_i\left(x_i^{(j)};\alpha_i\right)$, i =1, 2 are the log-likelihood contributions from each margin: observe that $L_1 + L_2$ 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, $\left(\hat{\alpha}_1^{IFM}, \hat{\alpha}_2^{IFM}\right)$ is 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 L_C with the marginal parameters α_i replaced by their first-stage estimators $\hat{\alpha}_i^{IFM} : \hat{\theta}^{IFM} = \arg\max_\theta L_C\left(\hat{\alpha}_1^{IFM}, \hat{\alpha}_2^{IFM}, \theta\right)$.

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

$\left(\widehat{\alpha}_1^{\mathrm{IFM}}, \widehat{\alpha}_2^{\mathrm{IFM}}, \widehat{\theta}^{\mathrm{IFM}}\right)$ is consistent and asymptotically normal under the usual regularity conditions (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 because it is necessary to compute many derivatives, and the use of jack-knife and related methods increases the difficulty (see Joe, 2001).

Efficiency comparisons based on the 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 IFM method 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 the uniform random variables, $U_1 = F_1(X_1)$ and $U_2 = F_2(X_2)$, respectively. In this case, given, $\left\{\hat{u}_{1j} = \hat{F}_1\left(x_1^{(j)}\right), \hat{u}_{2j} = \hat{F}_2\left(x_2^{(j)}\right), j = 1,\dots,n\right\}$, and a copula C, the dependence parameter θ can be estimated as follows:

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

A.5 Goodness of fit of the selected copula

We study the goodness of fit of the estimated model M given by equations (8)-(9), by calculating the p-values given by:

$$\min\left\{P\left[\hat{\rho} \geq \rho_{\mathrm{observed}} \mid M\right], P\left[\hat{\rho} \leq \rho_{\mathrm{observed}} \mid M\right]\right\} \tag{A.1}$$

where ρ_{observed} is the value of the Spearman ρ coefficient observed in the sample and $\hat{\rho}|M$ is the sample Spearman ρ distributions assuming that M is the true model. These p-values are calculated using the Monte Carlo method by means of the following algorithm:

A.5.1. Algorithm

Let $\left\{\left(\mathrm{ATR}^{(j)}, \mathrm{EA}^{(j)}, \mathrm{SIZE}^{(j)}, \mathrm{RISK}^{(j)}, \mathrm{SECTOR}^{(j)}\right), j=1,\dots,n\right\}$ be the dataset. Let ρ_{observed} the Spearman ρ value of $\left\{\left(\mathrm{ATR}^{(j)}, \mathrm{EA}^{(j)}\right), j=1,\dots,n\right\}$

Step 0: Fix S the number of simulations.

Step 1: For s=1,…, S carry out the steps 1 A to 1 D

Step 1 A Draw $\left(u_{1,j}^{(s)}, u_{2,j}^{(s)}; j = 1,...,n\right)$ from copula C(u_1,u_2)

Step 1 B Calculate $\left(\varepsilon_j^{ATR(s)} = F_{\varepsilon^{ATR}}^{-1}\left(u_{1,j}^{(s)}\right), \varepsilon_j^{EA(s)} = F_{\varepsilon^{EA}}^{-1}\left(u_{1,j}^{(s)}\right); j = 1,...,n\right)$

Step 1 C Calculate

$$ATR_j^{(s)} = \beta_0^{ATR} + \beta_1^{ATR} Size_j + \beta_2^{ATR} Risk_j + \boldsymbol{\beta}_3^{'ATR} Sector_j + \varepsilon_j^{ATR} \;;\ j=1,\ldots,n$$

$$EA_j^{(s)} = \beta_0^{EA} + \beta_1^{EA} Size_j + \beta_2^{EA} Risk_j + \boldsymbol{\beta}_3^{'EA} Sector_j + \varepsilon_j^{EA} \;;\ j=1,\ldots,n$$

Step 1 D Calculate $\rho^{(s)}$ Spearman ρ coefficient of $\left\{\left(ATR_j^{(s)}, EA_j^{(s)}\right); j = 1,...,n\right\}$

Step 2 Calculate

$$\min\left\{\frac{1}{S}\sum_{s=1}^{S} I\left(\rho^{(s)} \le \rho_{observed}\right), \frac{1}{S}\sum_{s=1}^{S} I\left(\rho^{(s)} \ge \rho_{observed}\right)\right\}$$

The calculation with (EA,ROA) is similar. In the paper we have taken S = 1000.

FIGURES

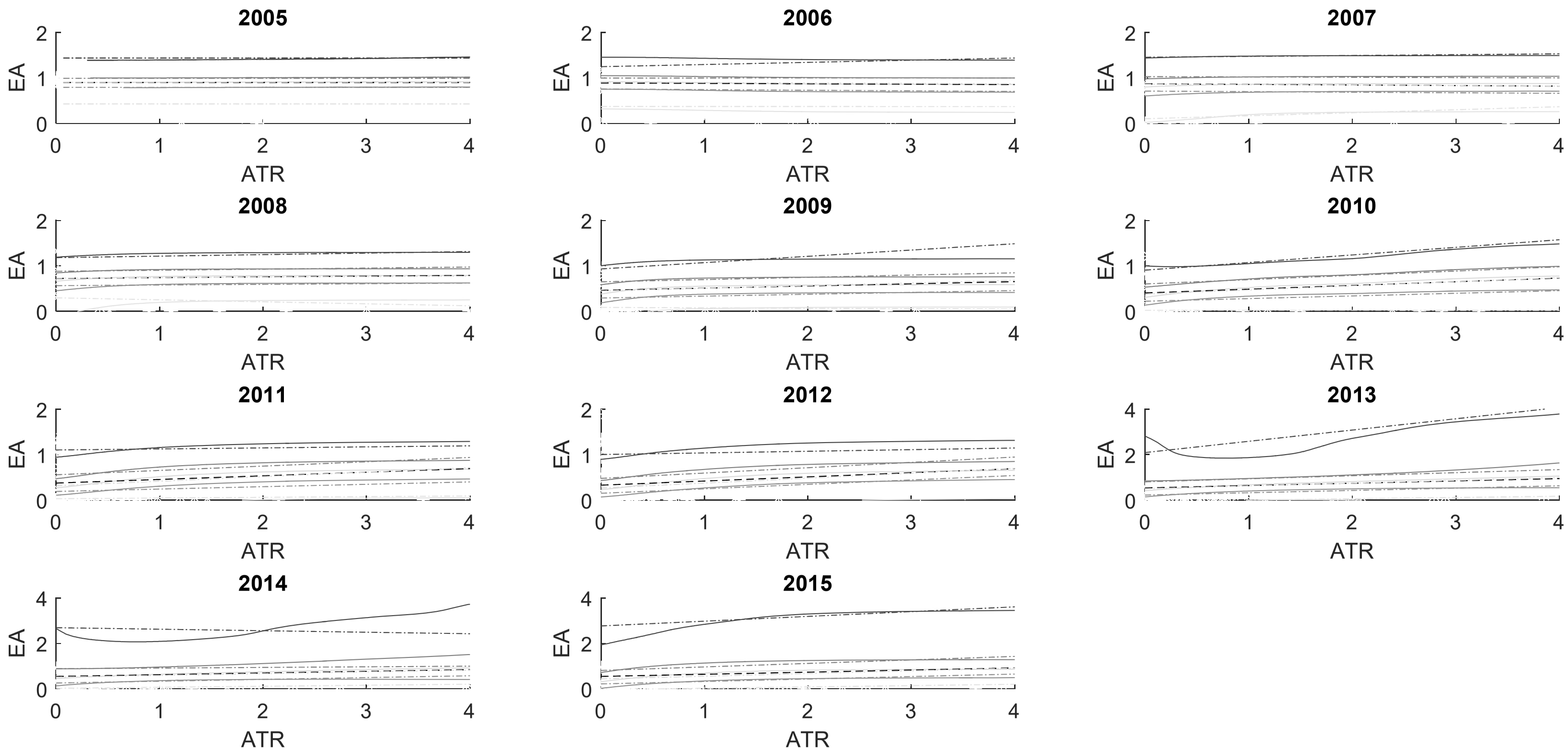


Figure 1: Quantile and linear regression of EA on ATR

Note: Copula quantile regression (continuous lines), linear quantile regression (dotted lines) and linear regression (dashed)

Quantiles: 2.5% (cyan), 25% (magenta), 50% (green), 75% (red) and 97.5% (blue)

Copula lines regression were obtained using the algorithm 4.4.2.; linear quantiles regression were obtained using the ***fminsearch*** *function of MATLAB and the linear regression was estimated using the* ***robusfit*** *procedure of MATLAB*

