Climate Change and Financial Performance

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Abstract

The late 20th and the early 21th centuries are characterised by significant changes to weather patterns. A growing number of environmental initiatives have been activated to harmonise this phenomenon, which has taken monstrous magnitude mainly thanks to the continuing increase in carbon dioxide emitted by firms. Social and regulatory forces push firms to adopt a friendly, towards the environment, behaviour. In turn, firms have to be prepared with adequate tools and knowledge about the potential climate change effects on their financial performance. These effects can be direct such as extreme weather events (heat waves, storms, etc.) and indirect such as environmental regulations. Amid climate change crisis, this thesis presents three empirical investigations on how climate change has affected the financial performance. Particularly: (i) "do environmentally performing firms gain financial benefits?" (ii) "does reporting environmental information ease investors' concerns?" and (iii) "can variations of temperature destabilise the financial system"?

To be more specific, the first empirical chapter investigates the impact of environmental performance on financial performance. It is argued that both environmental and financial performance follow a non-linear endogenous relationship. Using data for 288 European manufacturing firms over the period 2005-2016, the said relationship is investigated under the *financial slack argument* and the contrasting paradigms of *neoclassical* and the *instrumental stakeholder theory*. Employing a quantile regression framework enriched with a set of instrumental variables to more effectively approximate environmental performance, the study finds (i) firms with superior environmental performance tend to be more profitable; (ii) the relationship between environmental and financial performance can be characterised as positive and heterogeneous across the conditional distribution; (iii) financial and environmental performance are endogenously related only when high profitability firms are examined.

The second empirical chapter analyses the impact of environmental disclosure on the idiosyncratic risk of European manufacturing firms. Utilising a panel data set of 288 firms covering the period from 2005 to 2016 in 17 European countries, the study provides evidence that environmental disclosure reduces risk asymmetrically. Findings further show that this relationship can best be justified by the *slack resource argument*, as well as, by both the *stakeholder* and the *legitimacy theory*. By contrast, predictions based on *managerial opportunism* appear to be invalid. In addition, results reveal that the reaction of idiosyncratic risk to environmental disclosure is highly heterogeneous throughout the conditional distribution. At the same time, we cannot establish a strong link between environmental disclosure and firm's total risk, implying that environmental activities are closely linked to idiosyncratic risk. Results remain robust under all different specifications suggested by three different econometric methods; namely, (i) panel data techniques, (ii) dynamic panel data and (iii) quantile regressions.

The third empirical chapter examines if temperature has an effect on the systemic risk of European firms. We employ a $\Delta CoVaR$ model in order to measure the potential impact of temperature fluctuations on systemic risk, considering all companies from the STOXX Europe 600 Index, which covers a wide range of industries for the period from 1/1/1990 to 29/12/2017. Furthermore, in this study, we decompose temperature into 3 factors; namely (i) trend, (ii) seasonality and (iii) anomaly. Findings suggest that, temperature has indeed a significant impact on systemic risk. In fact, we provide significant evidence of either positive or nonlinear temperature effects on financial markets, while the nonlinear relationship between temperature and systemic risk follows an inverted U-shaped curve. In addition, hot temperature shocks strongly increase systemic risk, while we do witness the opposite for cold shocks. Additional analysis shows that deviations of temperature by 1°C can increase the daily Value at Risk by up to 0.24 basis points. Overall, higher temperatures are highly detrimental for the financial system. Results remain robust under the different proxies that were employed to capture systemic risk or temperature.

Climate change has profoundly shaped the modern view of finance. This thesis examines the prominent role of climate change in financial markets and provides important implications suggesting managerial decisions, recommending policy-making directions, understanding theoretical connections between environment and profitability and providing optimal investment decisions.

Keywords: Climate change; Financial performance; Environmental performance; Environmental disclosure; Idiosyncratic risk; Panel data; Quantile regressions; Conditional Value at Risk; Systemic risk; Temperature

JEL Classification: C14; C21; C33; C36; G12; G18; G32; L25; Q51; Q54

Contents

Declaration

Whilst registered as a candidate for the above degree, I have not been registered for any other research award. The results and conclusions embodied in this thesis are the work of the named candidate and have not been submitted for any other academic award.

Word count: 62,269

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Abbreviations

CO_2 - Carbon emissions

GHG - Greenhouse gases

EU - European Union

US - United States

FP - Financial performance

EP - Environmental performance

CSR - Corporate social responsibility

CER - Corporate environmental responsibility

Disc - Environmental Disclosure

CoVaR - Conditional Value at Risk

IPCC - Intergovernmental Panel on Climate Change

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Risk: Evidence from European manufacturing firms

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1 Introduction

HUMAN *activities are estimated to have caused approximately 1° C of global warming above pre-industrial levels* (IPCC, 2018). The increasing consumption for goods, that our modern civilisation demands, has raised atmospheric carbon dioxide levels from 280 parts per million to 409 parts per million in the last 150 years. Given that the current rate of anthropogenic CO_2 emissions continues, global warming is likely to reach 2°C in the next 50 years (IPCC, 2014). In December 2018, the United Nations Climate Change Conference which held in Poland, had as its main conclusion that if we do not tackle climate change, model civilisation will extinct. Thus, the main challenge is to maintain global warming below the threshold of 1.5 °C. Beyond this level, extreme weather events will be more frequent and as a result the macroeconomic conditions will be deteriorated significantly (Stern, 2007; Dell et al., 2012).

Keeping global warming below 1.5°C demands firms to adopt an environmental approach towards the natural environment. However, this proactive approach might be opposed with the main objective of the firms (e.g., maximise shareholders' value) (Dahlmann et al., 2019). Therefore, firms will agree to comply with the social and regulatory actions against climate change only if the net benefit from environmental actions out-weights the compliance costs (Hatakeda et al., 2012). Besides, global warming has multidimensional characteristics whereby can potentially affect the financial performance of firms. For instance, firms can be influenced by the environmental regulations such as environmental reporting, carbon tax or carbon trading as well as by the perception of the market participants whose behaviour deviate from the traditional theory of finance and they might extract utility by turning into environmental investments (Fama and French, 2007). On the top of that, the contemporaneous topic of climate change in a micro-economic level is a rather unexplored field of study and for this reason, there is an uprising stream of scholars, managers and policy-makers that attempts to make an inference between the firm and the environment (Bebbington and Larrinaga-González, 2008).

Climate change has profoundly shaped the modern view of finance. In order to disentangle this nascent field of research, this thesis presents three empirical examinations. The unedited research questions, that the thesis attempts to posit and are related to the three empirical examinations, are the following: (i) do "environmentally performing firms gain financial benefits?", (ii) "does reporting environmental information ease investors' concerns?" and (iii) "can variations of temperature destabilise the financial system"?

1.1 Motivations of Thesis

The climate change effects on the financial performance is a topical area with interdisciplinary interest. From an economic point of view, climate change has an impact on GDP, consumption and productivity (Dell et al., 2014). Even though, there is well established literature between macro-economy and the environment (known as climate-economy literature) (e.g., Stern, 2007; Schlenker and Roberts, 2009; Dell et al., 2012) there is still an large unexplored part which is related to the climate-finance literature.

First, literature has not yet concluded if firms should operate "green" (Busch and Lewandowski, 2017). For example, empirical literature shows contradicting findings which further stresses the relationship and makes it imperative to initially understand what is the main reason of controversy. There is an increasing volume of funds allocated to "green" projects (Eurosif, 2016). Nevertheless, are these investments sustainable? In other words "does it pay to be green?". This is analysed extensively in Chapter 3, which scrutinises the connection between environmental and financial performance.

Second, regulators underline the importance of disclosing the environmental activities in an attempt to monitor rising temperature (EU Commission., 2014). At the same time, reporting environmental information can be described as "win-win" situation. Thus, not only regulators can gauge the carbon footprint of the firms but also firms comply with the existing regulations (Aggarwal and Dow, 2012). The question arises is whether symmetric environmental information increases the market concerns about climate change or not. Are investors attracted by environmental disclosing firms? Or climate change information has a negative tone for them and results to higher risk. The connection between environmental disclosure and idiosyncratic risk is examined in Chapter 4. Idiosyncratic risk is emphasised and consequently analysed because (i) this is referred to specific-firm characteristics and (ii) it is responsible for the volatility of a market index (Ang et al., 2006).

Third, global warming is a risk factor which has a negative effect on equity returns (Bansal and Ochoa, 2011; Balvers et al., 2017). In a similar vein, increasing temperatures can spread uncertainty to the whole financial system (Battiston et al., 2017). This can be explained by the fact that climate-sensitive assets are affected directly by the extreme temperatures. Given that these assets are highly interconnected, someone can argue that the entire financial system can be affected. Hence, Chapter 5 explores the probability that climate change is a systemic risk factor that can destabilise the financial markets.

Furthermore, economic theories do not provide a clear inference between financial performance and climate change (Brooks and Oikonomou, 2018). This is because, some theories suggest that it is profitable to operate "green", while others advocate otherwise. This intense conflict among theories generates a fruitfully environment to further investigate the reasons behind it and to validate theories that characterise this relationship. A detailed description of the economic theory can be found in Chapter 2; in Chapters 3 and 4 theories are empirically tested.

Finally, this thesis is motivated by the increasing number of environmental regulations particularly in the European Union. Environmental reporting standards demand firms to disclosure more and more items (EU Commission., 2014). For instance, not only firms should "cap and trade" their emissions (EU emissions trading scheme) but also they have to comply with different mitigation policies, such as Kyoto Protocol and Paris Agreement. It seems that EU officials are highly committed to deal with climate change and thus high concerns are generated, questioning whether EU firms can still be profitable when they also have to bear the environmental compliance costs. For this reason, all three empirical chapters test samples including EU firms.

1.2 Research Philosophy

Before proceeding to delve more into the relationship between climate change and financial performance, it is important to understand the research approach philosophy of this thesis.

Heraclitus (535–475 B.C) a Greek philosopher is known for his quotes regarding the perpetual changes in cosmos; "*there is nothing permanent except change*" (Wheelwright, 1959). Amid climate change, this is a unique opportunity for firms to change technology and thus gain a competitive advantage (Hart and Ahuja, 1996). However, how can firms sustain a competitive advantage when they are between the inertia and the inaction (Durand and Calori, 2006)? How can managers help diffuse long term objectives while have to integrate the need for environmental adaptation? How can a firm arbitrate between exploration and exploitation while respond to environmental constraints? Among many others, these are some philosophical considerations leading to the main question which is; if firms can afford the change towards a green era.

In order to investigate the above considerations, the research philosophy of this thesis is based on the epistemology approach with positivism doctrine. The main goal of the epistemological approach is to assess economic theories by collecting real world data. Positivism underlines that the researchers should take an objective position and should not be driven by their own preferences. In order to satisfy this assumption, existing theoretical framework should be primarily considered and tested in order to derive and develop new principles. Positivism is more closely related to testing theories rather than generating new ones. For this particular reason, the empirical chapters of this thesis are constructed by, first deriving the research hypotheses, then collecting the data and finally using the appropriate methodology.

Moreover, the adopted methodology is a quantitative methodology of econometrics while the data used are secondary from credible sources. Methods employed in this thesis are checked for their robustness and are chosen adherent to the previous empirical studies. Similarly, the chosen variables reflect both the theoretical predictions as well as suggestions from previous studies. Regarding the methodology of econometrics, in fact this method is closely related to the positivism doctrine because inferences are made using a deductive approach (theory driven) and less inductive (data driven) approach. Inductive approach is only employed in order to compare our main findings with previous literature. Therefore, our econometrics methods have the main objective to use mathematics and statistics prevailed by the economic theory.

1.3 Aims and Objectives

Having discussed about the research philosophy, we now turn to list the aims and objectives of the study. Besides the obvious aim/ objective of the study, which is to present an up-to-date review of literature about financial performance of the firms under climate change (Chapter 2), this thesis develops three empirical examinations and therefore three aims and several objectives are listed below.

The first aim of the study is to investigate the relationship between environmental and financial performance by exploring the distributional properties of financial performance. The second aim of the thesis, is to examine if a portfolio with environmental disclosing assets has, on average, less risk than a non-disclosing asset portfolio. The third aim is to test if weather conditions can destabilise the financial system.

The objective of the first empirical chapter (Chapter 3) is to examine the connection between environmental and financial performance for 288 EU manufacturing firms for the period 2005-2016. Particularly, we test if the efficiency of environmental performance (EP) is conditional on the profitability level of the firm. Existing literature is focused on the conditional mean of the FP distribution and neglects the highly skewed financial data (e.g. Misani and Pogutz, 2015; Lewandowski, 2017). By using quantile regressions, we are able to provide new evidence of the said relationship in different parts of the FP distribution. Existing literature has addressed the question "does it pay to be green?", we take one step further and address "how does green react to different parts of the profitability distribution?"

The second objective (Chapter 4) is to test if disclosing environmental information can affect the idiosyncratic risk of firms, considering 288 EU manufacturing firms for the period 2005-2016. By using panel, dynamic panel and quantile estimations, we provide evidence that the information regarding climate change is priced in the financial markets. Modern finance shows that investors critically evaluate all available information. Therefore, in a period when climate change predominates in the headlines, a proportion of the investment uncertainty might be attributed to the environmental information asymmetries.

Finally yet importantly, the third empirical chapter (Chapter 5) examines if temperature changes can affect the systemic risk of the European market. Given that temperature can directly trigger macroeconomic alterations (Dell et al., 2014), we investigate if climate sensitive firms absorb the initial temperature shock and then, in turn, they generate spillovers to the whole financial system.

1.4 Contributions

The study attempts to provide newcomers in the field; managers, researchers and policy-makers with an overview of the existing literature regarding the financial performance (FP) of firms under climate change. Additionally, the climate-finance research is rather limited, the majority of the studies can be categorised in the climate-economy literature. Hence we fill this important, yet unexplored part of the literature with new empirical evidence. Even though, the thesis has a few conceptual and theoretical contributions (Chapter 2), the main contributions are empirically related. Particularly, we provide empirical evidence regarding the climate change and financial performance relationship in an area which is highly committed to deal with the climate change, the European Union.

1.4.1 First Empirical Chapter: Chapter 3

In the first empirical chapter (Chapter 3), the study goes beyond the traditional literature and allows environmental performance (EP) estimates to vary across the conditional distribution of FP. To the best of our knowledge, this is the first attempt to evaluate the EP-FP relationship with non-parametric techniques. Particularly, standard quantile and two-stage quantile regressions are employed (Koenker and Hallock, 2001; Lee, 2007). These techniques help us provide novel evidence of the relationship at the tail of the FP distribution. At the same time, we address calls by Horvathova (2010); Albertini (2013); Baboukardos (2018) who underline that the unambiguous previous results in this examination are attributed to the intense endogeneity. So, the chapter deals with the role of endogeneity and non-linearity simultaneously.

1.4.2 Second Empirical Chapter: Chapter 4

The second empirical chapter (Chapter 4) contributes to the literature regarding the effects of corporate social actions on firm risk (Lee and Faff, 2009; Oikonomou et al., 2012; Linciano et al., 2018). Particularly, we test the effects of environmental disclosure on idiosyncratic risk. The relationship is testing by using various econometric techniques, such as panel data estimations (pooled OLS, fixed and random effects), dynamic panel estimations (system GMM) and quantile regressions. Moreover, while previous literature uses simple capital asset pricing model to estimate idiosyncratic risk, we employ the contemporaneous method of Fama and French (2015) by using a five factor model. This chapter also demonstrates that the environmental disclosure has heterogeneous effects on the conditional distribution of idiosyncratic risk, implying that by adding environmental disclosing firms in a risky portfolio, the overall risk can be diversified.

1.4.3 Third Empirical Chapter: Chapter 5

The third empirical chapter (Chapter 5) provides three main contributions. First, while previous studies examine the connections between temperature shocks and stock returns (Cao and Wei, 2005; Apergis and Gupta, 2017), this is the first study that examines the effect of temperature shocks on the systemic risk. Systemic risk is defined, in line with Adrian and Brunnermeier (2016), as the value-at-risk of each firm and can be easily estimated with quantile regressions at 99% of the losses distribution. Then we regress temperature and other important control variables on systemic risk with simple pooled OLS regressions. Second, contrary to existing literature that used low frequency data, we use 28 years of daily observations, which can directly account for both the short-term and long-term temperature effects. Finally, we decompose the temperature series as suggested by environmental studies (Vecchio and Carbone, 2010) and thus the chapter provides with meaningful results about the temperature effects. Existing literature did not decompose the temperature data and this might be problematic in terms of the interpretation and reliability of the results (Jacobsen and Marquering, 2009).

1.5 Research Hypotheses

Each of the empirical chapters develops a hypotheses section. The main research question of this thesis is whether climate change can affect the financial performance of firms. Particularly, the ensuing hypotheses that we have attempted to posit are:

In Chapter 3

Hypothesis 3.1: *The effect of environmental performance on financial performance varies across different levels of financial performance.*

While existing literature investigates the mean of the financial performance distribution, we advocate that the efficacy of environmental performance is probably based on the financial condition of every firm. This can be well supported by the *slack resource argument*, which implies that important distinction should be made between high and low profitability firms. This is because different profitability firms manage their available resources differently.

In Chapter 4

Hypothesis 4.1: *High environmental disclosure has a negative impact on idiosyncratic risk, under the stakeholder theory.*

Hypothesis 4.2: *Environmental disclosure can heterogeneously affect idiosyncratic risk at different levels of idiosyncratic risk.*

There is a debate in the literature regarding the wider corporate social responsibility of firms and if social actions have positive or negative outcome. Similarly, there are competing theories indicating that social actions have different effects on the firm risk. In this instance, hypothesis 1 aims to test for the relevance of these theories in our context. The second hypothesis is related to the different levels of risk and thus we ask how disclosing assets can affect portfolios with high, low or medium risk.

In Chapter 5

Hypotheses 5.1: *Temperature has asymmetric effects on systemic risk.*

Hypothesis 5.2: *Temperature anomaly has asymmetric effects on systemic risk.*

Hypothesis 5.3: *Hot and Cold temperature shocks increase systemic risk.*

There is an ongoing discussion about the temperature effects on the financial markets. At the same time, financial stability is connected with the systemic risk and it is questioned how financial stability could be agitated. We hypothesise that temperature can play this role. Hypothesis 1 tests how raw temperature might influence the financial markets. Hypothesis 2 adopts a superior measure to test the relationship between temperature and financial markets, namely temperature anomaly. Hypothesis 2 inspects that the asymmetric relationship between temperature and systemic risk can be explained by disaggregating temperature data into hot and cold shocks, in turn, we examine the effect of these shocks on the systemic risk (Hypothesis 3).

1.6 Linkage among the Empirical Chapters

Large corporations have been accused that are the root of global warming since they are responsible for the gradual increase in the anthropogenic emissions, and consequently this causes the gradual increase of the average global temperatures. Amid climate change, firms should be informed and equipped with adequate tools in order to be prepared to deal with one main threats of humanity. This thesis explores potential relationships between climate change and firm's performance and gives recommendations about strategies that firms should adopt.

Particularly, the thesis brings together three major issues. The first issue, which is described in the first empirical chapter (Chapter 3), is if all type of firms can sustain a competitive advantage under climate change. This chapter ascertains that investing in environmental performance can both lead to superior financial performance, irrespective of the financial condition of the firms, and ease regulatory and social concerns about climate change. In close relation to that, Chapter 4 asks if disclosing environmental performance can decrease the information asymmetries and lead to lower risk in the financial markets. Therefore, the first two empirical chapters investigate the pro-activeness of the firms and if it is worth investing and communicating their environmental actions. Although, Chapters 3 and 4 offer a different view in topics that have already been tested in the literature, Chapter 5 provides an unique dimension of the relationship between climate change and FP. This is that climate change can harm the financial stability. The damage from climate change is, to a certain extent, irreversible and this damage can, in fact, destabilise the financial system. Even though, the damage from climate change is still minor, Chapter 5 shows that firms are suffering the climate change consequences and as global warming becomes more intense these consequences become more unbearable.

Another link among the empirical chapters is that they pertain evidence to establish a strong connection between climate change and financial performance in a particular area, the EU. EU has become increasingly committed to promote climate change mitigation (e.g. Kyoto Protocol, Paris Agreement, EU emissions trading scheme, etc.) and specifically the European Parliament has underlined the importance of corporate environmental actions, in an attempt to monitor the rising temperatures. For this reason, climate change effects have shaped the perception of various stakeholders such as investors, managers and employees in the EU area. Thus, in order to understand if all these talks about climate change are eventually considered by stakeholders, all three empirical chapters are based on a sample of European firms.

1.7 Structure of Thesis

The remainder of the thesis is structured as shown in Table 1.1. In Chapter 2, the literature review is described, which includes a conceptual and theoretical framework along with a systematic literature review. Chapters 3, 4 and 5 are the three empirical investigations. All three of them follow the same structure, adhering to a standard empirical paper. Particularly, each empirical chapter has its own introduction, specific literature review with its hypotheses, then methodology is described, results are presented and finally some important remarks. The final part of the thesis, Chapter 6, concludes with the overall findings, implications of the results and limitations of the study.

Table 1.1: Structure of Thesis

Chapter #	Title	Contents
Chapter 1	Introduction	Background of the topic, motivation, aims and contribution
Chapter 2	Literature Review	Conceptualising climate change effects, systematic literature review, presenting economic theories and suggestions for future research
Chapter 3	Environmental & Financial Performance	The three empirical chapters of the thesis have similar structure with subsections: (i) Introduction (ii) Literature Review (iii) Research Design (iv) Results (v) Conclusion
Chapter 4	Environmental Disclosure & Idiosyncratic Risk	
Chapter 5	Temperature & Systemic Risk	
Chapter 6	Conclusion	Presenting the main findings, policy implications, limitations and future directions

2 Literature Review

2.1 Introduction

THE US and EU account for 11% of the world population and they are responsible for 25% of world's carbon emissions. China follows a similar pessimistic trend, which accounts for 30% of the total Carbon dioxide (CO_2) emissions. This statistic underlines that few countries pollute; however the social cost is attributed to all of us. Researchers in this field focus mainly on CO_2 because once in the atmosphere its effect can last for thousands of years compared to other Greenhouse Gases (GHG). Bebbington and Larrinaga-González (2008) suggest that the CO_2 in the pre industrial era was approximately 280 ppm[1], vis-à-vis 409 ppm today, and at this rate the average global temperature is expected to increase by more than 2°C by the end of the century. In close relation to this, Stern (2007) argues that an increase in temperature of 2°C would cause extreme weather events such as storms and floods and that would reduce global GDP by either 0.5% or 1%; a negative impact that that would become even worse with the rise of temperature.

The effects from global warming typically break down into two categories. On one hand, there are direct damages which relate to the falling food production, increasing sea levels and increasing risk of large scale climate changes (see among others, Stern, 2007; Schlenker and Roberts, 2009; Dell et al., 2014). On the other hand, the indirect impact of the climate change can be observed in the financial markets in the form of pollution prevention regulations, as policy-makers make an effort to stabilise the carbon concentration by regulating the emissions of companies (Ambec and Lanoie, 2008; Chapple et al., 2013; Oestreich and Tsiakas, 2015). Apparently, global warming seems to have an effect not only on the non-

[1] ppm is parts per million e.g. 408ppm CO_2 is 0.0408% CO_2 in the atmosphere

financial sphere, but also, on financial performance (Bebbington and Larrinaga-González, 2008).

Financial performance is the ability of the firm to use its assets in a way that generates profit. Corporate environmental responsibility (CER) is the relationship between the firm and the natural environmental. In this very chapter, the term CER reflects all the different actions that firms do regarding the environment, such as GHG reduction, disclosing environmental information, waste reduction, adopting environmental management system, buying carbon allowances etc. This should not be confused with the EP variable of the next Chapter; EP, in Chapter 3, will be just related to the carbon performance (GHG reduction) (Busch and Lewandowski, 2017). A growing number of firms have considered practises to enhance their environmental responsibility in order to minimise their ecological footprint and consequently to increase its revenues. For this reason, there is a strong link between CER and FP. However, the existing literature has not concluded if it pays to be green. On top of that, neither economic theories clearly show whether it is profitable to operate green. For instance, while legitimacy theory proposes a greener performance, neoclassical theory discourages this adaptation (Li et al., 2018a).

This chapter provides a critical review of the existing literature on the relationship between FP and CER. We identified different empirical studies that not only present ambiguous results about the sign and the significance of the said relationship but also, refer to different economic theories that provide different explanations. In this regard, we fill the void stemming from the fact that the theoretical framework bringing together CER and FP has rather been neglected by existing literature. The study also attempts to provide newcomers in the field, managers and policy-makers with an overview of all the possible climate change channels that affect FP. More importantly, we make suggestions for future research. In particular, we propose that the construction of a composite environmental variable is imperative in order to shed light on the relationship between CER and FP.

The remainder of the chapter is structured as follows. Section 2.2 presents the conceptual background of the study. Section 2.3 analyses the economic theories that CER and FP predicate upon. Section 2.4 sets out the variables and the methods employed by empirical papers, followed by the most noteworthy findings. Section 2.5 concludes with suggestions for future research, emphasising the importance of coming up with a component variable that captures developments in CER.

2.2 Conceptual Background

2.2.1 Climate Change, Output and Consumption

In this section, the indirect impact of climate change on FP through the output is being presented. Stern (2007) argues that climate change will have a direct effect on countries' GDP due to the fact that they have to bear the consequences of the extreme weather events, such as rainstorms, extreme temperatures and floods. Dell et al. (2014) maintain that temperature shocks are inevitably connected with the consumption, agricultural outcome, health, productivity and to some extent with economic performance.

We begin by looking at the effect on agricultural production and health. Schlenker and Roberts (2009) identify that temperature changes can have an impact on agricultural products due to the fact that crop yields can thrive under certain climate circumstances. Their findings indicate that different temperature-change scenarios can decrease the average crop supply between 30% and 82% by the end of the century. Moreover, Deschenes (2014) underscores that the direct recipients of climate change are people and the main threat is whether people are able to adapt to the new environment or not. According to World Health Organization[2] the direct cost to health will be 2-4 billion USD annually by 2030 due to the increasing number of deaths caused by climate change. Dafermos et al. (2017) underline that extreme weather events and health problems would make households to save more for precautionary reasons and consequently consume less. Therefore, global warming affects directly the components of aggregate demand and supply.

We then turn our attention to the impact on oil production and investment. The scarcity of fossil fuels along with the continuous increase in the taxes imposed by governments on the goods made from fossil fuels lead to higher prices of these goods (Busch and Hoffmann, 2007). In order to overcome this issue and reduce the long term cost, companies might need to consider research and development (R&D) innovations that are not reliant on fossil fuels. However, Batten et al. (2016); Semmler et al. (2016) argue that R&D innovations will generate a transition risk which eventually destabilises the economy.

On the top of that, productivity shocks are inevitably connected with the climate change. Donadelli et al. (2016) support that temperature shifts have a long run negative effect on labour productivity. Further, Hsiang (2010) finds that an increase in temperature by 1°C can have a negative effect of 2.4% on labour productivity. Similar finding is supported by Graff Zivin and Neidell (2014) who identify that a temperature rise reduces the hours worded in industries. Thus far, less consumption, higher prices of goods and R&D innovations might cause a productivity shock for firms (Kumar, 2006). In turn, productivity shocks can explain a high variation of the cross section stock returns (Garlappi and Song, 2016) which accordingly affect the FP of the firms.

[2] Retrieved from http://www.who.int/mediacentre/factsheets/fs266/en/

2.2.2 Climate Change and Financial Markets

Having discussed about the consequences of climate change on output and consumption, we now proceed to examine if the temperature related risk is depicted in financial markets.

From a firm-level perspective, Dobler et al. (2014) place emphasis on the components of the environmental risk of the firms. This risk arises through the regulations, operations and natural environment. Particularly, temperature has often been reported to influence the profitability of climate-sensitive sectors[3] such as agriculture, energy, tourism and manufacturing (Perez-Gonzalez and Yun, 2013). Firms in these sectors should hedge their risk management by purchasing weather derivatives. Weather derivative is the instrument that protects firms from the temperature related risk changes. Considering for example the study of Perez-Gonzalez and Yun (2013), who identify that 70% of the US energy firms hold weather derivatives. Their findings indicate that companies which hold weather derivatives lead to higher equity valuations.

From a shareholder point of view, temperature is a risk factor (Bansal and Ochoa, 2011) that might affect the portfolio returns. However, there is not sufficient evidence that temperature variations can describe the volatility of stock returns (e.g. Cao and Wei, 2005; Bansal and Ochoa, 2011; Balvers et al., 2017). Futures and options market is better at reflecting all available information (Christensen and Prabhala, 1998). Therefore, a possible outcome is that temperature changes are absorbed by the derivatives market. This interconnection has not been examined by the literature and therefore we cannot conclude about the effect of climate change on the derivatives market.

[3] Climate sensitive sectors are defined as the sectors which are affected directly by the climate change. See more on http://unfccc.int/cooperation_support/response_measures/items/5003.php

Overall, the direct effect of climate change on the financial markets needs further examination. The negative externality of temperature can be hedged with weather derivatives at company-level. However, the question that still remains is how to hedge the temperature risk from a stock portfolio.

2.2.3 Environmental Regulations

We now turn to consider the regulatory regime against climate change. Stabilising the carbon emissions is a complicated and ineffective task. According to Stern (2007) tackling climate change considers four main actions; a) regulating the emissions, b) incentivise the green investments, c) minimising asymmetric information and transaction costs and d) building informative network to the society. Different climate change policies are listed below.

The first policy is the Intergovernmental Panel on Climate Change (IPCC[4]) which was set up in 1988 and is an international body for assessing climate change. The IPCC presents scientific, technical and socio-economic information in order to understand the future risk arising from the human-induced climate change. Its main contribution is to inform about potential impacts and provides with options for adaptation and mitigation. Furthermore, the United Nations Framework Convention on Climate Change (UNFCCC[5]) is a treaty which was signed in 1992 and having as a main target to stabilise the GHG in a harmless level to the environment. UNFCCC is probably the most serious attempt made against climate change and it is a treaty supporting posterior actions such as the Kyoto protocol, Clean Development Mechanism (CDM) and Paris Agreement. Regarding the Kyoto Protocol[6], it is an agreement made by UNFCCC with its main objective being to regulate a permissible limit of GHG. The Protocol had

[4] http://www.ipcc.ch/pdf/tor/TOR_Bureau.pdf
[5] http://newsroom.unfccc.int/about/
[6] http://unfccc.int/kyoto_protocol/status_of_ratification/items/2613.php

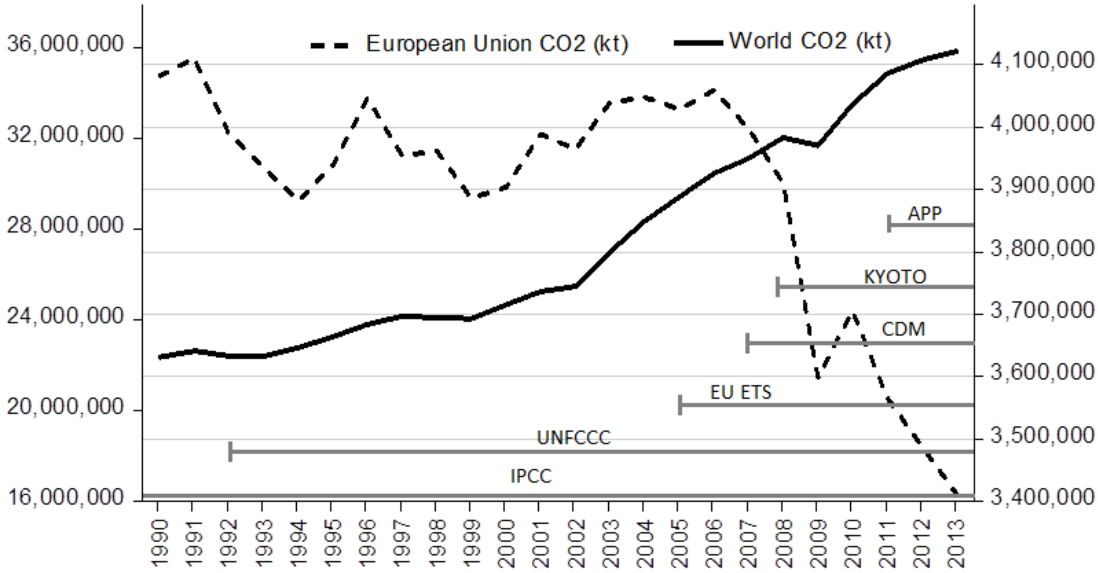
been negotiated since 1997 and was set in action in 2008. It requires ratification and signed members ought to decrease their emissions at a level of 5% below that in 1990. Similar to the Kyoto Protocol, Asia Pacific Partnership (APP[7]) has attempted to meet goals for national air pollution reduction and climate change in a way that will not harm the growth and the sustainability of countries and firms. APP partners are Australia, Canada, China, India, Japan, Korea, and the United States. Additionally, the CDM[8] is a mechanism that promotes the low emission technologies in developing countries. Moreover, it motivates sustainable development emission reductions by giving developed countries some flexibility in how they meet their emission reduction limitation target under the Kyoto Protocol. Meeting the demands of CDM will cause an earning on certified emission reduction credit (CER) each equivalent to a tone of CO_2. Accordingly, CDM supports the green investment and gives incentives for emission reductions. The most recent and prominent attempt against climate change took place in Paris on December of 2015. Paris agreement[9] is being ratified by 148 out of 197 countries and was taken into force on November 2016. The agreement incorporates three main targets, a) holding the world temperature increase below 2°C (after the industrial revolution the temperature has increased by almost 1°C), b) facilitating the adaptation of low GHG technologies in respect to the food production and c) making finance flows consistent and continuous to low climate-resilient development.

However, the Paris agreement cannot be evaluated yet for its contribution. Other actions have been taken all over the world but do not offer a substantial solution. Keohane and Victor (2011) argue that complicated climate regime is ineffective and this can be justified by the fact that world CO_2 emissions keep

[7] http://www.asiapacificpartnership.org/english/default.aspx
[8] http://cdm.unfccc.int/about/index.html
[9] http://unfccc.int/paris_agreement/items/9444.php

increasing (figure 2.1). In addition to this, stringent environmental regulations not only have neutral effect on the carbon emissions, but also a negative impact on the labour productivity of firms (Ambec and Lanoie, 2008).

Figure 2.1: CO_2 Emissions.



Note: The vertical axes correspond to the kiloton (kt) of CO_2 emissions. On the left is the world carbon emissions, while on the right is the European carbon emissions. The horizontal axis is the year. IPCC, UNFCCC, EU ETS, CDM, Kyoto Protocol and APP are referred to different climate change policies under the years of their implementation. CO_2 data were reviewed from World Bank Indicators.

2.2.4 Climate Change and the Carbon Market

Carbon trading is tool for reducing GHG cost-effectively. In some regions such as California, New Zealand, Korea, Australia and in EU[10], CO_2 has been financialised as a commodity and is exchanged in a cap and trade system. Cap and trade system indicates that the quantity of emissions has to be capped. Polluters have allocated allowances, either free or by auctions (Schultz and Swieringa, 2014). Every year companies must surrender enough allowances to cover all of their emissions, otherwise they are penalised according to the state-law. If com-

[10] https://ec.europa.eu/clima/policies/ets/

panies achieve the emission target, they can keep the additional allowances either for their future needs or trading purposes. Therefore, CO_2 is not just limited to be regulated under the governments but also carbon market has an equal responsibility for stabilising the climate change.

It is notable that after the implementation of the EU emissions trading system (EU ETS), the primary objective of decreasing the CO_2 emissions in the EU region has been attained (figure 2.1). However, a question that has to be addressed is whether the stringent regulation, especially in the EU area, has made companies to outsource capital. More specifically, in the past decade, an ever increasing number of US and western EU firms are moving their operations to Asia, particularly to India and China (Massini and Miozzo, 2012), where the environmental regulations have not been ratified yet and the marginal cost of manufacturing is much lower (Belcourt, 2006).

2.2.5 Political Intervention

We now turn to consider the potential effect of environmental announcements, made by politicians, on a firm's value. Consider, for example, the following headline: *"Coal resurgent, renewables in retreat after Trump's win. [...] If you want a snapshot of what the global energy map will look like, look no farther than the stock market"*.[11] Apparently, the newly elected president of the US has publicly announced he does not believe in climate change. In a recent study by Ramiah et al. (2015) the authors identify that green announcements made by the former eco-friendly US president increse stock market volatility. Obama's priority was to mitigate the global warming while Trump's agenda schedules to "alt control delete"[12] the policy of his predecessor. Similarly, Ramiah et al.

[11] Coal resurgent, renewables in retreat energy after trump's win. Retrieved from: https://www.bloomberg.com/news/articles/

[12] See more on:http://www.bbc.co.uk/news/science-environment-38746608

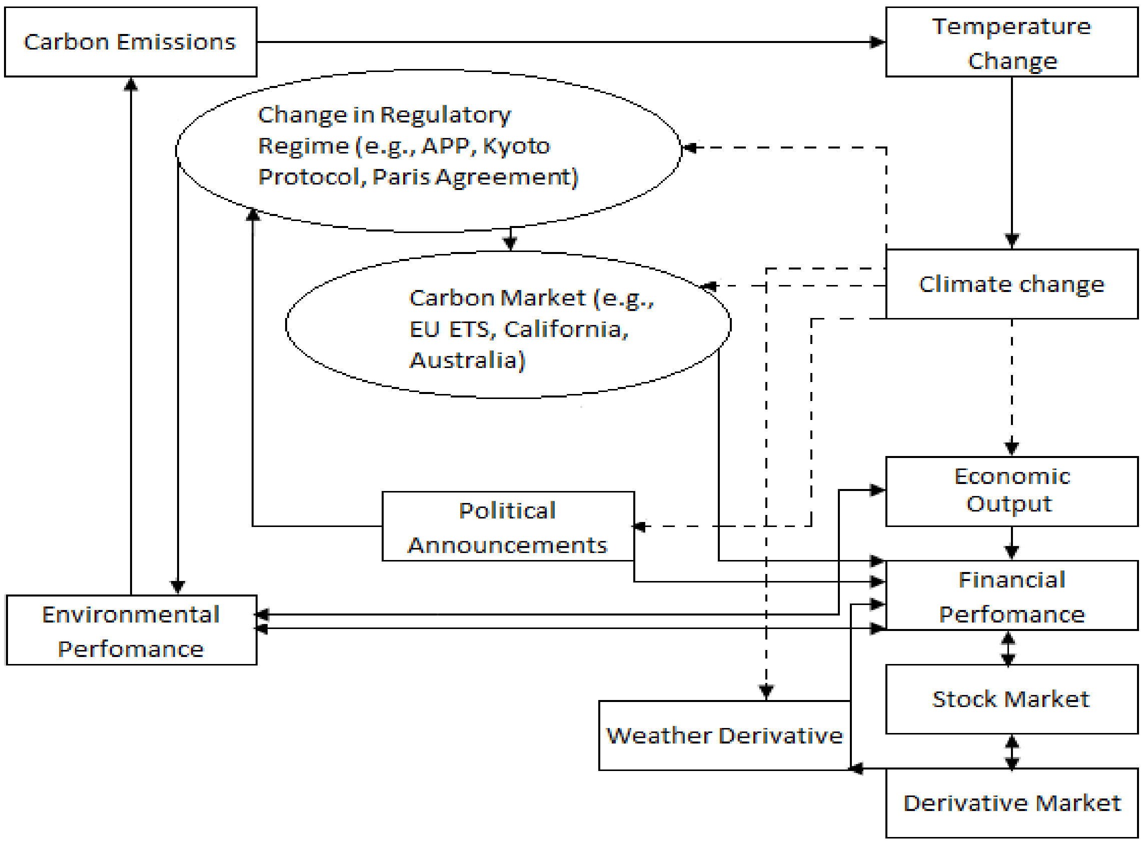
(2016) assess the effect of green announcements on the stock returns of British companies and they detect a short and long run surge of systematic risk of the companies. Typically, political announcements occur in order to introduce or alternate a political regime (Pastor and Veronesi, 2013). For instance, changes in environmental policies indicate a political shock which is reflected on the stock market, because investors are driven by uncertainty of a potential modification of the existing legislation and they have to reassess whether the new situation is aligned with their objectives. Therefore, the new political regime in the US has caused uncertainty to the investors which is reflected on the volatility of stock returns. Pastor and Veronesi (2013) notice that uncertainty instigates a higher risk premium and it varies according to the magnitude of firms' association with the new policy. Even though, anecdotal evidence suggests that energy stock prices surge while clean power stocks sink under "anti-green" announcements, methodological framework has to thoroughly examine this observation.

2.2.6 Financial Performance and Climate Change

In this regard, temperature dynamics, regulations, carbon market and political interventions bring us to the focal point of this report which is to evaluate the effect of climate change on FP. The particular channels that confirm this connection are represented in figure 2.2. The aggregated environmental performance of firms generates an amount of CO_2; the higher the carbon concentration in the air, the warmer the planet gets. The effects of the temperature changes on the environment can be defined as the climate change which subsequently has an indirect effect on FP.

This indirect effect occurs through five channels: The first one is the environmental regulation (Ambec and Lanoie, 2008) due to the fact that companies have to operate in a new environment to which they need to adapt so they change their productivity levels. Second, the carbon market (Schultz and Swieringa, 2014) where firms cap their emissions via carbon allowances that are traded in the market. The third channel is the economic output, because an increase in the temperature decreases labour productivity (Hsiang, 2010) along with the real GDP growth (Dell et al., 2012). The fourth channel involves the political initiatives, such as environmental announcements which have been proven to cause volatility in the financial market (Ramiah et al., 2015). The last channel has to do with the weather derivatives which are issued to hedge the temperature risk (Perez-Gonzalez and Yun, 2013).

Figure 2.2: Conceptualising Climate Change Effects.



Note: Rectangles show potential effects stem from climate change and ovals represent the mitigation policies against climate change. Dotted lines underscore the indirect channels between climate change and financial performance. Solid arrows represent some additional interconnections.

On top of the established channels that link climate change to FP, our analysis puts forward the argument that we should also investigate the following. First, high CER admittedly seems to have a positive and significant effect on the FP (Orlitzky et al., 2003; Albertini, 2013), with a need to further investigate their bidirectional relationship. Second, one of the functions of derivatives market is to hedge against unexpected events. Similarly, the weather derivatives hedge against extreme temperatures and therefore possibly the temperature risk can be hedged by other securities such as futures or options. Third, reassessing whether regulations have created barrier to operate in some regions and have companies outsourced in a less regulated environment. Overall, firms should certainly reconsider their environmental actions and therefore the next section attempts to clarify and evaluate the benefits and the drawbacks of high CER in regard with the economic theories.

2.3 Economic Theories

The papers that have been reviewed for this section utilise a wide range of economic theories. We classify these theories based on how they answer the following prompt: "How is FP affected if we invest in CER?" There exists three distinct cluster of theories. First, the economic theories that support the positive impact of CER on FP because firms eventually gain sustainable competitive advantage. Second, theories of negative impact claim that investing in CER will deteriorate the FP. Third, neutral theories have to weigh many different aspects in order to conclude about the direction of FP.

2.3.1 Theories of Positive Impact

The following part of this section moves on to describe in greater detail the economic theories that support the positive impact of CER on FP. These theories are the: (i) natural based view of the firm, (ii) legitimacy theory, (iii) instrumental stakeholder theory, (iv) slack resource argument, and two of the environmental strategies, (v) accommodative and (vi) proactive approach. The positive impact of CER on FP stands on the notion that firms, engaging in environmental practises, would decrease the long-term operational cost, improve the future profitability and create barriers to entry for new competitors; attributes that lead to a competitive advantage.

Among others Judge and Douglas (1998); Gil et al. (2001); De Burgos Jimenez and Cespedes Lorente (2001); King and Lenox (2001); Molina-Azorin et al. (2009); Delmas et al. (2015) examine the relationship between FP and CER under the natural resource based view of the firm. Hart (1995) claims that firms should: a) prevent the pollution by minimising their emissions, b) increase the life of goods by developing new technologies and c) sustain the development in order to manage their resources efficiently. Companies have not understood the environmental opportunities yet. Eco-friendly firms abate the risk and the cost as they become technological advanced. Subsequently, corporate governance aims to enhance the CER by minimising emissions and life cycle cost of products as a result the future position of the corporation can be ameliorated (Hart and Ahuja, 1996). Also, the future prosperity stands on the notion that green customers will be attracted by firms' ethical behaviour to the environment (Elkington, 1994).

Moreover, the ethical approach of the relationship is best described with the legitimacy theory by suggesting that firms are more likely to report environmental factors such as economic, political and social information in order to legitimise corporate actions (Guthrie and Parker, 1989). The notion of this theory is that firms operate in a society where they have to contribute and inform the public about their environmental actions. Therefore, firms would voluntarily agree to disclose social information in order to meet the demands of the public. For instance, disclosing firm's ecological performance will have a result to alleviate the external pressure for climate change. Also, transparent information regarding the CER means that they have to operate eco-friendly in order to make visible their environmental sensitivity and so they expect to have FP boosted (Ben-Amar and McIlkenny, 2015). On the other hand, large emitting firms will be punished by the society and such firms will avoid to disclose that kind of information (Lee et al., 2015). For that reason, the companies that they disclose environmental information are expected to have positive relationship with the FP under the legitimacy theory.

An application of legitimacy theory combining with the agency theory (described at 2.3.2) results the instrumental stakeholder theory which focuses on the contracts between the agents and principals and claims that trust and cooperation within company help solve problems (Jones, 1995). The theory is based on an integration of the agency theory combining with a behavioural science and ethics underling that under those criteria a firm can create a competitive advantage. Hence, a framework relied on the instrumental stakeholder theory is more likely to present a positive relation between CER and FP.

In addition, many studies (Karagozoglu and Lindell, 2000; Gil et al., 2001) built their research under the environmental strategies. According to Buysse and Verbeke (2003) the environmental CSR (corporate social responsibility) approaches are the accommodative, proactive, defensive and reactive. Accommodative and proactive approaches appear to influence the company positively. The former posits that firms have incentives to inform stakeholders about their environmental management. Dawkins and Fraas (2011) also hypothesise that visible[13] firms are more likely to disclosure environmental reports in order to diminish the asymmetric information due to the fact that their actions are seriously taken into account by the society and consequently stakeholders are attracted by high visible firms (Pfeffer and Salancik, 1978), argument which is also supported by the legitimacy theory. Thus, firms create a brand reputation with transparent information which not only gives a cost advantage but also a source of differentiation (Porter, 1991). Aragon-Correa and Sharma (2003) state that competitive advantage can be created if only firms adopt long term proactive environmental objectives while competitive advantage is highly unlikely to occur in a limited period of time. Likewise, the latter approach focuses on the level of the environmental engagement of the firm, suggesting that high proactive companies have cost savings due to technological improvements and avoid regulation (Reinhardt and Stavins, 2010), argument which is also supported by the nature resource based view of the firm. The rest two environmental approaches are described in the negative theory content (section 2.3.2).

