Environmental and financial performance in the European manufacturing sector: an analysis of extreme tail dependency

Environmental and Financial Performance in the European Manufacturing Sector: An Analysis of Extreme Tail Dependency

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Abstract

In this study, we investigate the impact of environmental performance on financial performance. We argue that environmental performance heterogeneously affects firms with different profitability level. Using data for 288 European manufacturing firms over the period 2005-2016, we investigate the said relationship 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, we find (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.

Keywords: Financial Performance, Environmental Performance, Quantile regressions

JEL: Q51, L25, C14

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1 Introduction

In the effort to mitigate climate change by reducing 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 was responsible for around 88% of the GHG emitted in the European Union (EU) in 2015 (Eurostat, 2019; World Bank, 2019). Large emitting companies 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) by setting a key target to reduce firms' GHG emissions by 21% in 2020 compared with 2005 (European Commission, 2019a). Thus, 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). It is shown that low-carbon investments by EU firms grew from €57 billion in 2011 to a staggering amount of €243 billion in 2015 (Eurosif, 2016).[1] Firms can 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 effects of firm's activi-

[1] 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).

ties on the natural environment (i.e. GHG) (Albertini, 2013), and is measured, by number of studies (e.g. Aggarwal and Dow, 2012; Misani and Pogutz, 2015), as the inverted ratio of firm's GHG emissions to its (i) book size, (ii) market value or (iii) industry mean GHG, whilst FP is approximated with accounting profitability ratios (i.e. ROA and ROE) (Dixon-Fowler et al., 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 relationship 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 supported by the *financial slack argument*, which indicates 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), Figure 1 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 do indeed tend to be more profitable than their non-green counterparts. However, as King and Lenox (2001); Qiu et al. (2016); Li et al. (2018) indicate, high profitability firms are more likely to invest more and to engage in environmental actions. Thus, the question that arises is whether the positive relationship depicted in Figure 1 is due to the reverse causality between EP and FP.

INSERT FIGURE [1] HERE

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 relationship 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 the question "*How does green react to different parts of the profitability distribution*?"

Our research provides new evidence on this conflict, which is evident in both empirical studies and economic theory, by utilising both quantile and two-stage quantile regressions. Our approach attempts 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 that 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 made (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 is associated with 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 context (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 2, we present the theoretical framework and discuss the relevant hypothesis. In section 3, we describe the data and present the methods of the study. The empirical results are reported in section 4. Finally, in section 5, we discuss the main results of the study and reach a conclusion.

2 Theoretical Framework and Hypothesis Development

EP plays an essential role in promoting stakeholders' interests and influencing the profitability of firms. The connection between EP and FP is based on a multitude of theoretical predictions which have been summarised in Figure 2. The overriding objective of all these theories was to respond to the following question: "How is FP affected if we invest in EP?" In order to achieve this objective, we provide a broad overview of the existing framework and further examine under what circumstances does EP affect FP.

INSERT FIGURE [2] HERE

2.1 A Brief Theoretical Background

The first theoretical prediction is the negative link between EP and FP, which is supported by the trade-off view, indicating that investments in EP merely reduce firms' profits. The negative relationship between EP and FP can be attributed to the higher cost that firms have to bear. The *neoclassical theory* suggests that some industries experience high environmental compliance costs because they operate under green management policies and therefore face a competitive disadvantage (Wagner et al., 2002). This is particularly the case for manufacturing firms since the cost of decreasing their emissions is relatively high and results in an increase in the marginal cost of production. Similarly, 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 prediction suggests that EP increases the value of the firm. This positive link between EP and FP, as proposed by the *instrumental stakeholder* theory, presumes 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*[2] and the *agency* theories. It focuses on the contracts between managers and stakeholders and claims that trust and cooperation within any company help to create a competitive advantage (Jones, 1995). For example, by satisfying stakeholder demands concerning climate change, firms may acquire better reputation, improve customers' loyalty and, overall, respond more effectively to external demands (Endrikat et al., 2014).

Finally, there is a third theoretical prediction according to which EP might have a non-linear impact on FP. What is more, this argument has largely been

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

supported by empirical research which provides evidence of a U-shaped relationship (Nollet et al., 2016; Trumpp and Guenther, 2017; Lewandowski, 2017). Initially, an increase in EP is expected to diminish profits, (i.e., in line with the trade-off view); however, in time, a continued increase beyond a certain level would bring benefits that would potentially offset costs, giving rise to the U-shape. In fact, the U-shaped relationship is also implied by the *natural resource-based view* of the firm. In particular, Hart (1995) opines that firms should develop new technologies in order to manage their resources efficiently. The implication is that corporate governance has a keen interest in investing in EP, expecting that this investment will help improving the future position of the corporation (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 (Broadstock et al., 2019).

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

Given that the relationship between EP and FP is explained by a number of competing theoretical frameworks, it is essential to investigate the specific conditions (e.g., company profitability) under which EP benefits outweigh EP potential costs.

Even though the majority of the empirical results point 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 geographical area under investigation, are dominant factors responsible for the variability of the results. Despite that, 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), they mainly focus on the mean of the FP distribution and neglect to examine EP effects deriving from (i) low and/or (ii) high profitability firms. This is why investigating the impact of changes in EP on different quantiles of the FP distribution is a very important task.

We should also consider the moderating role of FP. In particular, existing literature suggests that FP by 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). Unequivocally, low profitability firms have limited resources while, at the same time, pressure from stakeholders for profit maximisation is higher compared to their high performing counterparts (Alissa, 2015). Poor performance poses a threat on firms and thus managers ought to take actions in order to improve profitability. It follows that such actions may also include investing in R&D projects, such as improving environmental performance. It should also be noted that investing in EP when profitability is low might give the impression that the current management is simply adding to poor company performance (see also absorbed slack resource theory). However, EP might become a sustainable strategy for low profitability firms, as it helps firms to build bonds with their stakeholders and signals their green attitudes towards the production processes (Porter, 1991;

Hart and Ahuja, 1996).

