Towards Green Companies: A Panel Data Study of The Environmental and Financial Performance Nexus

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Abstract

Providing evidence that companies with better Corporate Environmental Performance (i.e. CEP) have also better Corporate Financial Performance (i.e. CFP) have been a lively debate in the literature. Two major opposite trends emerged. Some scholars provided evidence of a positive link between CEP and CFP while others demonstrated a negative relationship. Using a panel data of 393 US publicly traded companies for the period 2012-2014, this study first investigates the impact of process-based CEP on outcome-based CEP. Then, it explores whether the combined effect of process-based and outcome-based CEP influences CFP. Finally, it observes the time influence (i.e. short-term vs long-term) on the relationship.

This study provides evidence that process-based CEP positively influences outcome-based CEP and supports the idea that it does pay to be green. More precisely, it demonstrates that both process and outcome-based CEP have a positive impact on CFP, no matter the time horizon, and is stronger with a long-term perspective than a short-term perspective. This study emphasizes strong incentives for companies to invest in environmental strategies.

Keywords — Corporate Environmental Performance, Corporate Financial Performance, Panel Data, Global Warming

Author's Note

This master's thesis has been written in `R Markdown` (ALLAIRE ET AL., 2018) to make it transparent and reproducible for the reader. All resources are available on my `GitHub` account[1] `https://github.com/pkinif/Thesis`. The latter is organized following the methodology of GANDRUD (2013). Each section of this thesis corresponds to an `R Markdown` file in the `Child` folder. The `Child/ThesisSkeleton.Rmd` file is the `parent` document which merges all the `child` directories into a consolidated pdf document, namely the one you are reading. The `Child/Analysis` sub-folder contains a list of makefiles whose outputs are saved into `Child/Analysis/DataBase`.

The platform I have used is `Rstudio` which is an open source software for `R` (R CORE TEAM, 2018). Here is the information of my session:

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[1] For now, the repository containing my thesis project is private. If you wish to get an access to it, please send me an email to `pierrick-kinif@hotmail.be`.

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Author's Declaration

I, Pierrick KINIF, certify that this master's thesis does not incorporate without acknowledgment, any material previously submitted for a degree or diploma in any university; and that to the best of my knowledge and belief, it does not contain any material previously published or written by another person where due reference is not made in the text.

SIGNED DATED

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List of Abbreviations

Abbreviation	Term
AS	Audit Score
BPLM	Breusch-Pagan Lagrange Multiplier
CaP	Carbon Productivity
CEP	Corporate Environmental Performance
CFP	Corporate Financial Performance
CSP	Corporate Social Performance
EDV	Environmental Disclosure Variables
EMV	Environmental Management Measures
EPV	Environmental Performance Variables
ESG	Environmental, Social and Governmental
FE	Fixed Effetcs
GICS	Global Industry Classification Standard
GS	Green Score
ISO	The International Organization for Standardization
KPI	Key Performance Indicator
NGR	Newsweek Green Rankings
OLS	Ordinary Least Square
PPM	Parts Per Million
RE	Random Effetcs
ROA	Return on Asset
ROE	Return on Equity
SA	Sensitivity Analysis
SPL	Sustainability Pay Link
SRI	Socially Responsible Investments
STC	Sustainability Themed Committee
VIF	Variance Inflation Factor
WastP	Waste Productivity
WatP	Water Productivity

1 Introduction

Over the past decades, humanity has progressively become aware of the finiteness of earth's resources and its impact on the current global warming. Meadows et al. (1972) (p23) concludes that *"if the present growth trends in world population, industrialization, pollution, food production, resource depletion continue unchanged, the limits to growth on this planet will be reached sometime within the next one hundred years"*. Houghton and Change (1996) also claim that *"in the absence of mitigation policies, greenhouse gas emissions will continue to rise during the next century"* (p9). This will *"increase the global mean surface air temperature relative to 1990 of about 2°C by 2100... leading to harsh climatic repercussions"* (p23).

Over the last 30 years, these predictions have come true. For the first time in 400 000 years, atmospheric carbon dioxide crossed, in 1950, the level of 300 Parts Per Million[2] (i.e. PPM) (Pieter Tans et al., 2018). According to the NOAA's Annual Greenhouse Gas Index, the atmospheric abundance of CO_2 increased by an average of 1.80 PPM per year from 1979 to 2016 (Butler and Montzka, 2016). In May 2018, the global level of carbon dioxide has reached 410 PPM (Pieter Tans et al., 2018). This increase led to direct effects.

Since the 19^{th} century, the average temperature of the planet increased (+1.1°C). Most of the warming occurred in the past 35 years, with 16 of the 17 warmest years on record occurring since 2001 (Gistemp Team, 2018; Hansen et al., 2010). Data from NASA's Gravity Recovery and Climate Experiment show Greenland lost 150 to 250 cubic kilometers of ice per year between 2002 and 2006, while Antarctica lost about 152 cubic kilometers of ice between 2002 and 2005 (Gistemp Team, 2018). Church and White (2006) showed that, in the last century, the global sea level rose (+8 inches). Due to a high carbon dioxide absorption level (Sabine et al., 2004), the acidity of surface ocean waters also increased (+30%) (NOAA's Pacific Marine Environmental Laboratory, n.d.) leading, *inter alia*, to harsh repercussions to corals.