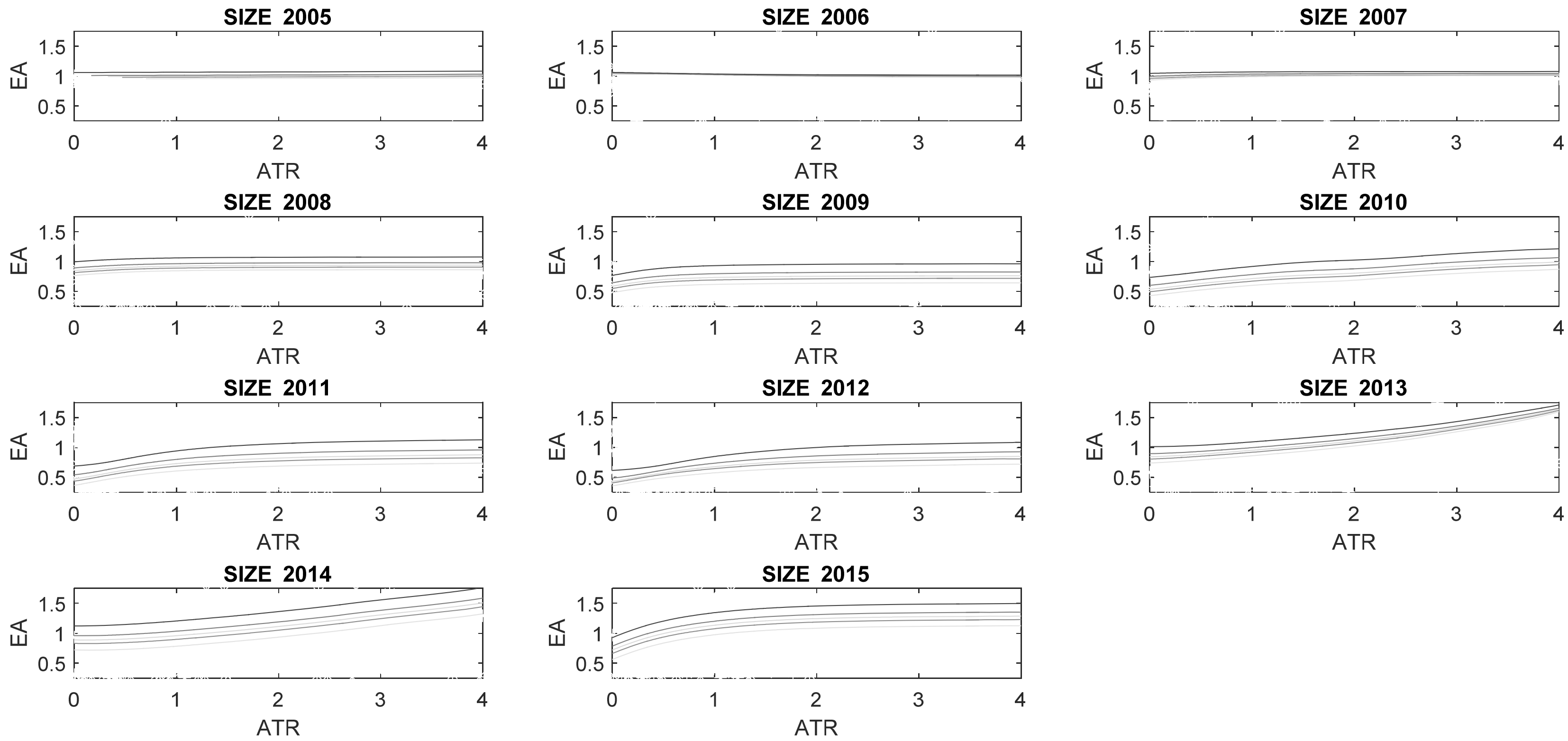


Figure 2: Median regression curves of EA on ATR. Size effect.

Note: Five median regression curves of EA on ATR are presented. We draw a median regression curve for a given quantile of the variable SIZE (quantiles 2.5%. 25%. 50%. 75%. 97.55%) with correspond to cyan, magenta, green, red and blue lines, respectively

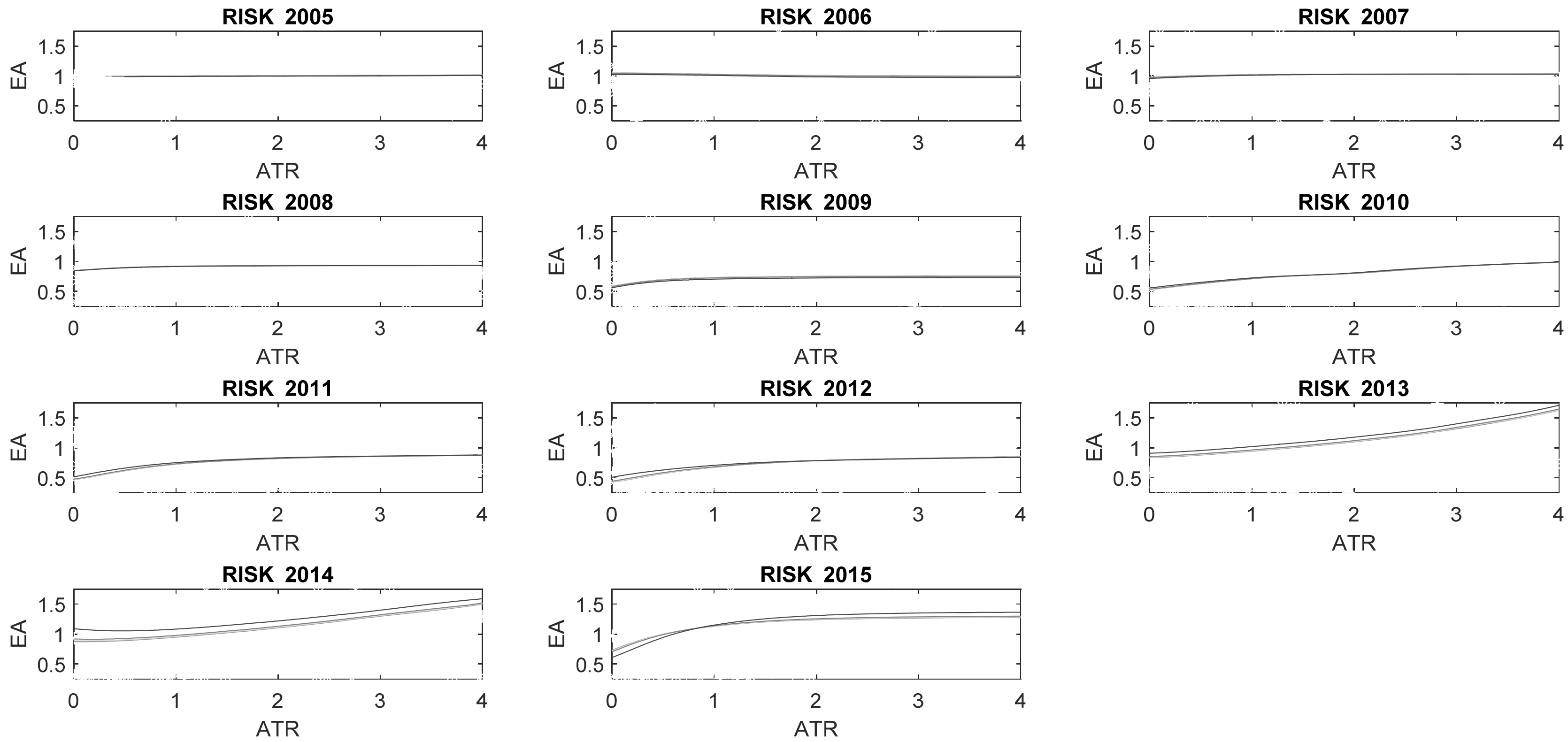


Figure 3: Median regression curves of EA on ATR. Risk effect.

Note: Five median regression curves of EA on ATR are presented. We draw a median regression curve for a given quantile of the variable RISK (quantiles 2.5%. 25%. 50%. 75%. 97.55%) with correspond to cyan, magenta, green, red and blue lines, respectively