Furthermore, investigating the time effect of the CER, Horvathova (2012) examines the relationship by dividing the environmental engagement into two sub periods. The author hypothesises that the competitive advantage has a time varying effect. Therefore, in a short term, firms will not be able to offset the cost of the investment but in the long run the CER and FP will be positively related; in other words, Porter Hypothesis starts having an effect after a substantial period of time. The time varying Porter Hypothesis can be also observed in the slack resource view. Very few publications (Daniel et al., 2004; Endrikat et al., 2014) can be found in the literature that discussing the relationship under the slack resource view. The theory is referred to the resource endowments in social and

[13] The visibility refers to the attention paid to a firm by the media

human capital and source constraints that can influence the performance of a firm in a competitive market. CER is inevitably connected with the source constrains (Busch and Hoffmann, 2007). George (2005) claims that the resources are not only correlated with the size of the firm but also with the industry in which it operates. The slack resource considers the bidirectional effect of the relationship suggesting that high FP will cause good environmental behaviour and *vice versa*.

Overall, six economic theories are found to promote the CER as a means of outweighing the negative climate change effect on the FP. Particularly, the positive spectrum of theories supports that investing in resources will not pay-off immediately but it facilitates the diffusion of the technology and firms will be capable of controlling the negative externalities such as environmental legislation and social pressure (Bansal, 2005). Firms will be able to be imitable and decrease the long run operational cost, representing the attributes of the competitive advantage.

2.3.2 Theories of Negative Impact

In contrast to the previous subsection, we now consider theories that claim that investing in CER will deteriorate the FP. Theories that are included in this group are: (i) the neoclassical theory,the rest two environmental strategies, (ii) defensive and (iii) reactive approach and (iv) the agency theory. The negative relationship between CER and FP can be justified due to the higher cost that firms have to endure.

Wagner et al. (2002) investigate the association under the scope of competitive advantage of the firm and postulate the neoclassical theory. Neoclassical theory suggests that some industries need high environmental compliance costs to operate under green management and therefore face a competitive disadvantage. So, the cost of decreasing their emissions are relatively high and it is predicted to increase productivity cost as a result increasing marginal costs. Neoclassical theory simply assumes that there is a direct trade-off between the cost and the benefit, indicating that investing in CER deducts profits and therefore decreases the firm's value.

Nollet et al. (2016) rely their research on the agency theory. Managers have incentives to invest in CER in order to increase their reputation, while shareholders are neutral (Barnea and Rubin, 2010). However, an over-investment will cause a deduction of profits and therefore lower shareholder value. Jensen (2001) underlines that the social responsibility as an investment strategy could create a higher shareholder value if the managerial discretion works under the objective of shareholder value maximisation, but this would better mirror the instrumental stakeholder theory, which was previously discussed (see section 2.3.1). Henceforth, under the agency theory, if managers choose to invest in CER, this will directly deduct profits from the firm.

Continuing with the two last environmental strategies and more particularly the defensive and reactive approach. The former is centred on a negative relationship between FP and voluntary environmental disclosure (Brown and Deegan, 1998) due to the fact that firms are exposed to unnecessary criticism, in a sense that can be characterised as a counter-legitimacy theory. Last environmental approach is the reactive, which disregards the environmental engagement merely because the opportunity cost is high and investing in other assets can generate greater returns (Buysse and Verbeke, 2003), argument which is in alignment with the neoclassical theory. Another reason to avoid CER is that if the majority of companies tend to adopt a clean operation, then companies that have not be differentiated, will eventually gain competitive advantage. Thus, the relationship between CER and FP varies according to the environmental strategy.

In general, four economic theories discourage the adaptation of high CER due to the extra cost imposed to the firms and at the same time the opportunity cost to invest in other assets will generate greater returns.

2.3.3 Theories of Neutrality

The last category of theories concentrates on how CER can enhance specific firm characteristics and whether these would be able to increase or decrease the value of the firm. Theories that fall in this category are: (ii) cost-benefit approach and (ii) finance theory.

Arora and Cason (1995) pay attention to the heterogeneity of the sample by measuring the net benefit of reducing GHG emissions among different firms. Similarly, Hatakeda et al. (2012) assess the difference between the cost of reducing GHG (CER) and the profitability (FP) as the net benefit of their relationship. They concentrate on a simple cost-benefit approach. Practically, as long as the net benefit is positive, firms will participate to activities to reduce GHG emissions and so that they can achieve high profitability. However, when the net benefit is negative, firms do not engage in environmental activities, which results to low green investments and hence cost saving, along with large GHG emissions.

Moreover, Chen and Wang (2012); Bansal et al. (2016); Balvers et al. (2017) rely their hypothesis on the finance theory. The value of the firm is connected with the riskiness of its underlined assets (Modigliani and Miller, 1958). De Jong et al. (2008) evidence that macroeconomic factors affect the capital structure of the firms. Since some climate sensitive industries have their assets exposed to temperature risk (Balvers et al., 2017) and temperature negatively affects macroeconomic variables (Dell et al., 2012). Then, it can be extracted that temperature is a factor that has a negative effect on equity evaluations. Along with the temperature effects, regulations, CO_2 reductions and carbon market increase the unsystematic risk for the companies (Chen and Wang, 2012). Normally, the unsystematic risk can be hedge through derivatives. For instance, holding weather derivatives, companies would be able to adjust a proportion of temperature risk that has an impact on FP. Finance theory recognises that the negative externality of the climate change cannot be evaded and therefore managers should take into consideration means of hedging.

Two economic theories cannot define the outcome of FP because they have to weigh many different factors in order to reach a decision. Particularly, neutral theories acknowledge that investing in CER will generate a transition risk along with some initial cost. However, the outcome of the investment might be deferred in a long run horizon.

2.3.4 Classifying the theories

This sub-section assembles all the economic theories that previous researches based on explaining the relationship between CER and FP (see table 2.2).

A total number of 12 theories are found with most of them supporting the positive impact of CER on FP, few neglecting the CER engagement, while some others just waver to provide with a clear resolution. The main difference amongst these theories is the time horizon. For instance, positive theories conceive that long-term environmental objectives establish a consistent strategy that reduces the asymmetric information and uncertainty of environmental issues, developing dynamic capabilities which are attractive by shareholders. On the other hand, negative theories maintain a trade-off view, indicating that CER deducts short-term profits that could generate long-term higher returns. Neutral theories support that likewise every investment, CER contains some risk which generates either gains or losses. Besides, the main objective is to test the Porter Hypothesis. FP is certainly depleted by the effects of climate change, amid that, positive economic theories argue that this might be an opportunity to gain competitive

Table 2.2: Economic Theory of CER and FP

Theory	**Expected FP outcome**	**Objective**
Legitimacy Theory	+	
Instrumental Stakeholder	+	
Slack Resource	+	Sustaining
Natural Resource Based	+	Competitive
Environmental strategies:		Advantage
(i) Accommodative	+	
(ii) Proactive	+	
(iii) Defensive	-	Increasing
(iv) Reactive	-	Total
Neo-classical Theory	-	Cost
Agency Theory	-	
Finance Theory	±	Combination
Cost-Benefit Analysis	±	

Note: The link between environmental and financial performance is observed in the aforementioned theories. The second column illustrates the expected sign of FP according to the underlined theory. The third column corresponds to the objective of its theory.

advantage. However, negative theories present this opportunity as a cost-trap disadvantage.

2.4 Systematic Literature Review

Having discussed about the economic theories about environmental CSR and firm performance, this section of the thesis aims to provide an up-to-dated literature review regarding the empirical investigations around the environmental CSR and financial performance. The significance of environmental responsibility in financial performance cannot be unobserved by scholars, managers and regulators. Over the past two decades, the former have attempted to understand the opportunities of investing in CER. We refer to CER as a specific term for the environmental CSR of the firms. Meanwhile, policy-makers attempt to stabilise the carbon emissions of the companies. Stabilising the emissions demands firms to comply with the environmental regulations. In turn, Reinhardt and Stavins (2010) indicate that high CER would make firms to avoid regulation. Also embracing the CER, firms would be technological advanced and decrease the long term operational costs (Hart, 1997). Therefore, this engagement can be described as a "win-win" situation (e.g. Elkington, 1994; Ambec and Lanoie, 2008).

However, the examination of the effect of CER on FP have brought ambiguous results with a tenancy of supporting the positive and significant relationship. For instance, meta-analytic papers (Busch and Lewandowski, 2017; Endrikat et al., 2014; Albertini, 2013; Horvathova, 2010) indicate that on average 60% of the empirical studies support the positive, 20% the negative and 20% the non-significant relationship between CER and FP. The studies jointly specify that the ambiguousness amongst studies is attributed to the different methodological artefacts. The geographical areas, the methods used, the length of the investigation, as well as, the variables to approximate CER and FP seem to moderate the relationship.

This section provides a systematic review of the existing literature on the relationship between FP and CER . We identified 49 empirical studies that present inconsistent results about the sign and the significance of the said relationship under different methodological specifications. In this regard, we fill the void stemming by providing more insights about the methodological trends of the investigation. More importantly, we make suggestions for future research. In particular, we propose that the construction of a composite environmental variable is imperative in order to shed light on the relationship between CER and FP.

2.4.1 Retrospect of Theoretical Studies: CER Definition

At this point, it is imperative to underline that CER in this chapter indicates all different environmental CSR activities and it is significantly different from what we define EP in the first empirical chapter (Chapter 3).

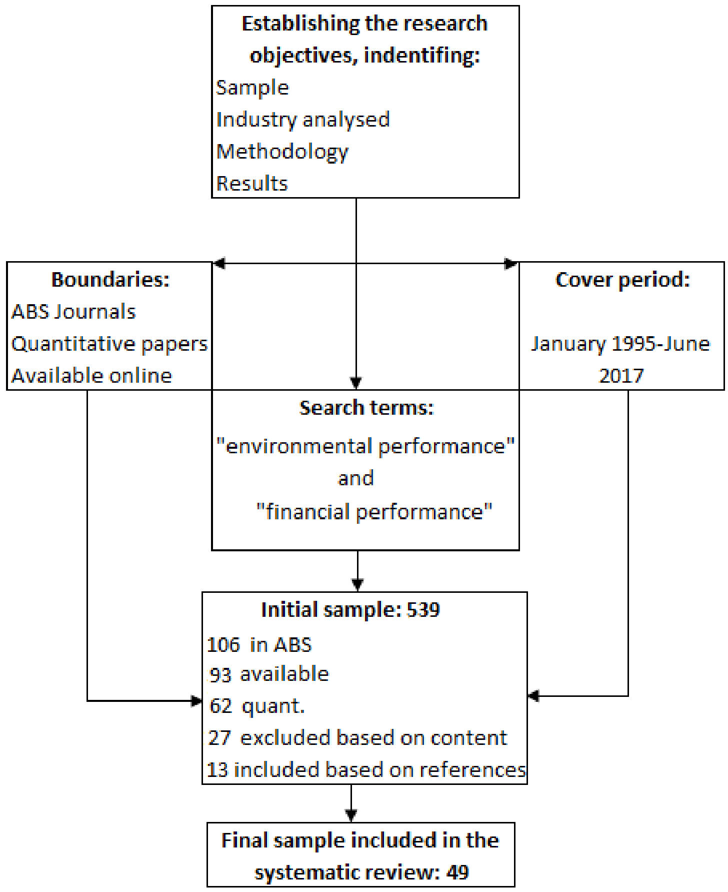
Analysing the relationship between FP-CER has reached 25 years with empirical (Hamilton, 1995) and conceptual (Hart, 1995) contributions. The first meta-analytic paper is dated in 2003 (Orlitzky et al., 2003), when CER is underlined as one of the most important components of CSR. The authors underline that CER can be used as a proxy for social performance. Even though, the results are not significant to establish a connection between CER and FP, the study was a virtue step to the upcoming analysis. Later, Ambec and Lanoie (2008) with a systematic review paper provide more insights regarding the aforementioned relationship. The study analyses a content associated with the competitive advantage by arguing that CER is the relationship of the firm to its natural resources. Boosting CER would result to indirect benefits by offsetting the cost of stringent regulation. Similarly, Horvathova (2010) postulates that the net benefit of CER is the difference between pollution abatement cost and cost of environmental policies. The author underlines the importance of the time length of the examination. Molina-Azorin et al. (2009) emphasise that green management promotes the values and ethics of firms. Their findings highlight that the direction of the relationship is depended upon the industry, country and method of the examination.

Recently, meta-analyses have dominated in the theoretical examination. Dixon-Fowler et al. (2013); Albertini (2013); Endrikat et al. (2014); Busch and Lewandowski (2017) define CER as the environmental practises of firms to reduce their ecological footprint. The studies catholically imply that the methodology moderates the relationship. More specifically, the variables to approximate CER and FP, the estimation method, the geographical area and time of the investigation are the most noteworthy findings.

Addressing the problem of homogeneity the study aims to investigate in depth the methodological artefacts. We take into account the econometric technique, a wide range of environmental variables, industry, country, the way of the examination (CER dependent or independent) and lastly we observe the results upon this specifications.

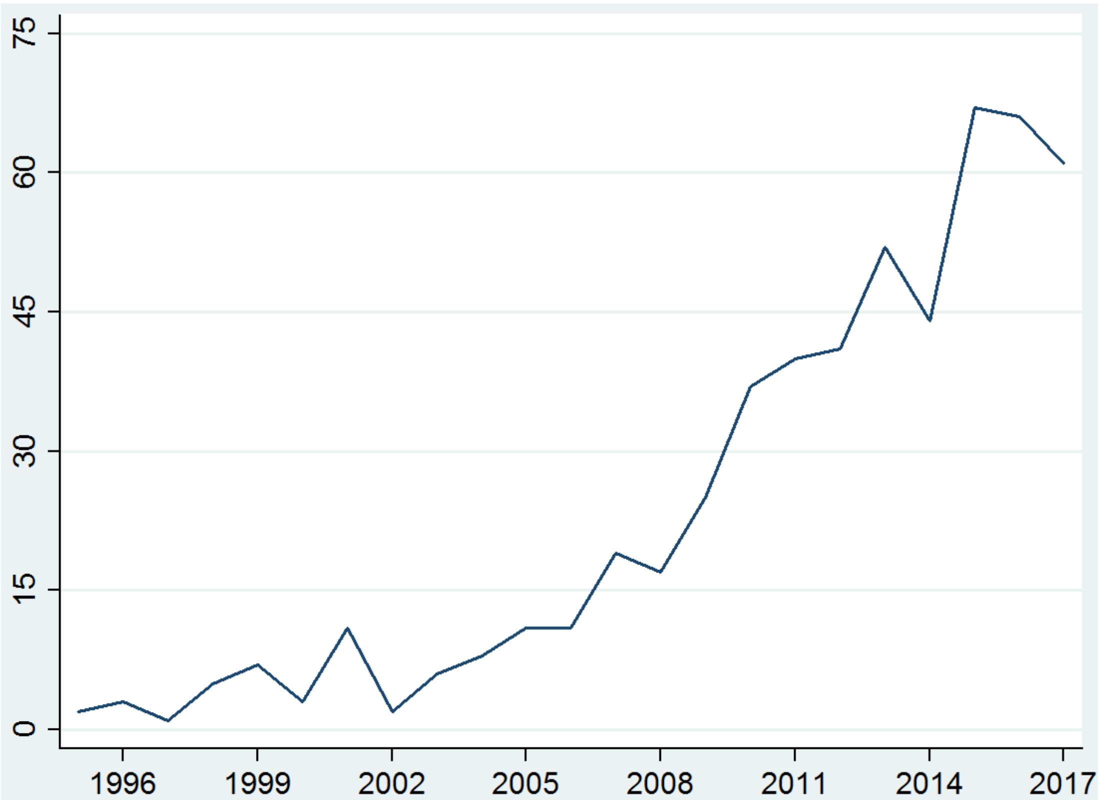
2.4.2 Methodology

Figure 2.3: Systematic Literature Review Process



Having discussed about the theory and definition of CER, we now proceed to systematically evaluate different empirical studies between CER and FP. The systematic review has conducted into two steps (figure 2.3). Firstly, we searched into Scopus database for published articles between 1995 and 2017, with terms in title, abstract and keywords: "environmental performance" or "environmental management" or "environmental disclosure" and "financial performance" or "economic performance". The analysis is centred on four aspects: (1) the data and proxies of FP and CER; (2) geographic area and industry covered (3) econometric technique; and (4) results obtained. In the second step we applied exclusion criteria. Even though, the initial sample was extensively large [539 (see figure 2.4)] we focused on peer reviewed articles that are published in high quality journals in ABS list. The total number of papers, that are both quantitative and theoretical from the ABS list and available online, are 81. These 81 paper are listed in Table 2.3. The Table 2.3 indicatively shows that climate-economy and managerial literature are ample, while climate - finance literature is still limited.

Figure 2.4: Number of Publications per Year



Note: studies included if use the following words: "environmental performance" or "environmental management" or "environmental disclosure" and "financial performance" or "economic performance".

Additionally, we only focused on quantitative studies with business, managerial, economic and finance content. Some papers, which were not appeared in the search, are added due to the fact that are found to be highly cited in this examination. Hence, we finally detect 49 empirical articles in 31 peer reviewed journals that examine the connection between CER and FP. Similar methodology for systematic review has been conducted by Molina-Azorin et al. (2009).

Table 2.3: Distribution of Papers by Discipline

Discipline	Journal Title	Number of Papers
Management & Social Responsibility	Academy of management review, Journal of Business Ethics, Journal of Management, Academy of management journal,Business & Society, Journal of Business Research, California Management Review, Management Decision, European Management Journal, Harvard business review, Journal of Management Studies,	19
Economics	Journal of Environmental Economics & management, Ecological Economics, Journal of Economic Literature, Energy Economics, Environmental & Resource Economics, Review of Economics & Statistics,Economic Modelling, Applied Economics, Oxford Review of Economic Policy, Journal of Labor Economics, American Economic Review	15
Finance	Journal of Banking & Finance, Journal of Finance, Applied Financial Economics, Journal of Financial Economics	14
Business & Environment	Business Strategy & the Environment, Journal of Industrial Ecology, Corporate Social Responsibility & Environmental Management	8
Accounting	European Accounting Review, Accounting & Business research, Pacific Accounting Review, Managerial Auditing Journal, Abacus	6
Strategy	Strategic Management Journal	5
Operation Research	Omega, Management Science	5
Human Resources	Human Resource Management, Human Resource Management Review	4
Operations & Technology Management	Journal of Operations & Production Management, IEEE Transactions on Engineering Management, Journal of Operation Management	3
Organisation Studies	Organization & Environment, Organization Studies	3
Innovation	Structural Change & economic dynamics	1

Note: Left column describes the area, the middle column lists the name of the journal and the right column counts the number of papers. ABS and ABDC lists were used to divide the journals according to their discipline.

2.4.3 Results

Data and Variables

This section identifies a number of methodological trends that are observed in the geographical area, industry covered and examined variables.

Initially, the majority of the studies (see for example, Judge and Douglas, 1998; Karagozoglu and Lindell, 2000; King and Lenox, 2001; Konar and Cohen, 2001; Stanny, 2013; Matsumura et al., 2014; Delmas et al., 2015) use a sample of U.S firms. More particularly, 22 studies focus purely on the U.S indicating that almost 50% of the examination corresponds to this area. Few others (Gil et al., 2001; Wagner et al., 2002; Horvathova, 2012; Broadstock et al., 2018) choose EU firms (n=9). While some other studies (Gilley et al., 2000; Busch and Hoffmann, 2011; Sariannidis et al., 2013; Gallego-Alvarez et al., 2014) investigate the relationship focusing on international sample (n=11). The three aforementioned areas predominate upon this examination by covering the 85% of our sample. The remaining percentage covers areas such as Japan (e.g. Nakao et al., 2007; Iwata and Okada, 2011; Hatakeda et al., 2012), Canada, Australia, Isreal and Egypt. Another important aspect is the examined industry. 33 studies conduct their research by dispersing on any industry, while the remaining researches focus on "dirty" firms.

Regarding the FP variables, profitability ratios are used as a proxy to capture FP and particularly accounting variables such as return on assets (ROA), return on sales (Sales), return on equity (ROE), stock returns and Tobin's Q (Q). Even though most of the researchers employed more than one financial performance variables, a dominant role in the analysis plays ROA (n=18) and stock returns (n=18), following by ROE (n=13), Q (n=12) and Sales (n=8). FP variables are obtained universally from Compustat, S&P Index, Bloomberg and Datastream.

All studies use annual frequency on their analysis apart from the event studies which use daily data.

More importantly, environmental variables are more complicated to be attributed (see table 2.4). There are three main categories of environmental variables (Albertini, 2013). First, variables that measure the environmental footprint of the corporations such as toxic release inventory (TRI), waste reduction, greenhouse gases and aggregated environmental performance (EP rating); this category of variables cover approximately 60% of the investigation. The second type of variables correspond to the environmental management variables, which reaches 20% of the examination. For instance, whether firms adopt an environmental management system, promote cleaner mechanisms and encourage waste reduction initiatives. The remaining 20% is attributed to the last category which is the environmental disclosure of firms. Those variables can be either reported by firms or media. Interesting is the fact that older chronologically studies use TRI as environmental variable while more recent studies incorporate disclosure into their analysis. The variables are commonly retrieved from KLD, Bloomberg, Trucost, S&P ESG Index and CDP.

Environmental disclosure variables interact stronger and more positively with FP variables regardless the geographical area and industry. Conversely, using environmental performance variables (e.g. TRI, GHG, EP rating, etc.), the results appear to have mixed association with FP variables, aligned with Albertini (2013); Endrikat et al. (2014). In the case of TRI the results are mixed. For instance, TRI influences FP in significant positive and negative direction in different studies (Hart and Ahuja, 1996; Cordeiro and Sarkis, 1997; Stanwick and Stanwick, 1998). Also, TRI and GHG have a significant negative and non significant effect respectively on Tobin's Q (Konar and Cohen, 2001; Delmas et al., 2015). 50% of studies (5/10) that incorporate GHG, indicate the negative effect of GHG and FP, the rest studies find no association and none supports the positive relation between GHG and FP. When EP rating is employed the majority of studies support the positive outcome (7/11). Therefore, there is a strong evidence that the selection bias is apparent in this relationship. Thus, the relationship heavily relies on the moderation effects and endogeneity has to be controlled. Although, the analysis differs according to industry level and country effects (Berman et al., 1999) the part which has to be prudentially faced is the variables of the examination. Detailed results from the systematic review output can be found in the table 2.4.

Methods and outcome

This subsection describes different econometric methods employed to test the said relationship, along with some noteworthy findings. The methods reported include the ordinary least square (OLS) regression, event study and other panel data methodologies.

Initially, we should point out that environmental performance variable (e.g. TRI, GHG, EP rating, etc.) dominates as independent variable in the analysis (n=37) while it is only examined as dependent variable in 9 studies. Few studies decide to test the relationship by having environmental performance as both dependent and independent variable (Judge and Douglas, 1998; Wagner et al., 2002; Al-Tuwaijri et al., 2004; Matsumura et al., 2014). Another finding is that 3 studies based their results solely on correlations (Turban and Greening, 1997; Montabon et al., 2007; Aragon-Correa and A. Rubio-Lopez, 2007).

The majority of the studies, employ OLS regressions (n=18) (Karagozoglu and Lindell, 2000; Konar and Cohen, 2001; Dawkins and Fraas, 2011; Hatakeda et al., 2012). The overall results from the OLS regressions vary with a tendency of supporting the positive (14/19) relation between CER and FP. More importantly, studies that based their research on mainly US firm sample have also positive results (Judge and Douglas, 1998; Karagozoglu and Lindell, 2000; Konar and Cohen, 2001).

Dominant role in CER-FP relationship plays the panel data methodologies. Panel data takes into account the time by including cross section firm observations. 9 of the empirical studies employ fixed and random effect estimations to capture the average effect of CER on FP (King and Lenox, 2001; Elsayed and Paton, 2005; Iwata and Okada, 2011; Horvathova, 2012; Gallego-Alvarez et al., 2014; Delmas et al., 2015; Nollet et al., 2016). Model-specifications may differ across studies. For instance, some studies examine the non-linear relationship by adding as an explanatory variable squared values of CER. Wagner et al. (2002); Dawkins and Fraas (2011); Hatakeda et al. (2012); Misani and Pogutz (2015); Nollet et al. (2016); Broadstock et al. (2018); Trumpp and Guenther (2017) support the evidence of non-linear relationship between CER and FP. The non-linear effects have been analysed by 8 mostly contemporaneous papers. The reason behind that is to test whether there is a direct association between CER and FP.

Also, Horvathova (2012) investigates the time variations by adding more than one period lagged values of CER, the time varying effect provides a clarification on whether the Porter hypothesis holds after a substantial period of time. Another important finding is the existence of time varying effect, particularly, Horvathova (2012); Delmas et al. (2015) identify that a high CER has a negative effect on the first year, while in the long run the effect becomes positive. This finding comes to an agreement with the trade off view because firms initially will not be able to bear the cost of an investment, but in the future, firms will have created a competitive advantage, argument which is supported by the legitimacy theory.

Moreover, Sariannidis et al. (2013) investigate the relationship between FP and environmental behaviour with time series approach. Taking monthly stock returns from world largest CSR companies and their GHG emissions in order to identify causality. Garch model is employed with expectation to measure if CO_2 "moving together" with the stock returns. Also, if the conditional variance found statistical significant means that there is a hidden information in the GHG which results in the asymmetric volatility of the stock returns. Garch model accounts mostly for the causality between CER and FP and whether CO_2 reductions boost the environmental pro-activity of the firm. Their findings indicate that carbon emissions affect negatively the stock price. This finding is more intense in a carbon oriented industries and firms with high CSR management. Likewise, Yamaguchi (2008) observe that environmental disclosure influences stock returns in a positive manner. Therefore, socially responsible investors are more likely to divert from a company with low CER communicator, as legitimacy theory proposes, and consequently CSR companies are exposed to a higher risk under a negative carbon information.

Event studies provide similar results. Among others (Fisher-Vanden and Thorburn, 2011; Hsu and Wang, 2013; Luo and Tang, 2014; Lee et al., 2015) use event study methodology (n=10). They examined the effect of environmental voluntary carbon disclosure or the green political announcements on the cumulative abnormal returns of the firms. Announcements are inevitably connected with the legitimacy theory of the firm. Therefore, upon a good environmental announcement, shareholders should reward the companies that legitimise their environmental behaviour. The majority of authors (8/10) conclude that environmental corporate disclosure increase the value of the firm.

Likewise, from a political point of view, Ramiah et al. (2015) investigate the announcements concerning climate change that have been made by the former US president Obama who is known for his environmental sensitivity. Ramiah et al. (2015, 2016) provide results which are twofold. First, upon an announcement high volatility have been observed in both the US and global financial markets; finding which is consistent with Pastor and Veronesi (2013) who claim that political announcement is a source of systematic risk. Also, there is no evidence that green companies experience some positive returns, indicating that "good" news have less effect than "bad" news. Second, large polluters do not seem to be affected directly from green announcement, finding which is supported by Gilley et al. (2000) as well. According to the legitimacy theory, large polluters should be penalised upon a "bad" news however this is not the case. The latter finding triggers some further questions, such as how large corporations can offset the risk of a political shock. The exegesis which is given by Ramiah et al. (2016) is that those companies are able to pass the extra cost to the consumers. Another exegesis can be supported by the defensive environmental strategy, which indicates that firms prefer to maintain a neutral position against climate change in order to keep low visibility (Lee et al., 2015).

Table 2.4: Systematic Review Output

Author(s)	**Variable**	**Method**	**Results**	**Industry**	**Country**	**IV**	**DV**	**FP term**
Hamilton, 1995	Toxic Release Inventory	Event study	−*	Cross-section	U.S	✓		Stock return
Hart & Ahuja, 1996	TRI	OLS regression	−*	Manufacturing	U.S	✓		ROA, ROE
Klassen et al., 1996	Environmental awards	Event study	+*	Cross-section	U.S	✓		Stock return
Cordeiro & Sakris, 1997	TRI	OLS regression	+*	Manufacturing	U.S	✓		EPS
Russo & Fouts, 1997	EP rating	OLS regression	+*	Cross-section	U.S	✓		ROA
Turban & Greening, 1997	EP rating	correlation	±	Cross-section	Global			ROA

Judge & Douglas, 1998	EP rating	Structural equation model	+	Cross-section	U.S	✓	✓	ROI, Sales
Stanwick & Stanwick, 1998	TRI	OLS regression and correlation	−	Manufacturing	U.S	✓		Net profits
Gilley et al., 2000	Waste reduction	Event study	null	Cross-section		✓		Stock return
King & Lexon, 2001	GHG	OLS regression	−	Manufacturing	U.S	✓		Q
Konar & Cohen, 2001	TRI	OLS regression	−*	Manufacturing	U.S	✓		Q
Wagner et al., 2002	EP index$^{(2)}$	Simultaneous equations	-	Paper	E.U	✓	✓	ROA, Sales, ROC

Al-Tuwaijri et al., 2004	Disclosure, waste reduction	Simultaneous equation	+*	cross-section	U.S	✓	✓	Stock return
Wagner & Schaltegger, 2004	Waste reduction	OLS regression	+	Manufacturing	EU	✓		Composite index
Elsayed & Paton, 2005	EP rating	Fixed, random effect, GMM regressions	±	Cross-section	U.K	✓		ROA, Q , Sales
Wagner, 2005	EP *rating*$^{(2)}$	Fixed, random effects and pooled OLS regressions	(U shape)*	Paper	EU	✓		ROE, Sales
Link & Naveh, 2006	EMS	OLS regression	null	Cross-section	Israel	✓		Net profit

Aragon-Correa & Rubio-Lopez, 2007	Organic emissions	Correlation	null	Food	UK, France			ROE
Montabon et al., 2007	EMS	Canonical correlation	+	Cross-section	U.S, Global			ROA, ROI
Nakao et al., 2007	EP rating	OLS, Granger Causality	+*	Manufacturing	Japan	✓		ROA, ROE, Q, EPS
Wahba, 2008	EMS	OLS regression	+*	Cross-section	Egypt	✓		Q
Yamaguchi, 2008	EP rating	EGARCH, OLS, Event study	+	Cross-section	Japan	✓		Stock return
Berrone & Gomez-Mejia, 2009	TRI	Fixed, random effect regressions	±	Cross-section	U.S		✓	ROE

Iwata & Okada, 2011	Waste reduction, GHG	Fixed effect regression	null, −*	Manufacturing	Japan	✓		ROA, ROE, Q
Busch & Hoffmann, 2011	GHG, EMS	OLS regression	−*, −*	Energy	Global	✓		ROE, ROA, Q
Dawkins & Fraas, 2011	Disclosure	OLS regression	±	Cross-section	U.S		✓	ROA, ROE
Fisher-Vanden & Thorburn 2011	Waste reduction initiatives	Event study	−*	Cross-section	Global	✓		Stock return
Clark & Crawford, 2012	EP rating	probit regression	+*	Cross-section	U.S	✓		Financial incentives
Chen & Wang, 2012	Kyoto protocol ratification	OLS regression	+	Cross-section	Global	✓		Leverage

Hatakeda et al., 2012	$GHG^{(2)}$	Switching regression	$\pm^*$	Manufacturing	Japan	✓	ROA
Horvathova, 2012	EP index, EMS	OLS regressions	$+^*$	Cross-section	Czech Republic	✓	Sales, ROE, ROA
Sariannidis et al., 2013	GHG	EGARCH	$-^*$	Cross-section	Global	✓	Stock return
Hsu & Wang, 2013	Media environmental news	Event study	$+$	Cross-section	U.S	✓	Stock return
Chakrabarty & Wang, 2013	TRI	Fixed effect regression	null	Manufacturing	U.S	✓	ROE
Delmas et al., 2013	EP rating	Random effect regression	$\pm$	Cross-section	U.S	✓	Q

Stanny 2013	Disclosure	Logit regression	null	cross-section	U.S		✓	Stock return
Luo & Tang, 2014	carbon tax	Event study	$-$*	Cross-section	Australia	✓		Stock return
Matsumura et al., 2014	Disclosure	OLS, logit regression	$+$*	Cross-section	U.S	✓	✓	MKT
Misani et al., 2015	$GHG^{(2)}$	OLS regression	(U shape)*	Manufacturing	Global	✓		ROA, ROE, Q, Sales
Delmas et al., 2015	GHG	Fixed effect regression	$\pm$*	Cross-section	U.S	✓		ROA, Q
Oestreich & Tsiakas, 2015	Carbon allowances	Pricing models	$+$*	Cross-section	U.K, Germany	✓		Stock return
Ramiah et al., 2015	Green policy news	Event study	-	Cross-section	U.S, Global	✓		stock return

Ben-Amar & McIlkenny 2015	Disclosure	OLS regression	+	Energy	Canada		✓	ROA
Nollet et a., 2016	*Disclosure*$^{(2)}$	Fixed, random effect regressions	−	Cross-section	U.S	✓		ROA, ROI, Stock return
Ramiah et al., 2016	Green policy news	Event study	+	Cross-section	U.K	✓		Stock return
Yadav et al., 2016	EP rating	event study	+*	cross-section	U.S	✓		Stock return
Trumpp & Guenther, 2017	*GHG*$^{(2)}$, waste *reduction*$^{(2)}$	One-way clustered OLS	(U shape)*	Cross-section	Global	✓		ROA, Stock return

Broadstock, et al., 2018	GHG, disclosure	Instrumental variable regression	(inverted U shape)*	Cross-section	U.K	✓	[ROE, Net profits, Stock return, Q][2]

2.4.4 The Case for a Composite Environmental Indicator

This sub-section proposes an environmental composite index in order to measure the overall environmental performance of the firms by including all the available environmental variables (see table 2.4). A composite index might draw a better picture between the EP and FP relationship, because the numerous different variables give us biased estimation (Albertini, 2013; Endrikat et al., 2014). By constructing a composite index we will overcome the problem of the selection bias and at the same time we would have control for different dimensions of the environmental responsibility (Albertini, 2017).

The liner combinations of the environmental variables might observe the variance of the data. Zhou et al. (2006) recommend that constructing environmental index with aggregating methods can be proven an objective measurement. Therefore the aim is to construct a principal composite variable[14]. Principal Component Analysis (PCA) can be used as a robust method because it validates the theory that harmonises the data (OECD, 2008). PCA is a multivariate technique that extracts essential information from complex data and clusters the variables in order to summarise the average effect of them. The output is factor weights for each variable. Using those weights, not only independent environmental variables can then be constructed for each firm but also can be ranked according to mean values of these scores. Moreover, dynamic panel data estimation is more suitable in cases where some unobservable factors affect both the dependent and independent variables and some control variables are strongly related to past values of the dependent variable (Coban and Topcu, 2013). This is likely to be the case in regressions of CER on FP.

2.5 Discussion and Future directions

This chapter combines empirical studies and reviews: (1) the theoretical framework behind the effect of CER on FP; (2) the methodological regime of FP-CER

[14]See more on Appendix A

examination; (3) geographical area and (4) variables for CER and FP. To this end, we analyse not only theoretical but also managerial and regulatory implications of climate change on FP.

Overall, the results are in alignment with previous theoretical papers (Orlitzky et al., 2003; Albertini, 2013; Dixon-Fowler et al., 2013; Endrikat et al., 2014) jointly indicate, CER and FP are positive correlated. Notably, causality involves the positive link of CER with FP and the partially positive link of FP with CER. The most important finding is the moderation effect of the methodology, addressing the problem of homogeneity. Particularly, the variables, geographical area, the time horizon of the study and the size of the firms moderate the relationship between CER and FP and therefore, we cannot decline the probability of biased estimations. Hence, the question that still remains is whether the indirect profits of CER can outweigh the direct cost of CER.

2.5.1 Implications

This study attempts to enhance our understanding of the effects of climate change on the FP. Researchers in the field can use this study as a handbook in order to familiarise themselves with the main issues and ideas in connection with this interdisciplinary topic. To this end, we analyse not only theoretical but also managerial and regulatory implications of climate change on FP.

From a managerial point of view, environmental management should decrease the asymmetric information as proposed by instrumental stakeholder theory. Shareholders should distinguish between their long and short term objectives. For instance, if they target to their long term satisfaction, firms should reconsider the green investment as a form of proactive environmental strategy. Thus, managers should evaluate investments oriented towards environmental technologies and pollution prevention in order to create a competitive advantage. The board of directors should carefully assess the climate change channels that have an effect on their company and seek for means of hedging. Also, industries differ substantially with regard to public visibility, social pressure and financial risk. Therefore, the opportunity cost to gain financial benefits from CER is likely to be depending upon several industry-specific factors.

Regarding the policy implications, regulators should carefully examine all the economic theories and especially the theories that do not embrace "high" CER. Having identified these theories and the reasons why they do not encourage firms to invest in CER, an effective practice would be to impose regulations that would give them disincentives to pollute. For instance, imposing a carbon tax should be considered as a way of tackling the climate change because it would increase the operational cost of "dirty" firms.

Shareholders should distinguish between their long and short term objectives. For instance, if they target to their long term satisfaction, firms should reconsider the green investment as a form of proactive environmental strategy. Thus, managers should evaluate investments oriented towards environmental technologies and pollution prevention in order to create a competitive advantage. The board of directors should carefully assess the climate change channels that have an effect on their company and seek for means of hedging. Also, industries differ substantially with regard to public visibility, social pressure and financial risk. Therefore, the opportunity cost to gain financial benefits from CER is likely to be depending upon several industry-specific factors.

2.5.2 Future Research

Potential avenues for future research should include (i) the effect of anti-green announcements, (ii) the decision making of companies regarding the stringent environmental regulation, (iii) the role of derivatives market, (iv) the causality of FP and CER, as well as, (v) the case of a composite environmental variable.

Ramiah et al. (2015) examine the connection between green announcements regarding Obama's initiates and stock return; they call this phenomenon Obama effect. It would be very interesting to investigate the stock returns under the

Trump effect. What is the reaction of the markets upon an anti-environmental announcement? Some firms, which are included in the carbon-sensitive industries, had a positive stock returns upon his election. Therefore, event study might be able to capture the alterations in the regime of the environmental policy in the US. Also, environmental regulations have brought transition risk and thus a future research could focus on the strategic decision of the firms. For instance, they might outsource capital in order to avoid regulations.

Another issue that has been neglected by the literature is the role of options and futures. Temperature is a risk factor that can be partially observed in the equity evaluations (Bansal and Ochoa, 2011; Balvers et al., 2017). On the other hand, weather derivatives are able to hedge a proportion of temperature risk. Also, option market reflects the expectations of the stock market and hence it might have better predictive power (Christensen and Prabhala, 1998). Therefore future research should be focused on the examination between climate change and the role of options.

Lastly, researchers should investigate the relationship between FP and CER afresh because there is a strong evidence of endogeneity among studies and more particularly the problem of simultaneity bias has to be underlined. The causality of the relationship has to be examined as slack resource view propose. There is also a significant evidence of non-linearity, suggesting that linear regression models might provide biased estimations. We call for the use of more sophisticated econometrics methods, a good example is the contemporaneous paper of Broadstock et al. (2018), whose study is one of the few that investigates the effect of FP on CER (literature commonly investigates the opposite; CER on FP). Further research should be undertaken to explore the ambiguity among environmental variables. Variables should posit in a way not to moderate the results. Hence, we propose the construction of a composite environmental index. The dimensionality of the CER analysis is a major issue (Albertini, 2017) and has to be examined with multivariate techniques such as PCA. Ranking of the environmental index could be a useful tool in order to extract information about the CER of the companies by using different weighted environmental indicators.

Hence, we propose an environmental composite index in order to measure the CER of the firms by including all the available environmental variables. A composite index might draw a better picture between the CER and FP relationship, because the numerous different variables give us biased estimation (Albertini, 2013; Endrikat et al., 2014). By constructing a composite index we will overcome the problem of the selection bias and at the same time we would have control for different dimensions of the CER(Albertini, 2017). The dimensionality of the CER analysis is a major issue and has to be examined with multivariate techniques such as Principal Component Analysis. Ranking of the environmental index could be a useful tool in order to extract information about the CER of the companies by using different weighted environmental indicators. Moreover, dynamic panel data estimation is more suitable in cases where some unobserved factors affect both the dependent and independent variables and some control variables are strongly related to past values of the dependent variable.

3 First Empirical Chapter: Environmental and Financial Performance, Evidence from Quantile Regressions

3.1 Introduction

IN the effort to mitigate climate change by preventing greenhouse gas (GHG) emissions, one of the most important policy areas that has attracted attention is the manufacturing sector (IPCC, 2014). Even though European manufacturing firms have 29.9 million employees (21.8% of employment) and generate more than €1,900 billion (15% of GDP), their industrial process together with fossil fuel combustion were responsible for around 88% of the total carbon dioxide emitted in the European Union (EU) in 2015 (Eurostat, 2019; World Bank, 2019). Large emitting companies in the EU have been monitored and regulated in order to decrease their emissions. Particularly, the EU has become increasingly committed to promoting climate change mitigation (e.g. Kyoto Protocol, Paris Agreement) with a key target being to decrease 21% in firms' GHG emissions by 2020 compared with their emissions in 2005 (European Commission, 2019). For this reason, environmental issues are of paramount importance to regulators, investors, employees, customers and managers (de Villiers and van Staden, 2010; Griffin and Sun, 2013; Qiu et al., 2016). For instance, low-carbon investments by EU firms grew from €57 billion in 2011 to a staggering amount of €243 billion in 2015 (Eurosif, 2016)[15]. Firms benefit from this kind of investment in two ways. First, they comply with the existing regulation (Reinhardt and Stavins, 2010). Second, they manage to reduce long-term operational costs (Hart, 1997).

Growing environmental awareness within the EU highlights the importance of investigating the effects of environmental performance (EP) on financial performance (FP) (Wagner, 2010). EP is typically defined as the firm's carbon

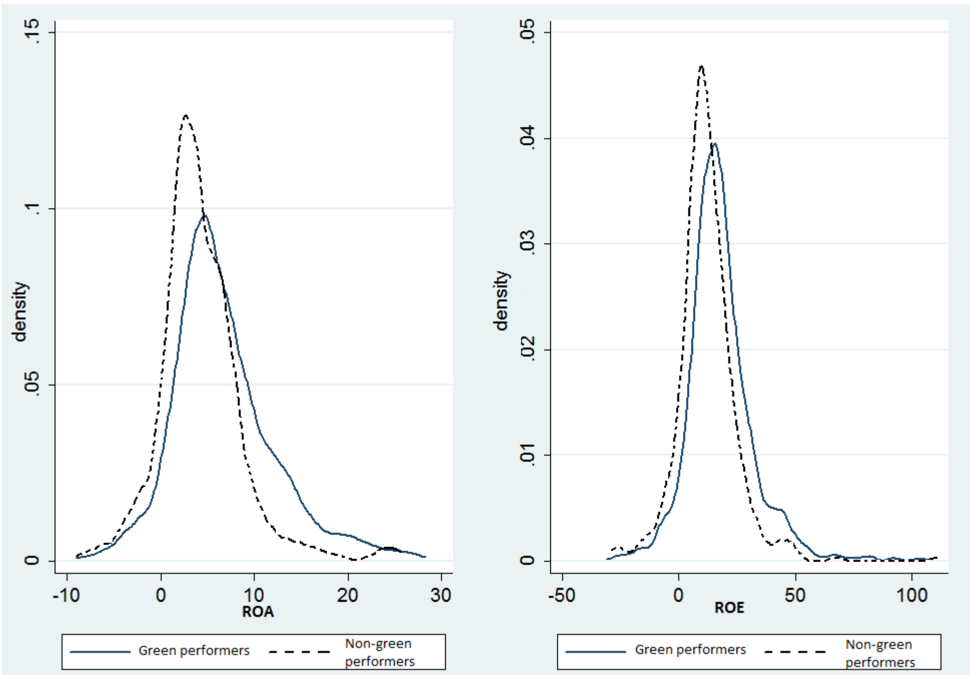
[15] There has been a growing number of environmental strategies being adopted by firms within the EU. Strategies such as the "*sustainability themed*" and "*impact investment*" accounted for €145 billion and €98 billion respectively in 2015, see more on Eurosif (2016).

footprint (i.e. GHG), whilst FP is approximated with accounting profitability ratios (i.e. ROA and ROE) (Dixon-Fowler et al., 2013; Albertini, 2013; Endrikat et al., 2014). To shed light on the EP-FP relationship, prior literature has addressed the main question "Does it pay to be green?" (Dixon-Fowler et al., 2013; Busch and Lewandowski, 2017). The majority of the literature (around 60%) supports a positive EP-FP relationship; however, 20% shows that greater EP is costly, while 20% reports an insignificant relationship (Horvathova, 2010; Busch and Lewandowski, 2017). These ambiguous research findings have encouraged researchers to delve deeper into this relationship. Accordingly, among others, Horvathova (2012) shows that EP has a time-varying effect on FP; in the short term the direction of the effect is negative due to the additional costs, while in the long term firms gain a competitive advantage (known in the literature as "When does it pay to be green?"). Barnett and Salomon (2012); Misani and Pogutz (2015) explore the possibility that the relationship might be curvilinear, depending upon the magnitude of EP engagement. At the same time, authors such as Hatakeda et al. (2012) underline that EP and FP are endogenously related. On general principles, a consensus has yet to be reached about the direction of EP effects on FP, the role of endogeneity and the type of non-linearity (Busch and Lewandowski, 2017; Baboukardos, 2018).

Furthermore, the lack of consensus regarding the EP-FP interaction is also evident in relevant theoretical studies. Economic theory suggests that the EP-FP relationship is complex (Brooks and Oikonomou, 2018). For instance, while the *instrumental stakeholder theory* proposes that a greener performance would result in higher profits, *neoclassical theory* opposes this suggestion. A different picture is implied by the *natural resource-based view*, which suggests that firms might initially experience high costs, but then might benefit from higher profits (e.g. Lewandowski, 2017; Trumpp and Guenther, 2017; Broadstock et al., 2018). Another example that further stresses the complex nature of the relationship is the one supported by the *financial slack argument*, indicating that the financial state of the firm can influence the efficacy of EP on FP.

Screening the relationship for EU firms (data explained in section 3.3), figure 3.5 represents the difference in FP probability density function between green performers and non-green performers, by incorporating kernel density estimation. The FP distribution for green performers is shifted to the right, indicating that green performers tend to be indeed more profitable than their non-green counterparts. However, as King and Lenox (2001); Qiu et al. (2016); Li et al. (2018b) indicate more profitable firms are more likely to invest more and to engage in environmental actions. Thus, the question that arises is if the positive relationship depicted in figure 3.5 is due to the reverse causality between EP and FP.