Ecosystem degradation and resources depletion engender a threat to firm's longevity (Dowell et al., 2000). Mark Carney, Governor of the Bank of England and Chair of the Financial Stability Board, identifies climate change as one of the most material threats to financial stability (Elliott, 2015). The Business and Sustainable Development Commission (2017) (p12) report states: *"... businesses need to pursue social and environmental sustainability as avidly as they pursue market share and shareholder value... If they don't, the costs and uncertainty of unsustainable development could swell until there is no viable world in which to do business."* In other words, adopting environmental strategies ensure

[2] A concentration of 300 PPM means that for every million air particles, 300 of them are carbon dioxide molecules, namely a carbon concentration of 0.03%.

companies' competitiveness and survival in the near future.

Testa et al. (2018) show that, due to institutional pressure or the influence of stakeholders, a majority of companies have integrated, either substantially or symbolically (i.e. greenwashing), proactive environmental practices. However, according to Scarpellini et al. (2016), green projects are still not common in companies of many countries because of significant barriers and a negligible culture of excluding sustainable development from an organization's strategy.

People's actions reflect a variable mix of altruistic motivation, material self-interest, and social or self-image concerns (Bénabou and Tirole, 2006). Hence, for more than 40 years, scholars have analyzed the Corporate Environmental Performance (i.e. CEP) and Corporate Financial Performance (i.e. CFP) nexus to provide evidence that it does pay to be green and to convince companies to incorporate environmental sustainability into their core values and strategies (Lu et al., 2014).

The International Organization for Standardization (ISO, 2013) defines CEP as *"measurable results of an organization's management of its environmental aspects"*. The CFP construct assesses the outcomes of business strategy (Bansal and DesJardine, 2014) and is a primary, fundamental indicator of organizational performance and long-term survival of an organization (Hamann et al., 2013).

The relationship between CEP and CFP is broadly discussed in the literature and is characterized by inconsistent empirical findings (Endrikat et al., 2014). Two major opposite trends have emerged. Some scholars (Chen et al., 2018; Manrique and Martí-Ballester, 2017; Miroshnychenko et al., 2017) provide evidence of a positive link between CEP and CFP while others (Busch and Hoffmann, 2011; Fernando et al., 2010; Fisher-Vanden and Thorburn, 2008) demonstrate a negative relationship. This inconclusiveness may come from the multidimensionality of both focal constructs (Albertini, 2013; Endrikat et al., 2014; Griffin and Mahon, 1997) given that commonly shared understanding or conceptualization of CEP and CFP has not been established so far (Etzion, 2007; Hamann et al., 2013).

Indeed, Endrikat et al. (2014) argue that a two-group classification of CEP can be deduced from the literature. (i) Process-based CEP which refers to *"a strategic level and focuses on managerial principles and processes such as environmental objectives, environmental policies, or environmental management structures"*. (ii) Outcome-based CEP which reflects *"the observable and quantifiable results of these efforts (*Delmas et al., *2011) and refers to measures such as the number of released pollutants or the ratio of recycled waste to total waste"*.

Regarding CFP, scholars have adopted three broad subdivisions: market-based (i.e. investor returns), accounting-based (i.e. accounting returns), and perceptual (i.e. survey) measures

(Lu et al., 2014). Furthermore, the multidimensionality of CFP includes a wide array of estimations that may capture a firm's ability to generate value in the short-term and company's future growth prospects assessed by the external stakeholders (Miroshnychenko et al., 2017; Opler and Titman, 1994).

Endrikat et al. (2014) highlight the need for a better understanding of the multidimensionality of both CEP and CFP constructs. Furthermore, King and Lenox (2002) suggest that *"When does it pay to be green?"* may be a more important question than *"Does it pay to be green?"*. Griffin and Mahon (1997) is the first to call for studies that look at the CEP-CFP relationship over time. To that extent, Busch and Friede (2018) demonstrate that, at a meta-research level, evidence of a time dependency on the CEP-CFP link are not significant and that the call of Griffin and Mahon (1997) remains, to date, unanswered. Therefore, using a panel data of 393 US publicly traded companies for the period 2012-2014, this study first investigates the impact of process-based CEP on outcome-based CEP. Then, it explores whether the combined effect of process-based and outcome-based CEP influences CFP. Finally, it observes the time influence (i.e. short-term vs long-term) on the relationship.

This study provides evidence that process-based CEP positively influences outcome-based CEP and supports the idea that it does pay to be green. More precisely, it demonstrates that both process and outcome-based CEP have a positive impact on CFP, no matter the time horizon, and is stronger with a long-term perspective than a short-term perspective. This study emphasizes strong incentives for companies to invest in environmental strategies.

The rest of the paper is organized as follows: the next section reviews the literature regarding the CEP-CFP nexus. Then, I describe the database and methodology. Next, the results are presented. Finally, I discuss the main contributions to the literature and highlight potential future research.

2 Literature Review

2.1 CFP as a Broad Meta-Construct

CFP is a broad meta-construct and scholars have adopted three broad subdivisions: market-based, accounting-based, and perceptual measures (Orlitzky et al., 2003).