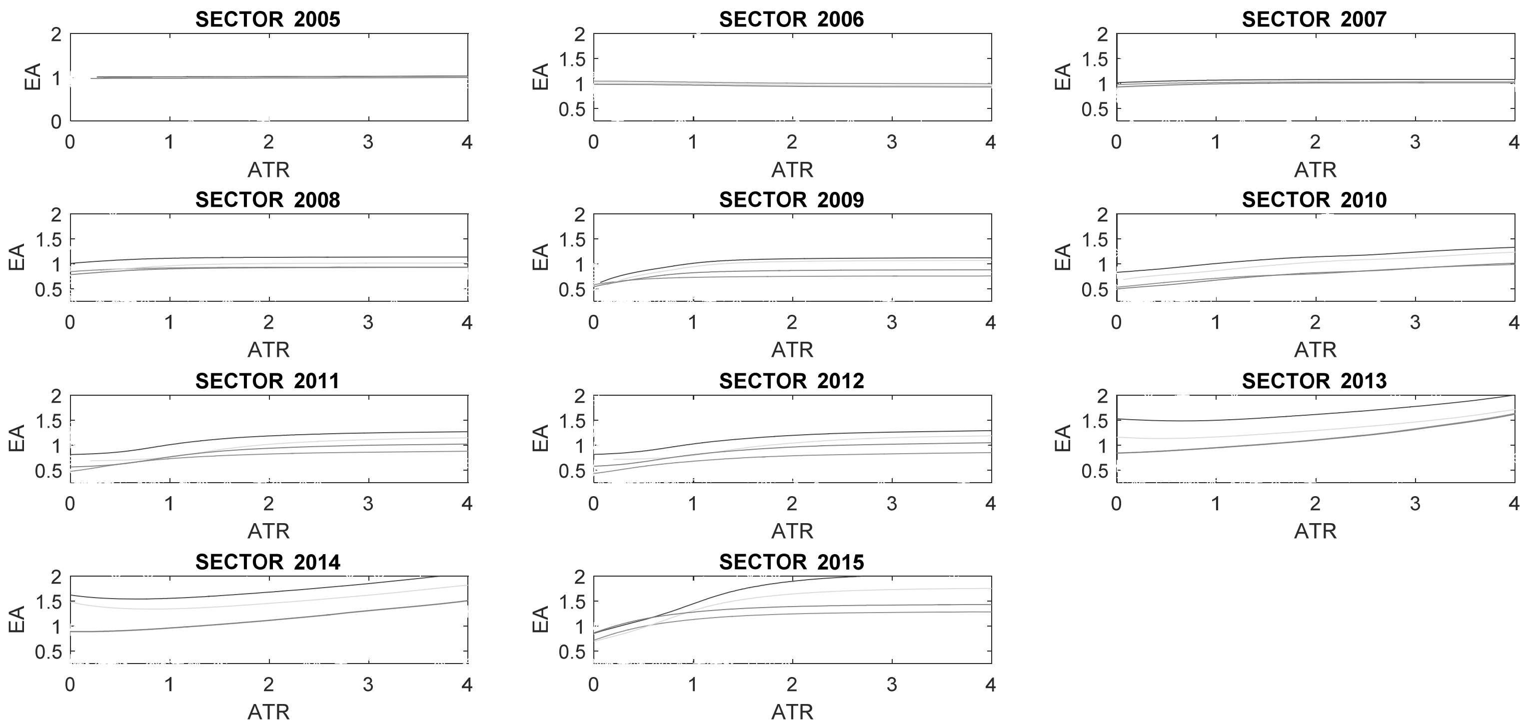


Figure 4: Median regression curves of EA on ATR. Sector.

Note: We draw two median regression curves. Blue line: energy sector; magenta: chemical and metal sector; green line: other manufacturing sector; red line: rest of sectors

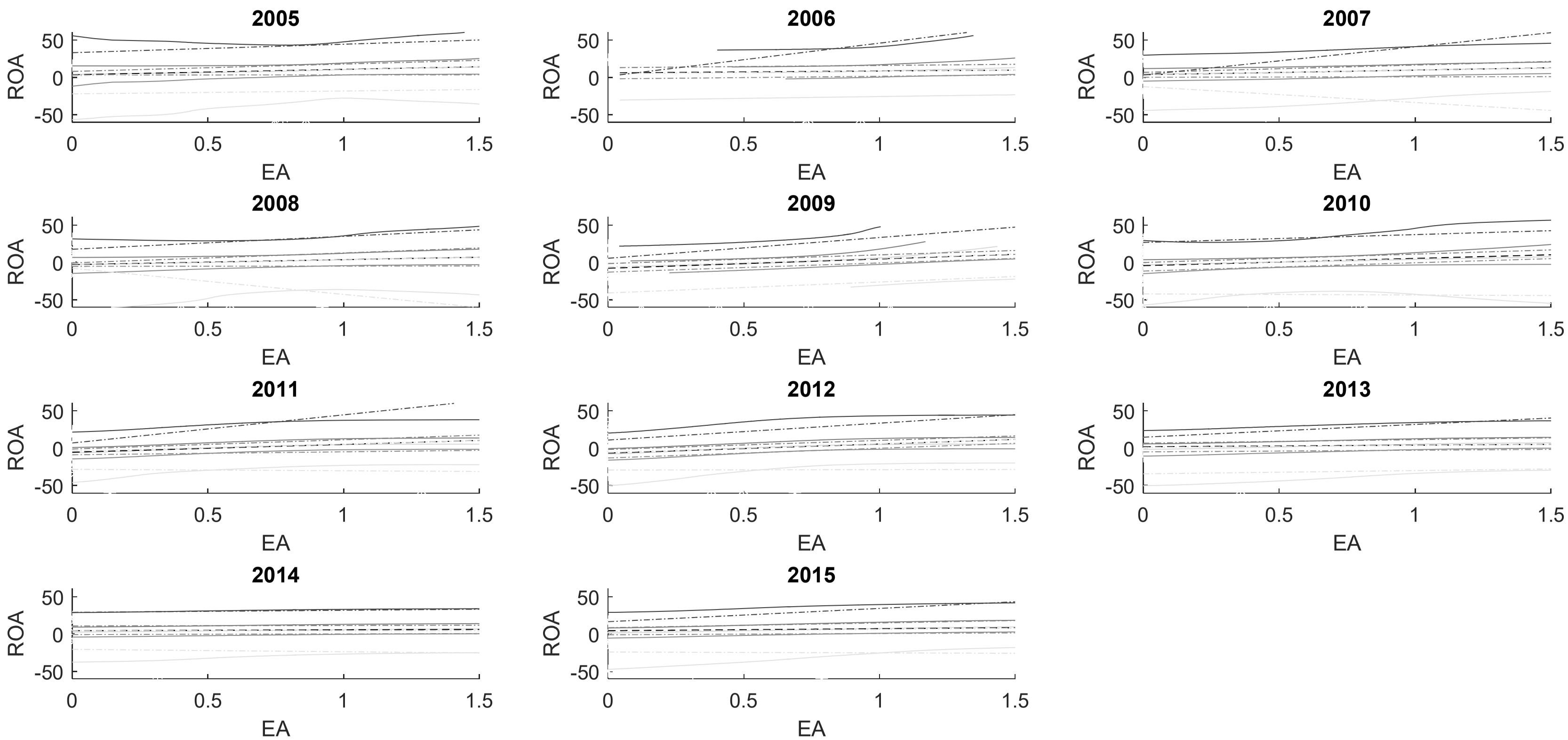


Figure 5: Quantile regression of ROA on EA.

Note: Copula quantile regression (continuous lines), linear quantile regression (dotted lines) and linear regression (dashed)

Quantiles: 2.5% (cyan), 25% (magenta), 50% (green), 75% (red) and 97.5% (blue)

*Copula lines regression were obtained using the algorithm 4.4.2.; linear quantiles regression were obtained using the **fminsearch** function of MATLAB and the linear regression was estimated using the **robusfit** procedure of MATLAB*