Figure 3.5: Kernel FP Density for Green and Non-green Performers



Notes: Green performers are firms distributed in the 4rd quarter of the EP variable [$EP = (-1) * Log(GHG/Total\ assets)$], while non-green performers are observations in the 1st quarter of the EP variable. Green performers > No-green performers (one side test for ROE, mean difference = 0.631, $\chi^2 = 9.6041$ with p-value=0; for ROA, mean difference = 0.471, $\chi^2 = 14.85$ with p-value = 0). Data are explained in section 3.3.1.

Existing literature has focused only on the conditional mean of the FP distribution neglecting the highly skewed distribution of the financial data (e.g., Misani and Pogutz, 2015; Nollet et al., 2016; Lewandowski, 2017). Understanding the effects of EP at different parts of the FP distribution might not only give a more complete picture about the managerial actions towards EP but also offer a potential avenue to reconcile ambiguous research findings. For instance, EP might have positive effects on the higher tail of the FP distribution while at the lower tail the EP effects might become negative. In this regard, we allow for a heterogeneous EP-FP relation and we evaluate the EP effects on FP for different profitability levels. Hence, our study engages in the EP-FP debate and takes one step further in order to answer "*How does green affect the different points of the profitability distribution*?"

Our research provides new evidence on this conflict that is evident in both empirical studies and economic theory, by utilising both quantile and two stage quantile regressions. Our approach attempts to to simultaneously address both major limitations inherent in previous studies. First, there are constraints stemming from the non-linearity of the relationship (see among others, Barnett and Salomon, 2012; Misani and Pogutz, 2015; Nollet et al., 2016; Trumpp and Guenther, 2017). While previous studies adopt quadratic values of EP in linear models in order to deal with the non-linearity (Barnett and Salomon, 2012; Misani and Pogutz, 2015), we maintain that the relationship is complex and therefore quantile regressions could lead to more insightful results. The second limitation relates to the implication that the EP-FP relationship is more likely to be endogenous. Studies have attempted to deal with this issue by adopting different econometric techniques in parametric models (see, *inter alia,* Al-Tuwaijri et al., 2004; Elsayed and Paton, 2005; Barnett and Salomon, 2012; Hatakeda et al., 2012; Delmas et al., 2015; Lewandowski, 2017). Our two stage quantile regression approach can control for endogeneity which arises through simultaneity or omitted variable bias in the EP-FP relationship (Horvathova, 2010; Hatakeda et al., 2012).

Our study goes beyond the standard literature by allowing the EP estimates to vary with the conditional quantiles of the FP, relaxing the distributional assumptions which were traditionally assumed (e.g., Misani and Pogutz, 2015; Lewandowski, 2017). To the best of our knowledge, this is a first attempt to evaluate the EP-FP relationship by means of non-parametric and semi-parametric models. Specifically, we provide novel evidence of this relationship on the tails of the FP distribution. Additionally, our approach effectively controls for firm heterogeneity which is regarded in the literature as one of the main factors that generates contradicting results in this field of study (see, for example, Horvathova, 2010; Albertini, 2013; Endrikat et al., 2014; Nollet et al., 2016; Baboukardos, 2018).

Using quantile instrumental variable regressions, we also estimate an EP model. EP estimations reveal some noteworthy implications for both economic research and European climate change policy. For example, we show how mitigation policies for climate change and other institutional characteristics can affect "dirty" (lower tail of EP distribution) and "clean" firms (higher tail).

Research findings from EU manufacturing firms for the period 1995-1997 appear to support a negative relationship between EP and FP (Wagner et al., 2002; Wagner, 2005). By contrast, using a sample of 288 EU manufacturing firms for the period 2005-2016, which was marked by stricter environmental regulations, shows that (i) EP has a positive effect on FP; (ii) the EP-FP relationship varies significantly across different quantiles; (iii) EP and FP are endogenously related for high profitability firms, while there is no evidence of endogeneity for low profitability firms. Our findings also imply that both a partially endogenous and positive view is more suitable to theoretically frame the relationship between EP-FP than the *neoclassical theory* suggested by previous studies in the EU area (Wagner et al., 2002). Further results show that the size of the firm and the period of investigation moderate the relationship. Particularly, large firms are unaffected by the EP effects, and EP had a minimum role before the financial crisis. The fact that large sized firms are unaffected by EP can be explained such as that they might need more time and higher investment in order to diffuse their

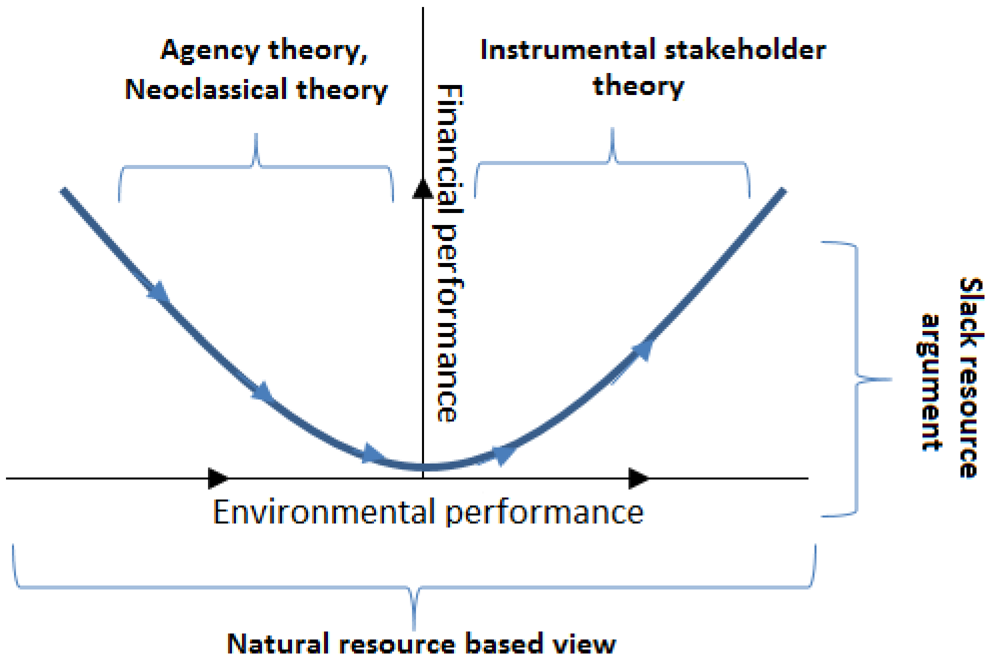
EP practices, while for small and medium sized firms, EP has easier and more efficient implementation Hoogendoorn et al. (2015); Yadav et al. (2016).

The remainder of the paper is organised as follows. In Section 3.2, we present the theoretical framework and discuss the relevant hypothesis. In Section 3.3, we describe the data and present the methods of the study. The empirical results are reported in Section 3.4. Finally, in Section 3.5, we discuss the main results of the study and reach a conclusion.

3.2 Theoretical Framework and Hypothesis Development

EP plays an essential role in promoting stakeholders' interests and influencing profitability of firms. The connection between EP and FP is based on a plethora of theoretical predictions which have been summarised in Figure 3.6; their main objective is to answer the following prompt: "How is FP affected if we invest in EP?" The purpose of this section is to provide a broad overview of the existing framework and move to scrutinise: "Under what circumstances do EP affect FP?"

Figure 3.6: Theory behind EP-FP



3.2.1 A Brief Theoretical Background

The first theoretical prediction is the negative link between EP and FP, and it is supported by the trade-off view, indicating that investments in EP will merely reduce profits from firms. The negative relationship between EP and FP can be justified due to the higher cost that firms have to endure. The *neoclassical theory* suggests that some industries experience high environmental compliance costs to operate under green management and therefore face a competitive disadvantage (Wagner et al., 2002). This is the case for manufacturing firms since the cost of decreasing their emissions is relatively high and results in an increase of the marginal cost of production. In a similar vein, the *agency theory* argues that EP is in conflict with the main objective of the firm (e.g. maximise shareholder value) and thus EP would only decrease shareholders' satisfaction (Jensen and Meckling, 1976).

The second theoretical perspective argues that EP will increase the value of the firm. The positive link between EP and FP, as proposed by *instrumental stakeholder* theory, supposes that long-term environmental objectives establish a consistent strategy that reduces the uncertainty of environmental issues and develops dynamic capabilities that in turn attract shareholders. The theory is a combination of the *legitimacy*[16] and *agency* theories, and it focuses on the contracts between managers and stakeholders and claims that trust and cooperation within a company help create a competitive advantage (Jones, 1995). For example, by satisfying stakeholder demands concerning climate change, firms may acquire a better reputation, improve customers' loyalty and, overall, respond effectively to external demands (Endrikat et al., 2014).

There is a third strand of literature suggesting that EP might have a non-linear impact on FP. Empirical literature supports the U-shaped relationship (Nollet et al., 2016; Trumpp and Guenther, 2017; Lewandowski, 2017). An increase in EP would decrease profits, as the trade-off view suggests, while a continuous

[16] *Legitimacy theory* suggests that firms will be adhere to social demands in order to legitimise their corporate actions (Guthrie and Parker, 1989).

increase beyond a certain level would cause additional benefits that offset the costs, and thus U-shaped is depicted. The U-shaped relationship can be implied by the *natural resource-based view* of the firm. Hart (1995) opines that firms should develop new technologies in order to manage their resources efficiently. Consequently, corporate governance aims to invest in EP with the expectation that the future position of the corporation will be ameliorated (Hart and Ahuja, 1996). Furthermore, Barnett and Salomon (2012) demonstrate that it is the least polluting firms that experience the highest financial returns (i.e., in consonance with the *"doing well by doing good"* hypothesis). Apparently, firms that engage in EP, gradually improve their stakeholders' satisfaction. In turn, gradually increasing stakeholders' satisfaction results in benefits outweighing the costs (i.e., the turning point in the EP-FP relationship). The threshold at which this turning point occurs varies considerably, depending mainly on firm-specific characteristics (Eichholtz et al., 2010; Eisenbeiss et al., 2015; Broadstock et al., 2019a,b).

3.2.2 Towards Unravelling the EP effects on FP: A Financial Slack Approach

Given that the relationship between EP and FP lies in a number of competing theoretical frameworks, it is essential to investigate the conditions under which the EP benefits outweigh the potential costs. Even though the majority of the empirical results tend towards a positive outcome between EP and FP (see the meta-analysis by Busch and Lewandowski, 2017), it is universally accepted that measurement characteristics, such as EP measures, FP measures, industry, period and area under investigation, are dominant factors responsible for the variability of the results. In fact, previous studies acknowledge the importance of the aforementioned factors (among others, Iwata and Okada, 2011; Hatakeda et al., 2012; Barnett and Salomon, 2012; Misani and Pogutz, 2015; Trumpp and Guenther, 2017); however, they all focus on the mean of the FP distribution and neglect to examine the EP effects for low or high profitability firms. For this reason, both theoretical and empirical gaps should be addressed in order to provide a detailed picture of the impact of changes in EP on different parts of the FP distribution.

A promising extension is to delve more into the moderating role of FP. Importantly, literature argues that FP itself is a contingency that might influence the efficacy of EP (Al-Tuwaijri et al., 2004; Hatakeda et al., 2012; Cai et al., 2016; Broadstock et al., 2018). Reasonably, low profitability firms have limited resources and, at the same time, pressure from stakeholders for profit maximisation is higher compared to their high performing counterparts. Low performance poses a threat for firms and thus managers ought to take actions in order to improve their profitability. Those actions may be towards investing in R&D projects, such as improving the environmental performance. On one hand, low profitability firms convey the impression that management is inefficient. Likewise investments in EP might purely deduct profits from firms (Wagner, 2005), as considered by the *absorbed slack resource* theory (Symeou et al., 2019). *Absorbed slack* refers to resources that cannot be re-deployed for other organisational purposes. On the other hand, EP might be a sustainable strategy for low profitability firms to build bonds with stakeholders and signal their green technology advances to society (Porter, 1991; Hart and Ahuja, 1996).

It is worth noting that low profitability firms are constrained by financial resources, which can limit their investment in EP. By contrast, firms with superior financial performance may utilise their after tax income in order to invest in eco-friendly technologies (Li et al., 2018b). At the same time, high profitability firms, are more likely to accomplish effective EP investments (i.e. *unabsorbed slack*)[17] (Symeou et al., 2019). However, there is less internal pressure for high profitability firms to adopt new strategies. According to the *agency* theory, if a firm is highly profitable, managers should prefer distributing profits to shareholders to investing in environmental projects. Even if managers invest in EP, we can conclude either that EP indeed improves FP, or that firms had extra reserves to invest in EP, so the relationship might be influenced primarily by high FP. An-

[17] *Unabsorbed slack* refers to resources that can be re-deployed for other organisational purposes.

other crucial point for highly performing firms is that managers might choose to invest in EP just for symbolic purposes, or because they aim to improve their reputation as environmentally sensitive managers, indicating that such investments are more likely to be costly and ineffective (Barnea and Rubin, 2010; Trumpp and Guenther, 2017).

In this regard, an important distinction should be made between high and low profitability firms. This can be well explained by the *slack resource argument*, which implies that FP causes EP and vice versa. The theory explains why firms with different resources have different levels of environmental engagement (George, 2005). Even though the theory is multifaceted (Shahzad et al., 2016), our study focuses on *financial slack resources* of the firms. For example, firms with *financial slack* are reflected on the upper tail of the profitability distribution (high profitability firms), while low profitability firms – which lack *financial slack* – are on the lower tail of the distribution. Informed by the above, we test for the relation between EP and FP, with a particular emphasis on the *financial slack resource argument*. To the best of our knowledge, no prior empirical research has examined the behaviour of EP on FP distribution, and given the competing theoretical perspectives as well as the underwhelming number of studies that discuss the relationship under the *slack resource argument* (Daniel et al., 2004; Endrikat et al., 2014; Symeou et al., 2019), our main expectation is that the strength of the relation between EP and FP will vary across the conditional distribution of FP, and thus we formulate a broader hypothesis:

Hypothesis: Under the *financial slack argument*, the effect of environmental performance on financial performance varies across different levels of financial performance.

3.2.3 Identification of causal effects

The main focus of the analysis is to examine the effect of EP on FP at different profitability levels. However, reverse causality between EP and FP and omitted variables bias are unquestionably the most topical issues that can distort the reliability of the results (Cai et al., 2016; Broadstock et al., 2018). A possible solution to this endogeneity problem is to identify factors that directly influence EP and indirectly FP. Almost every study defines EP as is a sequence of managerial actions in order to deal with the economic, institutional and regulatory pressure in respect to the natural environment (among others, Al-Tuwaijri et al., 2004; Matsumura et al., 2014; Hassan and Romilly, 2017). Particularly, an increasing number of environmental regulations push firms to remove their obsolete coal technologies and deploy a greener energy generation. Thus, a great proportion of the EP variation is explained by environmental law, which, in turn, is the only exogenous factor that can influence the EP (Brunel and Levinson, 2016).

Adhering to the regulations, firms try to legitimate their actions. For example, the Kyoto Protocol and the Paris agreement are some of the most serious attempts made, with their main objective being to regulate a permissible limit of firms' carbon emissions. Particularly, in the EU, polluting firms are supposed to participate in the EU emissions trading system (ETS). Carbon emissions have been financialised as commodities and they are exchanged in a cap and trade system[18]. A cap and trade system indicates that the volume of emissions has to be capped, or the offender is obliged to pay a fine. Participation in the EU emissions trading scheme will thus significantly affect the level of EP (Ellerman and Buchner, 2008; Luo et al., 2012). Similarly, pressure about climate change is usually reflected in the decision making when adopting environmental strategy such as ISO 14001. ISO 14001 standards are provided by a non-profit organisation to firms that want to comply with the regulatory limits; guidance is offered in order to minimise and manage firms' carbon footprints (Quazi et al., 2001). In order to have firms qualified for ISO certification, they should fulfil some requirements. For example, they should (i) establish environmental management department, (ii) identify their environmental compliance requirements (regula-

[18]More information about the European emission scheme can be found on the European commission website: https://ec.europa.eu/clima/policies/ets/.

tions), (iii) clarify how firm interacts with the environment (e.g. GHG emissions) and (iv) monitor, review and measure their environmental performance (ISO, 2015). Hence, EP is the channel through which ETS and ISO affect the FP of firms. We methodically address the role of environmental regulations and we examine the extent to which the above hypothesis holds.

3.3 Data and Methods

3.3.1 Data

The sample consists of 288 European firms of the manufacturing sector that are included in the STOXX Europe 600 Index, covering large, mid and small capitalisation companies across 17 countries of the European region, for a 12 year period 2005-2016. Thus far, several studies have investigated the effects of EP on FP, focusing on US (Hart, 1995; Clark and Crawford, 2012; Chakrabarty and Wang, 2013; Delmas et al., 2013; Nollet et al., 2016), UK (Elsayed and Paton, 2005; Aragon-Correa and A. Rubio-Lopez, 2007; Broadstock et al., 2018) and Japanese firms (Nakao et al., 2007; Yamaguchi, 2008; Iwata and Okada, 2011; Hatakeda et al., 2012), while the literature concerning the wider EU economy is rather scarce and outdated (Wagner et al., 2002; Wagner, 2005). In addition, EU manufacturing firms have been chosen because they are inevitably connected with climate change, since they emit large amounts of carbon dioxide. For this reason, EU environmental regulations have enforced firms to be transparent about their environmental actions (variables). We choose 2005 as the initial year, a period when not only were talks against climate change escalated, but also when the first phase of the EU emissions trading scheme was activated. Table 3.5 classifies the sample into industry and country, with most of the firms (30.5%) being in the industrial sector and approximately 25% coming from the United Kingdom.

Table 3.5: Industry and Country Composition

Panel A: Industry Composition		
Industry	**Frequency**	**Percent**
Technology	11	3.82
Telecommunications	12	4.17
Consumer Discretionary	56	19.44
Consumer Staples	40	13.89
Industrials	88	30.56
Basic Material	40	13.89
Energy	17	5.9
Utilities	24	8.33
Panel B: Country Composition		
Country	**Frequency**	**Percent**
Germany	36	12.5
United Kingdom	71	24.65
France	47	16.32
Italy	14	4.86
Spain	14	4.86
Netherlands	15	5.21
Switzerland	18	6.25
Sweden	24	8.33
Norway	8	2.78
Austria	4	1.39
Belgium	6	2.08
Denmark	5	1.74
Finland	14	4.86
Ireland	7	2.43
Czech Republic	1	0.35
Portugal	3	1.04
Luxembourg	1	0.35
Total	288	100

Note: Firms are allocated to industries according to the Industry Classification Benchmark (ICB).

3.3.2 The Regression variables

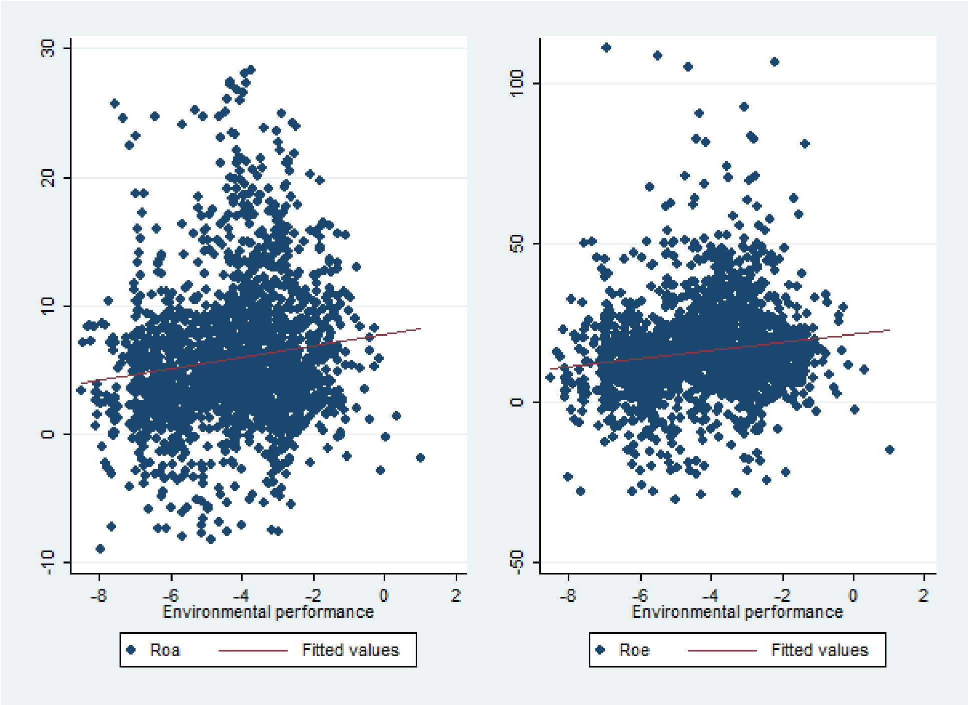
Dependent variables

Table 3.6 displays the source and concept of each variable employed. Four FP variables are used as dependent variables. Financial profitability is linked to accounting profitability ratios. Return on assets (ROA) measures the ability of the firm to generate profits from its assets and is used as a proxy for financial profitability. Similarly, return on equity (ROE) measures the shareholder's satisfaction. We also use industry-adjusted ROA and ROE as dependent variables in order to control for the variability of the results between industries; this is because some industries might be more efficient than others (Aggarwal and Dow, 2012). Adjusted ROA is calculated as the ratio of firm's ROA to average industry ROA ($Adj.ROA_{i,t} = \frac{ROA_{i,t}}{ROA_{j,t}}$, where i is the firm, t is the year and j is the industry where firm i is classified). Similarly, we compute adjusted ROE ($Adj.ROE_{i,t} = \frac{ROE_{i,t}}{ROE_{j,t}}$). A great number of studies use ROA and ROE as dependent variables in their regressions (see, for example, Busch and Hoffmann, 2011; Qiu et al., 2016; Lewandowski, 2017). The indicators reflect the managerial efficiency and shareholders' satisfaction rather than market responses to organisational actions (Albertini, 2013).

Explanatory Variables

We employ three alternative measures for EP as an explanatory variable. Following Aragan-Correa (1998); King and Lenox (2001); Wagner (2005); Aggarwal and Dow (2012); Cormier and Magnan (2015); Misani and Pogutz (2015), we define (i) $EP(ta)$ as *the reverse logarithmic ratio of the carbon emissions reported by the firm (scope 1 and scope 2) to the total assets [*$EP(ta)_{i,t} = (-1) * Log\frac{GHG_{i,t}}{TA_{i,t}}$*]*, (ii) $EP(mv)$ *the reverse logarithmic ratio of the carbon emissions reported by the firm to the market value [*$EP(mv)_{i,t} = (-1) * Log\frac{GHG_{i,t}}{MV_{i,t}}$*]* and (iii) adj.EP *the reverse logarithmic ratio of the carbon emissions reported by the firm to the average*

Figure 3.7: Scatter Graph of EP-FP



Notes: The figure illustrates two scatter diagrams. The dots correspond to ROA (ROE) observations plotted by EP $[EP = (-1) * Log(GHG/Total\ assets)]$.

industry carbon emissions $[adj.EP_{i,t} = (-1) * Log\frac{GHG_{i,t}}{GHG_{j,t}}]$, where i is the firm, t is the year and j is the industry where firm i is classified. Higher values correspond to better performance, and our variables avoid high skewness; they control for both book and market size of the firms, as well as capturing industry-relative EP performance.

In order to capture and explain EP, it is instrumented with two exogenous variables: (i) EU emissions trading scheme (ETS) and (ii) ISO 14001 standards (ISO). ETS and ISO have been retrieved by Datastream and both have been reported in various studies as EP determinants (Quazi et al., 2001; Ellerman and Buchner, 2008; Luo et al., 2012; Horvathova, 2012; Bye and Klemetsen, 2018).[19]

[19]see more at section 3.3.4

Other Control Variables

What is more, we employ a set of different variables that affect FP. Firstly, the probability of default measured by Altman's (1968) Z-score (Z), higher Z-score corresponds to lower probability of default and thus it is expected to have positive sign to the FP (Psillaki et al., 2010). Also, leverage (LEV) is used as a proxy of financial risk and it represents the level of debt to equity. It can be measured by summing the short and long term liabilities divided by the market value. Risk proxies are imperative to be included in the analysis (Busch and Hoffmann, 2011; Hatakeda et al., 2012; Matsumura et al., 2014).

Furthermore, larger firms have been found to perform poorer (King and Lenox, 2001). We use a size proxy as the logarithm of total assets ($LOGTA$), firm size is the most common variable in the examination (Hatakeda et al., 2012; Delmas et al., 2013). Another size proxy, that is employed, is the logarithm of the number of employees (EMP)(Broadstock et al., 2018). This variable can capture a part of stakeholders that exercise pressure to the firm regarding social activities (Luo and Bhattacharya, 2009).

Annual growth rate of total sales (GRO) displays the firm's cash flows and hence is expected to increase the profitability (King and Lenox, 2001; Konar and Cohen, 2001; Delmas et al., 2013; Matsumura et al., 2014).

Future prosperity can be represented by intangible assets ($INTA$). They cannot be easily collateralised but they add value to the firm (Psillaki et al., 2010), intangible assets have also attributes of research and development (R&D) of the firm (Elsayed and Paton, 2005). For instance, an investment in EP might either generate future profits or losses. Also, tangible assets ($TANG$) can be a proxy for the collateral of the firm. Ambiguous relation between FP and tangibility is expected because creditors can liquidate assets easily and thus they face less risk (Konar and Cohen, 2001), however, funds lying idle tend to increase the marginal costs.

Lastly, real GDP growth (GDP) captures different economic conditions among firms that operate in different counties (Chen and Wang, 2012). GDP might be able to explain a part of the variation of the firm's profitability.

Apart from GDP, the rest of the control variables are firm-specific ones. Because, we additionally test for industry adjusted results, the firm-specific control variables have been transformed into industry adjusted control variables as $adj.Variable_{i,t} = \frac{Variable_{i,t}}{Variable_{j,t}}$, where i is the firm, t is the year and j is the industry where firm i is classified.

Table 3.6: Variable Description and Source of Data

Variables	**Concept**	**Source**
ROA	Return on assets (Net income/TA)[a]	Bloomberg
ROE	Return on equity (Net income/MV)[a]	Bloomberg
adj.ROA	ROA/average industry ROA	Bloomberg
adj.ROE	ROE/average industry ROE	Bloomberg
EP(ta)	(-1)*[Log(total GHG/TA)], high values correspond to good EP	Datastream, Bloomberg
EP(mv)	(-1)*[Log(total GHG/MV)], high values correspond to good EP	Datastream, Bloomberg
adj.EP	(-1)*[Log(total GHG/average industry GHG)], high values correspond to good EP	Datastream, Bloomberg
ETS	Participation in EU emissions trading scheme : 1 when participate, 0 otherwise	Datastream

Continued on next page

Table 3.6: continued from previous page

ISO	ISO 14001, it takes values: 0 for non-adaptation, 1 when adopting ISO standards	Datastream
Z	(Financial distress) Altman's Z = 1.2* (WC/TA)+1.4* (RE/TA)+3.3* (EBIT/TA) +(Sales/TA)+0.6* (MV/TL). High values correspond to low probability of default	Datastream, Bloomberg
LEV	(Financial leverage) Leverage = total debt[a]/total equity[a]	Datastream
EMP	Log of number of employees	Datastream
LOGTA	Log of total assets	Datastream
GDP	Country's real GDP growth[a]	World bank Indicators
TANG	Tanglible assets/TA[a]	Bloomberg
INTA	Intangible assets/TA[a]	Bloomberg

Continued on next page

Table 3.6: continued from previous page

GRO	Annual growth rate of total sales[a]	Bloomberg
[MV, WA, TA, Sales, EBIT, RE, TL][a]	Variables for calculations, MV= market value, WA= working capital, TA= total assets, EBIT= earnings before interest and taxes, RE= retained earnings TL= total liabilities	Datastream, Bloomberg

[a] All money-based indicators for all countries, for each given year, are adjusted into current Euro.

3.3.3 Descriptive Statistics and Correlations

We continue this section by presenting some descriptive statistics and correlations of the variables employed in the regressions. Firstly, our final sample numerates 3465 firm-year observations. The three measures for EP [EP(ta), EP(mv) and adj.EP] have the most missing values compared to the rest of the data-set with around 2180 valid observations. The first three years of our examination (2005-2007) coincide with the first pilot phase[20] of EU emissions trading scheme, when disclosing environmental data was not mandatory. In 2008, EU regulations began monitoring more and more sites. This is why our sample suffers from many missing values at the beginning of the examination and gets improved at the latest years.

Regarding the rest of the variables (see, table 3.7), for instance, the firm size in our sample is quite heterogenous with a mean of current €8.6 bn ($LOGTA \approx$ 9.06), minimum of €30 m and maximum of €400 bn. ROA has a mean (median) of 6.0641 (5.2056) with the highest value being 28.28 and standard deviation of 5.341. ROE has a value of 8.7269 at the first quartile, 15.1781 at the median and 22.5526 at the third quartile. ROA (ROE) has skewness 0.9383 (1.13718) and kurtosis 4.9285 (8.2505); our dependent variables do not follow normal distribution and thus the use of quantile regressions is further motivated. In terms of the distribution of the explanatory variables EP, ISO, ETS, EMP and INTA are very close to satisfy the normality conditions (Skewness= 0 and Kurtosis= 3). However, the aforementioned variables seem to follow a slightly platykurtic distrubution. Other variables such as Z, LEV, GRO and TANG have a leptokurtic distribution and they also have fat upper tails apart from LEV with a thick lower tail.

Additionally, table 3.8 reports the correlations. Spearman matrix, is a non-parametric correlation measurement robust to outliers, gives some insights into the association of the variables. Note that most of the examined variables have

[20]See more about Phase 1 on https://ec.europa.eu/clima/policies/ets/pre2013_en.

a negative and low correlation with FP variables. The relation between EP and FP is shown in figure 3.7. From a first glance, EP slightly increases the FP. Testing only the mean distribution of EP and not all conditional distribution might lead to distorted results. Finally, we plot ROA and EP by country in order to detect any country specific differences (Figure 3.8). Most of the countries report positive EP-ROA relationship apart from Italy, Luxembourg and Austria. In order to provide a clearer picture of the relationship, we proceed to examine our hypothesis non-parametrically.

Figure 3.8: Plot ROA and EP by country

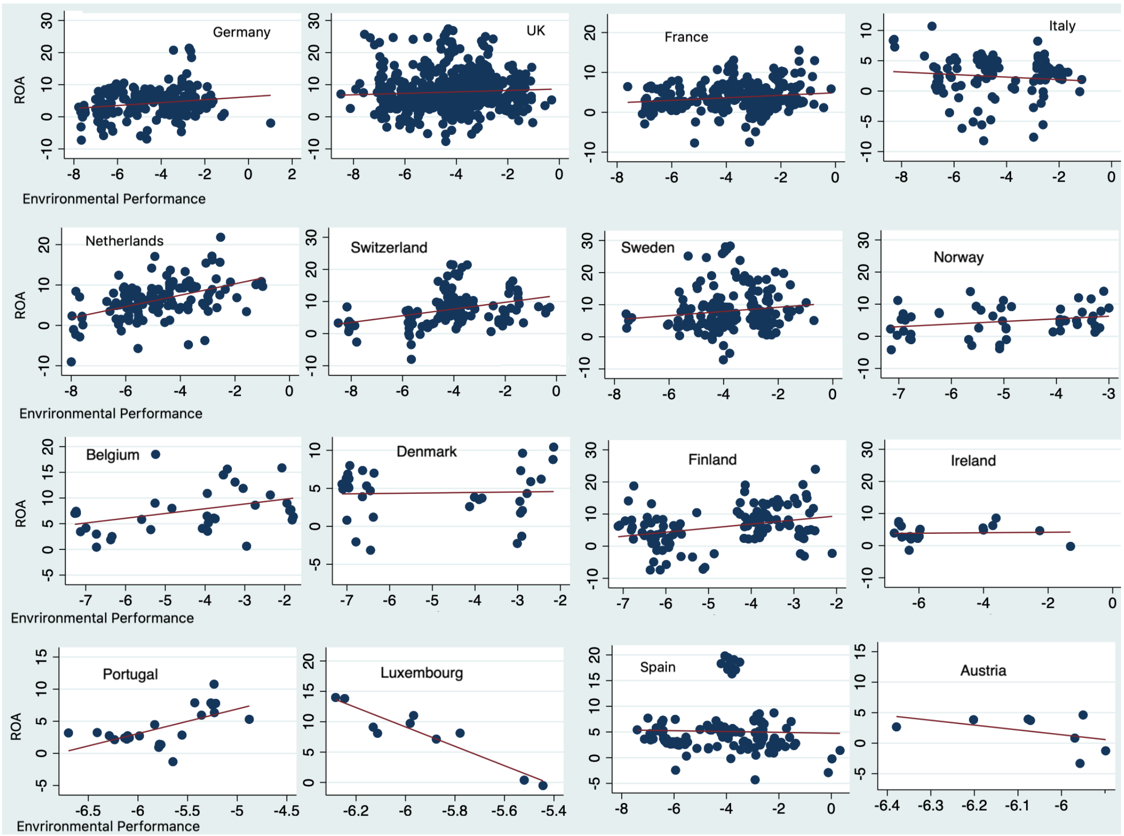


Table 3.7: Descriptive Statistics

	mean	max	min	std	1^{st} quartile	median	3^{rd} quartile	skew	kurt	Obs
ROA	6.064	28.280	-9.028	5.342	2.831	5.206	8.427	0.938	4.928	3341
ROE	16.512	110.710	-31.177	14.209	8.727	15.178	22.553	1.137	8.250	3291
adj.ROA	1.000	96.323	-67.445	3.256	0.492	0.891	1.385	9.195	509.095	3341
adj.ROE	1.000	21.293	-16.197	1.128	0.553	0.913	1.375	0.776	75.344	3291
EP(ta)	-4.251	1.014	-8.503	1.630	-5.594	-4.061	-2.987	-0.156	2.348	2184
EP(mv)	-4.568	0.130	-9.979	1.941	-6.060	-4.340	-3.129	-0.208	2.329	2175
adj.EP	1.690	7.901	-3.333	2.039	0.028	1.687	3.196	0.086	2.376	2190
ETS	0.353	1	0	0.478	0	0	1	0.617	1.380	3159
ISO	0.796	1	0	0.403	1	1	1	-1.465	3.147	3159
Z	4.858	328.075	-0.519	9.973	2.315	3.456	4.986	19.831	524.369	3232
LEV	90.246	10020.930	-22583.330	601.481	34.980	64.570	114.720	-20.691	872.524	3437
EMP	9.992	13.348	2.890	1.497	9.023	10.038	11.141	-0.513	3.780	3412
LOGTA	9.063	12.899	3.407	1.462	8.041	8.997	10.147	0.041	2.624	3437
GDP	1.323	26.276	-8.269	2.525	0.576	1.699	2.556	1.038	22.883	3456
TANG	0.804	2.721	0.002	0.225	0.677	0.848	0.960	-0.079	8.825	3350
INTA	0.223	1.164	0.000	0.188	0.062	0.176	0.345	0.916	3.289	3282
GRO	9.029	2290.132	-91.056	66.807	-1.251	5.087	12.562	27.657	868.328	3390

Note: Description of the variables can be found on table 3.6.

Table 3.8: Spearman Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) ROA	1																
(2) ROE	0.83*	1															
(3) adj.ROA	0.91*	0.80*	1														
(4) adj.ROE	0.74*	0.90*	0.81*	1													
(5) EP(ta)	0.15*	0.16*	0.10*	0.09*	1												
(6) EP(mv)	0.40*	0.34*	0.34*	0.26*	0.91*	1											
(7) adj.EP	0.25*	0.22*	0.30*	0.22*	0.55*	0.62*	1										
(8) ETS	-0.18*	-0.14*	-0.13*	-0.08*	-0.40*	-0.45*	-0.34*	1									
(9) ISO	-0.17*	-0.09*	-0.10*	-0.05*	-0.08*	-0.14*	-0.08*	0.14*	1								
(10) Z	0.69*	0.41*	0.63*	0.39*	0.09*	0.41*	0.34*	-0.18*	-0.22*	1							
(11) LEV	-0.42*	-0.04*	-0.32*	-0.02	-0.06*	-0.25*	-0.18*	0.17*	0.16*	-0.52*	1						
(12) EMP	-0.19*	-0.10*	-0.28*	-0.16*	-0.04*	-0.17*	-0.66*	0.13*	0.11*	-0.39*	0.12*	1					
(13) LOGTA	-0.33*	-0.18*	-0.32*	-0.17*	-0.09*	-0.28*	-0.72*	0.33*	0.20*	-0.50*	0.33*	0.73*	1				
(14) GDP	0.19*	0.15*	0.08*	0.03	0.01	0.10*	0.03	-0.11*	-0.09*	0.20*	-0.11*	-0.01	-0.06*	1			
(15) TANG	-0.02	-0.03	0.02	-0.01	-0.28*	-0.27*	-0.01	0.09*	-0.09*	0.06*	-0.11*	-0.17*	-0.09*	0.03	1		
(16) INTA	0.07*	0.09*	0.02	0.07*	0.25*	0.27*	0.00	-0.08*	0.10*	-0.01	0.09*	0.17*	0.05*	0.01	-0.81*	1	
(17) GRO	0.28*	0.28*	0.18*	0.15*	0.05*	0.11*	0.08*	-0.06*	-0.04	0.13*	-0.08*	-0.05*	-0.08*	0.22*	-0.02	0.04*	1

Notes: *, Significant at 5% level. Description of the variables can be found on table 3.6.

3.3.4 Econometric Method

Quantile Regression Methodology

To test our hypothesis, we employ Quantile regression which was introduced by Koenker and Bassett (1978) with a purpose to estimate an equation expressing at a quantile of the conditional distribution. In this paper, we investigate parameters that describe the 5%, 50% and 95% of the conditional distribution. In order to linearly represent our regressions, we consider the following equation:

$$FP = \pi(\tau) + \theta(\tau)EP + \mathbf{Y}'\vartheta(\tau) + \varepsilon, \quad \tau \in (0,1) \tag{3.1}$$

Where, FP is the dependent variable, π is the intercept, $\mathbf{Y}$ is a vector that contains all explanatory variables, $\theta(\tau)$ and $\vartheta(\tau)$ are the parameters, ε signifies the error term and τ is the quantile of FP. We assume that the error is equal to zero at the conditional τ^{th} quantile $[Q_{\varepsilon|EP,\mathbf{Y}}(\tau|ep,\mathbf{y}) = 0]$. Also, the parameter θ for any given quantile (τ) for a sample of N observations can be calculated with linear programming as follows:

$$\hat{\theta}(\tau) = arg\ \underset{\theta}{min} \frac{1}{N} \sum_{i=1}^{N} \rho_\tau[FP - \pi(\tau) - \theta(\tau)EP - \mathbf{Y}'\vartheta(\tau)] \tag{3.2}$$

where the check function $\rho_\tau(.)$ is defined as:

$$\rho_\tau(\varepsilon) = \begin{cases} \tau\varepsilon, & \text{if } \varepsilon \geq 0; \\ (\tau - 1)\varepsilon, & \text{if } \varepsilon < 0 \end{cases}$$

In order to investigate our main hypothesis, which predicts heterogeneous EP effects on FP distribution, $\theta(\tau)$ coefficients should be significantly different across the quantiles, thus $H_0 : \theta(0.05) = \theta(0.50) = \theta(0.95)$ should be rejected.

We use bootstrap estimates of $\hat{\theta}(\tau)$ in order to calculate the covariance matrix. We compute standard errors with 1000 bootstrap replications and thus we obtain asymptotically normally distributed estimators which are valid under heteroskedasticity and misspecification. We use the Wald test to test whether EP coefficients are statistically different across quantiles. Statistically significant values denote that EP parameters heterogeneously affect FP.

At this stage of the examination, we let equation 3.1 be affected by the potential endogeneity, then this problem is treated with two stage quantile regressions.

Two stage Quantile Regression Methodology

We employ a semi-parametric technique to deal with the endogeneity. More particularly, we account for the endogeneity in our estimations by considering a control function approach. Therefore, we exploit the linear nature of the setting in an non-parametric environment. There are several ways to treat endogeneity in quantile estimations, however these are mainly for binary variables. Due to the fact that we have continuous endogenous variables, we follow the methodology proposed by Lee (2007).

$$FP = \beta(\tau)EP + \mathbf{X_1'}\gamma(\tau) + \mathbf{U} \tag{3.3}$$

$$EP = m(\alpha) + \mathbb{X}'\delta(\alpha) + \mathbf{V} \tag{3.4}$$

$$Q_{U|EP,\mathbb{X}}(\tau|ep, \mathbf{x}) = Q_{U|V,\mathbb{X}}(\tau|v, \mathbf{x}) = Q_{U|V}(\tau|v) \equiv \lambda_\tau(v) \tag{3.5}$$

$$Q_{V|\mathbb{X}}(a|\mathbf{x}) = 0 \tag{3.6}$$

Where FP is the dependent variable of financial performance and EP is the endogenous term of environmental performance. $\mathbb{X} \equiv (\mathbf{X_1}, \mathbf{X_2})'$ is a vector of explanatory variables, where $\mathbf{X}_1$ a vector of FP covariates and $\mathbb{X}$ a vector of EP covatiates which includes both $\mathbf{X}_1$ and at least one or more instruments ($\mathbf{X}_2$) for identification. U and V are the error terms of equations 3.3 and 3.4 respectively. Also, $m(\alpha)$ is an unknown constant, $\gamma(\tau)$ and $\delta(\alpha)$ vectors of unknown parameters and $\beta(\tau)$ the parameter of interest, τ and α denote the quantile area where $\tau, a \in (0,1)$. Term $\lambda_\tau(v)$ is a real-valued unknown function of V and $Q_{U|EP,\mathbb{X}}(\tau|ep,\mathbf{x})$ is the τ^{th} quantile of U conditional on EP=ep and $\mathbb{X}$=$\mathbf{x}$, whereby ep and $\mathbf{x}$ are projections of EP and $\mathbb{X}$ on the τ^{th} quantile respectively. In equation 3.5 [$Q_{U|V}(\tau|v)$] U is independent of $\mathbb{X}$ but conditional on V, where $v = ep - m(a) - \mathbf{x}'\delta(a)$. Our semi-parametric approach allows us to estimate V (eq. 3.4) by the residuals of a linear (a^{th}) quantile regression and then $\hat{V}(\alpha)$ can be included as explanatory variable in the quantile regressions of FP.

$$Q_{FP|EP,\mathbb{X}}(\tau|ep,\mathbf{x}) = ep\beta(\tau) + \mathbf{x}_1'\gamma(\tau) + \lambda_\tau(v) \tag{3.7}$$

$$Q_{EP|\mathbb{X}}(a|\mathbf{x}) = m(a) + \mathbf{x}'\delta(a) \tag{3.8}$$

Henceforth, the probability density functions of FP and EP are given by equations 3.7 and 3.8 respectively. Under those assumptions, we are able to estimate the effect of EP on FP in a two step procedure as linearly represented in equation 3.9:

$$FP = \beta(\tau)EP + \mathbf{X_1'}\gamma(\tau) + \psi(\tau)\hat{\mathbf{V}}(\alpha) + \mathbf{U} \tag{3.9}$$

Endogeneity

We thus re-examine our hypothesis, accounting for endogeneity by employing a two-stage regression approach. A great number of studies (Al-Tuwaijri et al., 2004; Cai et al., 2016; Broadstock et al., 2018) have reported the problem of endogeneity in the examination between EP and FP. In order to deal with the endogeneity, first we need to identify characteristics (instruments) that are both conceptually and methodologically correct and that are correlated with the first stage dependent variable (i.e. EP) but not with the residuals of the second stage regression. As has been explained in section 3.2.3, regulatory pressure can be really exogenous to EP (Brunel and Levinson, 2016) and thus we include two instruments ($\mathbf{X}_2$). The first instrument is the participation of firms in the European emissions trading scheme (ETS) (Bye and Klemetsen, 2018) and the second is the adoption of ISO 14001 standards (ISO) (Quazi et al., 2001). It is worth noting that across firms both instruments vary over time (within variation) and thus they can potentially explain abrupt EP changes. For this reason, various empirical studies have used ETS and ISO as determinants to explain the variation of EP (see, for example, Quazi et al., 2001; Melnyk et al., 2003; Ellerman and Buchner, 2008; Albino et al., 2009; Engels, 2009; Hatakeda et al., 2012; Conrad et al., 2012; Cormier and Magnan, 2015).

Regarding the first stage results, an EP model is estimated as shown in equation 3.4. The expectation is that firms participating in ETS and ISO should have on average worse EP than non-participants. This is because carbon allowances are allocated according to firms' needs and therefore carbon-intensive firms would have more certified emissions to trade; similarly, ISO is adopted when firms need assistance with their environmental behaviour. The second stage estimates a FP model (equation 3.9). The residuals estimated from the first stage are now included non-parametrically as an additional explanatory variable along with the other control variables (Lee, 2007). The two-stage quantile regression as a semi-parametric approach would detect if there is a problem of endogeneity, confirming or rejecting the previous estimates. Hence, we focus on the $\hat{V}(\alpha)$ coefficients; if $\hat{V}(\alpha)$ appears to be statistically significant then our previous estimations are problematic (Wooldridge, 2015). We are now able to proceed with the results.

3.4 Results

3.4.1 Quantile Regression Results

This session reports the results from the quantile regressions based on equation 3.1. Columns 1-6, as shown in tables 3.9, 3.10 and 3.11, display the coefficients of EP(ta), EP(mv) and adj.EP respectively along with their standard errors. Columns 1-3 report the results for ROA at the 5%, 50% and 95% of the conditional distribution, likewise columns 4-6 report ROE results for the lower, median and upper part of the distribution. Table 3.11 reports the adjusted industry results.

We begin by analysing the control variables of our estimations, all 3 tables report similar coefficients and so we focus on table 3.9. Z-score appears to have significant and positive relation for all different quantiles with all FP variables, signifying that lower probability of default increases the profits (Psillaki et al., 2010). Leverage has a positive and significant effect on ROE, but does not seem to influence ROA. Intangible assets, that have characteristics of R&D, positively influence FP, especially at the lower tail of the distribution. Consistent with our expectations, size (LOGTA) is negative and significant for the whole probability distribution (Konar and Cohen, 2001; Hatakeda et al., 2012). Number of employees (EMP) has on average a positive effect on FP. GDP growth (GDP) and sales growth (GRO) do not seem to affect ROA and ROE. Overall, irrespective of the geographical area, the effects of our control variables on FP are in line with previous literature (see, for example, Elsayed and Paton, 2005; Clarkson et al., 2011; Nollet et al., 2016). Another interesting finding is that Pseudo R-squared[21] (R^2) explains a larger part of the variation at the upper tail rather than the lower tail of the conditional distribution; for example R^2 for ROA (ROE) at $\tau = 0.95$ is 49.25% (26.10%), while at $\tau = 0.05$ is 19.45% (20.17%). Comparing the benchmark specification for ROA with models including EP(ta) (Table 3.9) and EP(mv) (Table 3.10), we witness an increase in the goodness of fit across the whole conditional distribution which is approximately 1 percentage point, indicating the important role of EP in the examination.