Market-based measures (e.g. price-earning ratio or Tobin's Q) consider that returns should be measured from the perspective of shareholders (Cochran and Wood, 1984). They incorporate intangible assets and reputational effects (Busch and Hoffmann, 2011) and can be highly influenced by speculations, rumors, and capital market breakdowns (Wright, 2004).

Accounting-based measures require profitability and asset utilization indicators such as Return on Asset (i.e. ROA) or Return on Equity (i.e. ROE) (Cochran and Wood, 1984; Wu, 2006). According to Orlitzky et al. (2003), these indicators are subject to managers' discretionary allocations of funds to different projects and policy choices and thus reflect internal decision-making capabilities and managerial performance. Accounting-based indicators are also highly influenced by the industrial sector characteristics (Montgomery and Wernerfelt, 1988).

Perceptual measures of CFP is a more subjective approach (Lu et al., 2014) based on external (e.g. Fortune magazine rankings) and internal (e.g. Management surveys) perceptual metrics (Peloza, 2009). These indicators ask survey respondents to provide subjective estimates of, for instance, the firm's *"soundness of financial position"*, *"wise use of corporate assets"*, or *"financial goal achievement relative to competitors"* (Orlitzky et al., 2003).

Based on a recent critical review, Lu et al. (2014) have shown that of the three types of CFP measures, accounting-based ones are the most frequency used, followed by market-based measures and perceptual measures. Scholars also tend to alleviate weaknesses of one type of indicators by the use of another (McWilliams et al., 2006). For instance, King and Lenox (2002) and Delmas et al. (2015) used ROA and Tobin's Q as proxies for approaching CFP. Menguc and Ozanne (2005) considered market share, sales growth, and profit after tax. Husted and Allen (2007) used management surveys while Verschoor (1999) adopted the Fortune magazine rankings.

2.2 CEP as a Broad Meta-Construct

CEP is also a broad meta-construct and no common definition exist in the literature (Albertini, 2013; Endrikat et al., 2014). Scholars have used a wide variety of indicators as proxies for approaching the green performance of companies. Albertini (2013) used a three-group classification to summarize CEP measures : (i) *Environmental Management*

Measures (i.e. EMV) which mostly refer to environmental strategy, integration of environmental issues into strategic planning processes, environmental practices, process-driven initiatives, product-driven management systems, ISO 14001 certification, environmental management system adoption, and participation in voluntary programs (Molina-Azorín et al., 2009; Schultze and Trommer, 2012). (ii) *Environmental Performance Variables* (i.e. EPV) which are measures quantified in physical units (carbon dioxide emissions, physical waste, water consumption, toxic release) that can be positive (emission reduction) or negative (emission generated) (Albertini, 2013). (iii) *Environmental Disclosure Variables* (i.e. EDV), such as information releases regarding toxic emission (Hamilton, 1995), environmental awards (Chen et al., 2018), environmental accidents and crises (Blacconiere and Patten, 1994), and environmental investment announcements (Gilley et al., 2000).

Endrikat et al. (2014) divided CEP into two sub-dimension. On the one hand, *process-based CEP* which can be linked to the EMV approach of Albertini (2013). It refers to *"a strategic level and focuses on managerial principles and processes such as environmental objectives, environmental policies, or environmental management structures"*. On the other hand, *outcome-based CEP* which can be linked to the EPV dimension of Albertini (2013). It reflects *"the observable and quantifiable results of these efforts (*Delmas et al., *2011) and refers to measures such as the number of released pollutants or the ratio of recycled waste to total waste"*. Xie and Hayase (2007) found that process-based CEP can be considered as a preliminary step of outcome-based CEP. Li et al. (2017) and Chen et al. (2018) demonstrated that the first approach has a positive impact on the second one which in turn has a positive impact on financial performance. Melnyk et al. (2003) observed that firms in possession of a formal EMS perceive impacts well beyond pollution abatement and see a critical positive impact on many dimensions of operations performance

CEP are also linked to the Environmental, Social, and Governmental (i.e. ESG) framework or also called Socially Responsible Investments (i.e. SRI). ESG investing provides criteria that allow investors and advisors to select investments that align with their values as well as their financial goals (Fulton et al., 2012). It applies a set of investment screens to select or exclude assets based on ESG criteria (Renneboog et al., 2008). A plethora of organizations has developed methodologies to attribute an ESG score to companies and support investors who consider corporate governance insights into their investment processes. For instance, Sustainalytics based in New York and Thomson Reuters with the Asset4 ESG database. Scholars (Halbritter and Dorfleitner, 2015; Miroshnychenko et al., 2017) have used these ESG scores as proxies for CEP.

2.3 Two Perspectives on CEP

Two perspectives on CEP can be observed in the literature. First, Friedman (1970) advocated investment in pollution efficient technology as a deviation from the profit maximization goal (i.e. an increase in cost). According to him, *"businessmen who want to promote desirably social ends... are unwitting puppets of the intellectual forces that have been undermining the basis of a free society"*. In recent decades, this paradigm has been widely challenged. The literature has shown growing evidence that improving CEP can lead to better economic or financial performance.