It is worth noting that low profitability firms are constrained by financial resources, which can limit their investments 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., 2018). At the same time, high profitability firms, are more likely to accomplish effective EP investments (i.e. *unabsorbed slack*)[3] (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 instead of investing those profits in environmental projects. At the same time, there are two main explanations as to why managers invest in EP. First, because they take on board the argument that EP does indeed improve FP. Second, firms invest in EP because they have excess funds in the first place, implying that the relationship might primarily be influenced by superior FP. Another possible explanation is that managers of high performing firms might choose to invest in EP just for symbolic reasons, or simply because they aim to improve their reputation as environmentally sensitive managers; which could backfire though, if it signals 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.* The theory can explain why firms with different resources have different levels of environmental engagement (George, 2005). Even though the theory is multifaceted

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

(Shahzad et al., 2016), our study focuses on *financial slack resources* of 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. In this respect, we test for the relationship between EP and FP, putting 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 the FP distribution. 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), we anticipate that the strength of this relationship will vary across the conditional distribution of FP. We thus 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.

2.3 Identification of causal effects

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

Adhering to these regulations, firms strive to legitimise their actions. Both the Kyoto Protocol and the Paris agreement are examples of the most serious attempts that have been made, given that their main objective is to regulate a permissible limit of firms' carbon emissions. Particularly, EU polluting firms are compelled 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 (European Commission, 2019a). A cap and trade system predicates 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, growing pressures against climate change are usually factored in the decision making when adopting an environmental strategy such as ISO 14001. ISO 14001 standards are provided by a non-profit organisation to firms that wish to comply with the regulatory limits while, guidance is offered in order to minimise and manage firms' carbon footprints (Quazi et al., 2001). In order to qualify for ISO certification, firms must fulfil certain requirements. In particular, they have to (i) establish an environmental management department, (ii) identify their environmental compliance requirements (regulations), (iii) clarify how the firm interacts with the environment (e.g. GHG emissions) and (iv) monitor, review and measure their environmental performance (ISO, 2015). Hence, EP is a channel through which both ETS and ISO affect the FP of firms. In this study, we methodically investigate the role of environmental regulations and further examine the extent to which the above hypothesis holds.

3 Data and Methods

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 GHG emissions. For this reason, EU environmental regulations have enforced firms to be transparent about their environmental actions. 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 1 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.

INSERT TABLE [1]

3.2 The Regression variables

Dependent variables

Table 2 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) reflects the firm's capital efficiency to generate profits. We also use industry-adjusted ROA and ROE as dependent variables in order to control for the variability of our research findings across 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's 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 operates). Similarly, we compute adjusted ROE ($Adj.ROE_{i,t} = \frac{ROE_{i,t}}{ROE_{j,t}}$). Extant literature uses ROA and ROE as dependent variables in their regressions (see, for example, Busch and Hoffmann, 2011; Qiu et al., 2016; Lewandowski, 2017). The indicators measure 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 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 from 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).[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

[4]See more at section 3.4.2.

corresponds to lower probability of default and thus it is expected to have a positive sign to the FP (Psillaki et al., 2010). Also, leverage (LEV) is used as a proxy of financial risk; 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. It is imperative to include risk proxies in the analysis (Busch and Hoffmann, 2011; Hatakeda et al., 2012; Matsumura et al., 2014).

Larger firms have been found to perform less well (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 on 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 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; nevertheless they can add value to the firm (Psillaki et al., 2010). Intangible assets also have attributes of research and development (R&D) of the firm (Elsayed and Paton, 2005). For instance, an investment in EP might generate future profits or losses. Tangible assets ($TANG$) can be a proxy for the collateral of the firm. An ambiguous relationship 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. 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.

INSERT TABLE [2]

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 of the EU emissions trading scheme, when disclosing environmental data was not mandatory.[5] From 2008, EU regulators began monitoring more and more sites. This is why our sample suffers from many missing values at the beginning of the examination and improves at the latest years.

INSERT TABLE [3] HERE

[5]See more about Phase 1 in European Commission (2019b).

Regarding the rest of the variables (see Table 3), for instance, the firm size in our sample is quite heterogenous, with a mean of current €8.6 billion ($LOGTA \approx 9.06$), a minimum of €30 million and a maximum of €400 billion. ROA has a mean (median) of 6.0641 (5.2056) with the highest value being 28.28 and a 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 4 reports the correlations. Spearman matrix 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 a negative and low correlation with FP variables. The relationship between EP and FP is shown in Figure 3. At first glance, EP slightly increases the FP. Testing only the mean distribution of EP and not the whole conditional distribution might lead to distorted results. In order to provide a clearer picture of the relationship, we proceed to examine our hypothesis non-parametrically.

INSERT TABLE [4] AND FIGURE [3] HERE

3.4 Econometric Method

3.4.1 Quantile Regression Methodology

To test our hypothesis, we employ quantile regression which was introduced by Koenker and Bassett (1978) in order 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 represent our regressions linearly, we consider the following equation:

$$FP_{i,t} = \pi(\tau) + \theta(\tau)EP_{i,t} + \mathbf{Y}'_{i,t}\vartheta(\tau) + \varepsilon_{i,t}, \quad \tau \in (0,1) \tag{1}$$

where FP is the dependent variable for every firm i at year t, 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 $N \times T$ observations can be calculated with linear programming as follows:

$$\hat{\theta}(\tau) = arg\ \underset{\theta}{min} \frac{1}{N \times T} \sum_{i=1}^{N} \sum_{t=1}^{T} \rho_\tau[FP_{i,t} - \pi(\tau) - \theta(\tau)EP_{i,t} - \mathbf{Y}'_{i,t}\vartheta(\tau)] \tag{2}$$

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

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

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 that 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 1 be affected by the potential endogeneity; then, this problem is treated with two-stage quantile regressions.