[21] Pseudo-R^2 has the same concept with the OLS R^2 but it refers to any given (τ) quantile (Koenker and Machado, 1999).

Table 3.9: Quantile regressions with independent variable: EP(ta)

τ	05	50	95	05	50	95	05	50	95
	Benchmark model			(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROA	ROA	ROA	ROA	ROA	ROE	ROE	ROE
EP(ta)				0.450***	0.152**	0.600***	1.982***	1.101***	1.312**
				(0.139)	(0.057)	(0.134)	(0.392)	(0.197)	(0.602)
Z	0.113	1.019***	1.560***	0.113**	1.015***	1.540***	0.387***	1.215***	1.857***
	(0.155)	(0.091)	(0.149)	(0.053)	(0.074)	(0.107)	(0.084)	(0.188)	(0.391)
LEV	-0.0026	-0.0006	0.0006	-0.0032	-0.0009	-0.0001	-0.0247***	0.0240***	0.0853***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.007)	(0.004)	(0.014)
EMP	0.459	0.181	0.390*	0.558*	0.232**	0.645***	0.734	1.258***	3.373**
	(0.324)	(0.117)	(0.216)	(0.321)	(0.103)	(0.283)	(0.536)	(0.367)	(1.641)
LOGTA	-1.109***	-0.303**	-0.456**	-1.132***	-0.306***	-0.535**	-1.367***	-1.157***	-3.754***
	(0.381)	(0.146)	(0.189)	(0.290)	(0.104)	(0.253)	(0.527)	(0.431)	(1.219)
GDP	0.101	0.0927**	0.00401	0.142	0.0913	-0.00223	0.116	0.185	-0.0445
	(0.122)	(0.046)	(0.054)	(0.115)	(0.057)	(0.058)	(0.344)	(0.171)	(0.416)
TANG	-0.149	-0.408	0.334	-0.0330	-0.320	0.435	0.814	-0.446	10.02
	(1.401)	(0.680)	(1.031)	(1.151)	(0.444)	(1.564)	(4.228)	(1.058)	(8.104)
INTA	3.614**	0.901	-3.412**	2.458**	0.608	-2.954*	7.612	2.922***	-4.138
	(1.678)	(0.687)	(1.348)	(1.133)	(0.609)	(1.689)	(5.100)	(1.034)	(10.083)
GRO	0.00105	0.00820	0.0274*	0.000656	0.00820	0.0220	0.0210	0.0200	0.121**
	(0.004)	(0.007)	(0.014)	(0.008)	(0.009)	(0.022)	(0.029)	(0.030)	(0.056)
cons	3.562	3.152**	6.534	4.602	3.216***	6.566	9.226	8.473**	14.01
	(3.900)	(1.573)	(4.715)	(3.110)	(1.334)	(4.583)	(9.549)	(4.145)	(17.116)
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs	2017	2017	2017	2017	2017	2017	1989	1989	1989
R^2	0.1867	0.2860	0.4842	0.1945	0.2875	0.4925	0.2017	0.1546	0.2610
Wald					22.76***			2.46*	

Notes: Description of the variables can be found on table 3.6. This table reports the results of the quantile regressions based on equation 3.1. Term τ shows the quantile of FP distribution under investigation. Significance based on bootstrap standard errors (1000 replications): ***,**,* significance level at 1%, 5%, 10%. Wald-test is for EP slopes $[\theta(0.05) = \theta(0.50) = \theta(0.95)]$.

Table 3.10: Quantile Regressions with Independent Variable: EP(mv)

τ	05	50	95	05	50	95
	(1)	(2)	(3)	(4)	(5)	(6)
	ROA	ROA	ROA	ROE	ROE	ROE
EP(mv)	0.910***	0.426***	0.649***	2.712***	1.829***	2.353***
	(0.167)	(0.076)	(0.116)	(0.399)	(0.231)	(0.448)
Z	0.117***	0.906***	1.353***	0.291**	0.908***	1.694***
	(0.043)	(0.117)	(0.232)	(0.130)	(0.165)	(0.485)
LEV	-0.00275	-0.000844	0.000215	-0.0146	0.0243***	0.0824***
	(0.003)	(0.001)	(0.001)	(0.010)	(0.004)	(0.014)
EMP	0.507**	0.423***	0.605***	1.374**	1.912***	4.234**
	(0.249)	(0.113)	(0.198)	(0.649)	(0.519)	(1.737)
LOGTA	-0.888***	-0.389***	-0.286	-1.275	-1.339***	-3.100**
	(0.300)	(0.147)	(0.177)	(0.776)	(0.500)	(1.567)
GDP	0.0906	0.0627	-0.00378	-0.0381	0.129	-0.0529
	(0.134)	(0.043)	(0.098)	(0.346)	(0.120)	(0.301)
TANG	0.741	-0.0374	-0.0289	-4.667	0.996	7.214
	(1.239)	(0.413)	(1.447)	(4.175)	(1.220)	(7.726)
INTA	1.457	0.560	-3.947**	1.399	1.848	-9.558
	(1.586)	(0.478)	(1.597)	(4.683)	(1.847)	(9.068)
GRO	-0.000335	0.00833	0.0174	0.0152	0.0205	0.101
	(0.009)	(0.010)	(0.017)	(0.036)	(0.039)	(0.066)
cons	3.109	3.020**	5.801	6.169	7.011**	4.205
	(3.068)	(1.374)	(5.302)	(12.511)	(3.575)	(15.053)
Year	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES
N	2017	2017	2017	1989	1989	1989
R^2	0.2279	0.2992	0.4996	0.2335	0.1772	0.2712
Wald		5.80***			2.34*	

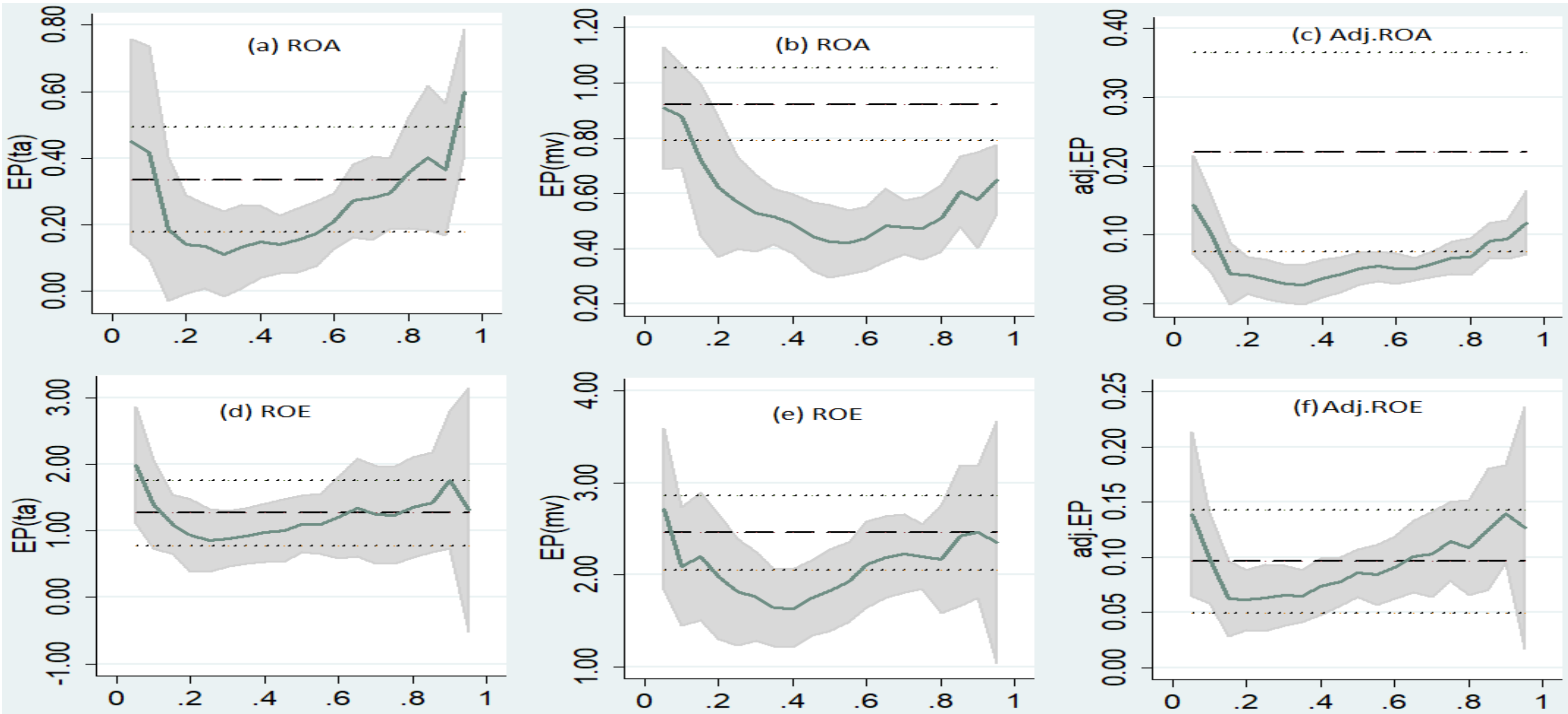
Notes: Description of the variables can be found on table 3.6. This table reports the results of the quantile regressions based on equation 3.1. Term τ shows the quantile of FP distribution under investigation. Significance based on bootstrap standard errors (1000 replications): ***,**,* significance level at 1%, 5%, 10%. Wald-test is for EP slopes $[\theta(0.05) = \theta(0.50) = \theta(0.95)]$.

Table 3.11: Quantile Regressions: Industry Adjusted Results

τ	05	50	95	05	50	95
	(1)	(2)	(3)	(4)	(5)	(6)
	adj.ROA	adj.ROA	adj.ROA	adj.ROE	adj.ROE	adj.ROE
adj.EP	0.143***	0.0510***	0.118***	0.139***	0.0856***	0.127***
	(0.032)	(0.010)	(0.033)	(0.033)	(0.017)	(0.045)
adj.Z	0.195**	0.758***	1.213***	0.256***	0.348***	0.414***
	(0.093)	(0.067)	(0.170)	(0.047)	(0.046)	(0.154)
adj.LEV	-0.0252	-0.00774	0.0136	0.0116	0.0504**	0.232***
	(0.018)	(0.014)	(0.009)	(0.043)	(0.024)	(0.058)
adj.EMP	1.263**	0.346	0.847*	1.045*	0.696**	2.070***
	(0.516)	(0.216)	(0.468)	(0.620)	(0.276)	(0.645)
adj.LOGTA	-0.974**	0.0701	0.103	0.384	0.373*	-1.268*
	(0.489)	(0.159)	(0.468)	(0.447)	(0.218)	(0.675)
GDP	0.0336	0.00498	-0.00124	0.0204	-0.00188	-0.0277
	(0.039)	(0.010)	(0.015)	(0.028)	(0.014)	(0.027)
adj.TANG	0.284*	-0.0274	-0.116	0.344	0.00582	0.487**
	(0.159)	(0.059)	(0.309)	(0.239)	(0.054)	(0.196)
adj.INTA	0.153***	0.0262	-0.224**	0.203***	0.0398**	-0.140**
	(0.045)	(0.024)	(0.096)	(0.065)	(0.018)	(0.063)
adj.GRO	0.00452	0.000563	0.00316	0.00379	0.000508	0.00295
	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
cons	-1.346	-0.102	0.343	-5.194***	-0.486	1.160
	(1.104)	(0.225)	(1.010)	(1.985)	(0.370)	(0.849)
Year	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES
Obs	2017	2017	2017	1989	1989	1989
R^2	0.1584	0.1813	0.2162	0.187	0.1016	0.2246
Wald		6.07***			2.75*	

Notes: Description of the variables can be found on table 3.6. This table reports the results of the quantile regressions based on equation 3.1. Term τ shows the quantile of FP distribution under investigation. Significance based on bootstrap standard errors (1000 replications): ***,**,* significance level at 1%, 5%, 10%. Wald-test is for EP slopes $[\theta(0.05) = \theta(0.50) = \theta(0.95)]$.

Figure 3.9: EP Effects on FP Distribution



Notes: The figure illustrates the non-linear effects of EP on FP, based on equation 3.1. The grey area corresponds to confidence intervals calculated with 1,000 bootstrap replications. The dash lines represent the OLS estimations with their confidence intervals (dot lines). The control variables are not reported for brevity but are available upon request.

Regarding the hypothesis, EP seems to increase FP significantly across the FP distribution at the 0.01 level. For example, in Table 3.9, an increase in EP(ta) of 1% will cause an increase in ROA (ROE) by 0.45% (1.982%), 0.152% (1.101%) and 0.6% (1.312%) at the low, median and high part of the distribution respectively. Having a closer look at the graphical representation at Figure 3.9, we detect that (i) EP always has positive effects on FP and (ii) the lower and upper parts of the distribution witness greater EP coefficients compared to the middle of the distribution. We should also underline that this Figure indicates that the linear regressions are insufficient to describe the data. Dash lines illustrate that ordinary least squares can only provide a broad idea of the relationship by ignoring the different conditional distributions that plays an important role in the investigation. Additionally, the heterogeneous EP effects on FP are supported for both ROA and ROE. Wald statistics, for testing equality, reports whether EP slopes have statistical differences across the distribution. EP seems to change dramatically over the FP distribution. Particularly, EP coefficients have statistical differences for both ROA (Wald-test statistics = 22.76, p-value < 0.01) and ROE (Wald-test statistics = 2.46, p-value < 0.10), indicating that the coefficients are not constant across the distribution. So far, this finding implies that EP-FP relationship exhibits a positive and heterogeneous association, as *financial slack argument* predicts, and we do have adequate evidence to support our hypothesis.

3.4.2 Robustness Checks

To corroborate our results, we split our sample in three different ways. First, due to the fact that we examine small, mid and large firms, we now run quantile regressions separately for each category. A crucial limitation of previous studies is that they examined mainly large firms and that their results were generalised for the whole population (Al-Tuwaijri et al., 2004). An advantage of the EU sample is that the firm size is quite heterogenous. Therefore, our results would provide evidence about whether firms with different book-size and profitability are affected by EP. Second, UK firms have dominated our sample (25%) and results might be driven by this country; previous studies show that UK firms pay attention to environmental practises (Salama et al., 2011), thus we exclude the UK as a post-Brexit scenario and we run the regressions again. Third, results might be highly dependent upon the timing. For instance, in the period during the recent financial crisis, firms had low profitability and they did not focus on their EP. Accordingly, we split the sample into before crisis (2005-2008) and after crisis (2010-2016) and we observe the sensitivity of the results.

Table 3.12 shows that our results are strong for small and medium size corporations, while very large firms are unaffected by EP. This is particularly interesting and indicates that not only profitability but also the size of the firms have a dominant role in the examination. In line with Hoogendoorn et al. (2015); Yadav et al. (2016), we find that smaller firms can better reap benefits from EP, while larger firms may require larger investments to make EP efficient. Also, in columns 10-12 of the same table, it is evident that a non-UK sample does not moderate the EP-FP relationship, and UK firms have the same characteristics as all the EU firms.

We continue with Table 3.13, showing that the period of the investigation can offer sightly alternate results. Particularly, the results are quite robust during the post-crisis period, while before crisis, only profitable firms seem to benefit from EP. So far, the results support the main hypothesis, that profitability is primarily responsible for the efficacy of EP. However, we would like to dig more into the EP-FP relationship by assessing whether these results are driven by the endogenous relationship between EP and FP (Endrikat et al., 2014).

Table 3.12: Robustness Checks 1: EP(mv) on ROA

τ	05	50	95	05	50	95	05	50	95	05	50	95
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
sample	small	small	small	medium	medium	medium	large	large	large	Non-UK	Non-UK	Non-UK
EP(mv)	1.655***	1.992***	1.302**	1.227***	0.508***	0.586***	-0.148	0.0764	0.0433	0.696***	0.370***	0.579***
	(0.618)	(0.384)	(0.506)	(0.334)	(0.128)	(0.211)	(0.282)	(0.100)	(0.203)	(0.197)	(0.070)	(0.137)
Z	-0.0248	0.226	0.764***	0.148	0.798***	1.236***	1.917***	1.687***	2.435***	0.796***	1.097***	1.434***
	(0.093)	(0.175)	(0.284)	(0.276)	(0.122)	(0.146)	(0.174)	(0.188)	(0.304)	(0.080)	(0.062)	(0.117)
LEV	-0.00240	-0.000163	0.000310	0.00342	-0.00519*	-0.00242	-0.00215	0.000128	-0.000375	-0.00449	-0.00177	-0.000173
	(0.002)	(0.001)	(0.002)	(0.004)	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)	(0.004)	(0.002)	(0.001)
EMP	0.553	2.489***	3.255***	0.927**	0.482**	0.00932	0.697	0.597***	0.221	1.356***	0.509***	0.754***
	(0.537)	(0.640)	(0.872)	(0.396)	(0.189)	(0.314)	(0.430)	(0.226)	(0.240)	(0.318)	(0.147)	(0.246)
LOGTA	-3.663***	-5.669***	-2.774**	-1.017**	-0.544**	0.666	0.881*	-0.112	0.123	-1.047***	-0.445***	-0.524**
	(1.256)	(0.968)	(1.319)	(0.510)	(0.228)	(0.542)	(0.469)	(0.325)	(0.439)	(0.298)	(0.151)	(0.257)
GDP	0.280	0.178	0.546	-0.0898	-0.0299	0.00638	-0.0295	0.0474	-0.119	0.140	0.0940**	0.0199
	(0.334)	(0.123)	(0.509)	(0.190)	(0.079)	(0.059)	(0.215)	(0.083)	(0.171)	(0.177)	(0.046)	(0.095)
TANG	-1.806	3.539	-4.000	-1.958	0.201	1.643	-1.529	-1.697**	0.398	-2.580***	-0.460	-1.405
	(3.146)	(3.687)	(7.776)	(2.239)	(0.742)	(3.587)	(1.352)	(0.670)	(1.325)	(0.814)	(0.438)	(1.308)
INTA	-0.0836	-6.506	-15.99*	-3.302	1.387*	-0.319	4.343**	0.185	-2.079	0.672	-0.160	-3.906**
	(7.531)	(4.434)	(8.410)	(2.251)	(0.733)	(3.526)	(1.787)	(1.084)	(2.441)	(1.204)	(0.544)	(1.790)
GRO	0.000706	0.00650	0.0101	0.00737	0.00832	0.00696	0.000900	-0.00322	-0.00263	0.00158	0.00889	0.0155
	(0.040)	(0.023)	(0.055)	(0.029)	(0.012)	(0.015)	(0.011)	(0.017)	(0.025)	(0.006)	(0.009)	(0.017)
cons	27.34**	25.32***	12.70	3.621	4.663*	1.736	-21.75***	-3.514	4.208	-5.063	1.846	5.745*
	(12.493)	(9.270)	(12.253)	(6.520)	(2.622)	(7.360)	(5.972)	(3.499)	(9.226)	(3.579)	(1.462)	(3.178)
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs	286	286	286	1050	1050	1050	681	681	681	1506	1506	1506
R^2	0.3196	.4090	0.5399	0.2732	0.3035	0.4913	0.4402	0.4045	0.5523	0.3206	0.3752	0.5738
Wald		0.96			5.30***			0.48			3.91**	

Notes: Small refers to firms falling in the lower quartile of total assets variable, similarly medium is firms in the middle quartile and large in the upper quartile. Description of the variables can be found on table 3.6. This table reports the results of the quantile regressions based on equation 3.1. Term τ shows the quantile of FP distribution under investigation. Significance based on bootstrap standard errors (1000 replications): ***,**,* significance level at 1%, 5%, 10%. Wald-test is for EP slopes $[\theta(0.05) = \theta(0.50) = \theta(0.95)]$.

Table 3.13: Robustness Checks 2: EP(mv) on ROA and adj.EP on adj.ROA

τ	05	50	95	05	50	95	05	50	95	05	50	95
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
sample	post	post	post	pre	pre	pre	post	post	post	pre	pre	pre
	ROA	ROA	ROA	ROA	ROA	ROA	adj.ROA	adj.ROA	adj.ROA	adj.ROA	adj.ROA	adj.ROA
EP	0.912***	0.469***	0.721***	0.355	0.191	0.542*	0.141***	0.0531***	0.120***	0.0931	0.0293	0.0585**
	(0.144)	(0.092)	(0.098)	(0.345)	(0.218)	(0.277)	(0.030)	(0.013)	(0.023)	(0.064)	(0.019)	(0.027)
(adj.)Z	0.0786	0.762***	1.318***	1.326***	1.595***	1.607***	0.150**	0.708***	1.046***	0.828***	0.861***	1.034***
	(0.060)	(0.124)	(0.184)	(0.302)	(0.206)	(0.389)	(0.075)	(0.072)	(0.162)	(0.142)	(0.068)	(0.240)
(adj.)LEV	0.0014	-0.0015	-0.0001	-0.00274	-0.00117	0.00113	-0.0226	-0.00541	0.00916	-0.0256	-0.0808***	-0.0385
	(0.003)	(0.001)	(0.001)	(0.003)	(0.002)	(0.003)	(0.022)	(0.013)	(0.011)	(0.049)	(0.030)	(0.091)
(adj.)EMP	0.583**	0.407**	1.070***	0.507	0.167	0.396	1.253**	0.306	1.664***	1.177	0.343	1.163
	(0.250)	(0.182)	(0.256)	(0.486)	(0.197)	(0.265)	(0.552)	(0.282)	(0.305)	(0.928)	(0.352)	(0.876)
(adj.)LOGTA	-1.147***	-0.579***	-0.768***	0.770	0.422	0.120	-1.191***	-0.113	-0.653	1.254	0.422	0.0651
	(0.301)	(0.168)	(0.272)	(0.489)	(0.268)	(0.621)	(0.434)	(0.255)	(0.446)	(1.059)	(0.295)	(0.609)
GDP	0.221	0.0401	-0.0107	0.155	-0.0588	1.046	0.0413	0.00705	-0.00188	0.0301	-0.000526	0.148
	(0.141)	(0.038)	(0.092)	(0.373)	(0.231)	(0.818)	(0.032)	(0.009)	(0.014)	(0.046)	(0.030)	(0.120)
(adj.)TANG	-0.941	-0.632*	1.141	0.984	-0.170	0.0111	0.168	-0.0806	-0.119	0.473*	-0.211*	-0.252
	(0.864)	(0.358)	(2.324)	(1.828)	(1.490)	(2.836)	(0.148)	(0.083)	(0.247)	(0.267)	(0.122)	(0.479)
(adj.)INTA	-0.544	0.149	-1.917	-0.227	1.664	-2.486	0.0837*	0.00728	-0.160*	0.0517	-0.0272	-0.130
	(1.281)	(0.664)	(2.564)	(2.477)	(1.164)	(3.790)	(0.048)	(0.028)	(0.090)	(0.071)	(0.039)	(0.133)
(adj.)GRO	-0.006	0.008	0.0191*	0.0005	-0.002	-0.0059	0.0067	0.005*	0.005***	-0.008	0.00005	0.0437
	(0.009)	(0.007)	(0.010)	(0.010)	(0.012)	(0.025)	(0.005)	(0.003)	(0.002)	(0.020)	(0.012)	(0.064)
cons	6.644*	5.175**	2.064	-23.42***	-3.696*	0.708	-1.045	0.117	-0.350	-4.658***	-0.453	-0.525
	(3.401)	(2.007)	(4.218)	(8.061)	(1.969)	(7.917)	(0.764)	(0.354)	(0.657)	(1.768)	(0.458)	(1.058)
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs	1465	1465	1465	375	375	375	1465	1465	1465	375	375	375
R2	0.2463	0.311	0.523	0.4345	0.4129	0.5637	0.2488	0.1716	0.2273	0.4053	0.3313	0.4671
Wald		6.63***			1.15			9.55**			0.42	

Notes: Columns 1-6 are referred to non industry-adjusted results with main independent variable the EP(mv), columns 7-12 are referred to industry adjusted variables with main independent variable the adj.EP. Pre-crisis is from 2005-2008, post-crisis from 2010-2016. Description of the variables can be found on table 3.6. This table reports the results of the quantile regressions based on equation 3.1. Term τ shows the quantile of FP distribution under investigation. Significance based on bootstrap standard errors (1000 replications): ***,**,* significance level at 1%, 5%, 10%. Wald-test is for EP slopes $[\theta(0.05) = \theta(0.50) = \theta(0.95)]$.

3.4.3 Detecting Endogeneity

To address the problem of the potential endogeneity between EP and the error term, we stress our results in a two-stage quantile regression approach. Reasonably, high profitability firms could allocate more resources to finance green projects. Accordingly, at the first stage, we estimate an EP model enriched with two instruments (ETS and ISO), and then the residuals from the first stage are used as an explanatory variable at the second stage FP regressions controlling for endogeneity.

As shown in table 3.14, columns 1,2 and 3 report the first stage for EP at 5, 50 and 95% of the conditional distribution respectively. Regarding the first stage results, it is important to underline the validity of the two instruments as they appear statistically significant below the 0.01 level. It should not be surprising that ETS values coincide with "bad" EP because participating companies emit more carbon dioxide. Also, firms might purchase carbon allowances in order to legitimate their pollutants. Due to the very low carbon price, firms do not have motives to reduce carbon emissions (Zhang and Wei, 2010). Specifically, by the end of Phase 1, one ton of carbon emission priced at €0.02 (Engels, 2009). In regard to the negative coefficient of ISO, this can be attributed to either ineffective environmental management to reduce carbon footprint or to the adoption of ISO by firms in order to ease stakeholder and regulatory pressure (Melnyk et al., 2003). Another explanation of the negative coefficients is that polluting firms receive pressure to adopt environmental proactive approaches and abide by the regulatory standards (Dixon-Fowler et al., 2013; Lee et al., 2015).

Turning to the second stage results, we are now able to provide more insights into our hypothesis (EP-FP relationship under endogeneity). All control variables, estimated by the two-stage quantile regressions report very similar coefficients to the previous estimates of the standard quantile regression (see section 3.4.1). Specifically, Z-score is positive, LOGTA is negative, LEV is negative and insignificant for ROE and ROA respectively, EMP is positive and insignificant for ROA and ROE respectively, while we do observe some variation of INTA coefficients across distribution for both ROE and ROA. As shown in Tables 3.15 and 3.16, EP coefficients are strongly significant and positive at the upper tail of the distribution, while at the median and upper tail, EP is insignificant. Particularly, column 1 for ROA (ROE) represents a firm at the lower part of the conditional distribution with $\alpha = \tau = 0.05$, and at this part EP is not significant. On the other hand, in column 9, a counterpart firm, at the upper tail of the distribution with $\alpha = \tau = 0.95$, reports a significant coefficient for ROA (ROE) of 1.111% (5.172%). Overall, firms with heightened environmental performance are more likely to experience financial benefits, compared to firms with high pollution propensity. At the same time, this finding shows that firms with higher FP get more benefits from EP engagement, while low profitability firms are unaffected by their EP.

Table 3.14: First-stage Quantile Regressions on EP(ta)

α	05	50	95
	(1)	(2)	(3)
ETS	-0.895***	-1.334***	-1.000***
	(0.157)	(0.118)	(0.101)
ISO	-0.198	-0.478***	-0.497***
	(0.292)	(0.100)	(0.176)
Z	0.00528	-0.00373	-0.0367**
	(0.007)	(0.011)	(0.015)
LEV	0.000203	0.000171	-0.000145
	(0.000)	(0.000)	(0.000)
EMP	0.312***	-0.113**	-0.418***
	(0.084)	(0.048)	(0.062)
LOGTA	-0.224***	0.117**	0.391***
	(0.084)	(0.047)	(0.067)
GDP	0.0242	-0.00284	-0.0661**
	(0.023)	(0.022)	(0.027)
TANG	-1.086***	-1.394***	0.258
	(0.282)	(0.222)	(0.790)
INTA	0.508	1.779***	1.828**
	(0.526)	(0.297)	(0.907)
GRO	0.000640	-0.000163	0.00172
	(0.002)	(0.001)	(0.002)
cons	-6.964***	-2.357***	-0.982
	(0.872)	(0.568)	(0.954)
Year	YES	YES	YES
Industry	YES	YES	YES
Country	YES	YES	YES
Obs	2033	2033	2033
R^2	0.1617	0.2056	0.2124

Notes: Description of the variables can be found on table 3.6. This table reports the results of the first-stage quantile regression (equation 3.4). Term a shows the quantile of EP distribution under investigation. Significance based on bootstrap standard errors (1000 replications): ***,**,* significance level at 1%, 5%, 10%.

Table 3.15: Two-stage Quantile Regressions on ROA

α	05			50			95		
τ	05	50	95	05	50	95	05	50	95
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EP(ta)	0.0727	0.0131	1.011**	0.159	0.0627	0.891***	0.0471	0.0222	1.111**
	(0.461)	(0.197)	(0.436)	(0.400)	(0.147)	(0.266)	(0.385)	(0.176)	(0.509)
$\hat{V}(\alpha)$	0.391	0.158	-0.527	0.285	0.108	-0.426*	0.400	0.147	-0.641*
	(0.429)	(0.173)	(0.477)	(0.302)	(0.149)	(0.240)	(0.358)	(0.189)	(0.344)
Z	0.119***	1.025***	1.562***	0.114	1.023***	1.559***	0.0981***	1.017***	1.562***
	(0.041)	(0.071)	(0.122)	(0.135)	(0.096)	(0.128)	(0.031)	(0.049)	(0.099)
LEV	-0.00304	-0.000935	-0.000292	-0.00309	-0.000954	-0.000312	-0.00317*	-0.000991	-0.000265
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
EMP	0.714***	0.334***	0.377	0.550**	0.277***	0.566**	0.391	0.231**	0.757***
	(0.251)	(0.128)	(0.272)	(0.251)	(0.101)	(0.238)	(0.372)	(0.093)	(0.293)
LOGTA	-1.250***	-0.388**	-0.221	-1.125***	-0.347***	-0.359	-0.978***	-0.308***	-0.521***
	(0.295)	(0.175)	(0.242)	(0.334)	(0.121)	(0.226)	(0.326)	(0.088)	(0.182)
GDP	0.105	0.0764	-0.0127	0.0882	0.0715	0.00380	0.0520	0.0651	0.0468
	(0.127)	(0.047)	(0.066)	(0.155)	(0.047)	(0.059)	(0.123)	(0.054)	(0.163)
TANG	-0.805	-0.873*	0.884	-0.795	-0.863	0.974	-0.293	-0.666	0.395
	(1.448)	(0.499)	(1.445)	(1.270)	(0.582)	(1.525)	(1.232)	(0.587)	(1.488)
INTA	2.576*	0.620	-3.406**	2.826***	0.750	-3.834*	2.962**	0.850	-4.139**
	(1.316)	(0.509)	(1.649)	(1.094)	(0.665)	(2.103)	(1.402)	(0.750)	(1.732)
GRO	0.000706	0.00838	0.0152	0.000463	0.00826	0.0143	0.00119	0.00853	0.0130
	(0.005)	(0.007)	(0.015)	(0.004)	(0.009)	(0.011)	(0.012)	(0.014)	(0.018)
cons	2.567	2.297*	9.146	4.408	3.085**	6.481	4.876*	3.185***	6.189
	(4.354)	(1.257)	(5.934)	(3.671)	(1.319)	(4.453)	(2.676)	(1.090)	(4.369)
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs	1992	1992	1992	1992	1992	1992	1992	1992	1992
R^2	0.2018	0.2878	0.4917	0.202	0.2878	0.4921	0.2022	0.2878	0.4926
Wald		3.16**			3.98**			3.58**	

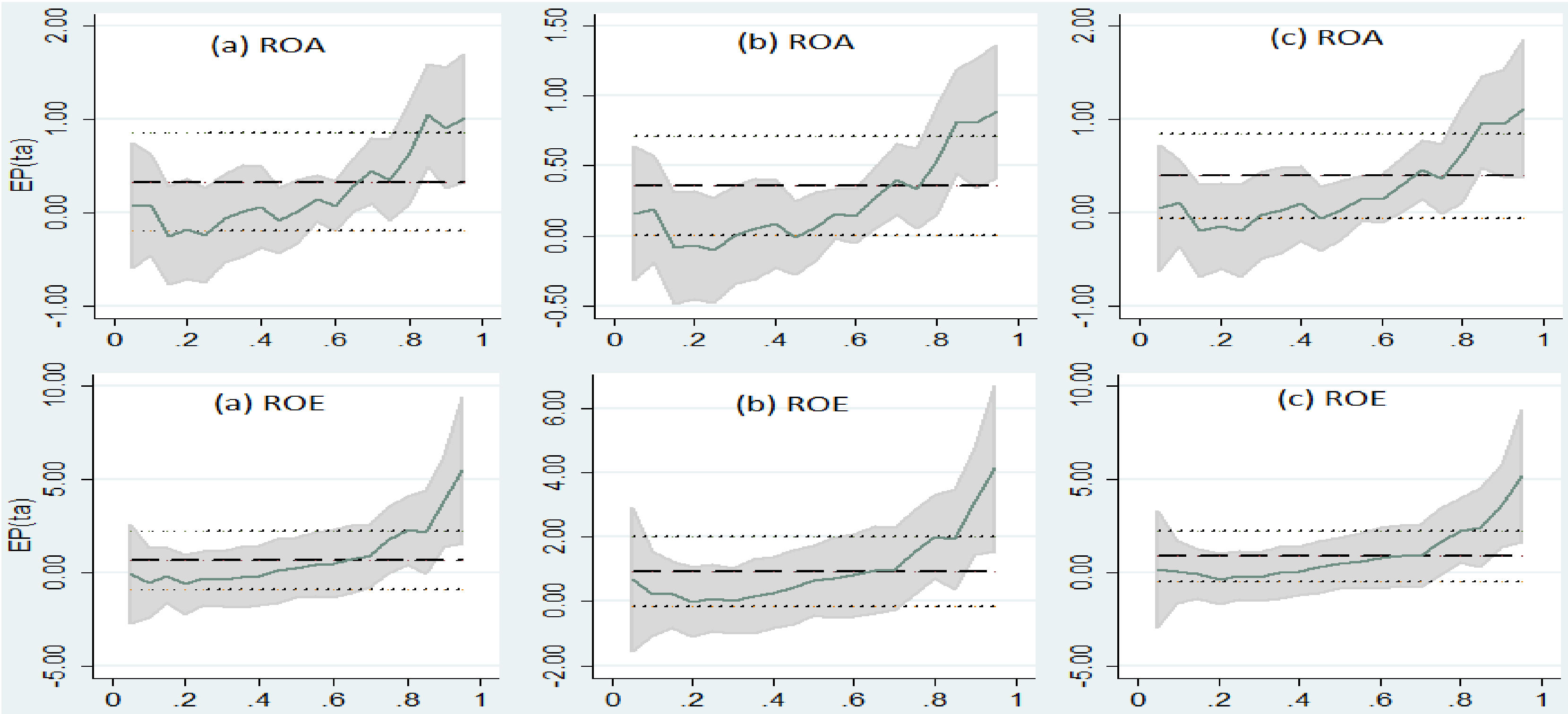
Notes: Description of the variables can be found on table 3.6. This table reports the results of the two-stage quantile regressions (equation 3.9), with τ showing different quantiles of ROA distribution. Term $\hat{V}(\alpha)$ corresponds to any α given based on the first stage estimates (equation 3.4). Significance based on bootstrap standard errors (1000 replications): ***,**,* significance level at 1%, 5%, 10%. Wald-test is for EP slopes for any α given [$\beta(0.05) = \beta(0.50) = \beta(0.95)$].

Table 3.16: Two stage Quantile Regression on ROE

α	05			50			95		
τ	05	50	95	05	50	95	05	50	95
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EP(ta)	-0.0877	0.249	5.486**	0.688	0.647	4.126***	0.171	0.496	5.172**
	(2.209)	(0.794)	(2.538)	(1.218)	(0.435)	(1.092)	(1.453)	(0.632)	(2.131)
$\hat{V}(\alpha)$	2.361	1.032	-4.724**	1.531	0.647	-3.344**	2.026	0.808	-4.306*
	(2.161)	(0.820)	(2.18)	(1.329)	(0.421)	(1.313)	(1.627)	(0.617)	(2.380)
Z	0.439***	1.188***	1.623***	0.418***	1.181***	1.641**	0.354***	1.158***	1.738***
	(0.134)	(0.199)	(0.588)	(0.125)	(0.207)	(0.679)	(0.108)	(0.157)	(0.409)
LEV	-0.0255***	0.0229***	0.0814***	-0.0250**	0.0228***	0.0809***	-0.0251***	0.0230***	0.0810***
	(0.008)	(0.005)	(0.019)	(0.011)	(0.004)	(0.021)	(0.008)	(0.005)	(0.015)
EMP	2.003*	2.018***	1.358	1.094	1.610***	3.255	0.432	1.348***	4.768***
	(1.035)	(0.655)	(1.948)	(0.932)	(0.489)	(2.076)	(1.192)	(0.511)	(1.626)
LOGTA	-2.263**	-1.933***	-2.130	-1.501*	-1.608***	-3.367	-0.788	-1.378***	-4.692***
	(1.061)	(0.698)	(2.070)	(0.859)	(0.494)	(2.063)	(0.969)	(0.444)	(1.478)
GDP	0.0832	0.214	-0.0909	0.0352	0.185	0.0258	-0.106	0.132	0.239
	(0.398)	(0.167)	(0.419)	(0.349)	(0.149)	(0.309)	(0.434)	(0.130)	(0.324)
TANG	-3.575	-1.912	12.94**	-3.396	-1.661	12.07*	-0.892	-0.487	5.817
	(4.270)	(1.272)	(5.259)	(4.267)	(1.258)	(6.815)	(4.713)	(1.243)	(9.561)
INTA	8.733	3.951***	-7.036	10.20**	4.398**	-10.27	11.00	4.708**	-12.00
	(5.384)	(1.486)	(5.676)	(4.236)	(1.763)	(10.739)	(6.886)	(1.844)	(11.719)
GRO	0.0233	0.0207	0.0878	0.0215	0.0199	0.0910	0.0252	0.0214	0.0824
	(0.019)	(0.049)	(0.066)	(0.047)	(0.054)	(0.058)	(0.040)	(0.040)	(0.056)
cons	-6.539	1.967	53.29**	5.606	7.697**	27.37*	5.473	8.331**	24.76
	(19.090)	(7.140)	(21.408)	(14.577)	(3.891)	(15.488)	(12.914)	(3.431)	(18.413)
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs	1963	1963	1963	1963	1963	1963	1963	1963	1963
R^2	0.2114	0.1542	0.2583	0.2114	0.1541	0.2587	0.2113	0.1541	0.259
Wald		5.38***			3.48**			3.74**	

Notes: Description of the variables can be found on table 3.6. This table reports the results of the two-stage quantile regressions (equation 3.9), with τ showing different quantiles of ROE distribution. Term $\hat{V}(\alpha)$ corresponds to any α given based on the first stage estimates (equation 3.4). Significance based on bootstrap standard errors (1000 replications): ***,**,* significance level at 1%, 5%, 10%. Wald-test is for EP slopes for any α given $[\beta(0.05) = \beta(0.50) = \beta(0.95)]$.

Figure 3.10: Two-stage Non-linear EP Effects on FP



Notes: The figure illustrates the two stage non-linear effects of EP on FP, based on equation 3.9. Panels a, b and c are calculated with a two step process at $\alpha = 0.05$, $\alpha = 0.50$ and $\alpha = 0.95$ respectively. For example (a) ROA shows how β estimator changes across the ROA quantiles (τ) when $\hat{V}(\alpha = 0.05)$ is given. The grey area corresponds to confidence intervals calculated with 1,000 bootstrap replications. The dash lines represent the OLS estimations with their confidence intervals (dot lines). The control variables are not reported for brevity but are available upon request.

Interestingly, the factor $\hat{V}(\alpha)$, controlling for endogeneity, is statistically significant only for high profitability firms, indicating that we can rely on the previous estimates (standard quantile regressions) regarding low and median profitability firms (Wooldridge, 2010), but the situation is much more complex for high profitability firms. The evidence of endogeneity is apparent at the upper part of the distribution ($\alpha = 0.95$), where firms with financial resources are projected. In fact, as predicted by the *financial slack argument*, these firms have the financial capacity to increase their EP even more. Similarly, $\hat{V}(\alpha)$ term in table 3.16 suggests that EP and ROE are endogenous only for high profitability firms. In other words, EP causes FP, while the reverse causality is valid only if firms have high financial resources. This result is consistent with previous studies; as meta analyses (Orlitzky et al., 2003; Albertini, 2013; Dixon-Fowler et al., 2013; Endrikat et al., 2014) jointly indicate, EP and FP are positive correlated. Notably, causality involves the positive link of EP with FP and the partially positive link of FP with EP.

The main results are graphically represented in Figure 3.10, depicting that superior EP results in better FP. The graph extracted from the second stage results represents a monotonically increasing sequence. In order to understand the asymmetries of the relationship, Wald statistics for testing equality indicate that EP coefficients have, on average, significant differences across quantiles. Therefore the non-linear, endogenous and positive relationship seems to be the most relevant framework for the EP-FP examination of the EU manufacturing sector. Therefore, *instrumental stakeholder theory*, under the prism of the *financial slack argument*, is the best way to describe our findings. Overall, EP seems to be an effective strategy for firms in order to sustain a competitive advantage, validating the *Porter Hypothesis* (Porter, 1991).

3.5 Conclusion

Our paper examined the effect of EP on FP using data from a sample of 288 EU manufacturing firms for the period 2005-2016. We used an innovative approach combining the standard quantile methodology (Koenker and Bassett, 1978) with instrumental variables for EP (Lee, 2007). This gave an opportunity to account for potential non-linearity and endogeneity between EP and FP.

The main results that emerge from this paper are that (i) EP has a positive effect on FP, (ii) the relationship between EP and FP is heterogenous across the conditional distribution, and (iii) FP and EP are endogenously related for high profitability firms. Taken together, these results suggest that a positive theoretical framework (i.e. *instrumental stakeholder theory*) under the *financial slack argument* mirror the relationship between EP and FP.

In particular, our evidence shows a statistically significant relationship depicting a U-shaped curve between the EP coefficients and the associated quantiles of FP. The schematic representation follows a steady process at the median quantiles and it increases at the beginning and the end of the distribution. For all regressions, the result suggests that lower emissions significantly increase ROA, ROE, industry-adjusted-ROA and industry-adjusted-ROE for firms across the whole distribution. Our findings are in line with studies that use a contemporary, large data-set for an international sample (Lewandowski, 2017; Trumpp and Guenther, 2017). On the contrary, previous studies conducted with EU samples have rather negative results (Wagner et al., 2002; Wagner, 2005). A possible explanation, apart from the small sample of the previous studies, is that during the examined period (1995-1997), companies were not subject to European regulations (i.e. EU ETS).

Another important aspect of the examination is that we have adequate evidence to support the endogeneity between EP and FP for high profitability firms. Thus, endogeneity is conditional on the profitability levels. A research implication of this is that empirical studies should avoid generalising results and they should distinguish between low and high profitability firm samples. We also show that estimations with low profitability firm samples are more likely to be unbiased, while it is risky to assume no endogeneity for high profitability samples; this problematic situation can be solved with an instrumental variable approach.

Additionally, we consider some regulatory and managerial implications. EP has a multidimensional nature and hence many interconnections can arise (Busch and Lewandowski, 2017). For instance, the finding that participation in the EU emissions trading scheme increases the carbon emissions of large polluting firms should generate regulatory concerns. Also, the role of ISO as a managerial strategy to loosen regulatory pressure is still unclear. Misani and Pogutz (2015) note that environmental management is done merely for symbolic purposes without improving the carbon footprint. More importantly, policymakers should develop cheap access to finance green investments particularly for low profitability firms; otherwise, such firms do not have clear benefits from EP. Despite the increasing volume of environmental regulations, mitigation policies to address climate change provide insufficient motives for adaptation.

Concluding this paper, we would like to offer some potential avenues for future research. First, it could be useful to examine the net benefit from the EP to the FP in the EU area for a greater number of industries (see Hatakeda et al., 2012). Second, a similar semi-parametric examination for the US market could reveal interesting results. Parametric studies have reported that EP positively affects FP in the US (Ben-Amar and McIlkenny, 2015; Dawkins and Fraas, 2011; Matsumura et al., 2014). It would be intriguing to investigate how EP behaves in different quantiles. Third, more information on the EU emissions trading scheme [the carbon price, the free carbon allowances and whether firms buy or sell those allowances (Clarkson et al., 2015)] would help us to establish greater accuracy in our results, along with a better understanding of EP. Fourth, a similar analysis could have used cash-flows instead of ROE or ROA in order to conceptualise the *slack resource argument*. Finally, more research should be devoted to dynamically and non-parametrically modelling of the relationship.

4 Second Empirical Chapter: The Nexus between Environmental Disclosure and Idiosyncratic Risk

4.1 Introduction

FOR the past several years, great consideration has been given to the economic implications of the environmental responsibility of firms, not only by company stakeholders including investors, managers, suppliers, employees and governments, but also by researchers and scholars (Zhang, 2017). More particularly, the disclosure of environmental information is rather crucial for shaping future actions of both investors and policy-makers (Qiu et al., 2016). At the same time, in an attempt to monitor rising temperatures, the European Parliament has underlined the importance of corporate environmental disclosure for identifying sustainability risks and for helping increase both investor and consumer trust (EU Commission., 2014). Reporting transparent environmental information not only mitigates information asymmetries, but also helps towards shaping an informative network within society which is rather crucial for dealing with climate change (Stern, 2007; Aggarwal and Dow, 2012; IPCC, 2014). In this paper, we add to the discussion about climate change by examining whether the disclosure of environmental-performance information by European manufacturing firms is conducive to less uncertainty in the relevant market.

Environmental disclosure[22] is the information that is publicly disclosed by firms and relates to climate change activities (Al-Tuwaijri et al., 2004; Luo et al., 2012; Matsumura et al., 2014). Transparent environmental information has the potential to appease market expectations because firms signal their smooth transition to the new climate era (Benlemlih et al., 2016). In turn, this signalling could have implications for the financial state of the firms. For instance, a rea-

[22] One example of transparent environmental disclosure is when firms report greenhouse gases, energy consumption, renewable energy consumption and total waste.

sonable question is whether disclosing such information reduces firm risk. To be more explicit, total risk of financial investment can be decomposed into systematic and idiosyncratic components. In this study, we concentrate on the latter because it is shaped by firm-specific characteristics; implying that, making the right decisions should diminish said risk. In retrospect, given the importance of idiosyncratic risk for investment decision making (e.g., Merton, 1987; Ang et al., 2006; Lin et al., 2014), in this study we investigate how environmental disclosure affects idiosyncratic risk.