Second, Ambec and Lanoie (2008) demonstrated that the expenses incurred to reduce pollution can be partly or completely offset by gains made elsewhere. Porter and van der Linde (1995) argued that properly crafted environmental standards can trigger innovation offsets, allowing companies to improve their resource productivity. He redefined the concept of value creation. According to him, companies have to create shared value. Sharing value creation involves building economic value which addresses current needs and challenges of the society (Porter et al., 2011; Porter and Kramer, 2011). In the same logic, Freeman (1984) called for a radical rethinking of the firm's model. He argued that companies have to consider their stakeholders (i.e. any group or individual who can affect or is affected by the achievement of an organization's objectives (p25)) or otherwise face negative contests from non-shareholder groups (e.g. boycotts, lawsuits, and protests). In other words, Freeman (1984) summarized the idea that companies should consider CEP as an undeniable cost of doing business.

2.4 Does It Pay to Be Green?

More and more companies have developed profitable business strategies that deliver social benefits (Testa et al., 2018) and that embrace the new business paradigm of Freeman (1984), Porter and van der Linde (1995) and Ambec and Lanoie (2008). However, others prefer keeping the old fashion way of Friedman (1970). This dichotomy has interested scholars and since they have sought to empirically answer the question, *"Does it pay to be green?"*. Lu et al. (2014) claimed that answering this question, in a competitive business world, is crucial to provide a genuine economic justification to the new paradigm.

The relationship between CEP and CFP has been broadly discussed in the literature and led to inconsistent empirical findings (Endrikat et al., 2014). Two major opposite trends emerged. Some scholars provided evidence of a positive link between CEP and CFP, others demonstrated a negative relationship and most of them got mixed results.

For instance, Delmas et al. (2015) found that improving CEP causes a decline in ROA while an increase in Tobin's q. Unlike Cavaco and Crifo (2014) and Muhammad et al. (2015) who obtained a positive relation between ROA and CEP and no relation between Tobin's Q and CEP. Miroshnychenko et al. (2017) showed that internal green practices (i.e. pollution prevention and green supply chain management) are the major environmental drivers of financial performance, while external green practices (i.e. green product development) play a secondary role in determining financial performance. Besides, they claimed that the adoption of ISO 14001 appears to have a negative impact on financial performance. Fernando et al. (2010) observed that all else equal, toxic firms can realize a higher valuation by becoming environmentally neutral but they found no such financial benefit to neutral firms becoming green. Busch and Hoffmann (2011) concluded that process-based CEP (in terms of carbon management) negatively affects CFP, while outcome-based CEP (in terms of carbon emissions) has a positive influence on CFP. Song et al. (2017) provided evidence that environmental management is significantly positively related to financial performance in the following year while no significant in the current year. Fisher-Vanden and Thorburn (2008) found that companies announcing membership in environmental programs experience significantly negative abnormal stock returns. Przychodzen and Przychodzen (2015) indicated that companies involved in environmental innovation process were generally characterized by higher ROA and ROE and lower earnings retention ratio.

Some scholars advanced that the multidimensionality of CEP and CFP constructs is one reason why the conclusion of the relationship had been so mixed (Albertini, 2013; Endrikat et al., 2014). However, the large number of studies in the last three decades allowed the appearance of recent meta-analyses[3] (Albertini, 2013; Busch and Friede, 2018; Dixon-Fowler et al., 2013; Endrikat et al., 2014; Lu et al., 2014; Orlitzky and Benjamin, 2001; Orlitzky et al., 2003; Wang et al., 2016; Wu, 2006) which concluded that indeed, it does pay to be green. More precisely, a positive and bidirectional relationship does exist between CEP and CFP meaning that successful companies may have the necessary resources to improve their environmental performance, which in turn increases financial benefits that can be invested back into further improvements of CEP (Endrikat et al., 2014).

2.5 When Does It Pay to Be Green?

While scholars have mainly answered the question: *"Does it pay to be green?"* some have recently tried to move forward and gained interest in: *"When does it pay to be green?"* (Manrique and Martí-Ballester, 2017). Griffin and Mahon (1997) were the first to

[3] Initially, the literature focused on the link between Corporate Social Performance (i.e. CSP) and CFP. Orlitzky and Benjamin (2001) were the first to consider CEP as apart from CSP. Given that Busch and Friede (2018) could not detect that the relation between CSP (excluding environmental aspects) and CFP is stronger than for CEP and CFP, this study considers CSP equals to CEP.

call for studies that look at the CEP-CFP relation over time.

Zhang and Chen (2017) showed that CEP has a negative relationship with short-term CFP and a positive relationship with long-term CFP. Delmas et al. (2015) observed that the more a company decreases carbon emissions, the more positive the investors' perceptions of future market performance, and the lower its short-term financial performance. Song et al. (2017) concluded that corporate environmental management has a significant positive correlation with future financial performance while no significant correlation with current financial performance. Manrique and Martí-Ballester (2017) demonstrated that in times of economic crisis, firms which improve their CEP improve their CFP, this effect being weaker for firms in developed countries, where only the short-term CFP improves than for firms in emerging and developing countries, where the short and long-term CFP improve. Chen et al. (2018) claimed that a firms green performance not only impact an organization's financial performance in that particular year but also impact the year that follows.