3.4.2 Two-stage Quantile Regression Methodology

We employ a semi-parametric technique to deal with the endogeneity. In particular, we account for the endogeneity in our estimations by considering a control function approach. Therefore, we exploit the linear nature of the setting in a 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).

$$FP_{i,t} = \beta(\tau) EP_{i,t} + \mathbf{X_1'}_{i,t} \gamma(\tau) + U_{i,t} \tag{3}$$

$$EP_{i,t} = m(\alpha) + \mathbb{X}'_{i,t} \delta(\alpha) + V_{i,t} \tag{4}$$

$$Q_{U_{i,t}|EP_{i,t},\mathbb{X}_{i,t}}(\tau|ep_{i,t},\mathbf{x}_{i,t}) = Q_{U_{i,t}|V_{i,t},\mathbb{X}_{i,t}}(\tau|v_{i,t},\mathbf{x}_{i,t}) = Q_{U_{i,t}|V_{i,t}}(\tau|v_{i,t}) \equiv \lambda_\tau(v_{i,t}) \quad (5)$$

$$Q_{V_{i,t}|\mathbb{X}_{i,t}}(a|\mathbf{x}_{i,t}) = 0 \quad (6)$$

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 and 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 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. 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.

$$Q_{FP_{i,t}|EP_{i,t},\mathbb{X}_{i,t}}(\tau|ep_{i,t},\mathbf{x}_{i,t}) = ep_{i,t}\beta(\tau) + \mathbf{x}'_{1i,t}\gamma(\tau) + \lambda_\tau(v_{i,t}) \quad (7)$$

$$Q_{EP_{i,t}|\mathbb{X}_{i,t}}(a|\mathbf{x}_{i,t}) = m(a) + \mathbf{x}'_{i,t}\delta(a) \quad (8)$$

Henceforth, the probability density functions of FP and EP are given by equations 7 and 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 9:

$$FP_{i,t} = \beta(\tau)EP_{i,t} + \mathbf{X_1'}_{i,t}\gamma(\tau) + \psi(\tau)\hat{V}_{i,t}(\alpha) + U_{i,t} \tag{9}$$

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 relationship between EP and FP. In order to deal with this problem, first we need to identify characteristics (instruments) that i) are both conceptually and methodologically correct, and ii) are correlated with the first-stage dependent variable (i.e. EP) but not with the residuals of the second-stage regression. Noteworthy, regulatory pressures can be exogenous to EP (Brunel and Levinson, 2016), and thus we include two instruments ($\mathbf{X}_2$), as discussed in section 2.3. 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). Arguably, time-variant firm-specific instruments can potentially explain abrupt EP changes. Thus, the two instruments do not contain information about firm, industry and country fixed effects, but uniquely reflect how firms respond to environmental change. For a similar reason, various empirical studies have used ETS and ISO as determinants to explain these EP variations (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).

In the first stage, we estimate Equation 4. It is our expectation that firms participating in ETS and ISO should feature a generally worse EP than non-participants. This is because carbon allowances are allocated according to firms' needs. Therefore, carbon-intensive firms would have more certified emissions to trade. Similarly, ISO is adopted when firms need assistance with their environmental practices. In the second stage, we estimate Equation 9. The residuals computed from the first-stage regression, $\hat{V}(\alpha)$, are now included non-parametrically in Equation 9 as an additional explanatory variable along with the other control variables (Lee, 2007). The two-stage quantile regression as a semi-parametric approach allows us to detect if the EP-FP relationship is plagued by endogeneity. Specifically, if the coefficient $\psi(\tau)$ appears to be statistically different from zero, then our previous estimations are problematic and should be interepreted with caution (Wooldridge, 2015). We now proceed to scrutinise our results.

4 Results

4.1 Quantile Regression Results

Tables 5, 6 and 7 display the coefficient estimates from the quantile regression, described by Equation 1 (see Columns 1-6), which feature EP(ta), EP(mv) and adj.EP as independent variables, respectively. In Columns 1-3, we report the results for ROA at the 5%, 50% and 95% of the conditional distribution, whereas in Columns 4-6, we report ROE results for the lower, median and upper part of the distribution. Table 7 summarises the adjusted industry results.

We begin by analysing the control variables in the quantile regressions. Because all three tables report similar coefficients, our analysis builds on Table 5. The Z-score (Z) appears to have a positive effect on FP, irrespective of how it is measured, at all quantiles. This signifies that a lower probability of default increases the firm's profitability (Psillaki et al., 2010). The leverage variable (LEV) has a positive effect on ROE, but does not seem to influence ROA. The intangible assets (INTA), which can be thought of to measure investment in $R\&D$, influence positively FP, especially at the lower tail of the distribution. Consistent with our expectations, the size (LOGTA) exerts a strongly negative effect on FP for the whole probability distribution (Konar and Cohen, 2001; Hatakeda et al., 2012). The number of employees (EMP) has in general a positive effect on FP. The GDP growth (GDP) and sales growth (GRO) rates do not seem to affect ROA and ROE. Overall, the effects of our control variables on FP are in agreement with the 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[6] (R^2) explains a larger share 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 model for ROA with models that incorporate EP(ta) (Table 5) and EP(mv) (Table 6), we witness an increase in the goodness of fit across the whole conditional distribution by approximately 1 percentage point, which highlights the value added of EP in the examination.