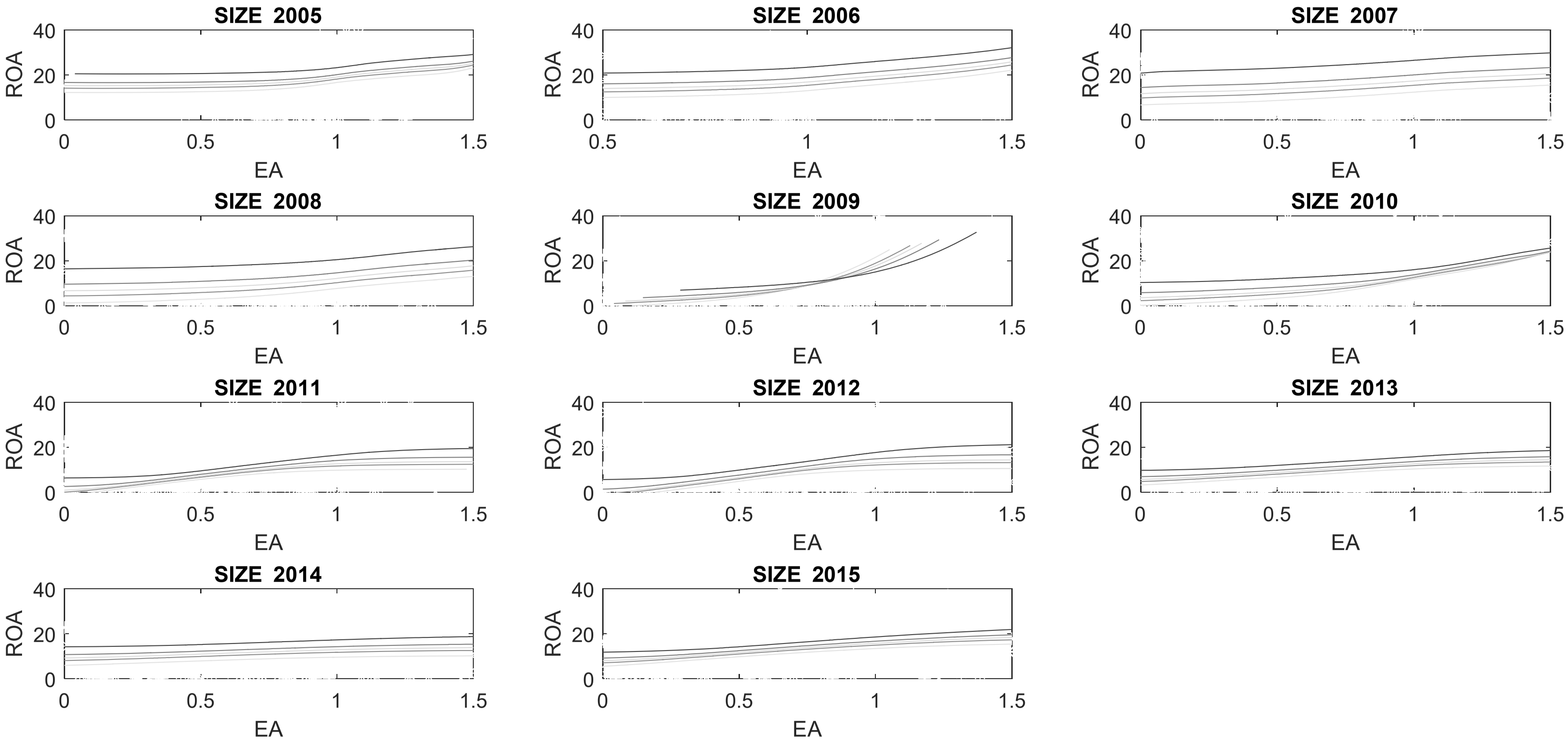


Figure 6: Median regression curves of ROA on EA. Size effects

Note: Five median regression curves of EA on ATR are presented. We draw a median regression curve for a given quantile of the variable SIZE (quantiles 2.5%. 25%. 50%. 75%. 97.5%) with correspond to cyan, magenta, green, red and blue lines, respectively

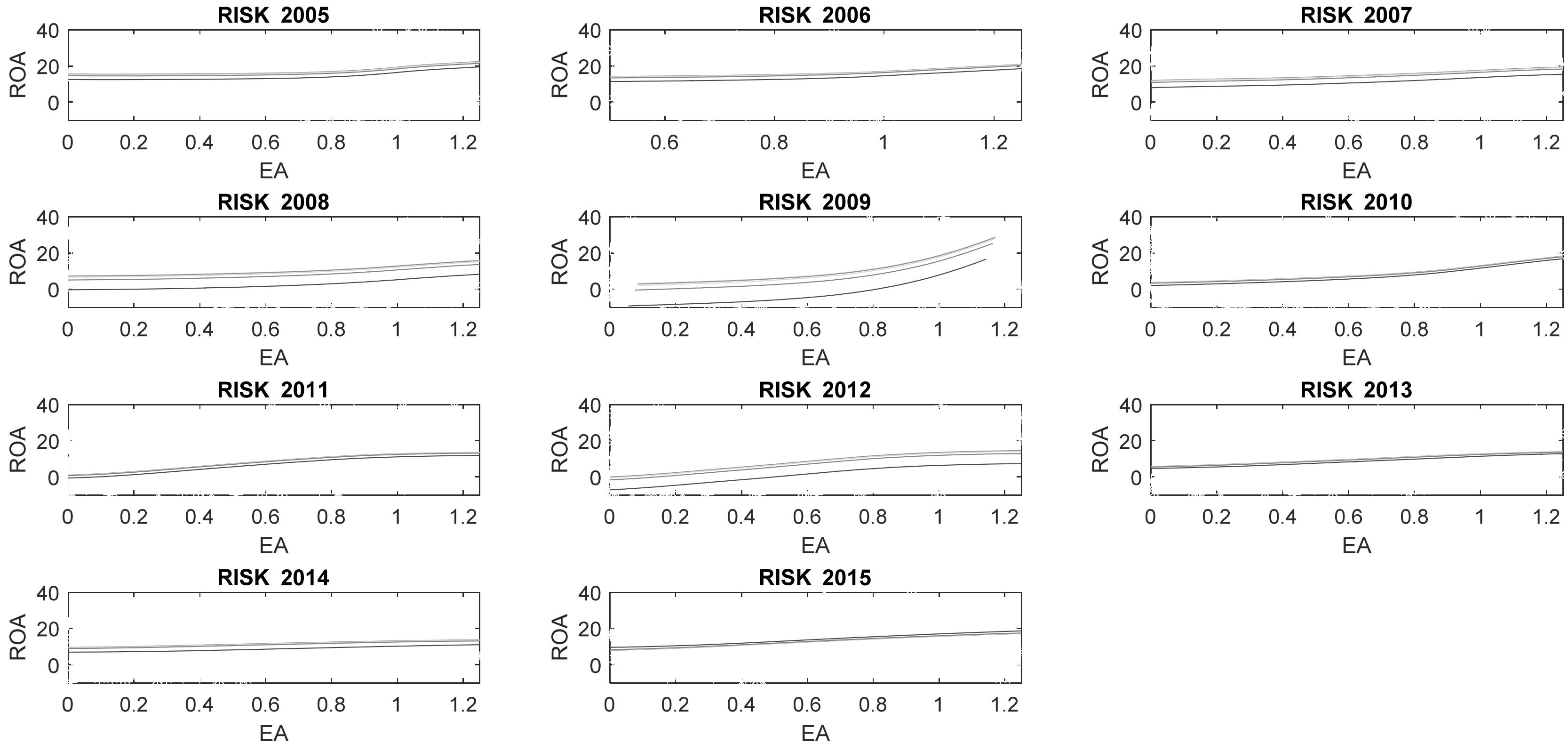


Figure 7: Median regression curves of ROA on SA. Risk effect.

Note: Five median regression curves of EA on ATR are presented. We draw a median regression curve for a given quantile of the variable RISK (quantiles 2.5%. 25%. 50%. 75%. 97.55%) with correspond to cyan, magenta, green, red and blue lines, respectively

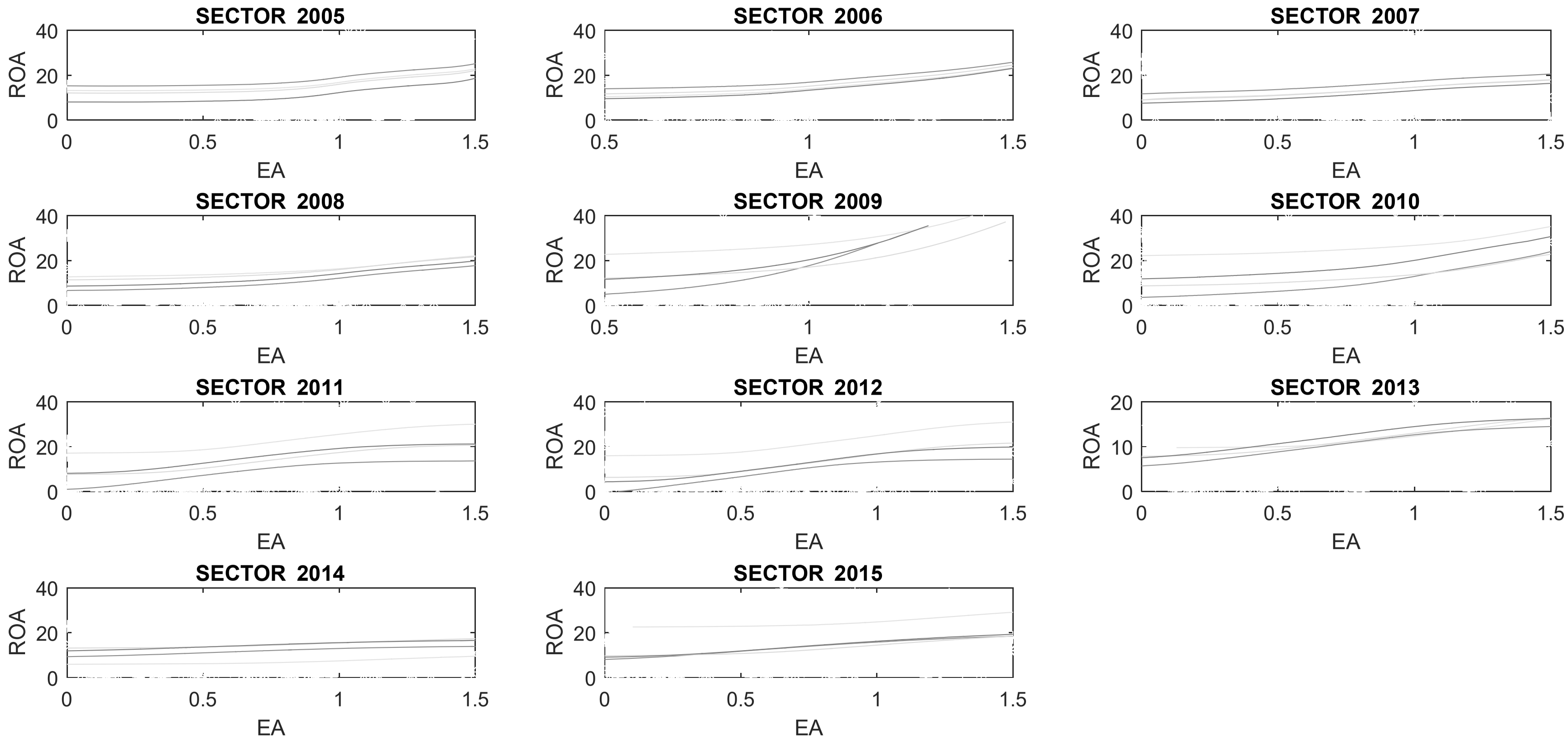


Figure 8: Median regression curves of ROA on EA. Sector effect.