These empirical results provide pieces of evidence that the literature has not found a consencus yet to answer the question: *"When does it pay to be green?"*. To that extent, Busch and Friede (2018) demonstrated that at a meta-research level, the evidence of a time dependency on the CEP-CFP link is not significant and that the call of Griffin and Mahon (1997) remains, to date, unanswered.

To capture the time dimension of the CEP-CFP nexus, scholars have considered accounting-based measures as a proxy for short-term CFP and market-based measures as a proxy for long-term CFP (Delmas et al., 2015; Endrikat et al., 2014; Manrique and Martí-Ballester, 2017; Miroshnychenko et al., 2017; Zhang and Chen, 2017). Indeed, Endrikat et al. (2014) highlighted that accounting-based measures capture immediate impacts but do not seize long-term effects, unlike market-based measures which integrate estimations of firm's future prospects and reflect the notion of external stakeholders.

Taking into account previous theoretical arguments and considering varying empirical findings with regards to the CEP-CFP nexus, this study hypothesizes the following :

Hypothesis 1. Process-based CEP has a positive impact on Outcome-based CEP
Hypothesis 2. Outcome-based CEP has a positive impact on short-term CFP
Hypothesis 3. Outcome-based CEP has a positive impact on long-term CFP
Hypothesis 4. Process-based CEP has a positive impact on short-term CFP
Hypothesis 5. Process-based CEP has a positive impact on long-term CFP

The research framework of this study, inspired by Li Suhong et al. (2017) and Chen et al. (2018), is summarized in figure 2.1. The following section explains each variable.

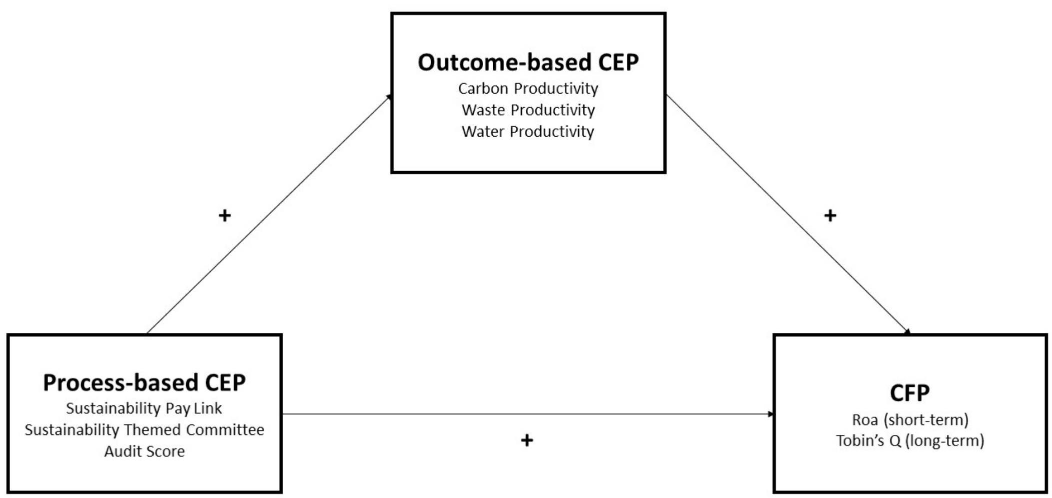

Figure 2.1: Research Framework

3 Data Description

3.1 Overview

The starting point of the data collection process was the Newsweek Green Rankings (i.e. NGR). This ranking has assessed the world's largest publicly-traded companies in the US and in the world since 2009. It was developed through a collaboration between Newsweek, Corporate Knights Capital, HIP Investor Inc and leading sustainability minds from nongovernmental organizations and the academic and accounting communities.

The NGR attributes an overall Green Score (i.e. GS) to companies. This score is based on a weighted average of key performance indicators (i.e. KPI). This study uses these KPI to approach both process-based and outcome-based CEP of the 500 largest publicly-traded companies in the US. As a result of making a transition to a 100% rules-based approach, the methodology for the 2014 NGR differs considerably from the framework used in the 2012 NGR. Therefore, this study considers only the `2014`, `2015` and `2016` NGR. Among those three rankings and of the 500 US companies, 405 companies were listed for each year.

Even though the NGR were published in 2014, 2015 and 2016, each company is evaluated based on the 2012, 2013 and 2014 company data. Therefore, measures for CFP will be based on the 2012, 2013 and 2014 fundamental data. Financial data have been collected on `Morningstar`, `Stockpup` and `Ycharts` using `R` technology. The data collection process is described in *"Appendix A: Database Construction"*. Of the 405 initial companies, a total of 12 were dropped because of missing data. The final sample includes 393 publicly-traded companies in the US covering the period from 2012 till 2014 inclusively.

Table 3.1 gives an overview of the variables of the econometric model. Following subsections deeply explain each variable.

3.2 Dependent Variables

Regarding dependent variables, Endrikat et al. (2014) claimed that accounting-based measures (e.g. Return On Asset, Return On Equity, Return on Sales) capture immediate impacts and can be used as a proxy to measure short-term CFP while market-based measures (e.g. Tobin's Q, market capitalization, market to book value) integrate estimations of firm's future prospects and can be better used as a proxy for long-term CFP. Among scholars which used both measures simultaneously, ROA and Tobin's Q are the most frequent (Cavaco and Crifo, 2014; Delmas et al., 2015; Lioui and Sharma, 2012; Manrique and Martí-Ballester, 2017; Muhammad et al., 2015; Semenova and Hassel, 2016). Therefore, this study uses ROA and Tobin's Q as proxies for both short-term and long-term CFP.