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

INSERT TABLE [5], TABLE [6] AND TABLE [7]HERE

Turning to our hypothesis, EP seems to increase FP significantly across the FP distribution at 1% significance level. For example, in Table 5, a 1% increase in EP(ta) 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. Eyeballing Figure 4, 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. Importantly, this Figure indicates that a linear functional form is likely to misrepresent the data. Indeed, dash lines illustrate that an OLS regression can only provide a broad idea of the EP-FP relationship. However, it ignores the fact that this relationship can vary significantly across the different conditional distributions. Additionally, the heterogeneous EP effects on FP are supported for both ROA and ROE. Tables 5, 6 and 7 also report the Wald statistic, which is used to test for the equality of EP slopes. We find that the effects of EP on FP can vary dramatically over the FP distribution. Particularly, the EP slopes are statistically different for both ROA (Wald-test statistics = 22.76, p-value < 0.01) and ROE (Wald-test statistics = 2.46, p-value < 0.10). So far, this finding implies that the EP-FP relationship follows a positive and heterogeneous association, which supports the *financial slack argument*.

INSERT FIGURE [4] HERE

4.2 Robustness Checks

To corroborate our results, we perform three robustness checks. First, an important limitation in the existing studies is that, although they centre mainly on large firms, their results are typically generalised to the whole population (Al-Tuwaijri et al., 2004). This neglects the fact that firms in the EU can vary significantly in size (book value). To address this limitation, we divide our sample into small, medium and large sized firms. Subsequently, we run quantile regressions separately for each sub-sample. An advantage of this exercise is that it allows us to delve deeper into the EP-FP relationship, while controlling for book value of firms. Second, it is worth noting that UK firms are relatively over-weighted in our sample, with a share of 25%. Therefore, in our second robustness exercise, we ask if our main research findings are not driven by environmental policy in the UK. In this regard, previous research shows that UK firms obtain financial benefits from engaging in environmental practices (Salama et al., 2011). Thus, we exclude UK firms from the sample. Third, results might be time and event dependent. For instance, during the global financial crisis of 2008/09, 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, but before Brexit (2010-2016).

Table 8 shows that our results are significant for small and medium sized firms, while the FP of large firms does not seem to respond to EP. This finding is particularly interesting and indicates that not only does the EP-FP relationship vary with the level of profitability, but it also appears to respond differently for small, medium and large firms. 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. This finding has a twofold explanation. First, small firms tend to be more innovative in advancing EP practices, because they are not hindered by fear of cannibalising their market segmentation; second, small firms are more likely to specialise in a particular activity, while large firms tend do be more diversified (Hoogendoorn et al., 2015). In general terms, large firms are usually less profitable (King and Lenox, 2001); their EP practises are likely to be followed by lower returns. Furthermore, excluding UK firms from our sample does not seem to alter our main research findings (Columns 10-12 of Table 8).

INSERT TABLE [8] HERE

We continue with our sub-sample analysis, which is informed by Table 9. The results demonstrate that the period of the investigation can offer additional insights into the EP-FP relationship. Particularly, the results are generally 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 arise endogenously from the relationship (Endrikat et al., 2014).

INSERT TABLE [9] HERE

4.3 Two-Stage Quantile Regression Results

To address the problem of potential endogeneity between EP and the random disturbance term, we undertake a two-stage quantile regression methodology. Indeed, one could argue that EP is not necessarily exogenous, since high profitability firms could afford to allocate more resources to finance green projects. Accordingly, in the first stage, we regress EP on two instruments (ETS and ISO). The residuals from the first-stage regression are used as an explanatory variable in the second-stage regression (see Equation 9), which controls for endogeneity.

INSERT TABLE [10] HERE

In Table 10, Columns 1, 2 and 3, the coefficient estimates of the first-stage regression for EP at 5, 50 and 95% quantiles of the conditional distribution are summarised, respectively. Considering the first-stage regression, the two instruments appear to be statistically significant at 1% level of significance. 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 legitimise their pollutants. Due to a very low carbon price, firms are not motivated to reduce carbon emissions (Zhang and Wei, 2010). Specifically, by the end of Phase 1 of the EU ETS, one ton of carbon emissions was priced at €0.02 (Engels, 2009). Regarding the negative coefficient of ISO, this can be attributed to either ineffective environmental management to reduce carbon footprints, 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 coefficient estimates is that polluting firms receive pressures to adopt proactive environmental approaches and abide by the regulatory standards (Dixon-Fowler et al., 2013; Lee et al., 2015).

INSERT TABLE [11] HERE

Turning to the second-stage regressions, we are now able to provide further insights into our hypothesis (EP-FP relationship under endogeneity). The effects of our control variables in general remain very similar as in the standard quantile regressions (see section 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 the distribution for both ROE and ROA. As shown in Tables 11 and 12, EP coefficients are positive at the upper tail of the distribution, but not at the median and upper tail. Particularly, column 1 for ROA (ROE) visualises results for a firm at the lower tail of the conditional distribution ($\alpha = \tau = 0.05$). At this quantile, EP does not appear to influence FP. On the other hand, in column 9, a firm at the upper tail of the distribution ($\alpha = \tau = 0.95$), has a significant coefficient for ROA (ROE) of 1.111% (5.172%). Overall, firms with heightened environmental performance are more likely to reap financial benefits, as opposed to firms with high pollution propensity. At the same time, this finding shows that firms with higher FP obtain more benefits from EP engagement, while low profitability firms are unaffected by their EP.

INSERT TABLE [12] HERE

Interestingly, the factor $\hat{V}(\alpha)$, which controls for endogeneity, is statistically significant only for high profitability firms. This endorses our coefficient estimates from the one-step quantile regressions for low and median profitability firms (Wooldridge, 2010), but the findings are 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, the factor $\hat{V}(\alpha)$ in Table 12 suggests that

EP and ROE are endogenous only for high profitability firms. In other words, EP appears to cause FP, while the reverse causality is valid only when firms have high financial resources. This result is consistent with previous studies and offers an in depth explanation on endogeneity; as meta analyses (Orlitzky et al., 2003; Albertini, 2013; Dixon-Fowler et al., 2013; Endrikat et al., 2014) jointly indicate, EP and FP are positively correlated; EP increases FP, while FP has a partially positive effect on EP.