The effects of environmental disclosure on the risk of financial investment build on a complex theoretical framework (Brooks and Oikonomou, 2018). On the one hand environmental disclosure promotes the values and ethics of firms, and thus firms are more likely to experience lower levels of risk (Jiang et al., 2009; Molina-Azorin et al., 2009), as it is predicted by both the *legitimacy* and the *stakeholder theory*. On the other hand, environmental disclosure can be detrimental (Friedman, 1970; Jensen and Meckling, 1976) because it exposes firms to unnecessary criticism and high pollution-abatement cost (Wagner et al., 2002; Lee et al., 2015), as *managerial opportunism* advocates. The theoretical controversy is further stressed by the *slack resource argument*, according to which, the financial state of firms affects their level of environmental engagement. In this regard, we investigate whether different levels of idiosyncratic risk affect both the strength and the sign of this relationship across firms.

Empirical studies conducted over the years have substantially improved our knowledge about the effects of environmental disclosure on firm performance. These studies imply that disclosure in general decreases the information asymmetries between firms and investors and thus it is negatively related to risk (Ferreira and Laux, 2007; Benlemlih et al., 2016; Qiu et al., 2016). However, due to the sensitive nature of environmental information, investors are advised to exercise caution when making future investment decisions (Cormier and Magnan, 2015). This is apparent from the body of research that examines the relation between environmental and financial performance, and reports inconclusive results. Meta-analytic papers (Horvathova, 2010; Dixon-Fowler et al., 2013; Albertini, 2013; Endrikat et al., 2014) suggest that the controversy of the results is attributed to intense endogeneity. To put it differently, empirical findings regarding the relationship between financial and environmental performance might vary depending on the measures employed to approximate these variables (Orlitzky and Benjamin, 2001; Delmas et al., 2015; Misani and Pogutz, 2015; Nollet et al., 2016; Trumpp and Guenther, 2017; Brooks and Oikonomou, 2018). It should also be noted that the majority of the studies utilise accounting profitability ratios (e.g., ROA, ROE, Sales) as measures of financial performance, but they typically neglect to examine how risk responds to environmental disclosure.

The main objective of this study is to examine how disclosing environmental information affects firm risk. We mainly focus on the idiosyncratic risk of financial investments. We further outline the controversial predictions of economic theory and evaluate the relevance of specific theories for examining the risk-disclosure nexus. Another important aim of our study is to investigate if the level of idiosyncratic risk moderates the magnitude of the environmental disclosure effect. Thus far, studies focus only on the average picture by neglecting to investigate how firms that operate in the tails of the distribution are affected. Finally, we evaluate the effect of voluntary environmental disclosure on a sample of manufacturing firms that are subject to stricter environmental regulation (Mallin and Ow-Yong, 2012).

Our study offers four important contributions. First, although prior studies have examined the effects of environmental disclosure on idiosyncratic risk (Lee and Faff, 2009; Salama et al., 2011; Oikonomou et al., 2012; Cai et al., 2016; Diemont et al., 2016; Utz, 2017; Linciano et al., 2018), we test the said relationship under the contradicting theoretical framework and we provide evidence about the relevance of these theories. Second, in contrast to previous literature that uses the traditional capital asset pricing model and at some occasions the four factor model

(Mishra and Modi, 2013; Bouslah et al., 2013; Benlemlih et al., 2016), we utilise both the four- and five-factor model to estimate idiosyncratic risk. Third, our study demonstrates that the financial slack of firms moderates the examination and thus the overall environmental disclosure of a portfolio has a heterogeneous effect on investments with different risk levels, an important yet under-researched area of the empirical finance literature (Ang et al., 2006). Fourth, this study offers new evidence from the highly regulated EU manufacturing sector.

By utilising a framework of multiple regressions in a strongly balanced data set of 288 manufacturing firms covering the period from 2005 to 2016 in 17 European countries, we find significant evidence that environmental disclosure reduces the idiosyncratic risk. This finding provides additional support to both the *stakeholder* and *legitimacy theory*, emphasising the importance of transparent environmental disclosure as a management practice for risk-reduction. After controlling for endogeneity within a dynamic panel data model, results remain robust. Additionally, consistent with the *slack resource argument*, quantile regressions reveal that there is asymmetric relationship; that is, disclosure is more likely to affect investments with high rather low idiosyncratic risk. Particularly, our results show that investors significantly value the environmental transparent practices of the EU firms,in line with the study of (Ziegler et al., 2011). While, as expected, a perfectly diversified portfolio does not seem to price in environmental actions, similarly to (Ang et al., 2006). Finally, in line with Benlemlih et al. (2016), the alternative model specifications help us determine that environmental disclosure has stronger link with idiosyncratic risk rather than other risk types.

This research has profound implications for CEOs, portfolio managers and investors. First, the negative environmental disclosure - idiosyncratic risk nexus can be perceived by CEOs as a signal to pledge to more transparent environmental policies, which will be rewarded by the stock market in terms of lower idiosyncratic risk of investment. Second, because idiosyncratic risk can be diversified away, the negative effect of environmental disclosure on idiosyncratic risk helps portfolio managers and investors identify stocks of companies that offer greater diversification benefits. Indeed, our results imply that portfolio investment in potentially fewer stocks of environmentally transparent than opaque companies can help portfolio managers and investors diversify the risk of portfolio investment. Third, if the volume of financial transactions is proportional to transaction costs, then a portfolio made up of fewer stocks may be associated with lower transaction costs.

The remainder of the paper is organised as follows. In Section 4.2, we present the main hypotheses. Section 4.3 describes the data and the methodology. In Section 4.4, we report the empirical results. We then conclude with Section 4.5.

4.2 Hypotheses Development

The aim of this section is to define the hypotheses that are based on the theoretical framework between environmental disclosure and idiosyncratic risk. From the lens of *signalling theory* (Connelly et al., 2011), information asymmetries between stakeholders and firm can be attenuated when firms provide transparent information about their practises. More specifically, environmental disclosure can strengthen the bonds with investors, customers, suppliers and regulators (*legitimacy theory*) and thus firms can be less vulnerable to external and internal shocks. A good firm-stakeholder relationship (*stakeholder theory*) acts as a protection-scheme and a firm can eventually sustain a competitive advantage which in turn will assist to attain its financial objectives. However, transparent environmental information does not necessarily suggest "good" environmental performance (Al-Tuwaijri et al., 2004) and it might be done for symbolic purposes as *managerial opportunism* implies. Overall, three main theoretical categories can be withdrawn according to how environmental disclosure contributes to the risk (see Table 4.17). First, transparent environmental information can increase the idiosyncratic risk due to the fact that firms are exposed to criticism. Second, complete environmental information reduces the risk because firms have stakeholders informed and thus can hold fully-diversified portfolios. Finally, the relationship is more complex and might be moderated by the financial slack of the firms (*slack resource argument*).

Table 4.17: Theory between Environmental disclosure and Risk

Theory	**Expected Risk outcome**	**Concept**
Managerial opportunism	+	Managerial discretion
Slack resource argument	-	Effective resource allocation
Stakeholder theory	-	Integrating management
Legitimacy theory	-	Transparent information
Natural resource based view	Initially + then - ($\cap$ shape)[1]	Competitive advantage
Finance theory	Initially $\pm$ then $\pm$	Investment uncertainty

Note: The link between environmental disclosure and idiosyncratic risk is observed in the aforementioned theories. The second column illustrates the expected sign of the risk according to the underlined theory. The third column corresponds to the concept of its theory. [1] Inverted U shape association.

4.2.1 Positive Association between Disclosure and Risk

We begin by considering the positive relationship between environmental disclosure and risk. The positive theoretical framework can be justified due to the higher cost that firms have to endure while at the same time, firms are exposed to unnecessary criticism (Brown and Deegan, 1998). Another justification of the positive association between social performance and risk is suggested by the *managerial opportunism theory* (Bouslah et al., 2013). The theory is referring to the principal-agent problem with the latter acting according to their own preferences and disregarding the principals' objectives (Jensen and Meckling, 1976). Particularly, managers might over-disclose environmental actions for symbolic purposes because they would like to be considered as environmental-sensitive managers. Such disclosure will increase the investors' concerns and as a result the uncertainty arises. Disclosure should be accompanied with "good" environmental performance, otherwise firms will not agree to provide this kind of information (Lee et al., 2015). Manufacturing firms would need to bear high environmental cost in order to operate "green" (Wagner, 2005). Therefore, there is a direct trade-off between the cost and the benefit, entailing that manufacturing firms will eventually face competitive disadvantage.

Few studies are found in the literature to document positive association between idiosyncratic risk and general transparency (Lin et al., 2014; Wu et al., 2016). While the majority of the studies that correlate corporate social actions with the idiosyncratic risk, obtain results in favor of the negative outcome (Ferreira and Laux, 2007; Mishra and Modi, 2013; Cai et al., 2016; Utz, 2017).

4.2.2 Negative Association between Disclosure and Risk

Regarding the negative theoretical justification, environmental disclosure may reduce the asymmetric information and signal an environmental sensitive to the investors firm (Bouslah et al., 2013). At the same time, such actions minimise the risk to damage the reputation of the firm and governments set less regulatory environmental pressure (Reinhardt and Stavins, 2010). For instance, a negative framework between disclosure and risk can be found in the *stakeholder theory*. The theory advocates that a green firm improves the efficiency, the visibility, reduces the operational cost and tightens bonds with ethical-investors, employees, consumers and government (Jones, 1995). In a stakeholder framework, Salama et al. (2011); Oikonomou et al. (2012) identify that social actions significantly decrease the systematic risk and wonder about the potential impact on idiosyncratic risk.

In addition, the notion of the negative association is that firms operate in a society where they have to contribute and inform the public about their environmental actions. The ethical approach of the relationship is best described by the *legitimacy theory*. Reporting environmental information would potentially lead to legitimise their corporate actions and abate the demands of the society (Guthrie and Parker, 1989). For instance, disclosing firm's ecological performance will have a result to alleviate the external pressure for climate change. Also, transparent information regarding the environmental performance means that they have to operate eco-friendly in order to make visible their environmental sensitivity and so they expect to have profitability boosted (Ben-Amar and McIlkenny, 2015). For this reason, according to the *legitimacy theory*, a firm which informs the investors and society will be awarded because (1) it legitimises its actions and (2) diminishes the asymmetric information.

There are numerous studies (Al-Tuwaijri et al., 2004; Dawkins and Fraas, 2011; Matsumura et al., 2014; Nollet et al., 2016) that examine the impact of environmental disclosure on the stock performance. The studies imply that higher disclosure improves the financial condition of the firms. Previous studies (Salama et al., 2011; Bouslah et al., 2013; Mishra and Modi, 2013; Cai et al., 2016; Diemont et al., 2016) examine whether corporate social strengths and concerns are linked to the idiosyncratic risk. The studies underline the effect of environmental initiatives and how the decisions from the board of directors can influence the investment climate. Environmental strengths are generally linked to the risk-reduction assumption. Benlemlih et al. (2016) is closely related to our paper. They examine the effect of corporate and environmental disclosures on idiosyncratic, systematic and total risk for a sample of British companies and they support that disclosure significantly decreases idiosyncratic but not systematic risk. However, we cannot reject that environmental disclosure affects idiosyncratic risk abnormally. So far, researchers pay major attention to the profitability of the firms, by neglecting the risk associated with this performance. The majority of the empirical literature is consistent with the negative association between corporate actions and risk. Therefore, we extract the following hypothesis:

Hypothesis 1: Following the *legitimacy* and *stakeholder theory*, high environmental disclosure has a negative impact on idiosyncratic risk.

4.2.3 Financial Slack and Disclosure

Slack resource argument is referred to the social and human capital resources that can influence the firm's performance (George, 2005). Empirically, Knight et al. (2019) show that firm resources can influence the adoption of environmentally sustainable strategies. In a similar vein, riskier firms normally undertake more environmental projects and therefore risk and disclosure are "co-determined" (Orlitzky and Benjamin, 2001). Therefore, financial state can influence the environmental disclosure of firms. This is because it involves a commitment to financially support environmental actions. Previous studies pinpoint that the level of environmental engagement can affect the financial performance of the firm by solely focusing on the mean of the financial performance distribution (e.g, Misani and Pogutz, 2015; Qiu et al., 2016; Trumpp and Guenther, 2017; Lewandowski, 2017). Herein, we argue that disclosure might behave differently across investment-portfolios with high and low risk.

Hypothesis 2: Under the *slack resource argument*, environmental disclosure can heterogeneously affect the idiosyncratic risk at different levels of idiosyncratic risk.

4.3 Research Design

4.3.1 Sample and Data

The sample consists of 288 European firms of the manufacturing sector that are included in the STOXX Europe 600 Index across 17 countries of the European region, covering a 12 year period from 2005 to 2016 (see table 4.18). Those firms are chosen because the unavailability of data creates constrains for investigating larger sample. In addition, manufacturing firms have been highly criticised because are connected with climate change since they emit large amount of carbon.

For this reason, the EU environmental regulations[23] have enforced firms to disclose essential information about their climate change actions and at the same time firms are monitored for the reliability of the data, implying that our sample includes firms with high visibility [controversially with Merton's (1987) model]. 2005 has been chosen as the initial year because the EU emissions trading scheme was activated and Kyoto Protocol set into force.

4.3.2 Variables of the Study

Idiosyncratic risk

To answer the hypotheses, idiosyncratic risk needs to be constructed. Previous studies (e.g., Ferreira and Laux, 2007; Fu, 2009) define idiosyncratic risk as the standard deviation of the residuals of the pricing models. Capital asset pricing model, three-factor (Fama and French, 1993) and four-factor (Carhart, 1997) models have been used for this type of examination extensively. We compute our risk results based on the four-factor model following Mishra and Modi (2013); Bouslah et al. (2013); Cai et al. (2016).

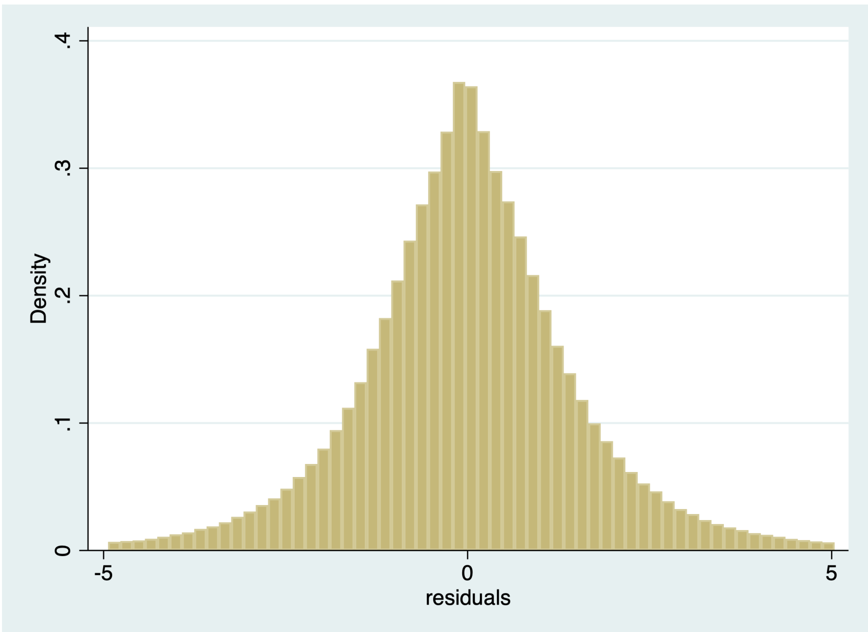
$$R_{i,t} - R_{f,t} = \beta_i + \beta_{i,1}(R_{m,t} - R_{f,t}) + \beta_{i,2}SMB_t + \beta_{i,3}HML_t + \beta_{i,4}MOM_t + u_{i,t} \quad (4.10)$$

The left part of the equation corresponds to the excess stock return, $(R_{mt} - R_f)$ is the excess return on the market portfolio , the second factor (SMB) measures the return of small over large stocks, (HML) the return of value over growth stocks, the momentum factor measures the portfolio returns of winner over loser stocks (MOM) and u_{it} is the residuals. R_{mt}, R_f, SMB_t, HML_t and MOM_t values for the

[23] Commission Regulation (EU) No 601/2012 of 21 June 2012 on the monitoring and reporting of greenhouse gas emissions. During the second compliance cycle of the greenhouse gas emissions trading scheme, covering the years 2008 to 2012, industrial operators, aviation operators, verifiers and competent authorities have gained experience with monitoring, reporting greenhouse gases and establishing guidelines for the monitoring and reporting of greenhouse gas emissions. The rules for the third trading period of the Union's greenhouse gas emission allowance trading scheme which begins on 1 January 2013 and for the following trading periods should build on that experience. See more on: https://ec.europa.eu/clima/policies/ets/monitoring_en

European market are retrieved from Kenneth R. French website. Stock returns ($R_{i,t}$) are downloaded from Datastream. Note that we could construct our own systematic factors endogenously from our sample, however, we wish to benchmark our findings across the whole European market. All the aforementioned values are on a daily frequency for all 288 firms for the 12 year period. We next run ordinary least squares (OLS)[24] regressions to eq.(4.10) by assuming that the residuals are normally distributed with zero mean and constant variance. In fact, Figure 4.11 shows that residuals $\sim \mathcal{N}(0, \sigma^2)$ We repeated this procedure for each year of the sample in order to obtain 12 different variances for every firm. Then, we define the idiosyncratic risk ($Risk$) as the annualised standard deviation of the residuals ($Risk = \sigma(u_{i,t}) \times \sqrt{K} \times 100\%$), where k corresponds to trading days of any year given with $k = 1, 2, ..., K$).

Figure 4.11: Histogram of residuals from four factor model



[24] Fu (2009) employed Egarch models to construct the idiosyncratic risk and found that OLS and Garch models provide with very similar idiosyncratic risk results.

Environmental disclosure

Answering the hypotheses, environmental disclosure score ($Disc$) is used. Disclosure is produced by Bloomberg database and it measures the quality and magnitude of the environmental information disclosed by each firm. While previous studies use binary or low range scores to account for the disclosure (see, Fisher-Vanden and Thorburn, 2011; Barnett and Salomon, 2012; Hsu and Wang, 2013; Matsumura et al., 2014), our score takes values from 0 to 100 with the lowest values corresponding to lack of climate change information. This indicates that our examination might varies substantially across different quantiles. The fact that contemporaneous literature has a growing interest in Bloomberg's scores strengthens the appropriateness of this variable as a proxy of environmental disclosure (Nollet et al., 2016; Broadstock et al., 2018; Petitjean, 2019). As examined by Qiu et al. (2016); Benlemlih et al. (2016), the score weights the information provided by firms for 60 different environmental actions and it is normalised according to the mean disclosure of the industry that firms operate, as well as disclosure score is also normalised by year (see more about environmental disclosure in Appendix B).

Other Control Variables

We employ a set of different variables that affect the idiosyncratic risk (table 4.19). First, the probability of default measured by Altman's Z-score (Z), low values correspond to higher probability of default and should induce higher idiosyncratic risk (Bouslah et al., 2013). Z-score sums up five weighted measures in order to classify firms according to their financial distress and it uses both accounting and market based indicators. Firms with high probability of default are closely tied to idiosyncratic risk (Lopez, 2004). In contrast to default risk, leverage (Lev) is debt to equity ratio which is measured by summing the short and long term liabilities divided by the market value. Leverage is a proxy of financial risk and it is expected to be positive because risky firms hold usually more debt (Ang et al., 2006; Psillaki et al., 2010; Mallin and Ow-Yong, 2012). High leverage implies that stakeholders bear a high amount of cash flow risk and therefore volatility of the stock return increases.

Furthermore, larger firms have diversified activities and hence less idiosyncratic risk. We use as a size proxy the logarithm of the total assets (LogTa) (Lee and Faff, 2009; Mishra and Modi, 2013; Cai et al., 2016). Profitability is linked to the risk. Return on assets (ROA) measures the ability of the firm to generate profits from its assets and it is used as a proxy for financial profitability. High profitability might act as signal to investors about the soundness of the firm (Mishra and Modi, 2013). Another profitability proxy is the the annual growth rate of total sales (Growth), growth displays the firm's cash flows and so it is expected to decrease the risk (Ang et al., 2006).

Additionally, the future prosperity can be represented by intangible assets (Inta). They cannot be easily collateralised but they add value to the firm (Psillaki et al., 2010). Intangible assets have characteristics of Research and Development (R&D) and it might either generate future profits or losses (Elsayed and Paton, 2005). Intangibility is generally expected to have negative association with risk. Also, tangible assets (Tang) can be a proxy for the collateral of the firm. Negative relation between risk and tangibility is expected because creditors can liquidate assets easily and thus they face less risk (Konar and Cohen, 2001).

Finally, we include year (Year), industry (Industry) and country (Country) dummies to control for the unobserved firm heterogeneity. Different industries have been observed to have different risk and different countries affect dis-similarly the idiosyncratic risk of their firms (Chen and Wang, 2012; Mishra and Modi, 2013; Wu et al., 2016).

Table 4.18: Industry and Country Composition

Panel A: Industry Composition		
Industry	**Frequency**	**Percent**
Technology	11	3.82
Telecommunications	12	4.17
Consumer Discretionary	56	19.44
Consumer Staples	40	13.89
Industrials	88	30.56
Basic Material	40	13.89
Energy	17	5.9
Utilities	24	8.33
Panel B: Country Composition		
Country	**Frequency**	**Percent**
Germany	36	12.5
United Kingdom	71	24.65
France	47	16.32
Italy	14	4.86
Spain	14	4.86
Netherlands	15	5.21
Switzerland	18	6.25
Sweden	24	8.33
Norway	8	2.78
Austria	4	1.39
Belgium	6	2.08
Denmark	5	1.74
Finland	14	4.86
Ireland	7	2.43
Czech Republic	1	0.35
Portugal	3	1.04
Luxemburg	1	0.35
Total	288	100

Same as Chapter 3 . Firms are allocated to industries according to the Industry Classification Benchmark (ICB).

Table 4.19: Variable description and source of data

Variables	Concept	Source
Risk	(Idiosyncratic risk) Annualised standard deviation of 4-factor model's residuals	Kenneth French[a]
5.Risk	(Idiosyncratic risk) Annualised standard deviation of 5-factor model's residuals	Kenneth French[a]
T.Risk	(Total risk) Annualised standard deviation of stock returns	Datastream
Disc	Environmental disclosure score	Bloomberg
Z-score	(Default risk) Altman's Z = 1.2* (WC/ TA)+1.4* (RE/ TA)+3.3* (EBIT/ TA) +(Sales/ TA)+0.6* (MV/ TL), higher score denotes lower probability of default	Datastream, Bloomberg
Lev	Leverage = total debt/total equity	Datastream
LogTa	Log of TA	Datastream
ROA	Return on assets	Bloomberg

Continued on next page

Table 4.19: continued from previous page

Growth	Annual growth rate of total sales	Bloomberg
Tang	Tanglible assets/ TA	Bloomberg
Inta	Intangible assets/TA	Bloomberg
Q	Tobin's Q = (MV + TL + PE + MI) / TA	Bloomberg
R&D	Log of research and development expenses	Datastream
[WC, TA, EBIT, RE, MV, TL, PE, MI][b]	Variables for calculations , WC= working capital, TA= total assets, EBIT= earnings before interest and taxes, RE= retained earnings, MV= market value, TL= total liabilities, PE= preferred equity, MI= minority interest	Datastream, Bloomberg

[a] The factors (SML, HML, MOM, RMW, CMA, R_M and R_f) to calculate idiosyncratic risk are retrieved from Kenneth R. French Data library (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

[b] All money-based indicators for all countries, for each given year, are adjusted into current Euro.

4.3.3 Descriptive Statistics and Correlations

We continue this subsection by presenting some descriptive statistics and correlations of the variables employed in the regressions. Firstly, our final sample numerates 3,465 firm-year observations. Having a closer look at panel A in table 4.20, disclosure is the variable with the most missing values comparing to the rest of the data-set with 2788 valid observations. In a pooled sample of 901,728 firm-daily observations, we extract 3389 annual idiosyncratic risk values, which have a mean (median) of 26.96 (24.11) with the highest value being 115.08 and standard deviation of 10.62. In terms of the distribution of the variables Disc, Inta, ROA and LogTA are very close to satisfy the normality conditions (Skewness=0 and Kurtosis=3). While Risk, Z, Lev, Tang and Growth have a leptokurtic distribution and they also have fat upper tails apart from Lev with a thick lower tail. Panel B reports the correlations. Pairwise correlations gives some preliminary view of the effect of independent variables on Risk. Note that most of the examined variables have a negative and very low correlation with Risk. Particularly, disclosure negatively correlates with Risk at a rate of 22.3%.

Table 4.20: Descriptive Statistics and Correlations for the Main Variables

Panel A: Descriptive Statistics									
	(1) Risk	(2) Disc.	(3) Z-score	(4) Lever.	(5) Inta.	(6) Tang.	(7) ROA	(8) LogTA	(9) Growth
Obs	3389	2788	3232	3437	3282	3349	3341	3437	3390
Mean	26.96	35.68	4.86	90.25	0.22	0.80	6.06	9.06	9.03
Std	10.62	16.21	9.97	601.48	0.19	0.22	5.34	1.46	66.81
Min	10.62	2.33	-0.52	-22583.33	0.00	0.00	-9.03	3.41	-91.06
1st Q	19.75	23.96	2.32	34.98	0.06	0.68	2.83	8.04	-1.25
Med	24.11	37.21	3.46	64.57	0.18	0.85	5.21	9	5.09
3rd Q	31.30	47.29	4.99	114.72	0.35	0.96	8.43	10.15	12.56
Max	115.08	75.97	328.07	10020.93	1.16	2.72	28.28	12.9	2290.13
Skew	1.90	-0.09	19.83	-20.69	0.92	-0.08	0.94	0.04	27.66
Kurt	9.14	2.31	524.37	872.52	3.29	8.84	4.93	2.62	868.33
Panel B: Correlations									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	1								
(2)	-0.2229*	1							
(3)	0.0563*	-0.1365*	1						
(4)	-0.0153	0.0291	-0.0244	1					
(5)	-0.0914*	-0.0895*	-0.0841*	0.0203	1				
(6)	-0.0005	-0.0192	0.1034*	-0.0091	0.0051	1			
(7)	-0.1165*	-0.1282*	0.1882*	-0.0411*	-0.03	-0.0242	1		
(8)	-0.2501*	0.4932*	-0.2642*	0.0543*	-0.0054	-0.0909*	-0.3482*	1	
(9)	0.0599*	-0.0485*	0.034	0.0149	0.0282	-0.0045	0.0721*	-0.0487*	1

All variables are defined in Table 4.19. * denotes 5% level of significance. Std= standard deviation, Q= quartile, Med=median, Skew= skewness and Kurt= kurtosis.

Table 4.21: Risk and Return, with average t-Statistics

Risk	Very low (q<5%)	Low (q<25%)	Lower middle (q<50)	Higher middle (q>50%)	High (q>75%)	Very high (q>95%)
Disc	43.528*	40.613*	38.623*	32.739*	30.862*	26.849*
	(-5.706)	(-9.399)	(-9.739)	(9.739)	(9.339)	(7.062)
Return	10.063	10.708*	10.979*	-0.314*	-11.446*	-26.535*
	(-1.445)	(-4.368)	(-8.039)	(8.039)	(14.436)	(10.874)

The table shows disclosure and return of portfolios with different idiosyncratic risk levels. T-Statistics are reported in parenthesis, comparing the different risk portfolios with the rest of the sample, where q denotes the quantile of $Risk$ variable. * denotes 5% level of significance.

In addition, there is a debate whether portfolio managers and investors should prefer firms with higher disclosure unconditionally. As expected, investing in disclosing assets implies lower idiosyncratic risk and thus lower risk should generate lower returns. As shown in Table 4.21, low risk portfolios are followed by higher disclosure and higher returns than the high risk portfolios. Therefore, in line with Ang et al. (2006), lower idiosyncratic risk does not necessarily indicate lower returns. We now proceed to econometrically test if indeed disclosing environmental information can decrease the idiosyncratic risk of a portfolio.

4.3.4 Empirical Model

This subsection presents three different types of econometric techniques. (1) Panel, (2) dynamic panel and (3) quantile regressions. We are trying to capture all different aspects of risk-disclosure relationship since there is no extensive literature on this particular topic. The methodology aims to deal with the endogenous and non-linear estimates and at the same time to provide insights into the overall effect of environmental disclosure on the firm risk.

Panel Model

Having discussed about how environmental disclosure and risk are connected, we now proceed to estimate their relationship. Following previous studies (e.g., Delmas et al., 2015; Nollet et al., 2016) we employ panel data methodology and we stress disclosure in risk regressions as shown below:

$$Risk_{i,t} = a_0+a_1 Disc_{i,t}+\mathbf{X}'_{i,t}\phi+\sum_{t=2}^{T}\delta_t Year_t+\sum_{m=2}^{M}\delta_m Industry_m+\sum_{j=2}^{J}\delta_j Country_j+e_{i,t} \tag{4.11}$$

Where the subscripts i and t correspond to firm and year respectively, $i = 1, 2, ..., n$ and $t = 1, 2, ..., T$ and $e_{i,t}$ the error term. *Risk* denotes the idiosyncratic volatility and $\mathbf{X}'$ is a vector that contains control variables (Z, Lev, Inta, Tang, ROA, LogTa, Growth). We also control for year, industry and country fixed effects, so a_0 intercept is refereed to the base year (2005), industry (Technology) and country (Germany) where $m = 1, 2, ..., M$ and $j = 1, 2, ..., J$. Particular attention should be place on the variable of interest which is *Disc* and the coefficient we should observe is a_1. According to the first hypothesis (**H1**), we perform one-tailed test, so the null hypothesis is $H1_0 : a_1 \geq 0$ and alternative $H1_1 : a_1 < 0$.

The results are presented under the pooled OLS, fixed effect and random effect models. For all different specifications, we use robust standard errors. Fixed effect model is appropriate when we focus on a specific firm characteristics (c_i) and therefore $e_{i,t}= v_{i,t} + c_i$ with $v_{i,t}$ being a time-varying error component. Note that in case of fixed effect model industry and country dummies are dropped from the model to avoid multicollinearity. Random effect model represents random draws from the population so that c_i allows for individual effects. In contrast with the previous models, pooled OLS estimates constant coefficients ($c_i = c$). Finally, we report likelihood ratio redundant fixed effects and Hausman test in order to identify if the individual effects c_i are unobserved and are correlated with explanatory variables (Baltagi, 2008; Oikonomou et al., 2012).

Dynamic Panel Model

The problem of endogeneity which has been reported continuously should be carefully considered (Tamazian and Bhaskara Rao, 2010; Coban and Topcu, 2013; Albertini, 2013; Endrikat et al., 2014; Busch and Lewandowski, 2017). A system of generalised method of moments (Sys-GMM), which is proposed by Blundell and Bond (1998) can control for endogeneity in our estimations. The use of this model is motivated by the study of Orlitzky and Benjamin (2001) who underscore that environmental actions and risk may be endogenously related and therefore the equation 4.11 is tested with dynamic panel model:

$$Risk_{i,t} = a_0 + a_1 Disc_{i,t} + \beta_1 Risk_{i,t-1} + \mathbf{X}'_{i,t}\phi + \sum_{t=3}^{T} \delta_t Year_t + e_{i,t} \tag{4.12}$$

Moreover, equation 4.12 is instrumented with lagged values of the explanatory variables. However, lagged values are usually weak instruments and thus sys-GMM combines the first-difference estimator with the estimator in levels in order to efficiently deal with the endogeneity. The description of the variables is as above and again $e_{i,t} = v_{i,t} + c_i$ is referred to the typical fixed effect components of the error term, with the assumption that $E(v_{i,t})= E(c_i)= E(v_{i,t}c_i)$ =0, for i=1,..,n and t=2,..,T. In order to avoid the over-identified restrictions and auto-correlation, we do not include industry and country dummies. The model is appropriate to re-address the hypothesis 1 (**H1**).

In order to satisfy the orthogonality condition, we collapse instruments as proposed by Roodman (2009) because large number of instruments would lead to finite sample bias and therefore we assume that $E(Risk_{i,t-1}\Delta v_{i,t})= E(\Delta Risk_{i,t}v_{i,t-1})=$ 0. We consider two lags for both the difference and system GMM instruments. Also, Hansen's (1982) J-test measures the validity of instruments and at the same time the two step estimates are based on corrected standard errors (Windmeijer, 2005).

Non-parametric Model

In order to observe how disclosure behaves to firms with different risk levels we employ quantile regression which was introduced by Koenker and Bassett (1978). We investigate parameters that describe the 5%, 25%, median, 75% and 95% of the conditional distribution. The main advantage of this method is that captures the abrupt changes of disclosure on Risk. It can be linearly represented as:

$$Risk = \pi(\tau) + \gamma(\tau)Disc + \mathbf{Y}'\theta(\tau) + \varepsilon, \quad \tau \in (0,1) \tag{4.13}$$

Where, Risk is the dependent variable, π is the intercept, $\mathbf{Y}$ is a vector that contains all explanatory variables, $\theta(\tau)$ is the parameters, ε signifies the error term and τ refers to the part the of $Risk$ distribution. We assume that the error is equal to zero at the conditional τ^{th} quantile $[Q_\varepsilon(\tau|\mathbf{Y}, Disc) = 0]$. Also, the parameter γ for any given quantile τ for a sample of N observations can be calculated with linear programming as follows:

$$\hat{\gamma}(\tau) = arg\ \min_{\gamma} \frac{1}{N}\sum_{i=1}^{N}\rho_\tau(Risk - \pi(\tau) - \gamma(\tau)Disc - \mathbf{Y}'\theta(\tau))$$

where check function $\rho_\tau(.)$ is defined as:

$$\rho_\tau(\varepsilon) = \begin{cases} \tau\varepsilon, & \text{if } \varepsilon \geq 0; \\ (\tau-1)\varepsilon, & \text{if } \varepsilon < 0 \end{cases}$$

We use bootstrap estimates of $\gamma(\tau)$ in order to calculate the covariance matrix. We compute standard errors with 1000 bootstrap replications and thus we obtain asymptotically normally distributed estimators which are valid under heteroskedasticity.

In order to investigate the hypothesis 2 (**H2**: Disc heterogeneously affects Risk), we consider that γ coefficients do not vary across the conditional distribution. Therefore jointly equality test is performed. The null hypothesis is that the slope of disclosure is the same across quantiles and can be written as $H2_0$: $\gamma_{0.05} = \gamma_{0.25} = \gamma_{0.50} = \gamma_{0.75} = \gamma_{0.95}$, otherwise disclosure unequally influences risk.

4.4 Results

4.4.1 Panel and Dynamic Panel Regression Results

Results relating to hypothesis 1 are reported in table 4.22. Columns 1, 2 and 3 report the pooled-OLS, fixed effect and random effect model respectively. Concerning the the control variables, Inta, Tang, ROA and LogTa reduce the idiosyncratic risk; finding which is according to our expectations and the previous literature (Konar and Cohen, 2001; Mishra and Modi, 2013; Cai et al., 2016), while higher leverage unexpectedly increases the idiosyncratic risk of the firms (Ang et al., 2006; Psillaki et al., 2010). Z and Growth do not appear to have an effect on the idiosyncratic risk. The results from the 3 models support **hypothesis 1**. Hence, transparent information about climate change significantly decreases the idiosyncratic risk of EU manufacturing firms. This finding is in line with both the *legitimacy* and *stakeholder theory* and it provides additional support to existing literature which acknowledges the benefits from the social corporate actions (Lee and Faff, 2009; Salama et al., 2011; Oikonomou et al., 2012; Mishra and Modi, 2013; Cai et al., 2016).

A noteworthy remark is that with the inclusion of the disclosure variable our baseline specification acquires higher explanatory power, as it highlights the importance of environmental disclosure as determinant of idiosyncratic risk. We should underline that the goodness of fit of the models reaches 60%, indicating that the chosen variables can explain a high proportion of the unobserved variance of stock returns. Also, the likelihood ratio specifies that the pooled-OLS model is not appropriate in this examination due to the fact that firms have different characteristics. We cannot reject though that pooled-OLS provides with unbiased estimations since we have control for a set of different attributes. On a final note, the random effect model is preferable in this instance; that is, according to the Hausman test; suggesting that our sample is representative for all manufacturing firms in the EU.

Regarding the dynamic panel results, column 4 of table 4.22 reports the two-step Sys-GMM based on equation 4.12. Dynamic panel regressions are appropriate to address the problem of endogenous variables and consequently to re-address hypothesis 1. In this regard, we cannot reject **hypothesis 1** that Disc-Risk relationship is negative; consistent with the previous estimates. Even if risk and disclosure are bidirectionally related (Orlitzky and Benjamin, 2001), results demonstrate that environmental disclosure is tied up with the risk-reduction hypothesis.

It is important to underline the validity of the model. Hansen J-test reports p-values of 38.5%, signifying the validity of the instruments. AR(1) and AR(2) related to the first differenced equation denote that there is first order autocorrelated disturbances and no second order autocorrelation. Windmeijer (2005) affirms that the two-step estimator with the finite sample correction for standard errors provides unbiased results. As expected the autoregressive term for Risk is positive and highly statistically significant, underlining the memory of the idiosyncratic risk (Ang et al., 2006).

Interestingly, the panel estimates report larger coefficients in comparison with the Sys-GMM. An explanation is that the autoregressive term in the Sys-GMM model absorb a large proportion of the systematic influence of the control variables. Also, we cannot reject that panel estimates are affected by endogeneity. Nevertheless, disclosure remains negative and statistically significant at 1% level. This finding is in line with the majority of empirical studies (Ziegler et al., 2011; Salama et al., 2011; Oikonomou et al., 2012; Mishra and Modi, 2013; Cai et al., 2016; Utz, 2017) and therefore we provide evidence supporting the negative theoretical framework for European firms. At the same time, results do reveal that environmental disclosure could be a rational managerial decision to reduce firm's specific and it is also evident that environmental disclosure can be priced in financial markets.

Table 4.22: Regression Results for Idiosyncratic Risk

	Pooled OLS		Fixed effect	Random effect	Sys-GMM
	(1a)	(1b)	(2)	(3)	(4)
$Risk_{t-1}$					0.474***
					(0.0908)
Disc		-0.0507***	-0.0608***	-0.0559***	-0.0328***
		(0.0113)	(0.0222)	(0.0182)	(0.0122)
Z	0.0534*	0.0520*	-0.0751	-0.0274	0.0423**
	(0.0317)	(0.0313)	(0.0729)	(0.0451)	(0.0167)
Lev	0.0003078*	0.000316*	0.000316**	0.000315**	0.0000782
	(0.0001634)	(0.000169)	(0.000144)	(0.000148)	(0.000306)
Inta	-5.294***	-5.422***	-7.115***	-6.869***	-3.140***
	(0.726)	(0.723)	(2.491)	(1.455)	(0.861)
Tang	-0.148***	-0.148***	-0.190	-0.127***	-0.0817***
	(0.040)	(0.0389)	(0.414)	(0.0464)	(0.0162)
ROA	-0.4058***	-0.388***	-0.381***	-0.374***	-0.260***
	(0.0468)	(0.048)	(0.0664)	(0.0622)	(0.0568)
LogTa	-1.731***	-1.424***	-2.669***	-1.666***	-0.829***
	(0.1235)	(0.142)	(0.737)	(0.261)	(0.212)
Growth	0.00479**	0.00430*	0.00361	0.00336	0.00332
	(0.00208)	(0.00221)	(0.00278)	(0.00263)	(0.00273)
Cons	41.73***	39.54***	49.47***	41.67***	23.73***
	(1.80)	(1.871)	(6.661)	(3.110)	(4.041)
Year	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	No	Yes	No
Country	Yes	Yes	No	Yes	No
Likelihood ratio			7.44 [0]		
Hausman $\chi^2_{(d.f)}$				$18.5_{(19)}$ [0.48]	
AR(1)					[0]
AR(2)					[0.193]
Instr					31
H-J					[0.385]
R^2	0.549	0.553	0.602	0.601	
Observations	2580	2580	2580	2580	2528

Standard errors are in parenthesis, p-values in brackets. Standard errors are robust correcting for heterogeneity. Idiosyncratic risk (Risk) is the dependent variable for all models. Disclosure's significance is based on one-tailed test. Hansen J-test (H-J) reports the instrument validity. AR(1) and AR(2) show the first and second order auto-correlation respectively. The number of instruments (Instr) is reported. All variables listed are defined in Table 4.19. ***,**,* significance level at 1%,5%, 10%.

4.4.2 Non-parametric Regression Results

The use of quantile regressions help us analyse the dependence between disclosure and Risk. Panel and dynamic panel regressions estimate the average effect of disclosure on Risk. In turn, quantile regressions are able to estimate the tails of the idiosyncratic risk distribution relationship (see, e.g., Ang et al., 2006). Table 4.23 considers 5 different quantiles based on equation 4.13.

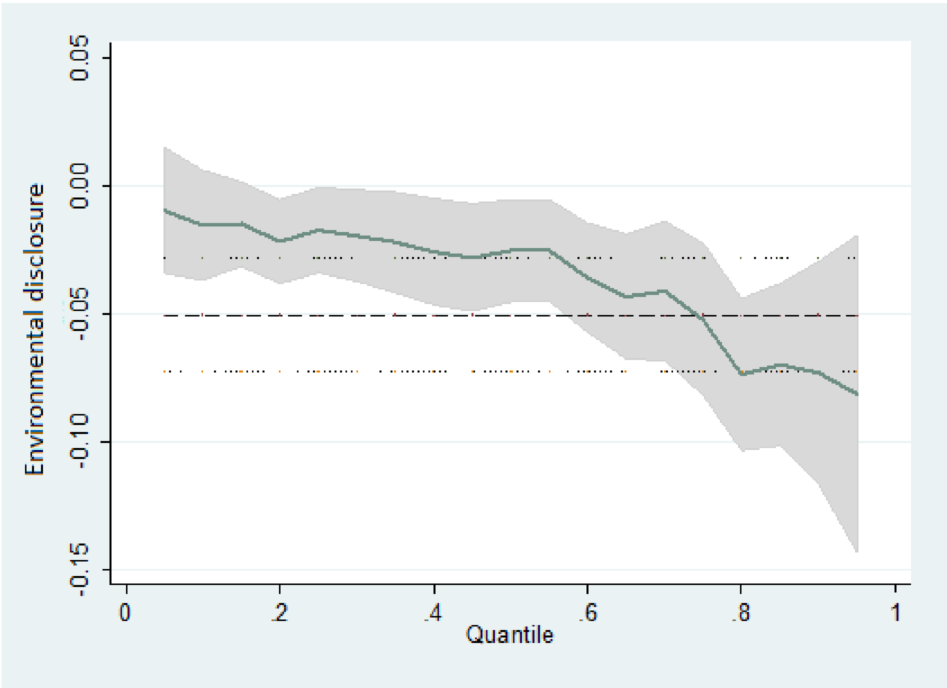
Table 4.23: Quantile Regressions for Idiosyncratic Risk

τ	0.05	0.25	0.50	0.75	0.95
	(1)	(2)	(3)	(4)	(5)
Disc	-0.00960	-0.0174**	-0.0255***	-0.0524***	-0.0815***
	(0.0117)	(0.00949)	(0.0102)	(0.0154)	(0.0311)
Z	0.0222	0.0204	0.0513	0.0615	0.0632
	(0.0607)	(0.0577)	(0.0385)	(0.0534)	(0.0676)
Lev	-0.0000211	0.000226	0.000210	0.0000194	0.000693
	(0.000292)	(0.000263)	(0.000189)	(0.000293)	(0.000902)
Inta	-2.362***	-3.598***	-3.864***	-5.100***	-2.229
	(0.750)	(0.720)	(0.626)	(1.141)	(2.682)
Tang	-0.0470	-0.0249	-0.0580	-0.168***	-0.567**
	(0.0669)	(0.196)	(0.0586)	(0.0503)	(0.234)
ROA	-0.198***	-0.256***	-0.328***	-0.436***	-0.606***
	(0.0427)	(0.0350)	(0.0304)	(0.0454)	(0.0898)
LogTA	-1.014***	-1.203***	-1.211***	-1.297***	-1.961***
	(0.139)	(0.120)	(0.142)	(0.192)	(0.371)
Growth	0.00616	0.00369	0.00576	0.00531	0.00757
	(0.00558)	(0.00327)	(0.00432)	(0.00593)	(0.0133)
Cons	26.80***	33.48***	37.06***	40.60***	56.51***
	(1.830)	(1.559)	(1.811)	(2.309)	(6.629)
Year	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes
Observations	2580	2580	2580	2580	2580
Pseudo R^2	0.3061	0.3425	0.3716	0.4007	0.3994

Significance based on bootstrap standard errors (1000 replications). Idiosyncratic risk (Risk) is the dependent variable for all models. Disclosure's significance is based on one-tailed test. τ denotes the different quantiles. All variables listed are defined in Table 4.19. Equality test of the environmental disclosure coefficients reports p-value = 0.042 [F(4, 2537)= 2.48]. ***,**,* significance level at 1%,5%, 10%.

Similar to the parametric models; Int, Tang, ROA and LogTa appear to significantly decrease idiosyncratic risk for the largest part of the conditional distribution. In particular, tangible assets significantly contribute to the Risk in the upper part of the distribution, whereas intangible assets are insignificant at the upper tail only. Also, Z, Lev and Growth are insignificant for the whole distribution. Another important aspect of the model is that it explains from 30 to 40% of the variability of Risk (see, Pseudo R^2).

Figure 4.12: Non-linear Environmental Disclosure on Risk



Notes: The grey area corresponds to confidence intervals calculated with 1,000 bootstrap replications. The dash line represents the OLS estimations with its confidence intervals (dot lines). The control variables are not reported for brevity but are available upon request.

Turning to **hypothesis 2**, quantile regressions reveal that disclosure and Risk exhibit a negative and heterogeneous association with risk as suggested by the *slack resource argument*. Figure 4.12 and table 4.23 jointly identify that higher disclosure significantly reduces the Risk. This is apparent at the upper part of the distribution, while the lower tail is insignificant with a coefficient close to null. The lower tail represents firms with low idiosyncratic risk and therefore perfectly diversified activities; such investments are unaffected by the environmental disclosure. The practical implications of this finding are particularly interesting. Environmental disclosure is valued by the investors and thus higher degree of diversification can be attained with a portfolio of disclosing firms. While, if the market is frictionless Merton (1987) (idiosyncratic risk is not priced), investors would be indifferent for environmental disclosure. Confirming the above, equality test shows that environmental disclosure coefficients have statistical differences across the conditional distribution. Therefore, we cannot reject that environmental disclosure heterogeneously affects idiosyncratic risk (**H2**).