ROA is a standard accounting measure of financial performance, which is calculated by dividing earnings before interest by total firm assets. ROA gives information about how a company can transform assets into profit.

Tobin's Q is defined as the ratio of the market value of a firm to the replacement cost of its assets (Chung and Pruitt, 1994). Firms displaying Tobin's Q greater than one are judged as using scarce resources effectively and those with Tobin's Q less than one as using resources poorly (Lewellen and Badrinath, 1997). In other words, investors prefer companies with Tobin's Q superior to one. Due to the complexity of calculating the replacement cost of a firm, the literature has described several attempts to approximate Tobin's Q (Perfect and Wiles, 1994). This study collected Tobin's Q data directly on `Ycharts`. This financial data platform uses the simple approximation of Chung and Pruitt (1994) which is summarized in equation 1. Due to a high right-skew (i.e. skewness = 2.51), I use a natural logarithm transformation to normalize the distribution of Tobin's Q (Honaker et al., 2011).

$$Tobin'sQ = \frac{MVE + PS + DEBT}{TA} \tag{1}$$

where MVE is the product of a firm's share price and the number of common stock shares outstanding, PS is the liquidating value of the firm's outstanding preferred stock, $DEBT$ is the value of the firm's short-term liabilities net of its short-term assets, plus the book value of the firm's long-term debt and TA is the book value of the total assets of the firm.

3.3 Independent Variables

Both process-based and outcome-based CEP has been measured with the KPI of the NGR. I use "Sustainability Pay Link", "Sustainability Themed Committee", and "Audit Score" as proxies for process-based CEP and "Carbon Productivity", "Water Productivity" and "Waste Productivity" as proxies for outcome-based CEP[4].

A Sustainability Pay Link (i.e. SPL) is a mechanism to link the remuneration of any member of a company's senior executive team with the achievement of environmental performance targets. A score of 1 accrues to the company when such a link exists and a score of 0 otherwise.

A Sustainability Themed Committee (i.e. STC) refers to the existence of a committee at the board of directors level whose mandate is related to the sustainability of the company, including but not limited to environmental matters. A score of 1 accrues to the company when such a link exists and a score of 0 otherwise.

An Audit Score (i.e. AS) refers to the case where a company provides evidence that the latest reported environmental metrics were audited by a third party. A score of 1 accrues to

[4]The NGR has another KPI that captures outcome-based CEP (i.e. Energy Productivity). Due to multicollinearity concern (Variance Inflation Factor superior to 5 for both Energy and Carbon Productivity), I do not consider this KPI into the econometric model.

the company if such an audit has been performed, and a score of 0 otherwise.

Carbon Productivity (i.e. CaP), *Water Productivity* (i.e. WatP) and *Waste Productivity* (i.e. WastP) are calculated through equation 2, 3 and 4.

$$CaP_{it} = \frac{Revenue_{it}}{TGGE_{it}} \tag{2}$$

$$WatP_{it} = \frac{Revenue_{it}}{TW_{it}} \tag{3}$$

$$WastP_{it} = \frac{Revenue_{it}}{(TWG_{it} - TWRR_{it})} \tag{4}$$

where $Revenue_{it}$ is the total revenue in USD, $TGGE_{it}$ is the total greenhouse gaz emissions in CO_2, TW_{it} is the total water in m_3, TWG_{it} is the total waste generated in metric tons and $TWRR$ is the total waste recycled and reused in metric tons.

3.4 Control Variables

Scholars argue that misspecified models may be a reason for the inconsistency of the empirical results in the CEP-CFP nexus (McWilliams et al., 2006; Surroca et al., 2010; Telle, 2006). To improve the construct and to avoid the endogeneity issue due to omitted variables (Roberts and Whited, 2013), Endrikat et al. (2014) highlighted some potential determinants of the relationship between CEP and CFP: firm size, industry sector, and capital structure. In a meta-analysis study, Lu et al. (2014) argued that growth rate is equally important. This study uses these four determinants as control variables.

The common way to approach *firm size* is to use the natural logarithm of total assets (Delmas et al., 2015; Miroshnychenko et al., 2017). To approach the company *industry sector*, I use the Global Industry Classification Standard (GICS) [5]. *Capital structure* is interpreted here as the financial leverage, namely the debt to equity ratio. The latter is measured as the ratio of long-term debt to common shareholders' equity (shareholders equity minus preferred equity). The *growth rate* is approached through the net margin (i.e. the ratio of earnings to revenue).

[5] The GICS classification is composed of eleven industry sectors, namely: Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Pharmaceuticals / Biotechnology, Telecommunication Services and Utilities.