Figure 5 summarises results of the second-stage regression. It shows that superior EP is conducive to higher FP. Noteworthy, EP slopes generally exhibit an increasing pattern as quantiles increase. To shed further light on the asymmetries of the EP-FP relationship, we test for equality of EP slopes by means of the Wald statistic. Results provide evidence of significant differences across quantiles. Therefore, a non-linear, endogenous and positive relationship seems to provide a reasonably accurate representation of the EP-FP relationship for 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).

INSERT FIGURE [5] HERE

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 employed an innovative approach that combines the standard quantile methodology (Koenker and Bassett,

1978) with instrumental variables for EP (Lee, 2007). This gave us an opportunity to account for potential non-linearity and endogeneity between EP and FP.

The main findings 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, the findings support theories that predict a positive EP-FP relationship (i.e. *instrumental stakeholder theory*) under the *financial slack argument*.

In particular, our evidence shows a statistically significant relationship depicting a U-shaped curve between the EP coefficients and the associated quantiles of FP. For all regressions, we find that lower emissions significantly increase ROA, ROE, industry-adjusted-ROA and industry-adjusted-ROE for firms across the distribution. Our findings are in line with the studies that use a contemporary, large international data-sets (Lewandowski, 2017; Trumpp and Guenther, 2017). On the contrary, previous studies conducted with EU data show evidence of a negative EP-FP relationship (Wagner et al., 2002; Wagner, 2005). A possible explanation, apart from the small sample of the two 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 this study is that it explains the endogeneity between EP and FP for high profitability firms. We underline that endogeneity is conditional on the profitability levels. An implication of this is that generalisation of research findings is likely to be misleading. Notably, studies should distinguish between low and high profitability firms. In this regard, we show that estimates for lower profitability firms are more likely to be unbiased. By contrast, for high profitability firms the assumption that EP is exogeneously given does not receive empirical support. However, we also show that the endogeneity problem can be solved by means of 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 trigger regulatory concerns. Also, the role of ISO as a managerial strategy to loosen regulatory pressures is still unclear. Misani and Pogutz (2015) note that environmental management is carried out merely for symbolic purposes without improving carbon footprint. More importantly, policymakers should consider developing 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 and complexity of environmental regulations, mitigation policies to address climate change provide insufficient incentives for adaptation.

Concluding this paper, we would like to offer some potential avenues for future research. First, it could be interesting to examine the EP effects on FP in the EU context for a greater number of industries. 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 responds in different FP 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. Finally, more research should be devoted to dynamic and non-parametric modelling of the EP-FP relationship.

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Table 1: 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).

Table 2: 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
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
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

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

Table 3: 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 2.

Table 4: 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 2.

Table 5: 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 2. This table reports the results of the quantile regressions based on equation 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 6: 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 2. This table reports the results of the quantile regressions based on equation 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 7: 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 2. The prefix *adj* signifies that variables have been adjusted per industry 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. This table reports the results of the quantile regressions based on equation 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 8: 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 2. This table reports the results of the quantile regressions based on equation 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 9: 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	pre	pre	pre	post	post	post	pre	pre	pre	post	post	post
	ROA	ROA	ROA	ROA	ROA	ROA	adj.ROA	adj.ROA	adj.ROA	adj.ROA	adj.ROA	adj.ROA
EP	0.355	0.191	0.542*	0.912***	0.469***	0.721***	0.0931	0.0293	0.0585**	0.141***	0.0531***	0.120***
	(0.345)	(0.218)	(0.277)	(0.144)	(0.092)	(0.098)	(0.064)	(0.019)	-0.027	(0.030)	(0.013)	(0.023)
(adj.)Z	1.326***	1.595***	1.607***	0.0786	0.762***	1.318***	0.828***	0.861***	1.034***	0.150**	0.708***	1.046***
	(0.302)	(0.206)	(0.389)	(0.060)	(0.124)	(0.184)	(0.142)	(0.068)	-0.24	(0.075)	(0.072)	(0.162)
(adj.)LEV	-0.00274	-0.00117	0.00113	0.0014	-0.0015	-0.0001	-0.0256	-0.0808***	-0.0385	-0.0226	-0.00541	0.00916
	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.049)	(0.030)	-0.091	(0.022)	(0.013)	(0.011)
(adj.)EMP	0.507	0.167	0.396	0.583**	0.407**	1.070***	1.177	0.343	1.163	1.253**	0.306	1.664***
	(0.486)	(0.197)	(0.265)	(0.250)	(0.182)	(0.256)	(0.928)	(0.352)	-0.876	(0.552)	(0.282)	(0.305)
(adj.)LOGTA	0.770	0.422	0.120	-1.147***	-0.579***	-0.768***	1.254	0.422	0.0651	-1.191***	-0.113	-0.653
	(0.489)	(0.268)	(0.621)	(0.301)	(0.168)	(0.272)	(1.059)	(0.295)	-0.609	(0.434)	(0.255)	(0.446)
GDP	0.155	-0.0588	1.046	0.221	0.0401	-0.0107	0.0301	-0.000526	0.148	0.0413	0.00705	-0.00188
	(0.373)	(0.231)	(0.818)	(0.141)	(0.038)	(0.092)	(0.046)	(0.030)	-0.12	(0.032)	(0.009)	(0.014)
(adj.)TANG	0.984	-0.170	0.0111	-0.941	-0.632*	1.141	0.473*	-0.211*	-0.252	0.168	-0.0806	-0.119
	(1.828)	(1.490)	(2.836)	(0.864)	(0.358)	(2.324)	(0.267)	(0.122)	-0.479	(0.148)	(0.083)	(0.247)
(adj.)INTA	-0.227	1.664	-2.486	-0.544	0.149	-1.917	0.0517	-0.0272	-0.13	0.0837*	0.00728	-0.160*
	(2.477)	(1.164)	(3.790)	(1.281)	(0.664)	(2.564)	(0.071)	(0.039)	-0.133	(0.048)	(0.028)	(0.090)
(adj.)GRO	0.0005	-0.002	-0.0059	-0.006	0.008	0.0191*	-0.008	0.00005	0.0437	0.0067	0.005*	0.005***
	(0.010)	(0.012)	(0.025)	(0.009)	(0.007)	(0.010)	(0.020)	(0.012)	-0.064	(0.005)	(0.003)	(0.002)
cons	-23.42***	-3.696*	0.708	6.644*	5.175**	2.064	-4.658***	-0.453	-0.525	-1.045	0.117	-0.350
	(8.061)	(1.969)	(7.917)	(3.401)	(2.007)	(4.218)	(1.768)	(0.458)	-1.058	(0.764)	(0.354)	(0.657)
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	375	375	375	1465	1465	1465	375	375	375	1465	1465	1465
R^2	0.4345	0.4129	0.5637	0.2463	0.311	0.523	0.4053	0.3313	0.4671	0.2488	0.1716	0.2273
Wald		1.15			6.63***			0.42			9.55**	