Note: We draw two median regression curves. Blue line: energy sector; magenta: chemical and metal sector; green line: other manufacturing sector; red line: rest of sectors

APPENDIX B: SCATTER HISTOGRAM DIAGRAMS OF THE SELECTED COPULAS

Figure B1: Scatter diagrams of the selected copulas to describe the joint distribution of (ATR,EA)

*Note: Each diagram contains the observed values of (ATR,EA)(blue * points) and the simulated points of the copula (o red points)*

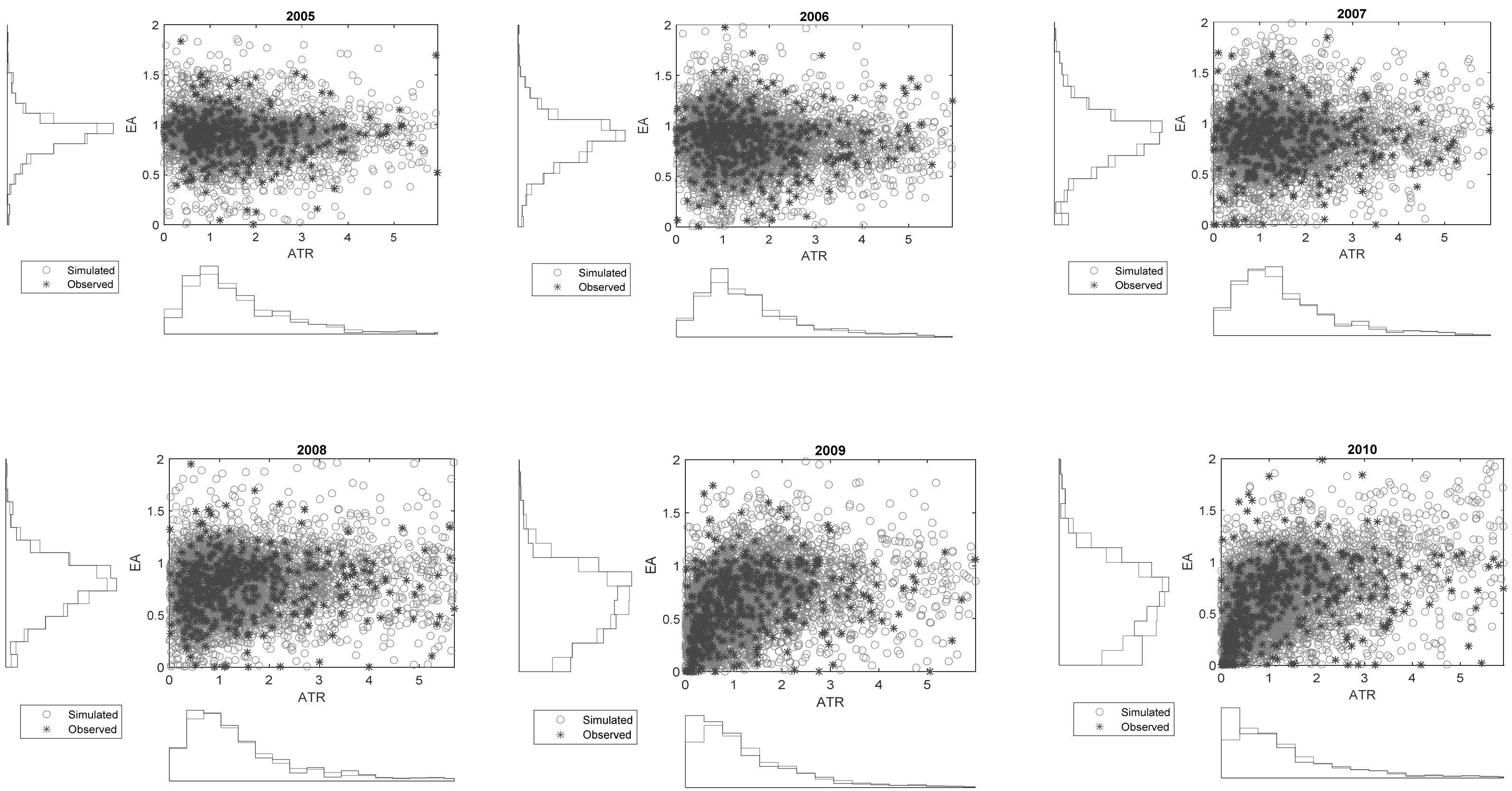


Figure B1: Scatter diagrams of the selected copulas to describe the joint distribution of (ATR,EA) (continuation)

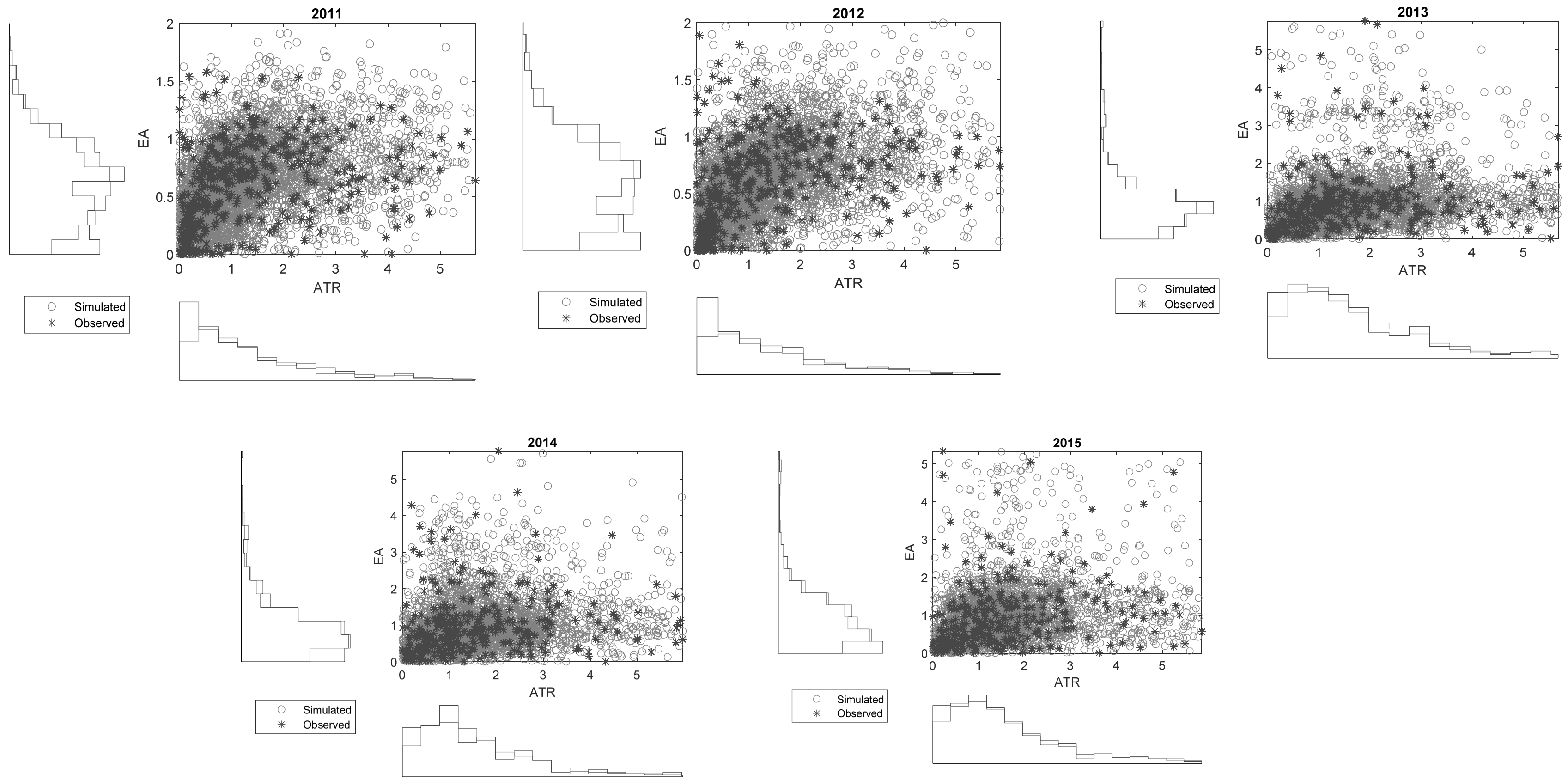


Figure B2: Scatter diagrams of the selected copulas to describe the joint distribution of (EA,ROA)