Table 3.1: Variables Description

	Variables	Description
1	ROA	Earnings before interest over total firm assets
2	Tobin's Q	The ratio of a firm's market value to the replacement cost of its assets
3	CaP	Revenue (USD) / Total Greenhouse Gas Emissions (CO2)
4	WaP	Revenue (USD) / Total water (m3)
5	WastP	Revenue (USD) / [Total waste generated (metric tons) – waste recycled/reused (tons)]
6	SPL	A mechanism to link the remuneration of any member of a company's senior executive team with the achievement of environmental performance targets. Dummy variable which equals 1 if such a link exists and 0 otherwise
7	STC	Refers to the existence of a committee at the Board of Directors level whose mandate is related to the sustainability of the company, including but not limited to environmental matters. Dummy variable which equals 1 if such a committee exists and 0 otherwise
8	AS	Refers to the case where a company provides evidence that the latest reported environmental metrics were audited by a third party. Dummy variable which equals 1 if such evidence exist and 0 otherwise
9	Leverage	The ratio of long-term debt to common shareholders' equity (shareholders equity minus preferred equity)
10	Growth	Net margin, namely the ratio of earnings to revenue
11	Firm Size	Natural logarithm of total assets
12	Industry	Global Industry Classification Standard (i.e. GICS) of the firm. The variable takes a value from 1 to 10 where 1 = Consumer Discretionary, 2 = Consumer Staples, 3 = Energy, 4 = Financials, 5 = Health Care, 6 = Industrials, 7 = Information Technology, 8 = Materials, 9 = Pharmaceuticals / Biotechnology, 10 = Telecommunication Services and 11 = Utilities

4 Methodology

4.1 Panel Data: A Theoretical Background

This study uses the panel data methodology. Panel data is a common approach to address the CEP-CFP nexus (Albertini, 2013). It is considered to be one of the most efficient analytical methods for data analysis (Dimitrios Asteriou, 2006). It usually contains more degrees of freedom, less collinearity among the variables, more efficiency and more sample variability than one-dimensional method (i.e. cross-sectional data and time series data) giving a more accurate inference of the parameters estimated in the model (Hsiao, 2007). Roberts and Whited (2013) also argued that using panel data can offer a partial solution to the problem of omitted variables in the econometric model (i.e. the most common causes of endogeneity in empirical corporate finance). Panel data takes the following econometric form :

$$Y_{it} = \alpha + \beta_k X_{itk} + u_{it} \tag{5}$$

Panel data, also called longitudinal data, includes observations on $i = 1, ..., N$ cross-section units (e.g. firms) over $t = 1, ..., T$ time-periods (Hsiao, 2007). Here, Y_{it} is the dependent variable, X_{itk} represents a K-dimensional column vector of independent variables, α is the intercept, β_k is a K-dimensional column vector of parameters and u_{it} is the random disturbance term of mean equals zero. The latter can be decomposed as $u_{it} = \mu_i + \epsilon_{it}$. The first term, μ_i, represents the individual error component and is time-invariant. It can be considered as the unobserved effect model. The second term, ϵ_{it}, is the idiosyncratic error which is assumed well-behaved and independent of X_{it} and μ_i.

The starting point of all panel data is to determine if μ_i is correlated with X_{itk}. In presence of correlation, then μ_i is considered as the *Fixed Effect* (i.e. FE) and the initial equation 5 becomes equation 6. Otherwise, μ_i is considered as the *Random Effect* (i.e. RE) and the equation 5 becomes equation 7.

$$Y_{it} = (\alpha + \mu i) + \beta_k X_{itk} + \epsilon_{it} \tag{6}$$

$$Y_{it} = \alpha + \beta_k X_{itk} + (\epsilon_{it} + \mu i) \tag{7}$$

Fixed (i.e. Equation 6) and Random (i.e. Equation 7) Effect models imply that the Ordinary Least Square (i.e. OLS) estimators of β_k are inconsistent. Five assumptions are required to produce consistent estimators with OLS : (i) a random sample of observations on Y and $(X_1, ..., X_k)$, (ii) a random sample of N observations, (iii) no linear relationship among the explanatory variables, (iv) an error term that is uncorrelated with each explanatory variables and (v) an error term with zero mean conditional on the explanatory variables. FE model violates the fourth assumption while RE model implies that the common error component over individuals induces correlation across the composite error terms making the third assumption violated (Croissant and Millo, 2008).

The R package plm provides pertinent estimation methods to estimate panel data model. (i) *The pooled OLS estimation* ignores the panel structure of the data and applies the same coefficient to each individual (Schmidheiny, 2015). (ii) *The random effects estimation* is the feasible Generalized Least Squares estimator. (iii) *The fixed effects estimation*, also called *within estimation*, transforms the original equation 5 in subtracting the time average from every variable, such as :

$$(Y_{it} - \frac{1}{T}\sum_{t=1}^{T} Y_{it}) = \beta_k(X_{itk} - \frac{1}{T}\sum_{t=1}^{T} X_{itk}) + (\epsilon_{it} - \frac{1}{T}\sum_{t=1}^{T} \epsilon_{it}) \tag{8}$$

The presence of RE in panel data is tested using the Breusch-Pagan Lagrange Multiplier (i.e. BPLM) test (Breusch and Pagan, 1980) which is represented by the plmtest function in R. It examines if time and/or individual specific variance components equal zero (Park, 2011). If H0 is verified, there is no RE in the panel data. The presence of FE is tested by an F test (i.e. the function pFtest in R). The latter tests the individual and/or time effects based on the comparison of the within and the pooling model (Croissant and Millo, 2008). If H0 is verified, there is no FE in the panel data.