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 2. The prefix *adj* signifies that variables have been adjusted per industry 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. This table reports the results of the quantile regressions based on equation 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 10: First stage Quantile regression 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 2. This table reports the results of the first-stage quantile regression (equation 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 11: Two-stage Quantile Regression 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**	

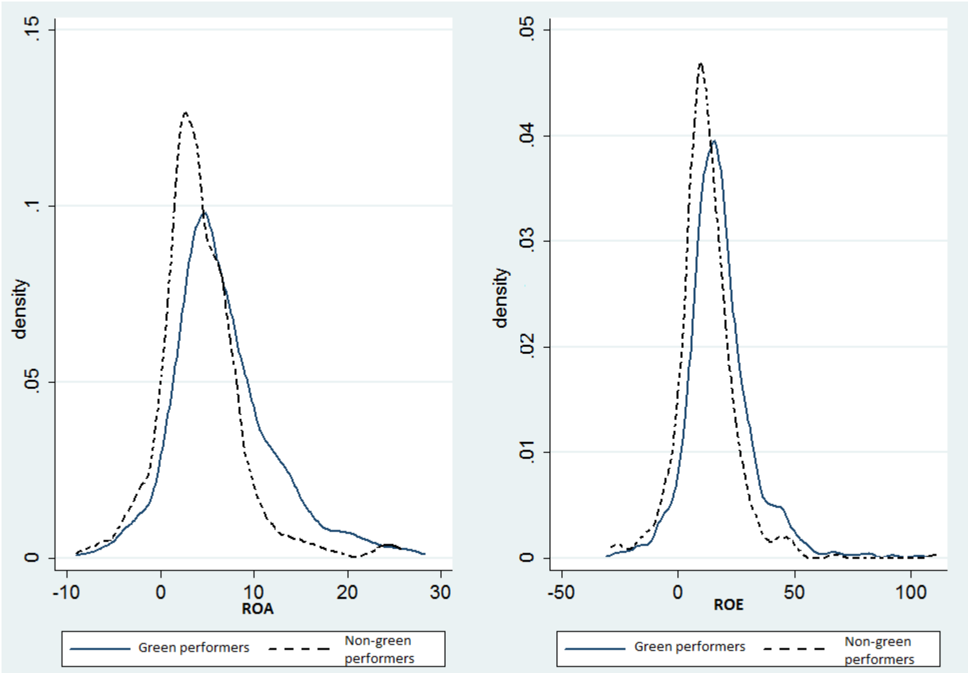
Notes: Description of the variables can be found on Table 2. This table reports the results of the two-stage quantile regressions (equation 9), with τ showing different quantiles of ROA distribution. Term $\hat{V}(\alpha)$ corresponds to any α given based on the first stage estimates (equation 4). Significance 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 12: 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**	

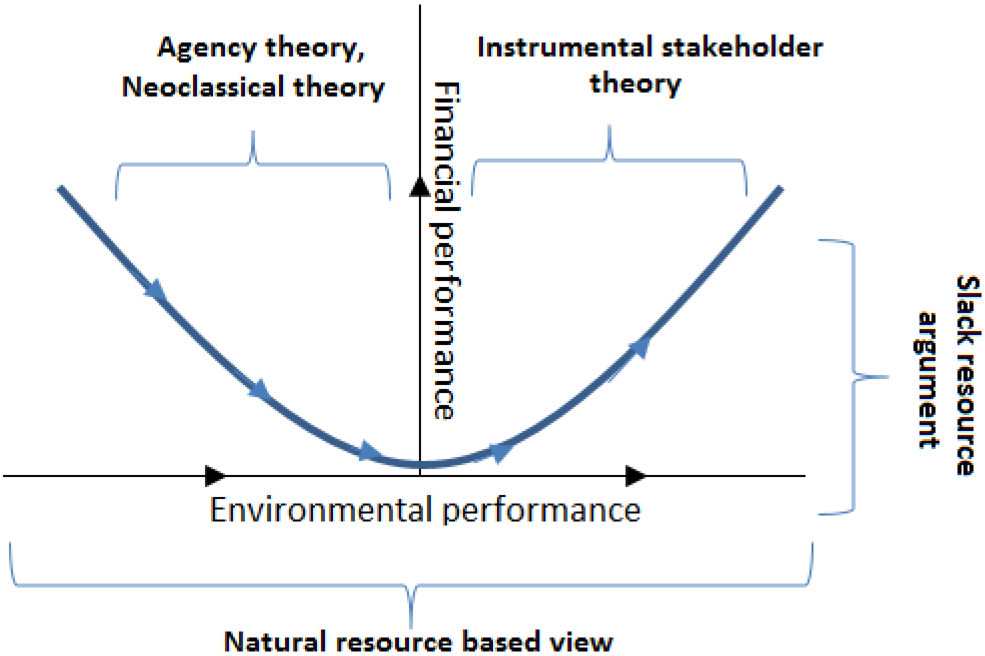
Notes: Description of the variables can be found on Table 2. This table reports the results of the two-stage quantile regressions (equation 9), with τ showing different quantiles of ROE distribution. Term $\hat{V}(\alpha)$ corresponds to any α given based on the first stage estimates (equation 4). Significance 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 1: Kernel FP density for green performers and non-green performers