*Note: Each diagram contains the observed values of (EA,ROA)(blue * points) and the simulated points of the copula (o red points)*

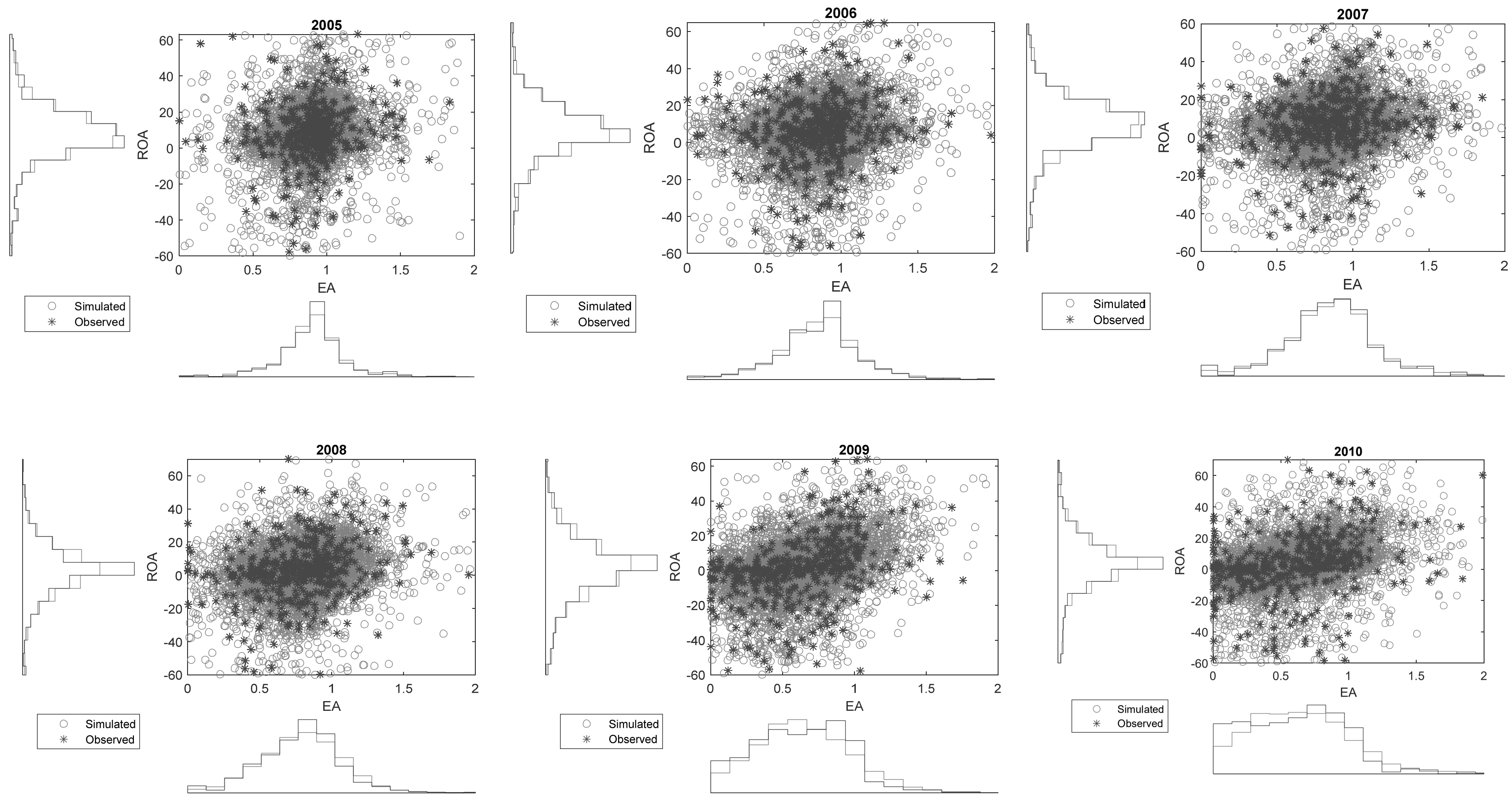
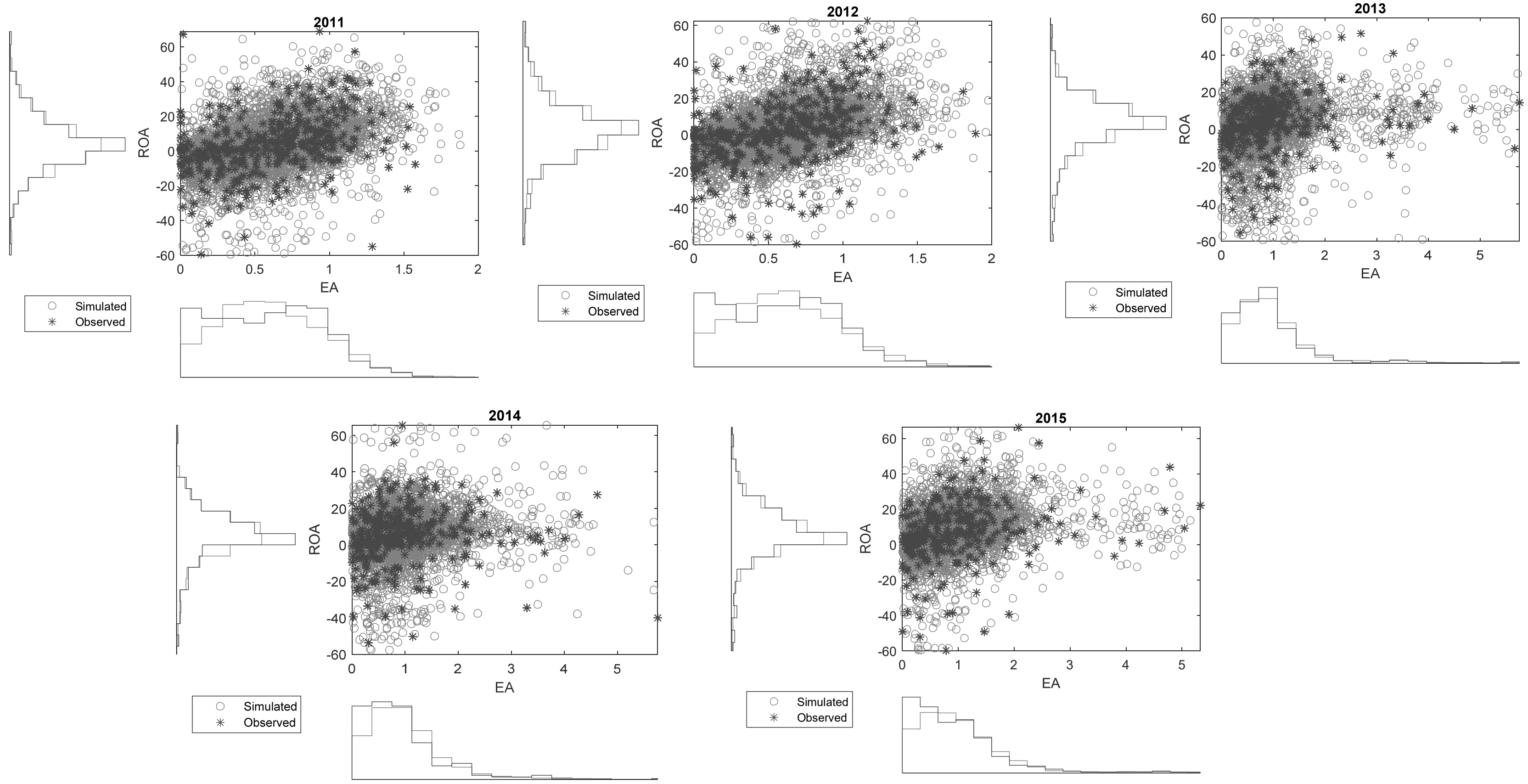


Figure B2: Scatter diagrams of the selected copulas to describe the joint distribution of (EA,ROA) (continuation)



TABLES

Table 1: Descriptive statistics of EA

	Year											
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
Firms	580	678	673	710	699	705	689	664	549	521	493	479
Emissions (Mean)	295545.82	232870.60	229023.48	207267.33	179330.46	155714.50	169088.52	185206.36	110143.78	115644.95	125828.07	127490.67
Allowances (Mean)	276477.91	226806.51	218833.26	203496.09	202536.21	200293.47	204875.14	216666.08	119458.85	113764.54	118727.67	120716.32
EA<=1(%firms)	75.17%	76.40%	72.51%	80.99%	84.69%	84.68%	84.18%	84.19%	64.48%	66.79%	62.07%	58.25%
Minimum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mean	0.90	0.89	0.92	0.85	0.69	0.69	0.70	0.66	1.03	1.19	1.23	1.34
Median	0.92	0.87	0.86	0.80	0.61	0.63	0.61	0.57	0.78	0.73	0.78	0.75
Maximum	3.78	14.22	24.93	52.71	50.15	57.49	59.20	52.82	14.59	32.61	39.80	47.62
Std. Deviation	0.30	0.79	1.21	1.98	1.91	2.18	2.30	2.08	1.22	2.70	2.52	2.97
Skewness	**2.76**	**11.55**	**15.34**	**25.46**	**24.88**	**25.08**	**23.97**	**23.82**	**5.36**	**8.86**	**9.59**	**10.00**
Kurtosis	**26.32**	**166.11**	**273.53**	**667.89**	**644.26**	**653.05**	**606.81**	**597.01**	**48.96**	**91.88**	**126.37**	**136.08**
JB (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: JB: p-value of Jarque Bera Test. * In bold, statistically different from zero at the 5% significance level