Overall, by testing the two hypotheses the following conclusions can be drawn: (1) environmental disclosure has a significant and negative impact on idiosyncratic risk; (2) the relationship is a subject of a different degree of independence across the conditional probability distribution; (3) this finding confirms hypotheses 1 and 2 and hence the negative theoretical framework enriched with *the slack resource argument* is more appropriate to model the relationship.

4.4.3 Robustness checks

In order to check the sensitivity and accuracy of the results, we substitute some variables from the initial specification (see, eq. 4.11) and we repeat the same regression procedure. In particular, we use two alternative dependent variables. First, firm's total risk also matters as it is indicated by Bouslah et al. (2013); Benlemlih et al. (2016). Total risk (T.Risk) is consisted by systematic and idiosyncratic risk components and can be defined as the annualised standard deviation of the daily stock returns. Second, we also consider an alternative approach to approximate idiosyncratic risk. Fama and French (2015) propose a five factor capital asset pricing model.[25] In eq. (4.10), the authors remove the MOM_t component and add two new terms as shown bellow:

$$R_{i,t} - R_{f,t} = \beta_i + \beta_{i,1}(R_{m,t} - R_{f,t}) + \beta_{i,2}SMB_t + \beta_{i,3}HML_t + \beta_{i,4}RMW_t + \beta_{i,5}CMA_t + u_{i,t}, \tag{4.14}$$

where RMW is the difference of stock returns between robust and weak profitability firms and CMA is the return of low over high investment firms. By running OLS regressions to eq. (4.14), the five-factor idiosyncratic risk (5.Risk) is the annualised standard deviation of the residuals.

Additionally, previous literature commonly uses accounting profitability ratios to examine the disclosure-performance relationship; instead of ROA, we add Tobin's Q (Q) as a measurement of market-based profitability indicator (Konar and Cohen, 2001; Broadstock et al., 2018). Lastly, intangible assets attempted to capture a part of R&D expenses which have been argued to be of a major importance of the examination (Konar and Cohen, 2001; Elsayed and Paton, 2005;

[25] An interesting extension of this analysis would be to examine the crash risk of stock returns. Jin and Myers (2006) show that stock price crashes as accumulated negative firm-specific information suddenly becomes publicly available. The authors measure the firm-specific information by detecting changes in the R^2 of CAPM regressions. Based on that, an alternative approach to measure idiosyncratic risk would be through a synchronicity measure. Stock price synchronicity is defined as the R^2 from asset pricing regressions and this shows the amount of information reflected in stock prices (Hutton et al., 2009). It can be simply measured as: $ln(\frac{1-R^2}{R^2})$.

Duqi et al., 2015). R&D was not included in our primary analysis due to the high number of missing values (similarly to Delmas et al., 2015).

Table 4.24 presents the robustness checks, columns 1, 2 and 3 report the random effect, Sys-GMM and median regression results respectively and the denotation a and b indicates that the dependent variable is either the idiosyncratic risk from the 5-factor model or the total risk. In terms of the idiosyncratic risk of the 5-factor model, our results are qualitative similar with the previous estimations. Interestingly, results cannot support a relationship between environmental disclosure and total risk. Since we have established that disclosure has an impact on idiosyncratic risk, it can be implied that disclosure and the systematic risk component are irrelevant (Benlemlih et al., 2016). We extend our analysis by excluding British firms. This is mainly done because the sample is over-represented by British firms and it is rational to consider a post-Brexit scenario. Previous literature shows that British firms are environmental sensitive (Salama et al., 2011) and thus this is how the negative sign (Disc-Risk) dominates. However, results reported in table 4.25 remain robust for the rest of the European firms.

Table 4.24: Robustness Checks I. Full-sample

	Random effect		Sys-GMM		Quantile(.50)	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Variable	5.Risk	T.Risk	5.Risk	T.Risk	5.Risk	T.Risk
$5.Risk_{t-1}$			0.340***			
			(0.109)			
$T.Risk_{t-1}$				0.418***		
				(0.101)		
Disc	-0.0650***	-0.0673**	-0.0381**	-0.0125	-0.0356***	-0.0241*
	(0.0252)	(0.0285)	(0.0174)	(0.0204)	(0.0134)	(0.0174)
Z	-0.816***	-0.773***	-0.403***	-0.339**	-0.479***	-0.347***
	(0.173)	(0.178)	(0.143)	(0.160)	(0.0769)	(0.080)
Lev	0.00020	0.00026	-0.000011	-0.0000099	0.000595	-0.0000264
	(0.00016)	(0.00017)	(0.000082)	(0.00012)	(0.000112)	(0.0002)
R&D	0.0248	0.1188	0.296*	0.550***	-0.027	0.0782
	(0.277)	(0.30)	(0.167)	(0.190)	(0.135)	(0.166)
Tang	0.292***	0.307***	0.138*	0.130	0.180	0.1482
	(0.10)	(0.105)	(0.0756)	(0.0849)	(0.531)	(0.352)
Q	-1.497**	-0.843	-1.665***	-2.185***	-1.456***	-1.873***
	(0.529)	(0.591)	(0.404)	(0.481)	(0.325)	(0.356)
LogTA	-1.815***	-1.08**	-1.458***	-1.420***	-1.579***	-1.029***
	(0.385)	(0.455)	(0.308)	(0.348)	(0.2242)	(0.247)
Growth	-0.0121	-0.00987	-0.00518	0.00452	-0.010	-0.00639
	(0.0232)	(0.0197)	(0.0189)	(0.0184)	(0.0126)	(0.0129)
Cons	46.84***	37.63***	32.06***	29.91***	43.70***	37.52***
	(3.835)	(4.277)	(4.702)	(4.817)	(2.222)	(2.692)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	No	No	Yes	Yes
Country	Yes	Yes	No	No	Yes	Yes
AR(1)			[0]	[0]		
AR(2)			[0.591]	[0.9]		
Instr			31	31		
H-J			[0.376]	[0.061]		
R^2	0.597	0.682			0.383	0.421
Obs	1708	1708	1668	1668	1708	1708

Standard errors are in parenthesis, p-values in brackets. Standard errors are robust correcting for heterogeneity. Disclosure's significance is based on one-tailed test. Hansen J-test (H-J) reports the instrument validity. AR(1) and AR(2) show the first and second order auto-correlation respectively. The number of instruments (Instr) is reported. All variables listed are defined in Table 4.19. ***,**,* significance level at 1%,5%, 10%.

Table 4.25: Robustness Checks II. Sub-sample without British Firms.

	Random effect		Sys-GMM		Quantile(.50)	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
	5.Risk	T.Risk	5.Risk	T.Risk	5.Risk	T.Risk
$5.Risk_{t-1}$			0.397***			
			(0.130)			
$T.Risk_{t-1}$				0.474***		
				(0.107)		
Disc	-0.0744***	-0.0707**	-0.0544***	-0.0272	-0.0478***	-0.0216
	(0.0270)	(0.0317)	(0.0199)	(0.0206)	(0.0159)	(0.0190)
Z	-0.819***	-0.795***	-0.320*	-0.260	-0.455***	-0.414***
	(0.248)	(0.260)	(0.176)	(0.181)	(0.122)	(0.146)
Lev	0.00214	0.00270	0.00265	0.00203	0.000253	0.00133
	(0.00315)	(0.00324)	(0.00380)	(0.00181)	(0.00103)	(0.00123)
R&D	0.431	0.481	0.376**	0.489***	0.525***	0.536***
	(0.310)	(0.341)	(0.179)	(0.172)	(0.156)	(0.186)
Tang	0.291**	0.324**	0.0859	0.0827	0.173**	0.185*
	(0.134)	(0.140)	(0.0904)	(0.0934)	(0.0874)	(0.105)
Q	-1.804***	-1.170*	-1.830***	-2.190***	-1.884***	-2.421***
	(0.621)	(0.666)	(0.517)	(0.517)	(0.450)	(0.538)
LogTA	-2.301***	-1.536***	-1.445***	-1.234***	-2.174***	-1.767***
	(0.439)	(0.533)	(0.359)	(0.334)	(0.226)	(0.270)
Growth	-0.0321**	-0.0252	-0.0178	0.00105	-0.0138	-0.0121
	(0.0155)	(0.0160)	(0.0141)	(0.0149)	(0.0125)	(0.0149)
Cons	47.77***	38.95***	31.06***	28.62***	47.51***	48.50***
	(4.157)	(4.665)	(5.779)	(5.438)	(3.489)	(4.171)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	No	No	Yes	Yes
Country	Yes	Yes	No	No	Yes	Yes
AR(1)			[0]	[0]		
AR(2)			[0.477]	[0.961]		
Instr			31	31		
H-J			[0.57]	[0.501]		
R^2	0.6019	0.6891			0.3948	0.4349
Obs	1325	1325	1291	1291	1325	1325

Standard errors are in parenthesis, p-values in brackets. Standard errors are robust correcting for heterogeneity. Disclosure's significance is based on one-tailed test. Hansen J-test (H-J) reports the instrument validity. AR(1) and AR(2) show the first and second order auto-correlation respectively. The number of instruments (Instr) is reported. All variables listed are defined in Table 4.19. ***,**,* significance level at 1%,5%, 10%.

4.5 Conclusion

This paper examines the environmental disclosure - idiosyncratic risk relationship for a panel of 288 EU manufacturing firms. In the main analysis, we use four factor model (Carhart, 1997) to extract the idiosyncratic risk of the firms, while the environmental disclosure score has been retrieved from Bloomberg database. Relevant empirical literature along with the economic theory suggest that environmental actions and financial performance exhibit an endogenous and non-linear relationship. For this reason, panel, dynamic panel and quantile regressions with the inclusion of different set of control variables attempt to shed light on the examination.

Our empirical investigation confirms the generic hypothesis that it is less risky to be informative. More particularly, the findings demonstrate that environmental disclosure heterogeneously reduces idiosyncratic risk. This result is robust under different specifications and it is consistent with a large part of literature that acknowledges the importance of high environmental visibility (Dawkins and Fraas, 2011; Matsumura et al., 2014; Ben-Amar and McIlkenny, 2015). For this reason, regulators should further advance environmental sensitivity and firms should be encouraged to increase their environmental transparency because eventually this engagement can be described as "win-win" situation; monitoring climate change risk (Stern, 2007) and decreasing idiosyncratic risk.

Furthermore, our results underline the prominent role of transparent information on the financial markets. The comprehensive and articulated picture of environmental disclosure on idiosyncratic risk suggests that the negative theoretical framework is more suitable to frame the relationship. Therefore, it can be extracted that management should consider to provide transparent environmental information as a means of cost-less risk reduction. At the same time, environmental disclosure seems to reveal a unique dimension of idiosyncratic risk which can potentially enhance our understanding about the information content of idiosyncratic risk (e.g., Fu, 2009; Wu et al., 2016).

The main limitation of the study is that the score of environmental disclosure is assumed to be objective (Nollet et al., 2016; Benlemlih et al., 2016). Future study should investigate the quality of environmental actions that are disclosed by firms. An alternative interesting avenue for future research would be to construct an environmental disclosure index and conduct a similar examination controlling for a larger number of countries and industries. Moreover, a greater number of risk measurements (as dependent variables) might be dis-similarly correlated with a larger number of environmental performance variables (as independent variables) (see for example meta-analysis, Horvathova, 2010; Albertini, 2013; Endrikat et al., 2014).

In turn, future studies could concentrate on whether portfolios with disclosing assets have generally more diversified risk from non-disclosing asset-portfolios. Furthermore, investigating the relationship between disclosure and systematic risk might also be a interesting area of future study. On a final note, our study motivates further research relating to diversification under complete or incomplete environmental information (see, Merton, 1987; Ang et al., 2006; Fu, 2009).

5 Third empirical Chapter: Temperature Variations and Systemic Risk

5.1 Introduction

UNDERSTANDING the empirical relationship between climate change and financial markets is gaining much prominence within the recent climate - finance literature. Literature has shown that temperature is a risk factor that can erratically affect economic activity (Dell et al., 2014; IPCC, 2014). At the same time, the persistent trend of rising temperature has been spreading uncertainty to the whole financial system and thus it significantly contributes to systemic risk (e.g., Battiston et al., 2017). The systemic risk element of temperature has a twofold justification. First, variations of temperature can trigger a direct revaluation of climate sensitive assets. Particularly, equity losses can occur due to direct exposures to climate shocks such as natural catastrophes, changes in climate policy and increased energy costs (ESRB Advisory Scientific Committee, 2016). Second, firms that possess climate sensitive assets could affect the financial system given their high interconnection with other businesses, thereby increasing systemic risk indirectly (Battiston et al., 2017). For instance, on one hand, temperature could affect agricultural output (i.e., direct impact of temperature) (Schlenker and Roberts, 2009), while on the other, agricultural firms that experience abnormal losses due to weather conditions might subsequently transmit uncertainty to their counterparts or to other industries with which they trade (i.e., indirect impact of temperature) (Miranda and Glauber, 1997). Amid climate change, *radical uncertainty*[26] impedes the capacity of financial markets to operate efficiently. The reason is that investors' expectations about future environmental regulations and

[26] *Radical uncertainty hypothesis* has been described by Aglietta and Espagne (2016) and defined as collective prudential actions that minimise the probability of occurrence of unforeseen events due to high uncertainty. For instance, investors might be driven away from climate sensitive firms (selling climate sensitive stocks) because they anticipate unexpected climate events.

climate change events are highly disparate and therefore climate sensitive assets are impossible to be reevaluated instantaneously (Aglietta and Espagne, 2016; Karydas and Xepapadeas, 2019). Instead, what can be observed, historically, is investors' reaction upon temperature changes. With these in mind, our overriding priority is to investigate whether systemic risk is conditioned on temperature changes. At the same time, we also address other noteworthy questions such as: Is climate uncertainty priced in financial markets? How much is the cost for the financial system? Do we have only losers or also gainers? What is the optimal temperature for the normal operation of financial markets?

As far as the motivation of our study is concerned, it should be noted that in this paper, we combine knowledge from (i) the effects of temperature on stock markets and (ii) the broader systemic risk literature. The first strand of literature concentrates mainly on how temperature innovations influence stock market returns (e.g., Cao and Wei, 2005; Bansal and Ochoa, 2011; Novy-Marx, 2014; Donadelli et al., 2017b; Balvers et al., 2017). This strand has mainly identified that temperature has macroeconomic risk characteristics that affect stock market returns. A possible explanation has been given by labour productivity scholars. In particular, Hsiang (2010); Donadelli et al. (2017b); Letta and Tol (2018) underscore that temperature and productivity are negatively related and this could potentially lead to financial turmoil, considering that their interaction might change the components of aggregate supply and demand. (ESRB Advisory Scientific Committee, 2016; Dafermos et al., 2017). By contrast, Cao and Wei (2005) offers an alternative justification by claiming that temperature variations can affect financial behaviour as temperature has been found to cause psychological disturbances.

The second strand of the literature highlights the importance of systemic risk on the financial stability; especially during financial crises (e.g., crisis 2007-2009) when financial stability seems quite vulnerable to rises in systemic risk. Systemic risk does not only affect financial markets but it can also have severe consequences to the real economy (Galati and Moessner, 2013). For this reason, policymakers and researchers have developed analytic tools in order to measure and predict rises in systemic risk (e.g., Engle and Manganelli, 2004; White et al., 2015; Adrian and Brunnermeier, 2016). Accordingly, the main objective of these tools is to stress the equilibria generated by exogenous shocks. Empirical examples are abundant, for instance, Reboredo and Ugolini (2015) who study systemic risk dependency across European sovereign debt markets, Mensi et al. (2017a) find that oil price volatility generates systemic risk to currencies and vice versa. Along a similar vein, de Mendonça and da Silva (2018) show that liquidity, profitability, leverage, as well as, interest rates, all have an important role in triggering systemic risk fluctuations in the financial sector.

In this regard, to empirically examine if temperature shocks affect systemic risk, we follow the Conditional Value at Risk ($CoVaR$) literature (Adrian and Brunnermeier, 2016). $CoVaR$ is a systemic risk measure that is robust to spillover effects and distribution assumptions and is defined as the spread between the Value at Risk of the financial system and that of an institution under distress. The attractiveness of $CoVaR$ lies in its ability to pinpoint the root of economic crises, while computationally can be easily facilitated through a quantile regression framework. The motivation of using $CoVaR$ stems from the fact that some firms might be affected by climate change while others not. This method offers a unique potential to identify both which asset has the highest risk exposure and the interconnectedness of this asset with other assets across the financial system. Given that temperature can directly trigger macroeconomic alterations (Dell et al., 2014), climate-sensitive firms inevitably absorb the initial shock emerging from these alterations and transmit it even further, generating spillovers to the whole economy. Hence, with the use of $CoVaR$, we can examine the Value at Risk dependency on temperature fluctuations.

Our study provides the following main contributions. First, while previous literature investigates whether temperature affects stock market returns (Cao and

Wei, 2005; Bansal et al., 2016; Apergis and Gupta, 2017; Balvers et al., 2017), this is the first study, to the best of our knowledge, to empirically investigate if temperature has an impact on systemic risk. Our study is motivated by prior literature underlining the systemic element of climate change (Aglietta and Espagne, 2016; ESRB Advisory Scientific Committee, 2016; Battiston et al., 2017). Second, the study provides strong evidence from the European Union; an area highly committed to climate change mitigation. Contrary to existing literature that uses lower frequency data, we use 28 years of daily data that might directly account for both short-term and long-term temperature effects. That is, either quarterly or annual data cannot fully detect temperature variations because crucial information about temperature is cancelled out. Thus, $CoVaR$ can measure the maximum daily losses attributed to changes in temperature. Finally, we decompose temperature as suggested by the climate change literature (Vecchio and Carbone, 2010; Ji et al., 2014) and thus we provide a more meaningful and articulate picture of temperature effects. More particularly, the decomposition employed in this study implies that we provide evidence about the unexpected temperature variations on the systemic risk of firms.

The main findings of the study indicate that, in a panel data sample of 600 firms for 7305 trading days in 17 different EU countries from 1/1/1990 to 29/12/2017, temperature has a prominent role in affecting the 99% daily and monthly $CoVaR$. In particular, we document that temperature has weak non-linear effects on the financial markets. Moreover, we observe that temperature shocks contain a systemic risk factor that strongly increases the losses of the firms. What is more, cold shocks have negative contribution to systemic risk, while the effects of hot shocks appear positive. Alternative model specifications, such as different systemic risk and temperature shock proxies as well as lower frequency examination, establish the robustness of the results with some small variations across different industries. Particularly, in line with Balvers et al. (2017), we demonstrate that manufacturing firms seem to be the ones mostly affected by temperature variations.

The findings of the study are very important to promote the climate- finance research. Scholars can monitor climate-sensitive firms that have spillover effects to the whole financial system. IPCC (2014) forecasts higher frequency and magnitude of extreme weather events and rising temperatures. For this reason, our study pinpoints a possible way to measure the climate systemic impact of firms and thus to help the financial system to be equipped with adequate tools and knowledge in view of further climate change deterioration.

The remainder of the paper is structured as follows: Section 5.2 outlines the previous climate change - financial literature and states the hypotheses. Section 5.3 presents the data, the $CoVaR$ methodology, the temperature components and the testable regressions. In Section 5.4, results are reported. Section 5.5 summarises and concludes.

5.2 Literature Review and Hypotheses

5.2.1 Systemic Risk

We commence this section by presenting a brief review of the literature of systemic risk. Systemic risk can be defined as the increase in losses due to the spreading of financial distress across firms (Engle and Manganelli, 2004; Adrian and Brunnermeier, 2016). There is a large body of literature that proposes different methods in order to model systemic risk. Assessing systemic risk has been highlighted especially during financial crises (Galati and Moessner, 2013).

Value at Risk (VaR) is the most widespread measure of losses due to its simplicity. The VaR for any firm given can be written as:

$$Pr(X^i \leq VaRq^i) = q\%,$$

where X^i is the stock return losses of a firm i for which $VaRq^i$ is defined and $q\%$ is the quantile of the probability distribution, where the upper tail of the distribution denotes the highest financial losses. However, VaR is not sufficiently focused on systemic risk and this is because VaR is a sample of returns of a firm i at isolation. Thus, VaR neglects the spillover effects which are responsible for spreading the risk. Another problematic setting in VaR computation is that financial time-series are highly skewed; indicating that VaR will underestimate or overestimate the actual risk. As described by (Angelidis et al., 2007), in order to forecast the risk accurately, VaR modelling needs to accommodate non-symmetrical fat tails.

Dealing with the skewness of the returns, Giot and Laurent (2003) propose univariate and multivariate ARCH models based on skewed student distribution. Furthermore, Engle and Manganelli (2004) use a combination of quantile regressions with GARCH models in order to allow for relaxation of any distribution assumption, but at the same time this method assumes that systemic risk has a short autoregressive memory. Similarly, White et al. (2015) propose a method that utilises vector autoregressive models simultaneously with the associated quantile of stock returns. This method is robust to outliers and also tailors different variables in order to deal with the spillover effects.

The most recent contributions to VaR modelling underline the importance of spillover effects (e.g., Girardi and Tolga Ergün, 2013; Reboredo et al., 2016; Mensi et al., 2017b; Karimalis and Nomikos, 2018). In the influential study of Adrian and Brunnermeier (2016), the VaR of the whole financial sector is conditional on one particular firm under distress; this is known in the risk literature as $CoVaR$. $CoVaR$ can be easily measured by quantile regressions. $\Delta CoVaR$ which is the main risk measure of this analysis, is the difference between the $CoVaR$ of a firm under distress and the $CoVaR$ of the median state of this firm. Adrian and Brunnermeier (2016) show that $\Delta CoVaR$ is a robust method which can capture the tail dependency of stock returns and more importantly the sensitivity of $\Delta CoVaR$ can be tested by accommodating different micro and macro risk variables.

5.2.2 Temperature and Economy

We now move on to discuss why temperature is a macroeconomic risk factor. Rising global temperature can have an impact on the economy and activate macroeconomic alterations. Fankhauser and Tol (2005); Stern (2007); Du et al. (2017); Colacito et al. (2018) argues that climate change will have a direct effect on countries' GDP due to the fact that they have to bear the consequences of the extreme weather events, such as rainstorms, extreme temperatures and floods. Having quantified this effect, Horowitz (2009) documents that 1°C of increase in average temperature would decrease the world GDP by 3.8%. Heal and Kriström (2002); Dell et al. (2014); Donadelli et al. (2017a); Arbex and Batu (2018) underline that temperature shocks are inevitably connected with agricultural outcome, health, tourism, productivity, energy consumption, research & development and to some extent the economic performance of firms. Schlenker and Roberts (2009) identify that temperature changes can have an impact on the agricultural products due to the fact that crop yields can thrive under certain circumstances. Their findings indicate that different temperature change scenarios can decrease the average crop yield from 30% to 82% by the end of the century. Moreover, Deschenes (2014) underscores that the direct recipient of climate change is humans and the main threat is whether humans will be able to adapt to the new environment or not. According to World Health Organization[27] (2016) the direct cost to health will be 2-4 billion USD annually by 2030 due to the increasing number of deaths caused by the climate change. Letta and Tol (2018) find a strongly negative relationship between total factor productivity and temperature. Donadelli et al. (2017b) support that temperature shifts have a long run negative effect on labour productivity. Hsiang (2010) finds that increasing temperature by 1°C can have negative effect of 2.4% on labour productivity. Similar finding is supported by Graff Zivin and Neidell (2014) who identify that a temperature rise reduces the hours worked in industries.

[27] Retrieved from http://www.who.int/mediacentre/factsheets/fs266/en/

Besides, literature supports that temperature is a risk factor that affects the economy. Dafermos et al. (2017) underline that global warming can bring financial instability because it affects directly the components of aggregated demand for energy. Therefore, to some extent macroeconomic consequences are attributed to climate change, however the main challenge is to test if temperature risk is transmitted to financial markets.

5.2.3 Temperature and Financial Markets

Before turning to the empirical climate - finance literature, it is sequential to understand the link between stock price movements and temperature. This link can be summarised in four main points: (1) evidence from psychological literature shows that temperature affects investors' mood (Kamstra et al., 2003; Cao and Wei, 2005); (2) temperature acts as a reminder and increases investors' concerns about the imminent de-carbonised policies (Karydas and Xepapadeas, 2019); (3) extreme temperatures increase energy consumption in order to maintain standard working conditions and (4) temperature shocks act as a systematic negative productivity shock, which in turn affect the stock valuations (Balvers et al., 2017; Donadelli et al., 2019).

A summary of the empirical literature is given by Table 5.26. In the seminal contributions of Kamstra et al. (2003); Cao and Wei (2005), a stock market anomaly was observed; high temperature causes apathy towards financial markets while cold temperature is followed by higher risk-taking. Temperature-stock anomaly is also supported by Novy-Marx (2014) who states that the global warming can be used as a proxy because it has a significant role in predicting financial performance anomalies.

Additionally, Bansal and Ochoa (2011) present that temperature is a source of aggregated risk and they identify a temperature beta in the stock market which is the risk exposure of stocks to the temperature. They perform cross sectional regressions for different portfolios sorted by country and their results indicate that countries closer to Equator hold a strong and negative temperature risk premium but moving away from Equator the effect becomes positive. Negative beta is followed by higher stock returns, implying that there is a higher compensation for assets that are exposed to higher temperatures. Bansal et al. (2016) add long-run temperature shifts in their analysis in order to separate the long from the short run effect of the temperature. They, overall, find that temperature risk has a negative effect on equity valuations. Similarly, Balvers et al. (2017) examine the effect of temperature shocks on the cost of equity. By taking different portfolios and incorporating temperature shocks in asset pricing models, the authors identify that temperature is a risk factor that has significant and negative effect on firms' stock returns that operate in climate sensitive industries. Also, their findings suggest that 0.22% of the total cost of equity is attributed to temperature risk. Therefore, it can be argued that temperature is an aggregated risk factor that influences the stock returns depending on the geographical latitude (Bansal and Ochoa, 2011) and the industry (Balvers et al., 2017). Temperature negatively affects productivity and therefore the results are not surprising since productivity shocks play a crucial role in equity valuations (Garlappi and Song, 2016). In align with the theory of finance, temperature risk can be categorised as a risk factor that has a negative effect on equity evaluations (Chen and Wang, 2012).

Table 5.26: Literature between stock returns and temperature

Authors	**Method**	**Area**	**Period**	**Results**
Kamstra et al. (2003)	OLS	US, Canada, Britain, Germany, Sweden, Australia, Japan New Zealand and South Africa	Daily data from January 4, 1928 to December 29, 2000	Higher temperature slightly increases stock returns for US, New Zealand and South Africa. Rest foreign stock market returns are unaffected by temperature
Cao and Wei (2005)	OLS	US, Canada, Britain, Germany, Sweden, Australia, Japan and Taiwan	Daily data from January 2, 1989 to December 31, 1999	Lower temperature leads to higher stock returns and higher temperature to both higher or lower stock returns
Bansal and Ochoa (2011)	OLS	38 countries and global temperature	Annual data from 1929 to 2009	Equity returns and temperature have high risk in countries closer to Equator while the risk is low in countries away from the Equator
Novy-Marx (2014)	OLS	New York	Monthly data from July 1973 to December 2012	Low and high temperatures have an abnormal predictive power of the financial markets.
Bansal et al. (2016)	OLS	US	Annual data from 1934 to 2014	Temperature has a negative effect on equity prices
Balvers et al. (2017)	OLS	US	Monthly data from April 1953 to May 2015	Temperature causes higher risk returns and higher cost of capital
Apergis and Gupta (2017)	GARCH	New York temperature and South African stock returns	Daily data from January 2, 1973 to December 31, 2015	New York temperature has a statistically significant negative effect on the stock returns in South Africa
Donadelli et al. (2017b)	VAR	US	Annual data from 1950 to 2015	High temperature increases the equity volatility and has negative correlation with market returns
Donadelli et al. (2019)	OLS	UK	Annual data from 1900 to 2015	Temperature volatility carries a positive risk premium in the equity market

5.2.4 Temperature Information

Before proceeding to state our hypotheses, it is important to investigate the different temperature proxies used in relevant analyses and the information content of temperature data.

There is a plethora of proxies about the temperature effects. While, Kamstra et al. (2003) employ daily raw temperature data as predictive variable of stock returns, most of the studies use temperature anomaly. Temperature anomaly is defined either as the difference between the daily temperature and the average historic temperature, or as the innovations of temperature, when lower frequency data are examined (Cao and Wei, 2005; Novy-Marx, 2014; Bansal et al., 2016; Apergis and Gupta, 2017; Donadelli et al., 2017b, 2019). This method eliminates the seasonality of the raw temperature data but at the same time, it contains information about both the trend and temperature shocks. Temperature trend and shocks are two different components which is imperative to be separated; according to IPCC (2014), temperature trend follows a linear gradual increase and can be observed for the last 150 years, while temperature shocks are more extreme since about 1950. Dealing with the different temperature components, Balvers et al. (2017) decompose the monthly temperature series and obtain temperature shocks. Even though, their paper estimates shocks through detrended analysis, they neglect to distinguish between cold and warm shocks as it was previously suggested by Cao and Wei (2005); Novy-Marx (2014). Temperature shocks can be either cold or hot and can have significantly different economic consequences Dell et al. (2012).

Notwithstanding the use of lower frequency temperature data in the climate - economy literature (Hsiang, 2010; Dell et al., 2012; Du et al., 2017; Colacito et al., 2018), climate - finance studies tends to use higher frequency data (Kamstra et al., 2003; Cao and Wei, 2005; Apergis and Gupta, 2017). This can be explained by the unavailability of higher frequency on macroeconomic and, sometimes, temperature data (particularly in developing countries) as well as, there are conceptually different research objectives between economy and finance scholars.

To provide more insights about temperature information, we now turn our attention to climate change literature. Daily temperature records are characterised by nonlinearities. By using monthly or annual aggregated data, critical information could be unseen and reduce temporal resolution (Vecchio and Carbone, 2010). For this reason an empirical decomposition on daily data can provide us with meaningful information. As Vecchio and Carbone (2010) explain temperature contains three equally important components; (i) trend, (ii) seasonality and (iii) anomaly. Trend is usually referred as the gradually increase in the average temperature which is a linear function that can vary over time (Ji et al., 2014). Seasonality is an oscillatory factor with constant frequency ($\approx$ 365 days) and it is probably the least important component in terms of the information contained. In contrast, the anomaly component corresponds to the temperature variation, which is the unexpected temperature deviations from the detrended and deseasonalised mean temperatures.

5.2.5 Hypotheses of the Study

According to Dell et al. (2014), temperature can be seen as a macroeconomic risk variable which can potentially affect not only different economies but also individual firms. We extend this concept and, particularly, the unedited research question we posit is whether and, if so, how systemic risk responds to temperature changes. For instance, assume that a highly leveraged firm experiences losses from unanticipated temperature changes. This may impair the firm's ability to meet its financial obligations, and pose a threat to the financial system as a whole (ESRB Advisory Scientific Committee, 2016). To put it differently, we ask whether a firm's losses that result from temperature changes can be causal of losses to other firms within the industry or the economy.

Synchronously, Horowitz (2009); Schlenker and Roberts (2009); Dell et al.

(2012, 2014); Aglietta and Espagne (2016); Du et al. (2017) underline the importance of nonlinear temperature effects on different economic activities. Aggregate economic losses accelerate with increasing temperature; according to different scenarios an average temperature increase beyond 2°C would amplify economic losses, while temperature increase below this threshold does not seem to cause a sizeable reaction to the economy (IPCC, 2014). For a similar reason, if temperature has nonlinear effects on the economy, then higher temperatures should amplify investors' concerns about climate change. Therefore, in the remainder of this research, we explore a nonlinear relation between temperature changes and systemic risk.

Hypothesis 1: Temperature has asymmetric effects on systemic risk.

It should be recognised that the multifaceted information content of temperature change might hinder a direct identification of its effects on the economy and financial markets. Moreover, if information about temperature is regarded as a significant pricing factor of stocks, then stock prices, returns and losses should respond to unanticipated changes in temperature, rather than to trend or seasonality. Therefore, to ascertain whether the asymmetric temperature effects are driven by unanticipated changes to temperature, and to delve deeper into the temperature-systemic risk nexus, we decompose the temperature variable into trend, seasonality component and anomaly, as suggested by Vecchio and Carbone (2010); Balvers et al. (2017). Temperature anomaly should lead to gradual devaluation of climate-sensitive assets (Bansal et al., 2016) and thus we expect the entire financial system to be affected. As Jacobsen and Marquering (2009) claim, raw temperature might be correlated with different seasonal patterns and thus results might be driven by seasonal unobserved characteristics. For this reason, similarly with Hypothesis 1, temperature anomaly should be an appropriate measure to account for the potential asymmetries.

Hypothesis 2: Temperature anomaly has asymmetric effects on systemic risk.

There is adequate literature to support that temperature shocks have an effect on the productivity of firms (see e.g., Hsiang, 2010; Graff Zivin and Neidell, 2014; Dafermos et al., 2017; Donadelli et al., 2017b). Productivity is depleted by temperature shocks; in turn, productivity shocks can explain a large variation in the cross section of stock returns (Garlappi and Song, 2016). To be more explicit, temperature shocks should generate concerns to investors about global warming and thus a positive impact of temperature shocks on systemic risk is expected.

It is worth noting that for its most part, the climate - finance literature does not distinguish between hot and cold temperature shocks. Yet, in practice, temperature shocks can either be positive (e.g. a heat wave) or negative (e.g., extremely low temperatures). Pilcher et al. (2002) puts forward the argument that, on one hand, exposure to cold weather can negatively affect reasoning and memory tasks, while on the other, hot exposure reduces attentional and perceptual tasks. Therefore, considering these distinct effects on performance, it would be interesting to investigate whether temperature effects hold given that the present study proceeds with a disaggregation of temperature shocks into hot and cold.

Based on the above, there are two main competing views on how hot or cold shocks should influence systemic risk. The first view relates to energy consumption. Authors such as Weagley (2018) maintain that extreme temperature deviations are associated with higher risk taking in financial markets. Weagley (2018) argues that this connection is justified by the additional energy needed in order to cool or heat a particular place in the light of a temperature shock, which can be regarded as an adverse shock to the demand for energy, and can be generally perceived as “bad” news by investors and traders. Therefore, continuous and extreme temperature shocks would increase the energy demand and, in turn, firms would have to factor in their profit functions higher long-term operational cost to maintain standard working conditions.

Hypothesis 3: Hot and Cold temperature shocks should increase systemic risk.

The second view relates to the psychological literature. More particularly, Heal and Kriström (2002); Cao and Wei (2005) identify that extreme temperatures are connected not only with different levels of productivity but also with psychological effects. Particularly, Cao and Wei (2005) find that cold temperature causes aggression and high risk-taking, while hot temperature can affect the mood of investors by causing either aggression or apathy and thus, either high or no risk-taking. In general, aggressive investors will tend to engage in more risky investments. As a result, investors will submit more demand orders for risky stocks, which will lead to an increase in stock prices and returns, and a decrease in the scale of losses. In turn, lower losses are associated with lower levels of systemic risk. Therefore, according with the psychological literature, it would not be surprising if hot and cold shocks decrease systemic risk.

5.3 Research design

5.3.1 Sample

The sample consists of 600 European firms that are included in STOXX 600 Index from the period 1/1/1990 to 29/12/2017. Firms are coming from 10 different industries from 17 different countries (see, Table 5.27). All the data are in daily frequency, making a strongly balanced panel of 4,383,000 firm-day observations. The mean temperature and the precipitation for all 17 different locations have been retrieved from the European Climate Assessment & Dataset (ECA&D)[28]. We match the firms' main market location with the closest weather station in

[28] https://www.ecad.eu/

order to extract the weather data (see, panel C in Table 5.27). The stock market returns are available at Datastream, while the macroeconomic data are collected from Federal Reserve Bank of St. Louis. We choose this period of examination for the subsequent two reasons. First, financial and weather daily data are scarce before this period. Second, the Intergovernmental Panel on Climate Change (IPCC) and the United Nations Framework Convention on Climate Change (UNFCCC), that are the two most prominent actions against climate change, were established relatively to this period.

A critical issue is the frequency of the data. In the climate-economy literature, temperature is commonly approximated with low frequency data (monthly, quarterly, annually) (Colacito et al., 2018); this is because climate change is a long term phenomenon which systematically affects macroeconomic conditions (e.g. Dell et al., 2014). However, in the case of financial markets, the situation is different. Due to the technology advances, high frequency traders react instantly to relevant news (O'Hara, 2015). Another example that further stresses the debate between low and high frequency data, is that if one day of the month is very hot and another day very cold, then the monthly aggregated result would be downward biased (Vecchio and Carbone, 2010). Therefore, the higher the frequency of data, the more precise results we obtain. Although, daily data are used is the main analysis, we also consider monthly data in order to test whether long-run temperature shifts can shape the perception of investors in the financial markets. On the contrary, someone might argue that algo-traders (high-frequency trading) can react within seconds to weather news. However, this is an argument that we cannot test since the highest frequency provided by the weather stations is daily. This might be a promising area for future investigation.

Table 5.27: Industry, Country and Weather Stations

Panel A: Industry composition		
Industry	**Number of Firms**	**Percentage**
1. Consumer Goods	74	12.33
2. Financials	138	23
3. Health Care	49	8.17
4. Oil & Gas	20	3.33
5. Technology	28	4.67
6. Industrials	123	20.5
7. Consumer Services	71	11.83
8. Basic Material	47	7.83
9. Telecommunications	21	3.5
10. Utilities	29	4.83
Panel B: Country composition		
Country	**Number of Firms**	**Percentage**
1. Switzerland	51	8.5
2. United Kingdom	160	26.67
3. France	90	15
4. Netherlands	29	4.83
5. Belgium	15	2.5
6. Germany	75	12.5
7. Spain	29	4.83
8. Denmark	22	3.67
9. Norway	13	2.17
10. Italy	30	5
11. Sweden	44	7.33
12. Austria	7	1.17
13. Finland	17	2.83
14. Ireland	9	1.5
15. Czech Republic	2	0.33
16. Portugal	4	0.67
17. Luxembourg	3	0.5
Total	**600**	
Panel C: Weather Stations		
Country	**Market**	**Ecad ID and Station Name**
1. Switzerland	Zurich	244 ZUERICH/FLUNTERN
2. United Kingdom	London	1860 HEATHROW
3. France	Paris	38 PARIS - MONTSOURIS
4. Netherlands	Amsterdam	161 DE KOOY
5. Belgium	Brussels	944 BIERSET
6. Germany	Frankfurt	2761 M-FLUGHAFEN
7. Spain	Madrid	230 MADRID - RETIRO
8. Denmark	Copenhagen	116 KOEBENHAVN
9. Norway	Oslo	193 OSLO BLINDERN
10. Italy	Milan	242 LUGANO
11. Sweden	Stockholm	10 STOCKHOLM
12. Austria	Vienna	16 WIEN
13. Finland	Helsinki	28 HELSINKI KAISANIEMI
14. Ireland	Dublin	121 DUBLIN PHOENIX PARK
15. Czech Republic	Prague	27 PRAHA-KLEMENTINUM
16. Portugal	Lisbon	229 BADAJOZ
17. Luxembourg	Luxembourg	203 LUXEMBOURG AIRPORT

Note: Firms are allocated to industries according to the Industry Classification Benchmark (ICB). Ecad ID is the weather station identifier as listed in the www.ecad.eu database.

5.3.2 $\Delta CoVaR$

In this sub-section, we define systemic risk as the contribution of Value at Risk (VaR) of one firm to the Value at Risk of the industry, in which this firm operates. For example, how HSBC Bank PLC under distress can transmit instabilities to the whole financial sector in the EU. In this study, a firm under distress is reflected in the 99% of the losses distribution. This part of the distribution represents the highest daily expected losses, which can easily be computed through the traditional VaR method. An alternative procedure to control for VaR, which is robust to outliers, spillover effects and is directly associated with systemic risk, is proposed by Adrian and Brunnermeier (2016):

$$Pr(X^j|C(X^i) \leq CoVaR_q^{j|C(X^i)}) = q\%, \tag{5.15}$$

where X^j is industry return losses conditional on the losses of a particular firm i (X^i) at any part of the distribution (i.e. $q = 99\%$). $CoVaR^{j|C(X^i)}$ is the Value at Risk of the industry j conditional on some event $C(X^i)$ of institution i. $CoVaR$ can be implicitly estimated by running the following quantile regression:

$$X_q^j = a_q^i + \beta_q^i X^i + u_q^i, \qquad q \in (0, 1), \tag{5.16}$$

where the predictive values of X_q^j are the Value at Risk of financial system conditional on X^i. Therefore $CoVaR_q^i = \widehat{X}_q^j$ and $CoVaR_q^i$ is the VaR of j conditional on VaR of i at any q given. Additionally, to more effectively approximate systemic risk we use the $\Delta CoVaR$ measure, which is the change in $CoVaR$ of institution i at $q = 99\%$ to its median state ($q = 50\%$). The median state of any institution can be estimated by running the Equation 5.16 at $q = 50\%$ and then saving its fitted values ($CoVaR_q^{j|VaR_{50}^i}$). In other words, we run Equation 5.16 twice at q=99% and at q=50%, and save the fitted values. Then, $\Delta CoVaR$ can be measured as shown in Equation 5.17:

$$\Delta CoVaR_q^i = CoVaR_q^i - CoVaR_q^{j|VaR_{50}^i}. \tag{5.17}$$

5.3.3 Temperature Decomposition

We focus on the short-term temperature variations related to the 28 years time-span of our sample. In order to extract the short behaviour of temperature, we consider time-series decomposition. In the traditional time-series decomposition, the data can be a product of three components as shown by Zarnowitz and Ozyildirim (2006):

$$Temp_t = Trend_t + Season_t + Anom_t, \tag{5.18}$$

where t denotes the time, $Temp$ is the time series of the raw temperature data, $Trend$ is the trend-cycle component, $Season$ is the seasonality and $Anom$ is the anomaly component. The frequency of the seasonality can be easily defined as a 365 day cycle by including all weekend temperatures and excluding the 29th of February when the year is leap. We repeat this procedure for the 17 different market locations over the 28 years of our sample period.

The trend-cycle component contains the long-term temperature characteristics and it corresponds to A persistent temperature increase. We are now able to remove the seasonality from the raw temperature data. Finally, anomaly is defined as the unexpected temperature variations for any given day of our sample. It is important to underline that superscript t is retained if only t corresponds to market calendar day.

5.3.4 Empirical Model

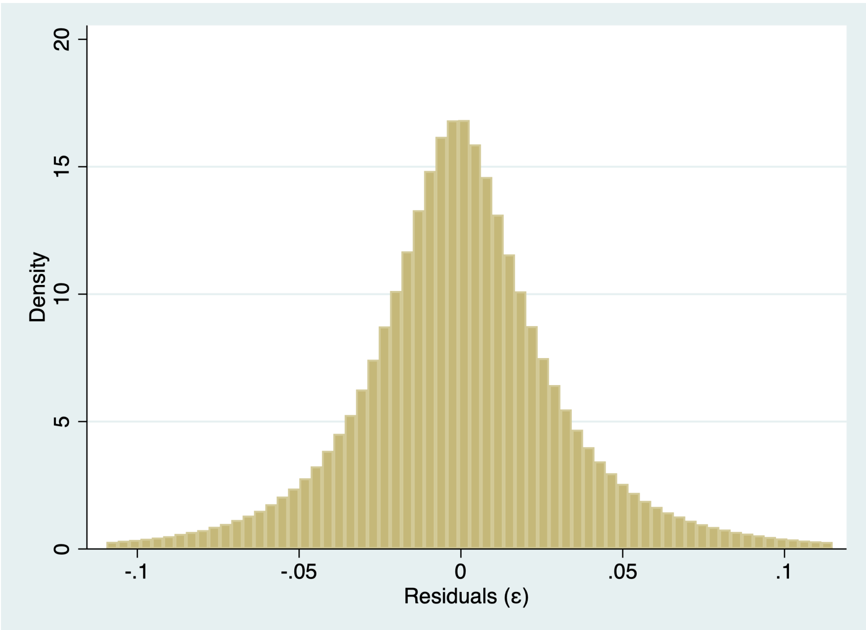
Having defined $\Delta CoVaR_q^i$ (hereafter, $\Delta CoVaR_{i,t}$), we are now in a position to examine if higher temperature can incite extreme losses of firms. Hence, we add a nonlinear setting in the following regression:

$$\begin{aligned}\Delta CoVaR_{i,t} = \gamma_0 + \gamma_1 \Delta CoVaR_{i,t-1} + \gamma_2 Temp_{k,t} + \gamma_3 Temp_{k,t}^2 + \gamma_4 Preci_{k,t} + \gamma_5 Mon_t \\ + \gamma_6 Jan_t + \gamma_7 TED_t + \gamma_8 Credit_t + \gamma_9 Mar.R_t + \gamma_{10} Vol_t + \gamma_{11} Yield_t + \\ \gamma_{12} Size_{i,t} + \sum_{\phi}^{28} \delta * Year_{\phi} + \sum_{k}^{17} \theta * Country_k + \sum_{p}^{10} \lambda * Industry_p + \varepsilon_{i,t},\end{aligned} \tag{5.19}$$

where, i and t denotes the firm and day respectively with $i = 1, ..., 600$ and $t = 01/01/1990, ..., 29/12/2017$ (7305 trading days), k corresponds to the geographical market location with $k = 1, ..., 17$, p is the industry with $p = 1, ..., 10$ (see, Table 5.27 Panel A and B) and ϕ is the year with $\phi = 1990, ..., 2017$. We add an autoregressive term of systemic risk ($\Delta CoVaR_{i,t-1}$) to account for the short memory of systemic risk. Following Apergis and Gupta (2017); Donadelli et al. (2017b), we add precipitation ($Preci$) as an alternative weather proxy and it is measured as the millimetres of water fallen at a particular site for any day given. We also use Monday dummy (Mon) and January dummy (Jan) in order to capture some seasonal effects (Zhang and Jacobsen, 2013; Apergis and Gupta, 2017). We then follow the finance literature and we add some important determinants of systemic risk (White et al., 2015; Adrian and Brunnermeier, 2016). TED, which is defined as the difference between the 3 month LIBOR rate and Treasury bill rate, can capture the short term liquidity risk. $Credit$ is the spread between Moody's Baa corporate bond and the 10-year treasury bond. TED and $Credit$ are known to capture variations of stock returns. Market return ($Mar.R$) as the daily return of STOXX 600 Index. Equity volatility (Vol) is defined as the 22-day rolling standard deviation of the daily stock market return. $Yield$ presents the 10-year government bond yields for the European Union which is available in a monthly frequency. Finally, we include $Size$ which is defined as the logarithm of the last daily market value of each firm. Our model also includes year, country and industry dummies in order to absorb the remaining heterogeneity of systemic risk.