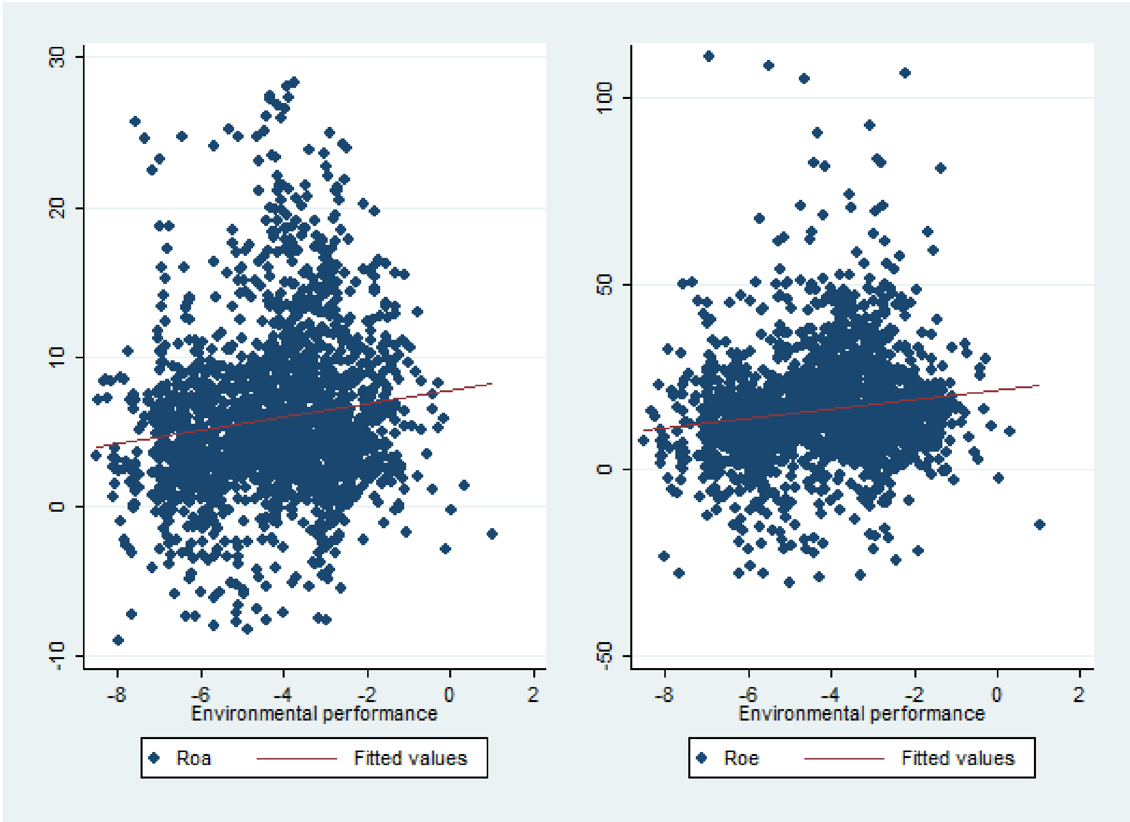
Notes: Green performers are firms distributed in the 4rd quarter of the EP variable $[EP = (-1) * Log(GHG/Total\ assets)]$, while non-green performers are observations in the 1st quarter of the EP variable. Data are explained in section 3.

Figure 2: Theory behind EP-FP



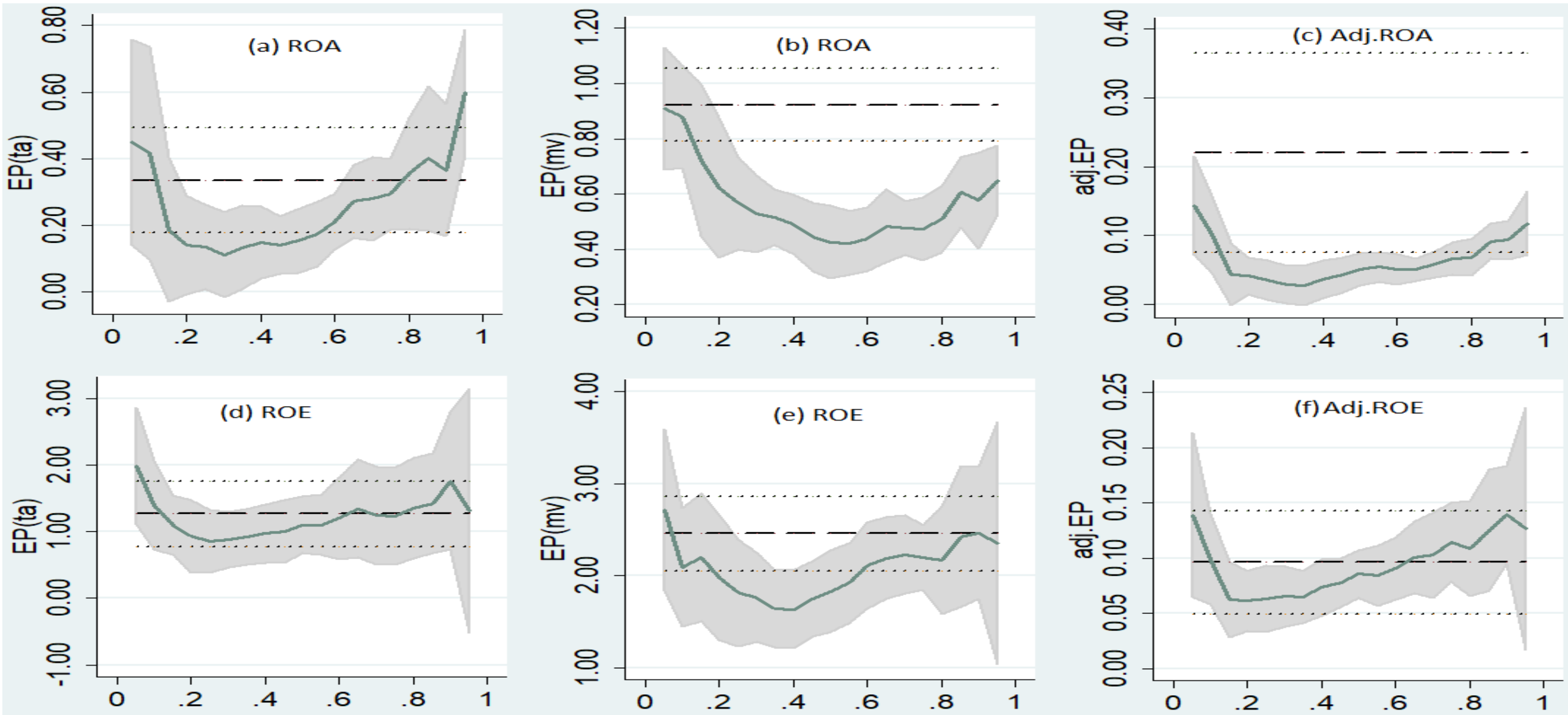
Notes: The figure shows the theoretical framework between EP and FP. The *agency* and *neo-classical* theories hypothesise a negative, while the *instrumental stakeholder theory* predicts a positive relationship. The *natural resource based view* supports a U-shaped curve, and the *slack resource argument* signifies that the relationship is conditional on the level of financial resources of the firm.