Table 2: Descriptive statistics of ROA

	Year										
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Firms	420	470	454	467	456	471	456	435	382	366	341
Minimum	-65.22	-68.71	-64.95	-68.13	-64.71	-58.43	-63.40	-62.95	-66.12	-53.49	-59.88
Mean	**8.00**	**5.80**	**6.81**	**2.27**	1.25	**3.40**	**3.58**	**2.49**	**2.78**	**5.47**	**7.18**
Median	**7.96**	**6.52**	**7.62**	**2.65**	1.04	**2.96**	**2.67**	1.21	**3.54**	**5.44**	**6.23**
Maximum	63.15	64.84	57.58	69.91	64.01	69.92	68.79	62.20	51.58	65.59	66.27
Std. Deviation	17.16	17.98	16.31	17.86	18.97	18.97	16.40	17.24	16.34	14.42	16.01
Skewness	**-0.46**	**-0.65**	**-0.71**	**-0.66**	-0.15	-0.28	-0.11	-0.05	-0.99	-0.40	-0.44
Kurtosis	**2.82**	**2.90**	**2.73**	**2.96**	**1.67**	**2.04**	**2.61**	**1.94**	**3.30**	**2.94**	**3.07**
JB (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: * In bold statistically different from zero at the 5% significance level

Table 3: Descriptive statistics of ATR

	Year										
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Firms	420	470	454	467	456	471	456	435	382	366	341
Minimum	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mean	1.55	1.58	1.53	1.44	1.18	1.25	1.26	1.28	1.58	1.53	1.54
Median	1.24	1.30	1.25	1.11	0.87	0.92	0.89	0.89	1.26	1.16	1.22
Maximum	5.95	5.94	5.99	5.70	5.99	5.91	5.67	5.85	5.68	5.97	5.86
Std. Deviation	1.08	1.10	1.10	1.14	1.08	1.19	1.20	1.23	1.25	1.25	1.22
Skewness	**1.37**	**1.32**	**1.36**	**1.53**	**1.66**	**1.56**	**1.33**	**1.34**	**1.18**	**1.39**	**1.28**
Kurtosis	**2.02**	**1.72**	**1.97**	**2.18**	**3.11**	**2.40**	**1.32**	**1.45**	**1.15**	**1.95**	**1.35**
JB (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: * In bold: statistically different from zero at the 5% significance level

Table 4: Descriptive statistics of Size

	Year										
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Firms	420	470	454	467	456	471	456	435	382	366	341
Minimum	5.71	1.39	5.92	6.07	1.10	1.10	0.69	0.69	1.10	4.25	1.10
Mean	9.91	10.24	10.28	10.38	10.44	10.43	10.47	10.54	10.84	10.93	10.96
Median	9.61	9.95	9.96	10.04	10.08	10.03	10.10	10.21	10.62	10.68	10.78
Maximum	16.89	16.93	17.55	17.72	17.73	17.67	17.68	17.68	16.89	16.94	16.94
Std. Deviation	1.89	1.99	1.96	1.91	2.03	2.11	2.08	2.13	1.93	1.76	1.83
Skewness	**0.79**	**0.36**	**0.65**	**0.72**	**0.41**	**0.39**	**0.24**	0.14	**-0.25**	**0.49**	-0.06
Kurtosis	**0.75**	**1.01**	**0.46**	**0.46**	**0.98**	**0.85**	**1.64**	**1.83**	**3.19**	**0.80**	**2.67**
JB (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: * In bold: statistically different from zero at the 5% significance level

Table 5: Descriptive statistics of Risk

	Year										
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Firms	420	470	454	467	456	471	456	435	382	366	341
Minimum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mean	67.53	69.94	67.78	79.18	77.42	72.88	76.23	68.61	65.96	66.47	67.76
Median	35.38	37.98	34.23	48.74	43.11	41.02	40.20	34.80	34.38	37.57	37.49
Maximum	446.44	456.42	495.55	498.78	473.12	485.12	496.48	499.90	475.51	467.44	460.60
Std. Deviation	83.43	85.46	86.09	88.73	91.42	88.05	97.59	90.77	83.86	84.98	85.15
Skewness	1.80*	1.74*	2.03*	1.75*	1.78*	2.01*	2.14*	2.21*	2.03*	2.17*	2.01*
Kurtosis	3.46*	3.13*	4.65*	3.35*	3.10*	4.50*	4.87*	5.32*	4.30*	5.23*	4.22*
JB (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

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

Table 6: Number of companies for each sector and year

	Year										
Sector	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Energy	46	41	36	47	43	56	53	52	24	25	17
Chemical and metal processing industries	267	291	288	283	279	278	268	251	242	230	221
Other manufacturing industries *	76	93	87	96	99	96	96	92	86	85	78
Rest of sectors **	31	45	43	41	35	41	39	40	30	26	25
Total	420	470	454	467	456	471	456	435	382	366	341

* Food, textile, leather, footwear and clothing, rubber and paper

** Building, Transportation and communications, trade, restaurants, financial institutions and other services

Table 7: Linear Regression of EA on ATR

	Year										
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Constant	**0.8771**	**0.8228**	**0.8588**	**0.7139**	**0.5428**	**0.3937**	**0.4810**	**0.4623**	**0.5331**	**0.5732**	**0.6584**
ATR	0.0002	-0.0089	-0.0123	0.0166	**0.0479**	**0.0820**	**0.0795**	**0.0910**	**0.1030**	**0.0743**	**0.0933**
Size	**0.0277**	0.0080	0.0174	**0.0565**	**0.0757**	**0.0776**	**0.0899**	**0.0891**	**0.0665**	**0.1008**	**0.0919**
Risk	-0.0021	-0.0075	0.0001	-0.0019	-0.0087	0.0031	0.0058	-0.0009	0.0165	0.0390	0.0137
Dummy energy sector	0.0365	0.0286	0.0648	**0.2250**	**0.2719**	**0.3647**	**0.2766**	**0.2488**	**0.6271**	**0.6382**	**0.6033**
Dummy chemical and metal industries	0.0273	0.0630	0.0138	0.0246	-0.0612	0.0408	-0.0712	-0.0975	0.0203	0.0134	-0.0876
Dummy other manufacturing industries	0.0020	0.0230	-0.0004	0.0612	**0.1609**	**0.2223**	0.0795	0.1064	**0.2217**	**0.3350**	**0.2537**
R^2 modified	0.0080	0.0091	0.0055	0.0656	0.2567	0.2722	0.2598	0.3031	0.1166	0.1390	0.1557

Note: in bold regression coefficients statistically different from zero at the 5%, significance level.

Table 8: AIC values corresponding to the compared families of copulas (EA-ATR)

(in bold signaled the selected copula)

	Year										
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Gaussian	0.99	0.64	0.86	-4.49	-26.55	-55.83	-46.54	-49.17	-23.40	-7.73	-15.69
Student	1.02	-0.94	-1.73	-7.46	-34.07	**-82.78**	-60.12	-65.19	**-57.24**	**-29.80**	-30.89
Clayton	1.00	1.00	**-3.09**	**-8.36**	**-36.92**	-78.38	-53.42	-59.72	-49.56	-22.72	**-32.20**
Frank	1.00	**-1.47**	0.76	-6.21	-34.44	-71.24	**-67.15**	**-71.36**	-34.83	-15.56	-22.52
Gumbel	**-0.03**	0.18	1.00	-2.93	-17.69	-45.59	-40.00	-42.57	-18.09	-4.23	-11.01

Table 9: Observed Pearson and Spearman correlations and goodness of fit of the selected copulas (EA-ATR)

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Selected copula	Gumbel	Frank	Clayton	Clayton	Clayton	t Student	Frank	Frank	t Student	t Student	Clayton
Observed Pearson Correlation	-0.0134	0.0089	0.0020	0.0777	**0.3100**	**0.3491**	**0.3598**	**0.3900**	**0.2122**	**0.1686**	**0.2430**
Observed Spearman's ρ	-0.0452	-0.0850	-0.0350	**0.1746**	**0.4543**	**0.5177**	**0.4933**	**0.5447**	**0.3968**	**0.3323**	**0.3618**
Model Spearman's ρ	-0.0143	-0.0921	0.0615	0.1568	0.3900	0.4637	0.4700	0.5151	0.3829	0.3092	0.3785
Pvalue Spearman ρ	0.3060	0.4210	0.0450	0.2510	0.0630	0.0790	0.3020	0.1650	0.4080	0.2820	0.4020