Equation 5.19 is tested with pooled OLS and it can provide an answer about Hypothesis 1. The standard errors are robust correcting for heteroskedasticity. Our model is free of multicollinearity according to the variance inflation factor (VIF) test and we also perform augmented Dickey-Fuller unit root test for all variables in order to observe the auto-correlation of our data[29]. Finally as shown in Figure 5.13 the error term is normally distributed.

Figure 5.13: Histogram of Residuals



To answer Hypothesis 2, $Temp$ and $Temp^2$ are substituted with (i) the $Trend$ to identify the deterministic process of the temperature data and (ii) the anomaly ($Anom$) and the sqaured value of anomaly ($Anom^2$) as stochastic temperature components.

$$\Delta CoVaR_{i,t} = \xi_0 + \xi_1 \Delta CoVaR_{i,t-1} + \xi_2 Trend_{k,t} + \xi_3 Anom_{k,t} + \xi_4 Anom^2_{k,t} + \mathbf{Z}' B + \epsilon_{i,t},$$

[29]Non-stationary data are transformed into stationary by taking their first difference (D.).

$$(5.20)$$

where $\mathbf{Z}$ is a vector that contains all of the remaining explanatory variables appearing in Equation 5.19.

Finally, answering Hypothesis 3 demands to incorporate hot and cold temperature shocks. We calculate positive and negative temperature shocks, in line with Weagley (2018). A simplified way to calculate these shocks is through the energy needed to cool or heat a place, which can be approximated similar to a standard temperature derivative contract. Such a contract would consider that for temperatures more than 18°C, any workplace needs to be cooled, while the place needs to be heated if the temperatures are less than 18°C. Based on this logic, the Chicago Mercantile Exchange trades weather derivative contract around this threshold (65 Fahrenheit degrees).

$$\begin{aligned} CDD_{k,t} &= Max\{Temp_{k,t} - 18, 0\}, \\ HDD_{k,t} &= Max\{18 - Temp_{k,t}, 0\}, \end{aligned} \tag{5.21}$$

where CDD is the cooling degree day and HDD is the heating degree day. In other words, if CDD=0 then it indicates that this is a cold day, while if CDD>0 this day is hot. Therefore, in Equation 5.19, $Temp$ and $Temp^2$ are substituted with either CDD or HDD:

$$\Delta CoVaR_{i,t} = \psi_0 + \psi_1 \Delta CoVaR_{i,t-1} + (\psi_2 CDD_{k,t} \text{ or } \psi_3 HDD_{k,t}) + \mathbf{Z}'B + \epsilon_{i,t}, \tag{5.22}$$

5.3.5 Descriptive Statistics

Table 5.28 reports the descriptive statistics for the variables of the study. 99% $\Delta CoVaR$ takes values from 0.43% to 7% with higher values indicating higher systemic risk. $Temp$ variable represents the raw temperature data. The 600 firms of our sample experience an average temperature of 10.6°C. A more articulated picture, of the variables of interest, is shown in Figures 5.14 and 5.15, while a more detailed picture of the temperature components is shown in Figure 5.16. Interestingly, for the 28 years of our examination the temperature has increased by 0.6 °C (see, $Trend$ in Figure 5.16). Also, $Anom$ variable reports minimum value of -22.25 and maximum of 13.2; displaying the most extreme unexpected cold and hot temperatures respectively. In terms of the distribution, apart from the temperature variables that are very close to satisfy the normality conditions, the rest of the variables are not normally distributed. Furthermore, comparing the mean, 1st percentile (Q1) and 99th percentile (Q99), we can conclude that our analysis does not seem to have extreme outliers except from the market capitalisation ($Size$), which is also a sign of the heterogeneity of our sample.

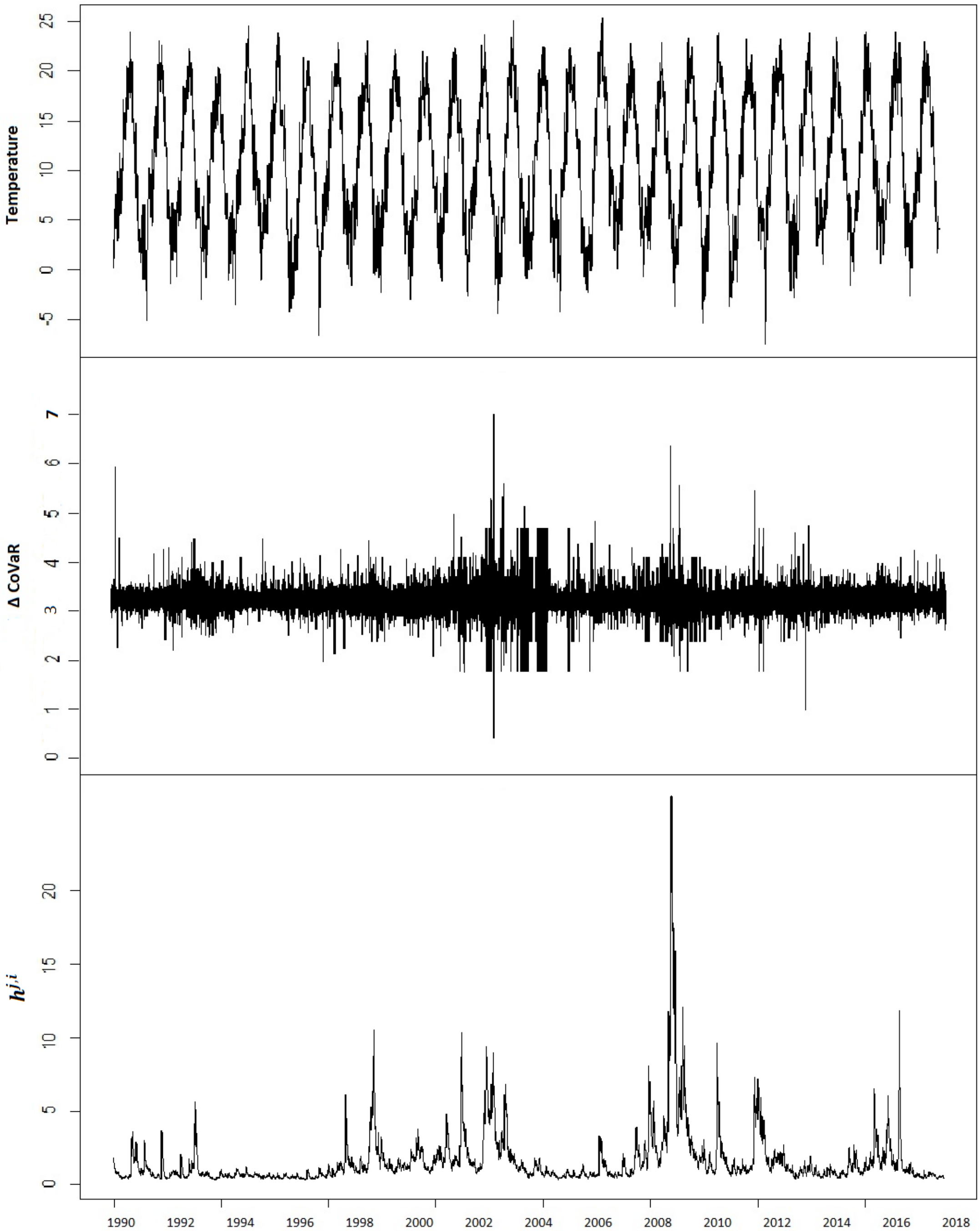
At a first glance, in line with our expectations, temperature seems to have a quadratic effect on systemic risk (Figure 5.17). In order to provide a clearer picture of the relationship, we proceed to examine each one of our Hypotheses.

Table 5.28: Descriptive statistics and Auto-correlations

	mean	std	min	max	skew	kurt	Q1	Q99	unit root (p-value)
X^i	-0.00028	0.0233	-1.3437	1.7918	0.776	98.039	-0.061	0.060	0
X^j	0.00018	0.0127	-0.1486	0.1359	0.142	11.497	-0.0342	0.0373	0
99% $\Delta CoVaR$	3.251	0.046	0.434	7.007	0.749	97.458	3.123	3.377	0
99% $\Delta^{€} CoVaR$	39	72.2	0.001	1180	4.392	29.826	0.2337	364	1*
PC1	≈ 0	1.2162	-43.053	57.391	0.2957	20.5319	-3.2413	3.5099	0
$h^{j,i}$	0.0135	0.0213	0.000	0.9213	7.0469	88.826	0.0003	0.1033	0
Temp	10.622	6.984	-23.300	33.800	-0.093	2.810	-5.500	26.000	0
Trend	10.619	1.916	5.805	17.789	0.309	4.600	6.213	15.777	1*
Season	-0.006	5.845	-13.902	12.823	0.114	1.816	-9.918	10.982	0
Anom	-0.077	3.204	-22.254	13.209	-0.186	3.671	-8.179	7.352	0
CDD	0.4762	1.5367	0.000	15.8	4.063	21.3937	0.000	8.000	0
HDD	7.8538	6.2396	0.000	41.3	0.5313	2.6966	0.000	25.500	0
Preci	2.211	4.960	0.000	176.800	6.483	90.669	0.000	21.700	0
Mon	0.200	0.400	0.000	1.000	1.500	3.250	0.000	1.000	0
Jan	0.085	0.279	0.000	1.000	2.979	9.875	0.000	1.000	0
TED	0.0049	0.0037	0.0009	0.0458	3.301	22.354	0.00140	0.002	0
Credit	0.0237	0.00759	0.012	0.0616	1.623	7.673	0.0138	0.0557	1*
Mar.R	0.0002	0.011	-0.079	0.094	-0.245	9.050	-0.033	0.030	0
Vol	0.009	0.005	0.002	0.047	2.187	10.403	0.003	0.028	0
Yield	0.0508	0.0267	0.00613	0.1114	0.624	2.636	0.0077	0.11	1*
Size	12	22	0.001587	360	4.49295	31.1174	0.063009	110	0.99*

Notes: $\Delta^{€} CoVaR$ and Size are compressed to millions of Euro. Augmented Dickey-Fuller test is reported as unit root test. (*)Asterisk denotes that the panel is not stationary but the first difference is. X^i is the return losses of firm i and X^j is the industry losses. $\Delta CoVaR$ is calculated as shown in Equation 5.17. $\Delta^{€} CoVaR = Size$ x$\Delta CoVaR$. $PC1$ is calculated as shown in Appendix 6.6 and $h^{j,i}$ is calculated as shown in Appendix 6.6. $Temp$ is the raw temperature data. $Trend$, $Anom$ and $Season$ are the decomposed temperature series as shown in Equation 5.18. CDD is the cooling degree day. HDD is the heating degree day. $Preci$ is the precipitation in millimetres of water. Mon is the Monday dummy and Jan the January dummy. TED is the difference between the 3-month LIBOR and Treasury bill rate. $Credit$ is the spread between Moody's Baa corporate bond and 10-year treasury bond. $Mar.R$ is the total market return of the STOXX 600 Index. Vol is the 22-day rolling standard deviation of the total market return. $Yield$ is the 10-year yield of the EU bond. $Size$ is the market capitalisation for every firm.

Figure 5.14: Temperature, $\Delta CoVaR$ and Interconnectedness.



Temperature corresponds to the average raw temperature data as recorded by the 17 weather stations. 99% $\Delta CoVaR$ is the average $\Delta CoVaR$ of the 600 firms of our sample and $h^{j,i}$ is the average dynamic conditional covariance of our sample and is calculated as shown in Appendix 6.6.

Figure 5.15: Macro Variables

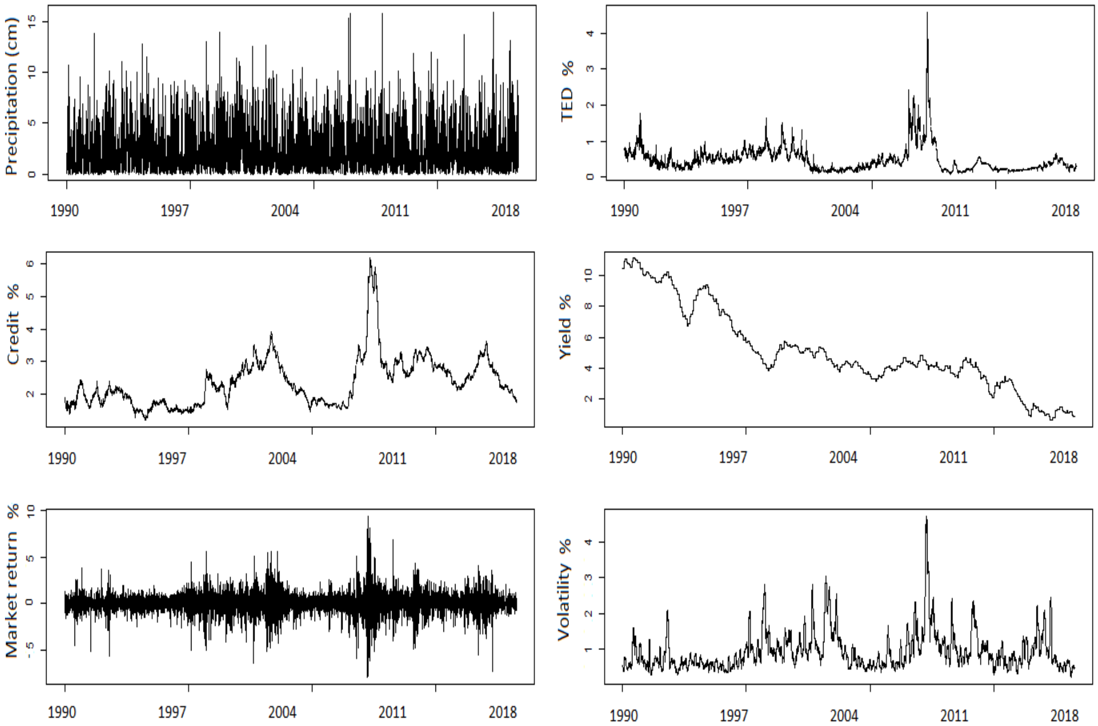
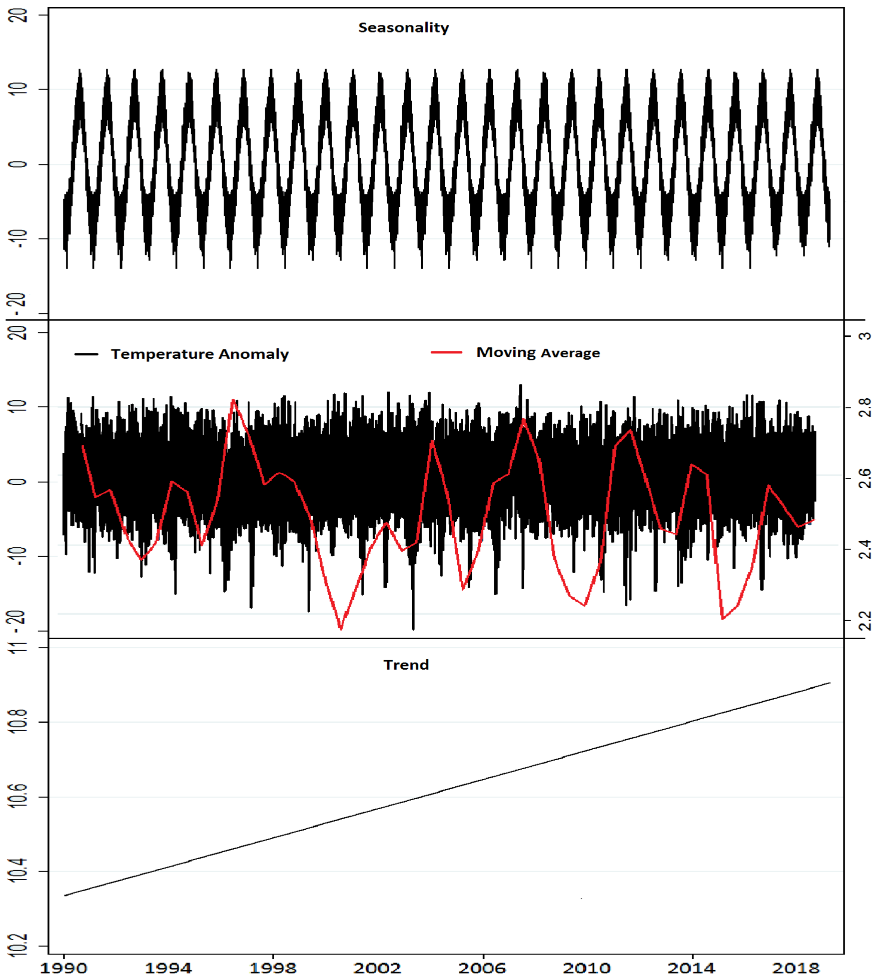
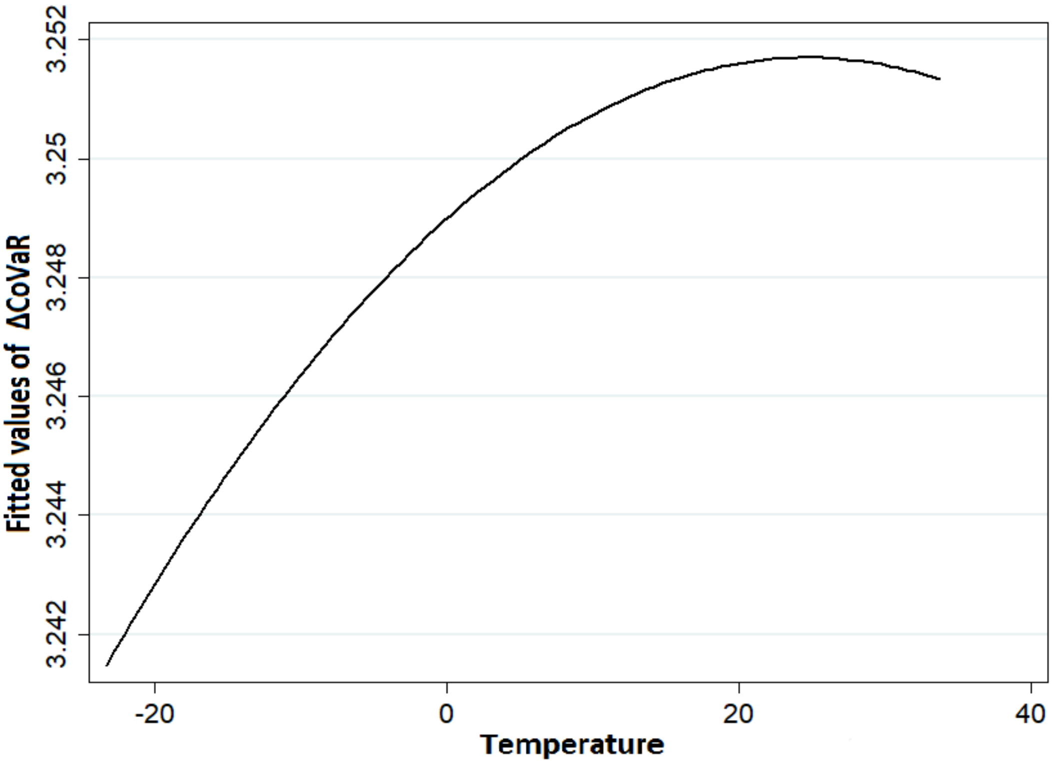


Figure 5.16: Temperature Series Decomposition



The decomposition is based on Equation 5.18. The data used are the weighted temperature records as retrieved by the 17 weather stations. The moving average of temperature anomaly has been calculated as the 260-day rolling average of the absolute values of temperature anomaly; the right vertical axis scales the red line.

Figure 5.17: 99% $\Delta CoVaR$-Temperature



The line shows a quadratic regression between 99% $\Delta CoVaR$ and temperature with no other covariates. Our full sample is used for the calculations.

5.4 Empirical Results

5.4.1 Regression Analysis

Table 5.29 reports the OLS regression results based on Equations 5.19 and 5.20, with dependent variable 99% $\Delta CoVaR$. The total number of observations reaches approximately 2.75 million while the R-squared is more than 20%. The economic interpretation of $\Delta CoVaR$ is similar to the interpretation of the correlation coefficients (Adrian and Brunnermeier, 2016). Most of the the control variables appear significant, with the January dummy, market return and market capitalisation being the ones decreasing systemic risk, while precipitation, Monday dummy, TED, credit risk, volatility and yield are associated with higher $\Delta CoVaR$. However, the lagged $\Delta CoVaR$, precipitation and volatility do not affect the systemic risk. Column 1 indicates that higher temperature ($Temp$) is associated with higher systemic risk. Columns 2 provides direct support of Hypothesis 1, that temperature has nonlinear effect on systemic risk. The coefficients of both linear and squared terms of temperature are statistically significant with the former being positive while the latter is negative, indicating that temperature-risk relationship follows an inverted U-shaped curve. This finding confirms our expectations and thus we can conclude that temperature has positive and asymmetric effects on the daily losses of firms (Hypothesis 1).

Table 5.29: Daily Data. Temperature on $\Delta CoVaR$

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta CoVaR_{t-1}$	0.000557	0.000540	0.000669	0.000653	0.000674	0.000672
	(0.00227)	(0.00227)	(0.00227)	(0.00227)	(0.00227)	(0.00227)
Temp	0.0000423***	0.0000811***				
	(0.00000394)	(0.00000968)				
Temp^2		-0.00000184***				
		(0.000000406)				
Anom			0.0000165**	0.0000131*		
			(0.00000791)	(0.00000795)		
Anom^2				-0.00000499***		
				(0.00000149)		
D.Anom					0.00000997	
					(0.0000108)	
D.Anom^2					0.00000712***	
					(0.00000168)	
EU.Anom						0.0000356***
						(0.0000118)
EU.Anom^2						0.00000481
						(0.00000296)
D.Trend			-1.976*	-1.971*	-1.964*	
			(1.036)	(1.036)	(1.036)	
D.EU.Trend						-40.20**
						(18.69)
Preci	0.00000255	0.000000840	0.00000436	0.00000408	0.00000450	0.00000464
	(0.00000508)	(0.00000509)	(0.00000508)	(0.00000508)	(0.00000509)	(0.00000508)
Mon	0.000850***	0.000851***	0.00107***	0.00107***	0.00107***	0.00559**
	(0.0000654)	(0.0000654)	(0.000131)	(0.000131)	(0.000131)	(0.00221)
Jan	-0.000344***	-0.000287***	-0.000668***	-0.000642***	-0.000670***	-0.000677***
	(0.000104)	(0.000105)	(0.0000993)	(0.0000995)	(0.0000993)	(0.0000993)
TED	0.00141***	0.00139***	0.00134***	0.00133***	0.00132***	0.00133***
	(0.000184)	(0.000184)	(0.000184)	(0.000184)	(0.000183)	(0.000183)
D.Credit	0.00932***	0.00927***	0.00964***	0.00962***	0.00970***	0.00972***
	(0.00116)	(0.00116)	(0.00116)	(0.00116)	(0.00116)	(0.00116)
Mar.R	-1.822***	-1.822***	-1.823***	-1.823***	-1.823***	-1.823***
	(0.00331)	(0.00331)	(0.00331)	(0.00331)	(0.00332)	(0.00331)
Vol	0.254	0.252	0.230	0.233	0.229	0.229
	(0.484)	(0.484)	(0.484)	(0.484)	(0.484)	(0.484)
D.Yield	0.000877***	0.000888***	0.000776***	0.000798***	0.000767***	0.000762***
	(0.000147)	(0.000147)	(0.000147)	(0.000147)	(0.000147)	(0.000147)
D.Size	-0.134***	-0.134***	-0.134***	-0.134***	-0.134***	-0.134***
	(0.00935)	(0.00935)	(0.00935)	(0.00935)	(0.00937)	(0.00935)
Cons	3.248***	3.248***	3.248***	3.248***	3.248***	3.251***
	(0.00738)	(0.00738)	(0.00738)	(0.00738)	(0.00739)	(0.00744)
Year	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES
Obs	2,754,821	2,754,821	2,750,000	2,750,000	2,749,118	2,750,000
R^2	20.82	20.82	20.83	20.83	20.83	20.83

Notes: The results are based on Equations 5.19 and 5.20. The dependent variable is 99% $\Delta CoVaR$. Robust standard errors reported in the parentheses, *,**,*** 10%, 5% and 1% significant level. D. indicates the first difference of the variable. *Temp* is the raw temperature data.*Anom* is the value of the temperature anomaly and *Trend* is the trend from the decomposed temperature series (Eq. 5.18). *EU.Anom* is difference between the *Anom* of the firm's market location and the average EU *Anom* as recorded by the 17 weather stations. *EU.Trend* is the average EU trend from the 17 market locations. *Preci* is the precipitation in millimetres of water. *Mon* is the Monday dummy and *Jan* the January dummy. *TED* is the difference between the 3-month LIBOR and Treasury bill rate. *Credit* is the spread between Moody's Baa corporate bond and 10-year treasury bond. *Mar.R* is the total market return of the STOXX 600 Index. *Vol* is the 22-day rolling standard deviation of the total market return. *Yield* is the 10-year yield of the EU bond. *Size* is the market capitalisation for every firm. The total number of estimates (i.e model 1) are 11 independent variables, 28 years, 17 countries and 10 industries (66); vif test shows no multicollinearity.

In columns 3-6 (Table 5.29), we add the decomposed temperature time series to test Hypothesis 2 (temperature anomaly). We consider three different specifications of temperature anomaly, (1) the temperature anomaly (*Anom*) from the decomposed temperature series, (2) the first difference of *Anom* ($D.Anom$= $Anom_{k,t}$-$Anom_{k,t-1}$) and (3) a relative measure of temperature which is the difference between the *Anom* and the average European anomaly ($EU.Anom = Anom - \Sigma_{k=1}^{K=17} Anom/K$) . In column 3, temperature anomaly seems to increase $\Delta CoVaR$ at 5% level of significance. Moving to column 4, we witness that temperature anomaly and systemic risk follow an inverted U-shaped curve. When testing for the innovations in temperature anomaly ($D.Anom$ and $D.Anom^2$ in column 5) and the average EU anomaly temperature ($EU.Anom$ and $EU.Anom^2$ in column 6), both seem to monotonically increase systemic risk of firms. This finding indicates that the temperature-risk relationship is both positive and non-linear and thus there is a strong evidence to support that temperature variations can influence the perception of financial markets about climate change. Thus far, Hypothesis 2, that temperature anomaly has an asymmetric effect on systemic risk, can be partially supported.

Table 5.30: Monthly Data. Temperature on $\Delta CoVaR$

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta CoVaR_{t-1}$	0.00698	0.00605	0.0163***	0.0163***	0.0168***	0.0262***
	(0.00451)	(0.00451)	(0.00443)	(0.00443)	(0.00448)	(0.00453)
Temp	0.0000195***	0.00000154				
	(0.000000749)	(0.00000190)				
Temp^2		0.000000838***				
		(8.54e-08)				
Anom			0.000170***	0.000235***		
			(0.00000885)	(0.0000106)		
Anom^2				0.0000588***		
				(0.00000425)		
D.Anom					0.0000588***	
					(0.0000110)	
D.Anom^2					-0.000199***	
					(0.0000199)	
EU.Anom						0.000167***
						(0.0000107)
EU.Anom^2						0.0000606***
						(0.00000446)
D.Trend			1.176***	1.018***	1.188***	
			(0.0782)	(0.0792)	(0.0782)	
D.EU.Trend						0.00449***
						(0.000244)
Preci	-0.00000267	-0.00000250	0.00000257	0.000000131	0.00000320	0.000000219
	(0.00000222)	(0.00000222)	(0.00000221)	(0.00000222)	(0.00000221)	(0.00000222)
Jan	-0.000280***	-0.000309***	-0.000460***	-0.000423***	-0.000517***	-0.000286***
	(0.0000117)	(0.0000119)	(0.0000100)	(0.0000107)	(0.00000987)	(0.0000127)
TED	0.00186***	0.00212***	0.000548***	0.000820***	0.000498***	0.00169***
	(0.000105)	(0.000106)	(0.0000858)	(0.0000917)	(0.0000859)	(0.0000989)
D.Credit	0.0000139	0.0000138	-0.00000398	-0.00000130	-0.00000744	-0.0000247***
	(0.00000931)	(0.00000931)	(0.00000935)	(0.00000935)	(0.00000934)	(0.00000934)
Mar.R	-0.966***	-0.966***	-1.058***	-1.035***	-1.082***	-1.030***
	(0.0101)	(0.0101)	(0.00948)	(0.00970)	(0.00955)	(0.01000)
Vol	-0.00669***	-0.00642***	-0.00528***	-0.00522***	-0.00544***	-0.00318***
	(0.00104)	(0.00104)	(0.00105)	(0.00104)	(0.00105)	(0.00104)
D.Yield	0.0000398**	0.0000436**	0.0000513***	0.0000478***	0.0000555***	0.0000104
	(0.0000172)	(0.0000172)	(0.0000173)	(0.0000173)	(0.0000173)	(0.0000172)
D.Size	-0.0000183***	-0.0000184***	-0.0000181***	-0.0000181***	-0.0000181***	-0.0000178***
	(0.00000208)	(0.00000208)	(0.00000208)	(0.00000208)	(0.00000208)	(0.00000208)
Cons	3.228***	3.231***	3.195***	3.196***	3.194***	3.166***
	(0.0146)	(0.0146)	(0.0144)	(0.0144)	(0.0145)	(0.0147)
Year	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES
Obs	144,647	144,647	144,395	144,395	144,395	144,395
R^2	14.50	14.55	14.41	14.48	14.27	14.46

Notes: The results are based on Equations 5.19 and 5.20. The dependent variable is 99% $\Delta CoVaR$. Robust standard errors reported in the parentheses, *,**,*** 10%, 5% and 1% significant level. D. indicates the first difference of the variable. $Temp$ is the raw temperature data.$Anom$ is the value of the temperature anomaly and $Trend$ is the trend from the decomposed temperature series (Eq. 5.18). $EU.Anom$ is difference between the $Anom$ of the firm's market location and the average EU $Anom$ as recorded by the 17 weather stations. $EU.Trend$ is the average EU trend from the 17 market locations. $Preci$ is the precipitation in millimetres of water. Mon is the Monday dummy and Jan the January dummy. TED is the difference between the 3-month LIBOR and Treasury bill rate. $Credit$ is the spread between Moody's Baa corporate bond and 10-year treasury bond. $Mar.R$ is the total market return of the STOXX 600 Index. Vol is the 22-day rolling standard deviation of the total market return. $Yield$ is the 10-year yield of the EU bond. $Size$ is the market capitalisation for every firm.

Spillover effects from a firm to the financial markets might need some time to be observed, similarly, temperature effects are commonly categorised as long-term phenomena. To ascertain whether the frequency of the data can potentially moderate the results, we aggregate daily data to a monthly frequency by taking the median values of every month. Table 5.30 reports the monthly estimations. Results are more positive compared to the daily data estimations (Table 5.29). Particularly, higher temperatures significantly increase systemic risk (columns 1 and 2), the shape of this relationship appears steeper and hence Hypothesis 1 is partially supported. Regarding Hypothesis 2, both *Anom* and *EU.Anom* strongly increase systemic risk, as both level and quadratic terms are positive, while temperature innovations (*D.Anom*) seem to exhibit inverted U-shaped curve with the $\Delta CoVaR$. Surprisingly, when examined daily data, the relationship appeared both positive and asymmetric, while in monthly examination, the positive sign dominates. A possible explanation is that the temperature changes have adverse long-term aspects while in the short-term this effect is weaker.

Furthermore, Table 5.31 presents the results on Hypothesis 3, regarding hot and cold temperature shocks. Columns 1 and 2 report the hot shock (CDD) and the cold shock (HDD) estimations, respectively. Columns 2 and 4 also test for nonlinear CDD and HDD. Our results suggest that hot shocks have linear and positive association with systemic risk, while the effect of cold shocks are strongly negative. Particularly, higher CDD by 1°C can increase systemic risk by 0.0000277% at 10% level of significance, while the same increase in HDD report a coefficient of -0.000051 at 1% level. Taken together, the results indicate that high temperatures are detrimental for the financial system, but low temperatures are not. At the same time there is not enough evidence to support nonlinear temperature shock effects. Additionally, there is a mixed evidence regarding the view which is the most appropriate to justify the temperature shock - systemic risk relationship; either energy consumption or psychological effects. Our findings indicate that the former is related to hot shocks, while the latter to the cold shocks. Particularly, hot shocks increase systemic risk, as stated in Hypothesis 3, while cold shocks decrease systemic risk, opposing Hypothesis 3.

Table 5.31: Daily Data. Temperature Shocks on $\Delta CoVaR$

	(1)	(2)	(3)	(4)
$\Delta CoVaR_{t-1}$	0.000644	0.000644	0.000542	0.000538
	(0.00227)	(0.00227)	(0.00227)	(0.00227)
CDD	0.0000277*	0.0000445		
	(0.0000162)	(0.0000402)		
CDD^2		-0.00000233		
		(0.00000500)		
HDD			-0.0000510***	-0.0000280**
			(0.00000444)	(0.0000113)
HDD^2				-0.00000124**
				(0.000000577)
Preci	0.00000434	0.00000433	0.00000175	0.00000107
	(0.00000508)	(0.00000508)	(0.00000508)	(0.00000509)
Mon	0.000840***	0.000840***	0.000852***	0.000852***
	(0.0000654)	(0.0000654)	(0.0000654)	(0.0000654)
Jan	-0.000663***	-0.000661***	-0.000301***	-0.000282***
	(0.0000995)	(0.0000996)	(0.000105)	(0.000105)
TED	0.00133***	0.00133***	0.00141***	0.00140***
	(0.000184)	(0.000184)	(0.000183)	(0.000184)
D.Credit	0.00966***	0.00966***	0.00926***	0.00925***
	(0.00116)	(0.00116)	(0.00116)	(0.00116)
Mar.R	-1.823***	-1.823***	-1.822***	-1.822***
	(0.00331)	(0.00331)	(0.00331)	(0.00331)
Vol	0.230	0.230	0.258	0.255
	(0.484)	(0.484)	(0.484)	(0.484)
D.Yield	0.000776***	0.000777***	0.000885***	0.000889***
	(0.000147)	(0.000147)	(0.000147)	(0.000147)
D.Size	-0.134***	-0.134***	-0.134***	-0.134***
	(0.00935)	(0.00935)	(0.00935)	(0.00935)
Cons	3.248***	3.248***	3.249***	3.249***
	(0.00738)	(0.00738)	(0.00738)	(0.00738)
Year	YES	YES	YES	YES
Country	YES	YES	YES	YES
Industry	YES	YES	YES	YES
Obs	2,754,821	2,754,821	2,754,821	2,754,821
R^2	20.82	20.82	20.82	20.82

Notes: The results are based on Equation 5.22. The dependent variable is 99% $\Delta CoVaR$. Robust standard errors reported in the parentheses, *,**,*** 10%, 5% and 1% significant level. D. indicates the first difference of the variable. CDD is the cooling degree day and HDD is the heating degree day. $Preci$ is the precipitation in millimetres of water. Mon is the Monday dummy and Jan the January dummy. TED is the difference between the 3-month LIBOR and Treasury bill rate. $Credit$ is the spread between Moody's Baa corporate bond and 10-year treasury bond. $Mar.R$ is the total market return of the STOXX 600 Index. Vol is the 22-day rolling standard deviation of the total market return. $Yield$ is the 10-year yield of the EU bond. $Size$ is the market capitalisation for every firm.

Table 5.32: Monthly Data. Temperature Shocks on $\Delta CoVaR$

	(1)	(2)	(3)	(4)
$\Delta CoVaR_{t-1}$	0.0133***	0.0102**	0.00779*	0.00520
	(0.00442)	(0.00444)	(0.00451)	(0.00452)
CDD	0.0000742***	0.000184***		
	(0.00000390)	(0.00000816)		
CDD^2		-0.0000197***		
		(0.00000132)		
HDD			-0.0000202***	-0.0000493***
			(0.000000815)	(0.00000236)
HDD^2				0.00000166***
				(0.000000123)
Preci	0.00000312	-0.00000297	-0.00000229	-0.00000337
	(0.00000220)	(0.00000223)	(0.00000222)	(0.00000222)
Jan	-0.000433***	-0.000403***	-0.000283***	-0.000308***
	(0.00000959)	(0.00000971)	(0.0000118)	(0.0000119)
TED	0.00133***	0.00173***	0.00171***	0.00219***
	(0.0000950)	(0.0000990)	(0.000103)	(0.000105)
D.Credit	-0.00000162	0.00000339	0.0000118	0.0000131
	(0.00000933)	(0.00000931)	(0.00000931)	(0.00000930)
Mar.R	-1.061***	-1.030***	-0.970***	-0.953***
	(0.00951)	(0.00954)	(0.0101)	(0.0101)
Vol	-0.00550***	-0.00546***	-0.00663***	-0.00627***
	(0.00105)	(0.00104)	(0.00104)	(0.00104)
D.Yield	0.0000333*	0.0000367**	0.0000368**	0.0000426**
	(0.0000173)	(0.0000173)	(0.0000172)	(0.0000172)
D.Size	-0.0000181***	-0.0000182***	-0.0000183***	-0.0000184***
	(0.00000208)	(0.00000208)	(0.00000208)	(0.00000208)
Cons	3.208***	3.218***	3.226***	3.234***
	(0.0144)	(0.0144)	(0.0147)	(0.0147)
Year	YES	YES	YES	YES
Country	YES	YES	YES	YES
Industry	YES	YES	YES	YES
Obs	144,647	144,647	144,647	144,647
R^2	14.33	14.49	14.44	14.54

Notes: The results are based on Equation 5.22. The dependent variable is 99% $\Delta CoVaR$. Robust standard errors reported in the parentheses, *,**,*** 10%, 5% and 1% significant level. D. indicates the first difference of the variable. CDD is the cooling degree day and HDD is the heating degree day. $Preci$ is the precipitation in millimetres of water. Mon is the Monday dummy and Jan the January dummy. TED is the difference between the 3-month LIBOR and Treasury bill rate. $Credit$ is the spread between Moody's Baa corporate bond and 10-year treasury bond. $Mar.R$ is the total market return of the STOXX 600 Index. Vol is the 22-day rolling standard deviation of the total market return. $Yield$ is the 10-year yield of the EU bond. $Size$ is the market capitalisation for every firm.

In order to provide evidence about the aggregated temperature shock effects, we transform our daily data into a monthly frequency. Table 5.32 reports estimations based on monthly data. It seems that the level coefficients for CDD and HDD remain positive and negative, respectively, in line with the daily examination. Surprisingly, the quadratic coefficients follow a different pattern than the one in the daily analysis. Hot shocks and systemic risk exhibit an inverted U-shaped curve, while cold shocks and systemic risk exhibit a U-shaped curve. Daily analysis clearly shows that temperature shocks have linear effect while monthly analysis demonstrates that this effect is asymmetric. It can be suggested that hot (cold) shocks are not adequately approximated, for instance if one day of the month is very hot while the other is very cold then the median effect is negligible (Vecchio and Carbone, 2010). Therefore, the results might be downward biased when lower frequency temperature shocks are examined.

Even though, extreme temperatures might be associated with higher energy consumption and thus one would expect a higher systemic risk, this is only true for the hot shocks. These findings can have a threefold explanation, in line with Cao and Wei (2005); Bansal et al. (2016); Apergis et al. (2016).

First, consistently with the energy-consumption-based view, hot weather is expected to increase demand and prices of electricity (Hypothesis 3). In turn, high energy prices may increase operational costs of firms, and eventually these firms may incur losses. The results imply that an imminent increase in electricity prices can be considered by stock market investors and traders as "bad" news. Subsequently, investors and traders tend to sell off stocks, which leads to a propagation of losses within and across the industries, which in turn destabilises the financial system. Thus, the results are supportive of the view, which postulates a negative relation between hot shocks and systemic risk. However, if hot weather causes apathy among stock market traders and investors, they are likely not to engage in riskier investments. Even if hot temperature causes aggression, Griffitt and Veitch (1971) assert that such aggression can be causal of an increased antisocial behaviour, which is not necessarily consistent with individual risk-taking. On the contrary, it can even lead to increased pessimism about future stock prices and returns, which can further translate into heightened risk aversion (Lucey and Dowling, 2005). Risk-averting investors tend sell off riskier stocks, which trigger a collapse (rise) in stock prices and returns (losses). The ensuing losses can propagate within and across the industries, and give rise to higher levels of systemic risk.

We now turn to cold shocks, which are expected to increase systemic risk, if the energy-consumption based view holds. However, the results do not accord with Hypothesis 3. Instead, they agree with the second view, which builds on investor psychology to predict a negative relation between cold temperature shocks and systemic risk. According to Cao and Wei (2005), lower temperatures are associated with increased risk-taking as investors become more aggressive. As a result, investors tend to buy risky assets. These purchases, in turn, drive up (down) stock prices and returns (losses), and are associated with a bull market stance. Therefore, the net effect on investors' risk preferences depends upon the balance between concerns about increasing energy demand and/or other psychological factors. Arguably, the latter dominates the former, which manifests in a negative effect of HDD. This leads to lower losses from securities trading, which are transmitted within the industry, in which the firm operates, and across to other industries of the economy.

Yet another explanation, which caters to both hot and cold shocks, underscores the geographical location. In this regard, Bansal et al. (2016) advocate that countries with hotter climate also perform poorly in terms of financial development and are not well equipped to deal with adverse shocks. Therefore, hot shocks might negatively affect countries such as Italy, Spain and Portugal as their financial markets are quite vulnerable to exogenous shocks (Engle et al., 2014). By contrast, cold shocks, occurring mainly in the northern Europe coincide with markets that have higher financial stability.

5.4.2 Portfolio Analysis

Climate change is a risk factor that should have more detrimental effect on industries such as Agriculture, Health Care and Manufacturing and less detrimental effect on Services (Schlenker and Roberts, 2009; Deschenes, 2014; Balvers et al., 2017). In order to test the sensitivity of the previous results, we construct industry portfolios. Ten portfolios are constructed in respect to Table 5.27 Panel A. Then, we run regressions separately for every portfolio to observe the temperature effects within each industry. According to Dell et al. (2014); Balvers et al. (2017), we expected to identify some variations of the results depending on how vulnerable the industry is to weather patterns. Table 5.33 presents the results for Hypotheses 1, 2 and 3. First, in column 1, temperature ($Temp$) coefficient is positive for 9 portfolios and in 6 of them is statistically significant, the squared term ($Temp^2$) is negative in 8/10 portfolios while it is only significant in 3 portfolios. The results illustrate that temperature asymmetrically affect the losses of Financials, Health Care and Oil & Gas portfolios, while 4 portfolios (Technology, Consumer Services, Telecommunications and Utilities) are unaffected and 3 portfolios (Consumer Goods, Industrials, Basic Materials) are linearly affected. Second, in order to test Hypothesis 2, we now pay attention to the decomposed temperature coefficient, namely $Anom$ (column 2). As it is shown, on average, Consumer Goods, Oil & Gas and Basic Materials are significantly affected by the temperature anomaly; findings are in line with Balvers et al. (2017) who underline the direct detrimental temperature effects on the manufacturing sector. Even though, we can partially support Hypothesis 1 about the nonlinear effect of temperature, we are unable to support the same for the temperature anomaly when examined at a sector level. Overall, results indicate that higher temperatures increase systemic risk.

Table 5.33: Industry Portfolios

	(1)		(2)		(3)	(4)		
Portfolio:	Temp	Temp^2	Anom	Anom^2	CDD	HDD	Obs ≈	R^2 ≈
Consumer Goods	0.0000994***	-0.00000125	0.0000389*	-0.00000616	0.000101*	-0.0000855***	355,000	16.4
	(0.0000346)	(0.00000138)	(0.0000228)	(0.00000424)	(0.0000568)	(0.0000145)		
Financials	0.0000462**	-0.00000209**	0.0000124	-0.00000336	-0.0000314	-0.00000391	647,000	26.5
	(0.0000193)	(0.000000823)	(0.0000160)	(0.00000306)	(0.0000408)	(0.00000898)		
Health Care	0.0000793**	-0.00000333**	0.0000245	0.00000156	-0.0000447	-0.0000159	217,000	13.9
	(0.0000325)	(0.00000146)	(0.0000264)	(0.00000505)	(0.0000713)	(0.0000141)		
Oil & Gas	0.000190***	-0.00000526**	0.000195***	-0.00000494	0.000131	-0.0000670**	89,000	21.9
	(0.0000575)	(0.00000218)	(0.0000508)	(0.00000939)	(0.000101)	(0.0000297)		
Technology	0.0000681	-0.00000237	-0.0000228	-0.00000667	-0.000252**	-0.0000325	131,000	20.8
	(0.0000508)	(0.00000224)	(0.0000431)	(0.00000747)	(0.000117)	(0.0000251)		
Industrials	0.000102***	-0.00000117	-0.0000111	-0.0000101***	0.000100**	-0.0000964***	609,000	20.3
	(0.0000186)	(0.000000818)	(0.0000164)	(0.00000302)	(0.0000450)	(0.00000930)		
Consumer Services	0.0000194	0.000000697	-0.0000204	-0.000000776	-0.00000360	-0.0000450***	289,000	21.2
	(0.0000315)	(0.00000134)	(0.0000245)	(0.00000488)	(0.0000713)	(0.0000142)		
Basic Material	0.000116***	-0.00000166	0.0000536*	0.00000358	0.000295***	-0.0000953***	205,500	23.8
	(0.0000317)	(0.00000145)	(0.0000279)	(0.00000489)	(0.0000821)	(0.0000162)		
Telecom-munications	-0.00000283	-0.00000152	-0.0000885*	-0.00000196	-0.000198*	0.0000274	85,500	22.5
	(0.0000456)	(0.00000193)	(0.0000471)	(0.00000819)	(0.000117)	(0.0000254)		
Utilities	0.0000152	0.000000825	0.0000221	-0.00000988	0.000108*	-0.0000291	125,000	21.2
	(0.0000393)	(0.00000137)	(0.0000312)	(0.00000657)	(0.0000563)	(0.0000182)		

Notes: The results are based on Equations 5.19, 5.20 and 5.22. The dependent variable is 99% $\Delta CoVaR$. Robust standard errors reported in the parentheses, *,**,*** 10%, 5% and 1% significant level. The rest of control variables are not reported here for brevity but are available upon request. *Temp* is the raw temperature data. *Anom* is the value of the temperature anomaly (Eq. 5.18). CDD is the cooling degree day and HDD is the heating degree day.

The importance of analysing very cold and hot temperatures has been also underlined by Luterbacher et al. (2004), whose results show that extreme temperatures can affect the economy. In columns 3 and 4 in Table 5.33, regression results are reported based on Equation 5.22 for different industries, using 99% $\Delta CoVaR$ as dependent variable. This table provides further evidence regarding Hypothesis 3. In line with previous estimations, hot shocks (CDD) have significantly positive effects on different industries (4 out of 10 industries) while cold shocks (HDD) decrease systemic risk (5 out of 10 industries). On average, there is a robust evidence that Consumer Goods, Industrials, Basic Materials and Utilities are industries that are most vulnerable to hot shocks; in line with Dell et al. (2014); Balvers et al. (2017). While, Consumer goods, Oil & Gas, Industrials, Consumer Services and Basic Materials can benefit from lower temperatures. Results also show that industries such as Technology, Consumer Services and Telecommunications are not negatively affected by temperature effects. This finding implies that temperature shocks can influence the investment climate, particularly when climate sensitive firms are considered. Therefore, institutional investors and traders make investment decisions based on two principles; (i) how industries are contingent on climate change and (ii) cold weather is "good" news while hot weather is 'bad" news for the financial markets.