Figure 3: Scatter graph of EP-FP



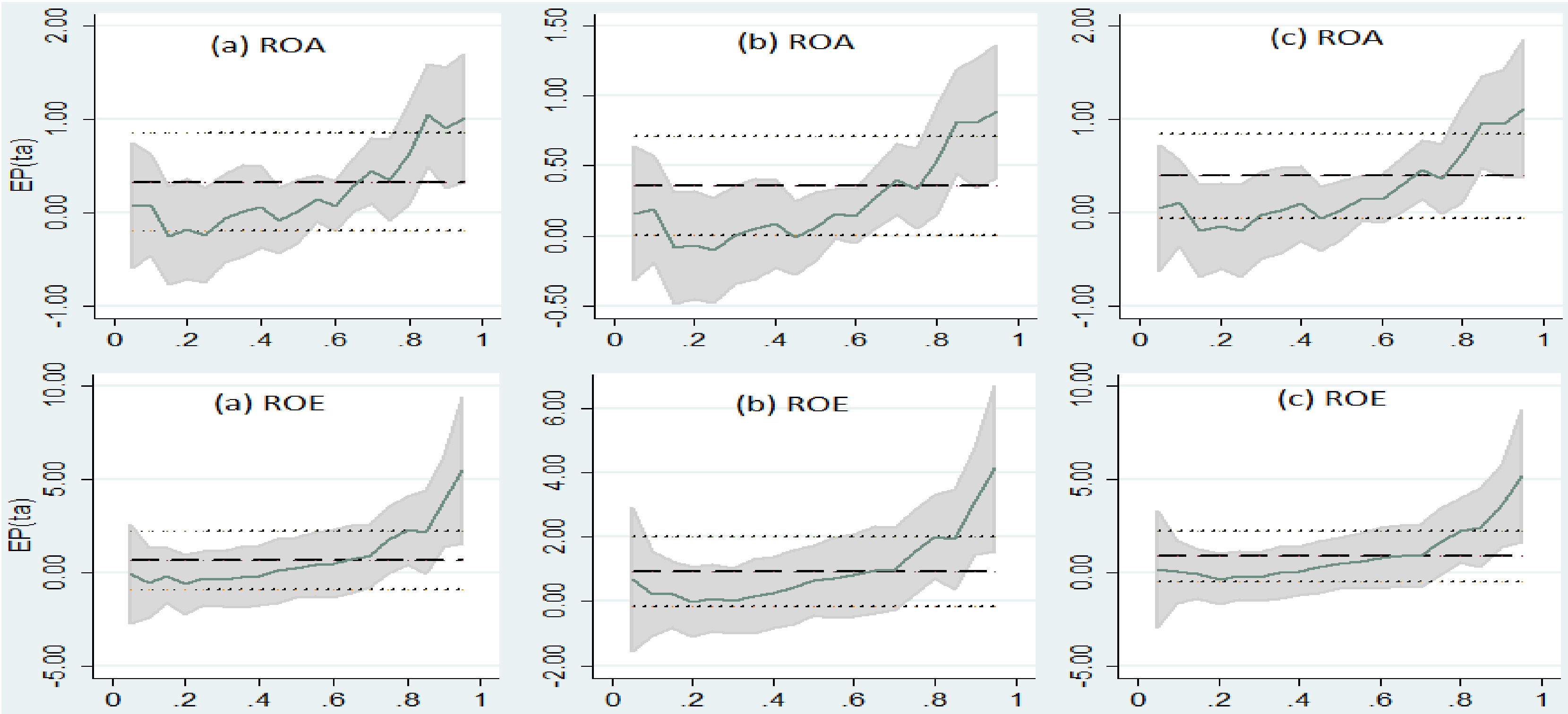
Notes: The figure illustrates two scatter diagrams. The dots correspond to ROA (ROE) observations plotted by EP [$EP = (-1) * Log(GHG/Total\ assets)$].

Figure 4: EP effects on FP distribution



Notes: The figure illustrates the non-linear effects of EP on FP, based on equation 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.

Figure 5: 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 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.