Note: The model Spearman's ρ were calculated applying the algorithm A.5.1. in the Appendix A
(in bold observed Pearson Correlation and Spearman's ρ statistically different from zero at the 5%, significance level)

Table 10: Linear Regression of ROA on EA

	Year										
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Constant	-3.9315	1.7715	0.1219	-0.8530	-3.4967	2.5718	0.4887	**-4.5848**	2.1613	**6.2441**	3.5985
EA	**7.2253**	2.4577	**6.1615**	**6.6003**	**12.4819**	**9.7051**	**10.5284**	**12.1833**	**2.1268**	1.1960	**2.6338**
Size	**2.0375**	**2.7430**	**3.8667**	**3.6700**	0.7792	**2.0653**	**1.6183**	**1.7942**	**1.8654**	**2.1719**	**1.7307**
Risk	-0.8040	-0.8331	-0.9665	**-1.9855**	**-3.6295**	-0.4623	-0.5250	**-2.0922**	-0.5043	-0.8236	0.4869
Dummy energy sector	4.9065	1.4742	1.5187	**5.6146**	**14.9109**	**10.1564**	**8.2578**	**11.4944**	3.0393	-4.7787	**15.6607**
Dummy chemical and metal industries	**7.5328**	**4.5241**	**4.0363**	-2.1391	**-6.0439**	**-6.4384**	**-5.5379**	-2.2847	-0.1249	-1.6849	1.4130
Dummy other manufacturing industries	3.1529	0.5397	-0.9397	0.6979	0.0222	**-4.9352**	-2.2673	0.4461	0.9858	1.0544	1.2099
R^2 modified	0.0530	0.0479	0.1210	0.1043	0.2642	0.1953	0.2175	0.2194	0.0468	0.0348	0.0700

Note: in bold regression coefficients statistically different from zero at the 5%, significance level.

Table 11: AIC values corresponding to the compared families of copulas (ROA-EA)
(in bold signaled the selected copula)

	Year										
	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Gaussian	-6.27	-5.65	**-11.38**	-8.67	-33.89	-20.85	-31.28	-44.80	-16.07	-1.90	-6.27
Student	**-8.49**	-7.19	-10.38	**-10.56**	-33.05	**-26.75**	-35.04	-50.58	-15.06	-3.20	**-8.49**
Clayton	-2.88	-1.73	-9.67	-5.96	-16.91	-14.51	-17.53	-27.26	-6.56	-2.46	-2.88
Frank	-7.57	-5.71	-10.67	-10.05	-35.31	-22.19	**-39.57**	**-53.37**	**-21.77**	**-5.34**	-7.57
Gumbel	-7.35	**-8.32**	-4.48	-9.09	**-35.64**	-24.48	-34.59	-49.58	-13.48	-0.72	-7.35

Table 12: Observed Pearson and Spearman correlations and goodness of fit of the selected copulas (ROA-EA)

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Selected copula	t Student	Gumbel	Gaussian	t Student	Gumbel	t Student	Frank	Frank	Frank	Frank	Frank
Observed Pearson Correlation	**0.1196**	**0.1268**	**0.1758**	**0.1933**	**0.3780**	**0.3184**	**0.3693**	**0.4063**	**0.1886**	0.0504	**0.2517**
Observed Spearman's ρ	**0.1583**	**0.1439**	**0.1721**	**0.2374**	**0.4463**	**0.3920**	**0.4404**	**0.4764**	**0.2928**	**0.1994**	**0.3281**
Model Spearman's ρ	0.1645	0.1367	0.1613	0.2351	0.4005	0.3573	0.4274	0.4870	0.2824	0.1805	0.3133
Pvalue Spearman ρ	0.4910	0.4750	0.4880	0.4160	0.0970	0.2340	0.3550	0.4990	0.4290	0.3350	0.4180

Note: The model Spearman's ρ were calculated applying the algorithm A.5.1. in the Appendix A
(in bold observed Pearson Correlation and Spearman's ρ statistically different from zero at the 5%, significance level)

APPENDIX C: Comparison study of sectors

Table C1: Average values of the variables used in the paper

Variable	Sector	Year										
		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
CO_2 Emissions	Energy	1350191.22	1250185.02	1329148.47	1088160.09	1175383.72	769004.20	844955.15	1062915.35	581912.33	561834.96	833730.35
	Chemical and Metal *	124596.05	136796.01	120555.92	131838.29	105841.47	111928.72	101601.06	97028.40	123845.61	127602.50	143553.29
	Other manufacturing **	50946.03	46313.30	47903.30	46511.89	44790.12	47411.18	49367.46	50896.97	46996.36	44505.78	46770.71
	Rest of sectors	545648.16	113168.42	99554.30	81118.78	90774.54	44067.49	86823.21	86518.28	58596.23	65128.69	104306.88
Allowance Allocation	Energy	1140190.78	1162937.98	1255984.39	812088.47	1086507.19	858659.96	740087.85	977960.60	915793.96	928044.52	1306375.06
	Chemical and Metal	131380.22	156711.30	139310.78	172663.74	176199.38	181383.33	179944.25	189076.87	309991.50	461703.35	623503.10
	Other manufacturing	57973.86	56689.23	57230.18	51107.72	52078.68	57626.21	59525.90	60905.66	53911.90	55496.75	72607.42
	Rest of sectors	351961.10	111603.96	89542.93	108331.83	126840.66	98378.07	90639.62	95914.35	79255.30	98726.12	131423.84
EA	Energy	0.96	0.99	0.91	0.88	0.90	0.88	0.96	0.86	2.99	3.97	5.28
	Chemical and Metal	0.90	0.90	0.98	0.94	0.70	0.71	0.70	0.69	0.92	0.96	1.00
	Other manufacturing	0.88	1.00	0.86	0.84	0.82	0.81	0.83	0.77	1.52	1.77	1.97
	Rest of sectors	1.02	0.96	0.84	0.78	0.65	0.64	0.66	0.68	1.91	2.79	1.52
EA≤1	Energy	74.16%	78.89%	75.00%	49.54%	51.40%	61.67%	56.30%	55.83%	17.86%	44.23%	28.95%
	Chemical and Metal	73.16%	74.93%	71.13%	89.32%	95.76%	94.09%	94.49%	95.09%	76.85%	77.05%	75.08%
	Other manufacturing	82.98%	79.84%	75.78%	82.86%	84.06%	82.35%	82.35%	83.97%	57.39%	51.33%	42.45%
	Rest of sectors	75.86%	75.00%	70.83%	80.52%	77.92%	79.22%	81.69%	79.10%	53.70%	62.75%	50.00%
ATR	Energy	1.47	1.51	1.46	1.59	1.64	1.61	1.50	1.47	2.16	2.17	1.94
	Chemical and Metal	1.48	1.49	1.36	1.22	0.88	0.93	0.99	0.98	1.38	1.34	1.29
	Other manufacturing	1.89	1.82	1.96	1.92	1.70	1.75	1.88	1.92	2.02	1.97	2.14
	Rest of sectors	1.41	1.80	1.80	1.73	1.55	1.77	1.35	1.44	1.54	1.23	1.61

Table C1: Statistical comparison of sectors (continuation)

		Year										
Variable	**Sector**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
ROA	**Energy**	6.45	1.67	6.08	7.67	21.53	20.18	17.90	16.70	11.42	3.06	13.73
	Chemical and Metal	9.55	6.42	7.34	0.14	-3.84	-1.07	-0.89	-1.95	1.67	5.01	6.34
	Other manufacturing	5.51	4.53	5.87	5.90	5.74	4.72	6.28	5.75	4.25	7.55	8.61
	Rest of sectors	2.99	8.24	5.72	2.29	4.24	7.70	8.22	4.42	0.63	5.09	5.70
Size	**Energy**	10.14	10.70	11.05	10.48	10.64	10.69	10.42	10.95	10.74	10.75	11.32
	Chemical and Metal	9.61	9.95	9.98	10.10	10.15	10.11	10.14	10.13	10.74	10.78	10.79
	Other manufacturing	10.72	10.87	11.00	11.11	11.09	11.06	11.21	11.12	11.08	11.27	11.23
	Rest of sectors	10.13	10.42	10.13	10.46	10.61	10.71	10.98	11.24	11.06	11.31	11.29
Risk	**Energy**	104.78	110.37	99.07	108.76	116.45	85.59	90.40	93.08	69.40	78.38	74.28
	Chemical and Metal	61.28	61.30	61.78	68.43	67.18	64.46	66.92	52.54	60.04	59.20	60.58
	Other manufacturing	66.12	74.17	70.01	93.24	88.96	83.54	84.84	78.95	66.20	72.47	78.97
	Rest of sectors	69.54	80.25	77.22	86.60	78.37	87.58	99.77	113.84	110.23	99.72	91.76

* Food, textile, leather, footwear and clothing, rubber and paper
** Building, Transportation and communications, trade, restaurants, financial institutions and other services