5.4.3 Robustness Checks

The degree of interconnection in stock returns can be seen as a proxy for return-spillover effects between a firm and the financial system (Billio et al., 2012)[30]. To corroborate our results, we use two additional dependent variables as measures of interconnectedness. First, we focus on the endogenous risk between firm and industry losses by taking the first principal component ($PC1$) (see more in Appendix 6.6). Second, we compute the dynamic conditional covariance ($h^{j,i}$) in

[30] An alternative methodology could be based on the study of Diebold and Yilmaz (2009). Their study provides a simple and intuitive measure of interdependence of asset returns and/or volatilities. In particular, the advantage of this framework is that it facilitates non-crisis and crisis episodes.

an endogenous system, constituted by losses of firm i and industry j (see more in Appendix 6.6). Because $h^{j,i}$ already accounts for the dynamics in the model, the autoregressive variable is omitted. Also, both variables account for a degree of volatility in the market and therefore volatility (Vol) variable is excluded in order to avoid any simultaneity problem.

The results are reported in Table 5.34, columns 1-4 and columns 5-8 show the estimations for $PC1$ and $h^{j,i}$, respectively. In line with the previous estimations, $PC1$ appears to confirm Hypothesis 1 and reject Hypotheses 2; temperature and $PC1$ exhibit an inverted U-shaped curve ($Temp$ and $Temp^2$ coefficients are positive and negative respectively, in column 1); the effect of temperature anomaly on $PC1$ does not follow a nonlinear pattern, but this linearly increases (column 2). Regarding Hypothesis 3, hot shocks (CDD) increase the interconnection of the financial markets (column 3), but cold temperatures (HDD) seem to decrease this interconnection (column 4). In terms of $h^{j,i}$, the results appear qualitatively similar with the previous specifications. The conditional covariances between a firm and its industry are equally affected by temperature effects, importantly, the only difference with $PC1$ estimations, is that both raw temperature and temperature anomaly monotonically increase the firm-industry interconnection (see $h^{j,i}$ in columns 5 and 6).

Table 5.34: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PC1				$h^{j,i}$			
$PC1_{t-1}$	0.0292***	0.0342***	0.0342***	0.0339***				
	(0.000957)	(0.000573)	(0.000576)	(0.000575)				
Temp	0.00120***				0.000000684			
	(0.000176)				(0.00000216)			
Temp^2	-0.0000243***				0.000000968***			
	(0.00000744)				(9.40e-08)			
Anom		0.000249*				0.00000769***		
		(0.000137)				(0.00000200)		
Anom^2		-0.00000662				0.00000178***		
		(0.0000261)				(0.000000357)		
D.Trend		-59.51***				-0.396		
		(17.47)				(0.251)		
CDD			0.00113***				0.0000911***	
			(0.000353)				(0.00000410)	
HDD				-0.000882***				-0.0000203***
				(0.0000782)				(0.00000107)
Preci	0.0000418	0.0000782	0.0000845	0.0000437	0.00000480***	0.00000496***	0.00000554***	0.00000371***
	(0.0000994)	(0.0000907)	(0.0000909)	(0.0000908)	(0.00000141)	(0.00000140)	(0.00000140)	(0.00000141)
Mon	0.0178***	0.0151***	0.00781***	0.00819***	0.0000701***	0.000111***	0.0000658***	0.0000708***
	(0.00122)	(0.00224)	(0.00111)	(0.00111)	(0.0000166)	(0.0000328)	(0.0000166)	(0.0000166)
Jan	-0.00336*	-0.00551***	-0.00521***	-0.000562	-0.000538***	-0.000684***	-0.000629***	-0.000524***
	(0.00199)	(0.00178)	(0.00178)	(0.00190)	(0.0000293)	(0.0000276)	(0.0000276)	(0.0000295)
TED	0.0230***	-0.0606***	-0.0605***	-0.0605***	0.00698***	0.00694***	0.00696***	0.00696***
	(0.00342)	(0.00309)	(0.00309)	(0.00311)	(0.000259)	(0.000259)	(0.000259)	(0.000259)
D.Credit	0.100***	-0.119***	-0.122***	-0.128***	-0.00129***	-0.00115***	-0.00118***	-0.00131***
	(0.0228)	(0.0193)	(0.0195)	(0.0194)	(0.000356)	(0.000356)	(0.000357)	(0.000356)
Mar.R	-81.39***	-77.04***	-77.01***	-77.01***	0.0190***	0.0187***	0.0188***	0.0190***
	(0.0700)	(0.0631)	(0.0636)	(0.0633)	(0.00103)	(0.00103)	(0.00103)	(0.00103)
D.Yield	0.0144***	0.0354***	0.0354***	0.0371***	-0.00487***	-0.00492***	-0.00489***	-0.00487***
	(0.00266)	(0.00247)	(0.00247)	(0.00248)	(0.000137)	(0.000137)	(0.000136)	(0.000137)
D.Size	-2.164***	-1.986***	-1.988***	-1.968***	-0.00213***	-0.00213***	-0.00212***	-0.00214***
	(0.148)	(0.140)	(0.140)	(0.139)	(0.000650)	(0.000650)	(0.000650)	(0.000650)
Cons	-0.00666	0.0889***	0.0842***	0.0907***	-0.00701***	-0.00680***	-0.00687***	-0.00667***
	(0.00484)	(0.00469)	(0.00444)	(0.00446)	(0.000118)	(0.000121)	(0.000119)	(0.000121)
Year	YES	YES	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES	YES	YES
Obs	2,673,025	2,696,545	2,673,025	2,673,025	2,630,428	2,626,327	2,630,428	2,630,428
R^2	57.83	57.92	57.83	57.83	44.96	44.95	44.96	44.96

Notes: The results are based on Equations 5.19, 5.20 and 5.22 by substituting $\Delta CoVaR$ with either PC1 or $h^{j,i}$. PC1 is the first principal component of industry and firm losses (see Appendix Appendix C) and $h^{j,i}$ is the dynamic conditional covariance between a firm and its industry (see Appendix D). Robust standard errors reported in the parentheses, *,**,*** 10%, 5% and 1% significant level. D. indicates the first difference of the variable. $Temp$ is the raw temperature data. $Anom$ is the value of the temperature anomaly (Eq. 5.18) and $Trend$ is the trend from the decomposed temperature series (Eq. 5.18). CDD is the cooling degree day and HDD is the heating degree day. $Preci$ is the precipitation in millimetres of water. Mon is the Monday dummy and Jan the January dummy. TED is the difference between the 3-month LIBOR and Treasury bill rate. $Credit$ is the spread between Moody's Baa corporate bond and 10-year treasury bond. $Mar.R$ is the total market return of the STOXX 600 Index. $Yield$ is the 10-year yield of the EU bond. $Size$ is the market capitalisation for every firm.

5.4.4 Additional Results

In order to provide more plausible results, we consider the $\Delta^{€}CoVaR$ methodology. In Equations 5.19, 5.20 and 5.22, we remove $Size$ variable since it is used to compute the $\Delta^{€}CoVaR$, which in turn is our new alternative dependent variable. Therefore, $\Delta^{€}CoVaR_{i,t} = Size_{i,t} \times \Delta CoVaR_{i,t}$. The € sign denotes the change of the size of the firm in Euro amounts conditional on any variable. $Size$ is the market capitalisation of any firm i at any day t and $\Delta CoVaR$ is defined as previously. We also consider both the 99% and 95% $\Delta^{€}CoVaR$ in order to measure a reasonable confidence interval of the losses. To attain stationarity, in line with Adrian and Brunnermeier (2016), we normalise the $\Delta^{€}CoVaR$ by the cross-sectional average market capitalisation and our new measure is now expressed in basis points. In contrast with the $\Delta CoVaR$, the $\Delta^{€}CoVaR$ takes into account the size of every institution which is closely related to the "Too big to fail" suggestion, indicating that poor performance of large firms would have amplified negative consequences to the financial system.

The results are reported in Table 5.35, where columns 1-4 use 99% $\Delta^{€}CoVaR$ and columns 5-8 use 95% $\Delta^{€}CoVaR$ as dependent variable. As shown, $\Delta^{€}CoVaR$ is substantially different from $\Delta CoVaR$. In column 1, $Temp$ is positive and significant at 1% but $Temp^2$ is insignificant. The $Temp$ coefficient of 0.147 implies that an increase in temperature by 1°C would increase $\Delta^{€}CoVaR$ by 0.147 basis points of daily market equity losses at the 99% quantile. In column 2, $Anom$ is positive and its squared term is negative, representing an inverted U-shaped curve, confirming Hypothesis 2. Regarding CDD and HDD, results illustrate that hot shocks increase and cold shocks decrease systemic risk (Hypothesis 3). Particularly, the impact of temperature shocks is estimated to cause daily losses ranging between -0.303 and 0.239 basis points. This findings show that temperature is priced in financial markets. Despite the relatively "small" effect, we can claim that information about climate change is appreciated by investors. Specifically, it can be implied that low temperatures are perceived as "good" news, while high temperatures as "bad" news for the financial market. Overall, results can be explained by the climate change uncertainty, expectations about increasing energy demand and by psychological factors. Hence, investors are highly uncertain about the probability distribution of future payoffs, since their future expectations are based on current weather events.

Table 5.35: OLS regressions on $\Delta^{€} CoVaR$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	99% $\Delta^{€} CoVaR$				95% $\Delta^{€} CoVaR$			
$\Delta^{€} CoVaR_{t-1}$	-0.366***	-0.366***	-0.366***	-0.366***	-0.458***	-0.458***	-0.458***	-0.458***
	(0.0154)	(0.0154)	(0.0154)	(0.0154)	(0.00590)	(0.00590)	(0.00590)	(0.00590)
Temp	0.147***				0.237***			
	(0.0490)				(0.0605)			
Temp^2	0.00284				0.00170			
	(0.00192)				(0.00235)			
Anom		0.190***				0.239***		
		(0.0301)				(0.0362)		
Anom^2		-0.0105**				-0.0148***		
		(0.00485)				(0.00573)		
D.Trend		9346.5***				9426.4**		
		(3492.8)				(3756.4)		
CDD			0.157**				0.160*	
			(0.0736)				(0.0906)	
HDD				-0.221***				-0.303***
				(0.0339)				(0.0410)
Preci	-0.0172	-0.0201	-0.0229	-0.0214	-0.0215	-0.0246	-0.0285*	-0.0258
	(0.0162)	(0.0161)	(0.0162)	(0.0161)	(0.0173)	(0.0172)	(0.0173)	(0.0172)
Mon	-0.493**	-1.557***	-0.507**	-0.485**	-0.652***	-1.722***	-0.671***	-0.642***
	(0.211)	(0.525)	(0.211)	(0.211)	(0.231)	(0.529)	(0.231)	(0.231)
Jan	0.783***	0.769**	0.783***	0.779**	0.238	0.219	0.239	0.234
	(0.304)	(0.304)	(0.304)	(0.304)	(0.356)	(0.356)	(0.356)	(0.356)
TED	-2.840***	-2.856***	-2.859***	-2.838***	-4.173***	-4.198***	-4.200***	-4.171***
	(0.455)	(0.455)	(0.455)	(0.455)	(0.570)	(0.570)	(0.570)	(0.570)
D.Credit	-57.66***	-57.75***	-57.68***	-57.68***	-73.46***	-73.57***	-73.48***	-73.47***
	(3.293)	(3.295)	(3.294)	(3.294)	(4.128)	(4.130)	(4.129)	(4.129)
Mar.R	-2045.8***	-2045.5***	-2045.5***	-2045.5***	-2835.2***	-2834.8***	-2834.7***	-2834.9***
	(10.48)	(10.49)	(10.48)	(10.48)	(12.81)	(12.81)	(12.81)	(12.81)
Vol	55.60**	55.04**	55.27**	55.66**	100.9***	100.1***	100.4***	100.9***
	(23.50)	(23.51)	(23.50)	(23.50)	(29.40)	(29.40)	(29.40)	(29.40)
D.Yield	-1.812***	-1.799***	-1.812***	-1.807***	-3.078***	-3.064***	-3.080***	-3.073***
	(0.454)	(0.454)	(0.454)	(0.454)	(0.493)	(0.493)	(0.493)	(0.493)
Cons	1.288**	0.539	1.317***	1.298***	1.189*	0.439	1.227**	1.199*
	(0.500)	(0.557)	(0.500)	(0.500)	(0.618)	(0.683)	(0.618)	(0.618)
Year	YES	YES	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES	YES	YES
Obs	2,753,672	2,748,810	2,753,672	2,753,672	2,753,672	2,748,810	2,753,672	2,753,672
R^2	15,72	15,71	15,72	15,72	24.34	24.33	24.34	24.34

Notes: The alternative dependent variable is either 99% $\Delta^{€} CoVaR$ or 95% $\Delta^{€} CoVaR$, where $\Delta^{€} CoVaR = Size$ x $\Delta CoVaR$. Robust standard errors reported in the parentheses, *,**,*** 10%, 5% and 1% significant level. D. indicates the first difference of the variable. $Temp$ is the raw temperature data. $Anom$ is the value of the temperature anomaly (Eq. 5.18) and $Trend$ is the trend from the decomposed temperature series (Eq. 5.18). CDD is the cooling degree day and HDD is the heating degree day. $Preci$ is the precipitation in millimetres of water. Mon is the Monday dummy and Jan the January dummy. TED is the difference between the 3-month LIBOR and Treasury bill rate. $Credit$ is the spread between Moody's Baa corporate bond and 10-year treasury bond. $Mar.R$ is the total market return of the STOXX 600 Index. Vol is the 22-day rolling standard deviation of the total market return. $Yield$ is the 10-year yield of the EU bond.

5.5 Discussion and Conclusions

The purpose of this paper is to examine if systemic risk is conditioned on temperature changes. Systemic risk is measured by making use of the $\Delta CoVaR$ methodology (Adrian and Brunnermeier, 2016), while temperature data are retrieved from the closest weather stations to the firms' main market locations. Using a sample of 600 European firms listed in STOXX 600 Index for 7305 trading days in 17 different financial markets, we find that temperature has a versatile effect on the losses of firms. To be more explicit, in line with existing climate change literature, we decompose the temperature series to (i) trend, (ii) seasonality and (iii), anomaly components. In turn, we make the following assumptions: (1) temperature has asymmetric effects on systemic risk, (2) similarly temperature anomaly has nonlinear effects on systemic risk and (3) hot and cold shocks are detrimental for the financial system. On general principles, all of our hypotheses can be partially supported to some extent, under all different specifications; however, we do record certain deviations among industries.

Our results provide support to the argument that temperature affects systemic risk. Specifically, raw temperature data and temperature anomaly seem to either increase or exert nonlinear effect on systemic risk. We argue that these asymmetries can be explained on the basis of decomposed temperature factors. For instance, on the one hand we show, in line with the psychological literature, that cold temperature shocks significantly decrease the $\Delta CoVaR$, while, on the other, we have adequate evidence to support, in line with the energy consumption view, that hot shocks positively influence systemic risk. More importantly, the portfolio analysis demonstrates that the manufacturing sector is strongly influenced by temperature changes (Balvers et al., 2017), while Technology, Telecommunications and Consumer Services firms seem to be unaffected by the climate. Finally, a numerical example based on the alternative measure of systemic risk, that is $\Delta^{€} CoVaR$, suggests that 1°C temperature change can increase systemic risk by up to 0.24 basis points.

Our study is important for many different stakeholders, as it provides informed insights in connection with the impact of climate change. While proposing hedging strategies and adaptation mechanisms is rather challenging, this paper underscores that the examination of the climate-finance relationship should receive priority and be further promoted. In addition, given the sample market of our study, our findings are quite useful to European firms that operate in relatively developed and well-informed markets and have the capacity to secure themselves against climate change (e.g., by purchasing weather derivatives)[31]. An interesting avenue for future research, would be to investigate how financial markets react to temperature changes in developing countries (Dell et al., 2012).

In turn, our findings can have important research implications. Scholars can gauge the effect of climate change on the financial system. The intuition for using $\Delta CoVaR$ is because of its unique capability to identify, among others, systemic climate sensitive firms that could potentially affect the entire financial system. Therefore, future studies should also investigate the particular characteristics of these firms. Our findings also suggest that temperature variations are priced in financial markets. This finding could be important for the asset pricing literature (Apergis and Gupta, 2017). It can be suggested that market participants fear the regulatory pressure rising from changes in climate patterns (Balvers et al., 2017); this can be an alternative channel that helps rationalise our results.

On a final note, the main limitation of this study is the assumption that temperature recorded on a firm's primary market location affects the activity and the performance of investors and employees, respectively; thus contributing to higher levels of risk. However, it is also true that firms are able to mitigate this impact by diversifying activities to different countries or even continents that are subject to very different weather patterns. In this regard, gathering temperature data from multiple business locations might help resolve this issue. In line with the arguments put forward above, our results do not apply to all

[31] See more information about weather derivatives in Perez-Gonzalez and Yun (2013).

the financial markets. EU is an area adherent to environmental regulations (e.g. emissions trading scheme) and thus investors might be highly driven by climate change effects. As Bansal and Ochoa (2011) assert, heterogeneous temperature effects depend on geographic location. For this reason, similar studies should be conducted about different areas of the world, such as the United States, in to order to determine (and compare) the accuracy of our findings.

6 Conclusion

THE purpose of this thesis was to examine if climate change effects can distort the financial performance of European firms. Arguably, different economic theories underline that this connection is plausible and rather negative. Empirical results follow suit, indicating that immediate actions should be taken in order to secure both the firms and the wider financial system by an imminent stronger climate change crisis. Thus, the study attempts to enhance our understanding of climate change effects on FP. Researchers in the field can use the study as a handbook in order to familiarise themselves and consider future ideas about this interdisciplinary topic. To this end, not only theoretical but also managerial and regulatory implications are discussed.

The remainder of this Chapter is structured as follows. The main findings of every empirical chapter are summarised separately, recommendations and implications are also listed. Then this Chapter syntheses the main conclusion from all three empirical investigations combined. This Chapter tabulates the limitations of the thesis and finally proposes directions for future studies.

6.1 First Empirical Chapter: Environmental and Financial Performance

6.1.1 Findings

The first empirical chapter (Chapter 3) examines the effect of EP on FP using a sample of 288 manufacturing EU firms from 2005 to 2016. Quantile and two-stage quantile regressions have been used to examine this relationship in different part of the FP distribution (Lee, 2007). The main results that merge from this chapter is that (i) EP has always a positive effect on FP, (ii) EP has heterogeneous effect across the conditional distribution and (iii) high profitability firms and EP are endogenously related. Overall, the results suggest that *instrumental stakeholder theory* can well explain the relationship between EP and FP.

Particularly, the relationship between EP and the associated FP quantiles exhibits a U-shaped curve. The schematic representation of EP follows a slightly steady process at the middle of the distribution and increases at the lower and higher FP quantiles. Irrespective of the part of the distribution, EP coefficients are always positive and significant. Our findings are in line with the majority of the studies (e.g Lewandowski, 2017; Trumpp and Guenther, 2017), but it contradicts previous research in the EU area (Wagner, 2005). The fact that the sign of the relationship has changed can be attributed to the strict environmental regulations during the examined period.

Moreover, two-stage quantile regressions are employed to deal with the potential endogeneity. In the first stage, EP model uses EU ETS participation and ISO adoption as its instruments. These two variables are conceptually chosen because arguably they exogenously determine EP (see Section 3.3.4). In turn, EP model provides with two very interesting results. First, EU ETS does not seem to motivate firms to perform environmentally better and second ISO either decrease or has no effect on the FP of the firms.

In the second stage FP model is examined, showing that the relationship between EP and FP is endogenous. Particularly, we have strong evidence that highly profitable firms can afford an investment in EP and thus this positive sign might be influenced primarily by the high FP. Having controlled for endogenous estimates with instrumental variable approach, the results remain robust. On the contrary, we do not observe the same problem for firms with low profitability, indicating that endogeneity is conditional on the profitability levels.

6.1.2 Implications

The finding that the participation in the EU ETS decreases the EP of firms is quite discouraging. The very low carbon price creates disincentives for firms to operate greener and thus they prefer to purchase their extra emissions; this finding should generate regulatory concerns. For this reason, policymakers should develop ease and cheap ways for firms to finance their green projects and increase the cost for firms to pollute, otherwise these firms do not have sufficient motives for climate change adaptation.

In addition, the role of ISO is still unclear. Environmental management is done for symbolic purposes and it does not really improve the EP of firms (Misani and Pogutz, 2015). Nevertheless, the main result show that firms clearly benefit from superior EP and thus managers should consider ways in order to increase their EP, which in turn will improve their overall FP.

A research implication of this chapter is that scholars should start considering the use of more sophisticated techniques, such as non-parametric. As it is shown, firms with different profitability have different characteristics and the efficacy of EP might be primarily affected by the ability of these firms to implement their investments successfully. On the top of that, the fact that endogeniety is more intense for highly profitable sample of firms, indicates that examining only the mean of the conditional distribution might provide us with a distorted picture of the reality. This problematic setting can be solve with instrumental and non-parametric approaches.

6.2 Second Empirical Chapter: Environmental Disclosure and Idiosyncratic Risk

6.2.1 Findings

The second empirical chapter (Chapter 4) investigates if environmental disclosing assets can affect the idiosyncratic risk for a panel of 288 EU manufacturing firms for the period 2005-2016 (same sample with the first empirical chapter). Idiosyncratic risk is measured from the residuals of the five factor model (Fama and French, 2015), while environmental disclosure is retrieved from Bloomberg database. The main results indicate that it is less risky to be informative. Also, environmental disclosure has heterogeneous effect across different parts of idiosyncratic risk distribution. This finding is robust under different specifications and is in line with the largest part of literature (Dawkins and Fraas, 2011; Matsumura et al., 2014; Ben-Amar and McIlkenny, 2015).

The results indicate the prominent role of environmental disclosure on the financial markets and that environmental information is of paramount importance for the market participants. Particularly, the negative coefficient of the relationship suggests that the dominant theoretical framework is adhering with the *legitimacy or stakeholder theory*. Overall, a portfolio enriched with disclosing firms can decrease the overall risk of this portfolio and at the same time, the same return is maintained.

6.2.2 Implications

Regulators as well as firms should further promote the environmental disclosure. Environmental transparent information can help regulators to monitor climate change risk (Stern, 2007) and at the same time firms can enjoy lower levels of risk; "win-win" situation. Therefore, the management should consider to provide transparent environmental information as means of cost-less risk reduction. Simultaneously, environmental disclosure seems to explain a high proportion of the variations of idiosyncratic risk, indicating that researchers should include environmental disclosure as determinant of idiosyncratic risk in their analysis.

6.3 Third Empirical Chapter: Temperature and Systemic Risk

6.3.1 Findings

The third empirical chapter (Chapter 5) examines the effect of temperature on the systemic risk using a sample of 600 EU firms listed in STOXX 600 Index from the period 1/1/1990 to 29/12/2017. Temperature data have been retrieved from the weather station closer to the firm's market location. Then, temperature is decomposed to trend, seasonality and anomaly, with anomaly being the main independent variable. Systemic risk has been constructed by employing the ΔCoVaR methodology of Adrian and Brunnermeier (2016).

The results show that (i) raw temperature has asymmetric effects on systemic risk; (ii) temperature anomaly has either positive or inverted U-shape relation with systemic risk; (iii) hot temperature shocks increase while (iv) cold temperature shocks decrease the systemic risk. In addition, portfolio analysis shows that manufacturing industries are the ones mostly affected by the variations of temperature, in line with Balvers et al. (2017). Using different variables to approximate systemic risk, the results appear very robust. Finally, an alternative measure of systemic risk, $\Delta^{€} CoVaR$, shows that an increase of 1 degree of Celsius can increase systemic risk by 0.24 basis points.

6.3.2 Implications

The engagement of field research in the climate-finance literature remains uneven and therefore the chapter aims to further promote this nascent literature. The chapter motivates scholars to further examine this relationship. Particularly, we provide a method that researchers can use to gauge the effects of climate change on the financial system. This can be done with the ΔCoVaR methodology. The unique capability of ΔCoVaR is that it can accommodate different micro and macro variables and measure the impact of these variables on the systemic risk. Based on this principal, the chapter finds that temperature is priced in financial markets and market participants take seriously into consideration the extreme temperature movements. The finding that climate change effects are not only limited to the real economy (see, Dell et al., 2014) but these effects are appreciated in the financial system, should generate some regulatory and managerial concerns.

The results of the study are very important for policy-makers. In particular, policy-makers can monitor climate-sensitive firms that have spillover effects to the whole financial system. IPCC (2014) forecasts higher frequency of extreme weather events and rising temperatures. For this reason, our study can be a useful handbook for micro-prudential policy. Measuring the climate systemic impact of firms can help financial system be equipped with adequate tools and knowledge towards climate change. In the long-run a micro-prudential policy would result to macro-prudential effectiveness within the climate change content. Prevention is the most prominent method to manage systemic risk and thus to secure financial stability. In other words, policy-makers can detect "environmental sensitive firms" and regulate upon them in order to ensure the financial stability.

The chapter can have additional implications for many other stakeholders, as it provides valuable insights about an unexplored relationship between climate change and financial markets. The finding that temperature can destabilise the financial system should be taken into account by the firms. While, proposing hedging strategies and adaptation mechanisms is rather challenging, one suggestions for the European firms, as they operate in a developed and well-informed markets and have the capacity to secure themselves, would be to purchase weather derivatives. Equally useful is the fact that managers can now measure their firm's exposure to temperature changes and probably estimate more precisely their future cash flows.

6.4 Synthesis

All three empirical chapters considered, two important conclusions can be derived. First, climate change, as externality, is undoubtedly harmful for the firms. Climate change can be induced within firms in a form of environmental regulations and/or investors concerns' about weather alterations, whereby their effects are highly detrimental on firm's performance. This result can be directly observed in Chapter 5 (temperature-systemic risk), which is in line with the previous climate-economy literature (e.g, Hart and Ahuja, 1996; Stern, 2007; Dell et al., 2014). Having re-established this connection for the climate-finance literature afresh (Bansal and Ochoa, 2011), our results lead to the second major conclusion of this thesis. This is the benefit from investing in environmental practises. Undeniably, results from Chapters 3 (EP-FP) and 4 (Disc-Risk) demonstrate that environmental investments (i.e. decreasing carbon emissions and disclosing environmental information) can establish long-term objectives, incorporate societal concerns and develop advanced technology for firms, which in turn firms will gain and sustain competitive advantage (Porter, 1991). Although, climate change has indeed profound impact on the firms' output, this is a unique opportunity for these firms to distinguish and signal their environmental responsible actions to the society. Eventually, lower firm's emissions (investing in EP, Chapter 3) and effective measurement of firm's carbon footprint (disclosing transparent environmental information, Chapter 4) would lead to increase financial performance and stabilise the global warming. Global warming under control also indicates higher financial stability (Chapter 5). In other words, this can be described as "win-win" situation, superior financial performance - effective climate change mitigation.

6.5 Limitations

The main limitation of this thesis is that environmental and other climate change variables are scarce. This scarcity is because there is no specific reporting standards, especially in the past, and the environmental disclosure of firms is mainly done voluntarily. On one hand, this scarcity is a major disadvantage for the first empirical chapter, which mainly uses carbon emissions in its primary investigation. On the other hand, the non-disclosure still reflects some information which can potentially be evaluated in the financial markets, hence this can turn to an advantage for the second empirical chapter.

Furthermore, both Chapter 3 and 4 employ the same sample, which includes EU manufacturing firms from 2005 to 2016. Large polluters have attracted the attention to regulators and investors and for this reason, investigating the environmental actions of these firms is quite intriguing. On top of that, recently, EU has become an area highly committed to deal with the climate change and therefore various stakeholder may overreact on such environmental practises. For this reason, our results should not be generalised for the whole population but are rather referred to a specific location and sector in a specific time-period.

A limitation in Chapter 3 is related to the estimation method. While previous studies use parametric techniques such as panel data estimations (e.g. fixed effects model, System GMM etc) to evaluate the EP - FP relationship, we employ a non-parametric technique. Our method can have main advantages compared to previous literature, as mentioned in Chapter 3, however, an important disadvantage is that we do not exploit the dynamic nature of the data. Panel techniques use both the time and cross-section nature of the data, while our method can merely accommodate the latter. This difference might result to contradicting findings.

A crucial limitation in Chapter 4 is the main independent variable, namely environmental disclosure, which is assumed to be objective. Even though, environmental disclosure accounts for the transparency of environmental information, it is an opaque measure constructed by Bloomberg. Thus, we cannot confidently argue that in case of using different measures for environmental disclosure, the results would be robust. Even if, this measure is not objective, Bloomberg disclosure scores have attracted the attention of many stakeholders and at least one can argue that our results indicate the influence of these scores on the perception of the investors about climate change.

Last but not least, in Chapter 5, we match the temperatures from the local weather station closer to the firm's market location. However, the assumption that these temperatures affect the risk of the firms might be unrealistic. This is because firms might have diversified activities to different countries or even different continents where the weather patterns might be substantially different from their main market location. Finally, as mentioned above regarding Chapters 3 and 4, results are based on a sample of EU firms; EU has signed many environmental regulations (eg. EU ETS) and thus investors might be highly driven by the climate change effects. We expect that the same investigation in a different area (e.g. US) would give statistically different results.

6.6 Direction for future studies

Concluding this thesis, some potential avenues for future research are offered. First, some general recommendations are presented and second we propose some ideas in order to extend each one of the three empirical chapters.

The effect of green news on the financial market is a promising area for future research (see Section 2.5). For instance, Ramiah et al. (2015) examine environmental announcements made by the previous president of the US Obama on the stock returns. It would be interesting to examine the same for the announcements made by president Trump. In addition, there are many studies that examine the macroeconomic uncertainty, measured by the number of related articles, on the financial markets. It would be equally interesting to construct an environmental uncertainty index, from relevant articles, and test how this influences the financial markets.

In addition, there is an upcoming literature regarding climate change and stock market returns (Bansal and Ochoa, 2011). What has been neglected from this literature is the role of options/futures market (see Section 2.5). If rising temperatures affect the stock market valuations then this effect should also be observed in the options market. Therefore, a future study should explore the effect of either the environmental performance of firms or weather patterns on the options evaluation. Options reflect future expectations about the stock market and therefore it would be interesting to test if options can absorb part of climate change uncertainty.

Moreover, a proposition has been made to construct an environmental performance composite index and then test this index with different business metric indicators (see Chapter 2 and Appendix A). Because different measures provide with alternated results (Albertini, 2017), an environmental performance composite index might include different environmental variables (e.g carbon emissions, environmental disclosure etc) and thus it would capture a more articulated picture of what we call “environmental performance”.

Regarding Chapter 3 (EP-FP), by considering a greater number of industries, it would be useful to examine in future research the effect of EP on FP with a similar non-parametric method, therefore, an essential next step is to confirm any variation of results among industries. In close relation to that, the US would be an interesting area for future research. Previous parametric studies in the US report positive results between EP and FP (Matsumura et al., 2014), therefore the tails of the FP distribution of US firms could provide some additional insights on this relationship. Also, gathering more variables (instruments) to better approximate the EP could by useful and at the same time this will strengthen the accuracy of our results. A last suggestion for this chapter, which can be quite challenging, is to model the EP-FP relationship by using synchronously both dynamic and non-parametric techniques.

In a similar vein, a future study related to Chapter 4 (Disc-Risk) is to gather more information about different countries and industries. What is more, a study with greater number of risk-measurements and environmental disclosure variables, could also be conducted to determine the robustness of our results. On a different note, future studies could examine if indeed a disclosing portfolio of assets can maintain the same return and at the same time exhibit lower risk comparing with a non-disclosing portfolio. More broadly, research is also needed to explore the diversification benefits under complete or incomplete environmental information (Ang et al., 2006).

Finally, an interesting avenue for future research related to Chapter 5 (Temperature-CoVaR) would be to investigate how financial markets react to temperature variations in developing countries, where the information asymmetries are greater than in the EU. Also, according to Bansal et al. (2016), temperature is a risk factor that heterogeneously affect different countries, for this reason different areas of the world, such as the US, would be interesting to be examined and compare the results with our study. On a final note, a similar study should be conducted by gathering temperature information from multiple business locations of the firms; this would help us establish a greater accuracy of our results.

Appendices

Appendix A

The appendix bellow proposes the construction of an environmental composite index with principal component factor analysis and then the new variable is used to test the relationship between FP and CER in a dynamic panel model.

Consider the following equation of financial performance (FP) that takes into account the time (t) by including cross section firm observations (i).

$$FP_{i,t} = \beta_0 + Q'_{i,t}\beta + CER'_{i,t}\gamma + \varepsilon_{i,t} \tag{6.23}$$

Where, β_0 is the constant which is the unobserved firm-level effect and Q' represents a vector of other control variables that have been reported to play a crucial role in the analysis (e.g. leverage, firm age, market share). Similarly, CER' is a vector of k CER variables (e.g. see table 2.4) and ε is the error term. If we used all the CER variables we would overcome the problem of selection bias but at the same time our model would suffer from multicollinearity. So, a linear model would provide biased estimations. For this reason, we use factor analysis with PCA extraction which assumes that CER variables $(cer_1, .., cer_n)$ are correlated. The variables have to be normalised with $E(cer_k) = 0$ and $\sigma^2(cer_k) = 1$, $k = 1, 2, ..., n$. Also, the principal components should be uncorrelated $(Z_1, .., Z_n)$, with n the number of variables and so the number of extracted factors.

$$\begin{aligned} Z_1 &= a_{1,1}cer_1 + a_{1,2}cer_2 + ... + a_{1,n}cer_n \\ Z_2 &= a_{2,1}cer_1 + a_{2,2}cer_2 + ... + a_{2,n}cer_n \\ &\vdots \qquad\qquad\qquad \vdots \\ Z_n &= a_{n,1}cer_1 + a_{n,2}cer_2 + ... + a_{n,n}cer_n \end{aligned} \tag{6.24}$$

Once the factor loadings $(a_{m,k})$ are extracted from the rotated factors[32], we can construct intermediate composite indices (C_j), $j = 1, ..., y$ and y corresponds to the retaining factors that have eigenvalues[33] more than the unity. This step involves the construction of weights (w_n). The weights are equal to the squared normalised values of the loadings $(a_{m,k})$ which aggregate the CER variables into intermediate composite indicators (C_j). The w_n express the proportion of the variance that is explained by an indicator in each factor. The y intermediate indices explain a proportion of the total variance (v_n) of the extracted factors. We can now proceed to aggregate C_j into constructing the overall composite index

[32]Factor rotation is a method which minimises the number of variables that have high scores on a factor. Rotation can be obtained using, among others, the Oblimin or Varimax method.

[33]According to Kaiser criterion, factors, with less than 1 eigenvalue, make no sense to be included in the analysis.

of CER (OECD, 2008).

$$CCER = \sum_{j,k=1}^{y} C_j \times v_k \tag{6.25}$$

Where ($CCER$) is the composite CER variable for every unit i in time t. This method would allow us to capture all the different dimensions of CER variables and we would overcome the problem of multicollinearity.

In addition, a system of generalised method of moments (sys-GMM), which is proposed by Blundell and Bond (1998), can control for endogeneity in our estimations. First, the standard GMM estimation is considered below:

$$FP_{i,t} = Q'_{i,t}\beta + \theta_1 CCER_{i,t} + e_i + \eta_{i,t} \tag{6.26}$$

Where e denotes the individual firm-level effect and η is the error term, with e and η being independent for each i over all t. The next step is to eliminate e by taking the first difference of equation (6.26).

$$FP_{i,t} - FP_{i,t-1} = (Q'_{i,t} - Q'_{i,t-1})\beta + \theta_1(CCER_{i,t} - CCER_{i,t-1}) + (\eta_{i,t} - \eta_{i,t-1}) \tag{6.27}$$

Moreover, equation (6.27) is instrumented with lagged values of the explanatory variables. However, lagged values are usually weak instruments and thus sys-GMM combines the first-differenced estimator (eq. 6.27) with the estimator in levels (eq. 6.26) in order to efficiently deal with the endogeneity. Lastly, the methodology should be tested by using different FP indicators as dependent variables.

The proposed methodology aims to answer the question; if it pays to be green, for two reasons. First, different CER variables provide inconclusive results and therefore a composite variable would be able to capture the maximum dimension of the environmental data. Second, sys-GMM is valid for micro-economic applications such as the outcome of an investment, this is likely to be the case for firms that engaging in environmental practices.

Appendix B

Advised by the study of Qiu et al. (2016), Bloomberg environmental disclosure has been constructed by 60 different items that have been retrieved by annual reports, sustainability reports and company websites. The overall score is standardised by industry. The 60 environmental items are not equally weighted, items appeared in the top of table 6.36 receive relatively higher weights than items in the bottom. So, the score captures both the quantity and quality of the disclosures.

Table 6.36: Environmental disclosure items

#		#	
1	Direct CO2 Emissions	31	Paper Recycled
2	Indirect CO2 Emissions	32	Fuel Used (Th Litres)
3	Travel Emissions	33	Raw Materials Used
4	Total CO2 Emissions	34	% Recycled Materials
5	CO2 Intensity (Tonnes)	35	Gas Flaring
6	CO2 Intensity per Sales	36	Number of Spills
7	GHG Scope 1	37	Amount of Spills (Th Tonnes)
8	GHG Scope 2	38	Nuclear % Total Energy
9	GHG Scope 3	39	Solar % Total Energy
10	Total GHG Emissions	40	Phones Recycled
11	NOx Emissions	41	Environmental Fines #
12	SO2 Emissions	42	Environmental Fines $
13	SOx Emissions	43	ISO 14001 Certified Sites
14	VOC Emissions	44	Number of Sites
15	CO Emissions	45	% Sites Certified
16	Methane Emissions	46	Environmental Accounting Cost
17	ODS Emissions	47	Investments in Sustainability
18	Particulate Emissions	48	Energy Efficiency Policy
19	Total Energy Consumption	49	Emissions Reduction Initiatives
20	Electricity Used (MWh)	50	Environmental Supply Chain
21	Renewable Energy Use	51	Management Green
22	Water Consumption	52	Green Building Policy
23	Water/Unit of Prod (in Litres)	53	Waste Reduction Policy
24	%Water Recycled	54	Sustainable Packaging
25	Discharges to Water	55	Environmental Quality Management Policy
26	Waste Water (Th Cubic Metres)	56	Climate Change Policy
27	Hazardous Waste	57	New Products - Climate Change
28	Total Waste	58	Biodiversity Policy
29	% Waste Recycled	59	Environmental Awards Received
30	Paper Consumption	60	Verification Type

These 60 items should not be strictly disclosed by every firm. For instance, the item "Phones Recycled" is only relevant for telecommunications industry and so firms from different industries are not penalised for not disclosing it.

Appendix C

The appendix bellow proposes the construction of a measure of connectedness with principal component analysis (PCA), methodologically similar to the study of Billio et al. (2012).

Instead of running PCA among all institutions simultaneously, we focus on the causal spillovers (endogenous risk) between a firm and its industry; we repeat this procedure for all the firms in the sample (600). Particularly, the two variables of interest are the firm (X^i) and industry (X^j) losses. In the PCA, the number of variables, that join the system, should be equal to the number of extracted components, also variables should be correlated; in fact, the correlation between (X^i) and (X^j) is, on average, 48%. As shown below, the principal components are new variables that combine the returns of firm i with the returns of industry j:

$$
\begin{aligned}
PC1_t &= a_{1,1}X_t^i + a_{1,2}X_t^j \\
PC2_t &= a_{2,1}X_t^i + a_{2,2}X_t^j,
\end{aligned}
\tag{6.28}
$$

where the weights a are chosen so that: (i) the components are uncorrelated and (ii) the first component accounts for the maximum possible variance of the set (OECD, 2008). The first component (PC1) is used as a measure of connectedness and it is our alternative dependent variable. PC1 satisfies the Kaiser criterion that components with more than 1 eigenvalue, make sense to be included in the analysis. In this instance, PC1 explains 74% of the variability between the returns of firms and their industries, with eigenvalue 1.48, while PC2 explains the remaining 26 % with eigenvalue 0.52.

Appendix D

Adrian and Brunnermeier (2016) build on a bivariate diagnonal VECH-GARCH to estimate the conditional covariance between the firm and industry's losses, an alternative dynamic systemic risk measure. Similarly, we employ a parsimonious DCC-GARCH(1,1) model to identify the dynamic conditional correlation and the conditional covariance between the firm and industry's returns; as proposed by Engle (2002):

$$\mathbf{X_t} = \phi_\mathbf{0} + \varphi \mathbf{X}_{t-1} + \epsilon_\mathbf{t}, \qquad \epsilon_\mathbf{t} = \mathbf{H}_t^{1/2}\mathbf{v}_t, \tag{6.29}$$

$\mathbf{X}_t \equiv (X_t^j, X_t^i)'$ is a vector of daily return losses of j industry and i firm, ϵ_t is a vector of random disturbance terms, $\mathbf{v_t}$ is a vector of normal, independent and identically distributed innovations, and $\mathbf{H_t}$ is the conditional variance and covariance matrix, defined as:

$$\mathbf{H}_t = \mathbf{D}_t^{1/2}\mathbf{R}_t\mathbf{D}_t^{1/2} = \begin{pmatrix} h_t^{j,j} & h_t^{j,i} \\ h_t^{j,i} & h_t^{i,i} \end{pmatrix}, \tag{6.30}$$

where $h_t^{j,i}$, the conditional covariance, is another measure of interconnection between firm and industry. It is conceptually similar to the alternative dynamic approaches of Billio et al. (2012); Adrian and Brunnermeier (2016). $\mathbf{D_t}$ is a diagonal matrix of conditional variances $[\mathbf{D}_t = diag({\sigma^j}_t^2),\ {\sigma^i}_t^2)]$ from the univariate GARCH(1,1), and $\mathbf{R_t}$ is the time-varying quasicorrelation matrix, which is calculated as:

$$\mathbf{R}_t = diag(\mathbf{Q}_t)^{-1/2}\mathbf{Q}_t diag(\mathbf{Q}_{,t})^{-1/2}, \tag{6.31}$$

$$\mathbf{Q}_t = (1 - a - b)\bar{\mathbf{Q}} + a(\mathbf{u}_{t-1}\mathbf{u}_{t-1}^{'}) + b(\mathbf{Q}_{t-1}) \tag{6.32}$$

and $\mathbf{R}_t$ has the following form:

$$\mathbf{R}_t = \begin{pmatrix} 1 & \rho_t^{j,i} \\ \rho_t^{j,i} & 1 \end{pmatrix}, \tag{6.33}$$

where $\mathbf{u_t} = \mathbf{D_t^{-1/2}}\epsilon_\mathbf{t}$ and $\mathbf{u_t}$ is used to estimate the parameters of the conditional correlation, $\mathbf{Q}_t$ is the time-varying covariance matrix of $\mathbf{u_t}$, $\bar{\mathbf{Q}}$ ($\bar{\mathbf{Q}} = E[\mathbf{u_t}\mathbf{u_t}']$) is the unconditional variance and covariance matrix of $\mathbf{u_t}$ and parameters a and b should be non-negative and less than unity in aggregate. The coefficients of conditional mean and conditional variance models are estimated by maximising the log-likelihood function for any t observation as shown below:

$$l_t = -\frac{1}{2}\sum_{t=1}^{T}[klog(2\pi) + 2log(|\mathbf{D}_t|) + \epsilon_{\mathbf{t}}{}'\mathbf{D}_t^{-2}\epsilon_{\mathbf{t}}] + \frac{1}{2}\sum_{t=1}^{T}[log|\mathbf{R}_t| + \mathbf{u}_t^{'}\mathbf{R}_t^{-1}\mathbf{u}_t - \mathbf{u}_t^{'}\mathbf{u}_t] \tag{6.34}$$

Appendix E

Certificate of Ethics Review

Project Title:	Climate Change and Financial Performance
User ID:	713541
Name:	Panagiotis Tzouvanas
Application Date:	10/07/2017 16:54:52

You must download your certificate, print a copy and keep it as a record of this review.

It is your responsibility to adhere to the University Ethics Policy and any Department/School or professional guidelines in the conduct of your study including relevant guidelines regarding health and safety of researchers and University Health and Safety Policy.

It is also your responsibility to follow University guidance on Data Protection Policy:

- General guidance for all data protection issues

- University Data Protection Policy

You are reminded that as a University of Portsmouth Researcher you are bound by the UKRIO Code of Practice for Research; any breach of this code could lead to action being taken following the University's Procedure for the Investigation of Allegations of Misconduct in Research.

Any changes in the answers to the questions reflecting the design, management or conduct of the research over the course of the project must be notified to the Faculty Ethics Committee. **Any changes that affect the answers given in the questionnaire, not reported to the Faculty Ethics Committee, will invalidate this certificate.**

This ethical review should not be used to infer any comment on the academic merits or methodology of the project. If you have not already done so, you are advised to develop a clear protocol/proposal and ensure that it is independently reviewed by peers or others of appropriate standing. A favourable ethical opinion should not be perceived as permission to proceed with the research; there might be other matters of governance which require further consideration including the agreement of any organisation hosting the research.

GovernanceChecklist
A1-BriefDescriptionOfProject: The project attempts to investigate a connection between financial markets and the environmental changes. This connection can be studied by analysing the EU ETS system; EU ETS is a system that

allows trading of emission allowances in order to reduce the GHG emissions in the region of Europe. Also, the project aims to examine if climate changes or environmental regulations can have an effect on the financial markets.
A2-Faculty: PBS
A3-VoluntarilyReferToFEC: No
A5-AlreadyExternallyReviewed: No
B1-HumanParticipants: No
HumanParticipantsDefinition
B2-HumanParticipantsConfirmation: No
C6-SafetyRisksBeyondAssessment: No
D2-PhysicalEcologicalDamage: No
D4-HistoricalOrCulturalDamage: No
E1-ContentiousOrIllegal: No
E2-SociallySensitiveIssues: No
F1-InvolvesAnimals: No
F2-HarmfulToThirdParties: No
G1-ConfirmReadEthicsPolicy: Confirmed
G2-ConfirmReadUKRIOCodeOfPractice: Confirmed
G3-ConfirmReadConcordatToSupportResearchIntegrity: Confirmed
G4-ConfirmedCorrectInformation: Confirmed
Certificate Code: 86C9-5B98-28A0-DD93-C7B1-7112-ECBA-5E7C

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