In case of the absence of both RE and FE, namely $\mu_i = 0$, pooled OLS estimation is the most efficient estimator (Croissant and Millo, 2008). Under FE, the random effects estimators are biased and inconsistent given that μ_i is omitted and potentially correlated with other regressors. Therefore, the fixed effects estimation need to be used. Under RE, the random and fixed effects estimators are unbiased and consistent. According to Schmidheiny (2015), scholars should prefer the random effects estimation only and only if μ_i is a random variable that is uncorrelated with the explanatory variables of all past, current and future time periods of the same individual, such as $E[\mu_i, X_{itk}] = 0$. This precondition is tested by the Hausman test (Hausman and Taylor, 1981). If H0 is verified, scholars should use the random effects estimation.

4.2 Econometric Model

This study uses equation 9 to study the link between outcome-based and process-based CEP and equation 10 to test their effects on CFP (short-term and long-term).

$$Y_{it} = \alpha + \beta_1 SPL_{it} + \beta_2 STC_{it} + \beta_3 AS_{it} + Controls_{it} + d_t + u_{it} \tag{9}$$

where Y_{it} is a proxy of outcome-based CEP measured as carbon productivity, water productivity and waste productivity, SPL_{it} is a proxy for a firm's sustainability pay link, STC_{it} is a proxy for a firm's sustainability themed commitment, AS_{it} is a proxy for a firm's audit score, $Controls_{it}$ is a vector of control variables that includes firm size, industry sector, financial leverage and growth, d_t represents the time effect and u_{it} is the error term.

$$\begin{aligned} Y_{it+1} = \quad & \alpha + \beta_1 SPL_{it} + \beta_2 STC_{it} + \beta_3 AS_{it} + \beta_4 CaP_{it} \\ & + \beta_5 WatP_{it} + \beta_6 WastP_{it} + Controls_{it} + d_t + u_{it} \end{aligned} \tag{10}$$

where Y_{it+1} is a proxy of CFP measured as ROA or Tobin's Q, SPL_{it} is a proxy for a firm's sustainability pay link, STC_{it} is a proxy for a firm's sustainability themed commitment, AS_{it} is a proxy for a firm's audit score, CP_{it} is a proxy for a firm's carbon productivity, $WatP_{it}$ is a proxy for a firm's water productivity, $WasP_{it}$ is a proxy for a firm's waste productivity, $Controls_{it}$ is a vector of control variables that includes firm size, industry sector, financial leverage and growth, d_t represents the time effect and u_{it} is the error term.

4.3 Endogeneity Concern

Endogeneity is a common issue in empirical corporate finance. It can be defined as a correlation between the explanatory variables and the error term in a regression, making assumption 4 and 5 of OLS rejected (Roberts and Whited, 2013). To that extent, Endrikat et al. (2014) claimed that the leak of endogeneity control, within the CEP-CFP nexus, could partly explain the inconsistency of the empirical results. To provide unbiased and consistent parameters, this study has controlled for endogeneity.

First, to avoid the first source of endogeneity (i.e. the omission of variables in a model), I include in equation 10, a vector of control variables $Controls_{it}$ that explain the relation between CEP and CFP.

Second, recent meta-analysis provided evidence of the bidirectional causality in the CEP-CFP nexus (Albertini, 2013; Busch and Friede, 2018; Dixon-Fowler et al., 2013; Endrikat et al., 2014; Lu et al., 2014, Wang et al. (2016); Orlitzky and Benjamin, 2001; Orlitzky et al., 2003; Wu, 2006). This could cause simultaneous causality between the dependent and independent variables and lead to endogeneity concern (Biørn and Krishnakumar, 2008; Roberts and Whited, 2013; Sánchez-Ballesta and García-Meca, 2007). To address this issue, I use a lagged instrument Y_{it+1} in lagging observations in independent and control variables one year behind the dependent variable (see equation 10). This increases the confidence of the direction of the relationship (Delmas et al., 2015; Hart and Ahuja, 1996; Miroshnychenko et al., 2017) and *in fine* reduces the potential simultaneity bias.

Finally, both equation 9 and 10, depending on the considered dependent variable, contains Fixed Effects (see respectively sections *"The Impact of Process-Based CEP on Outcome-Based CEP"* and *"The Impact of CEP on CFP"* for further details) and has been estimated with the fixed effects estimation. In presence of FE, endogeneity is clearly a concern since the explanatory variable is correlated with a component of the error term (Roberts and Whited, 2013). However, using the fixed effects estimation implies that FE is removed as $(\mu_i - \frac{1}{T}\sum_{t=1}^{T}\mu_i) = 0$ (see equation 8), and solves this particular endogeneity problem (Roberts and Whited, 2013).

5 Results

The R script of this section is available in *"Appendix B: Results - R Script"*.

5.1 Descriptive Statistics

This section provides an overview of the database. Table 5.1 presents the main descriptive statistics of each variable. The sample size of ROA (i.e. N = 0) is superior to the sample size of TobinsQ (i.e. N = 1038). Compared to ROA, calculating Tobin's Q requires a relatively high number of financial variables and is more susceptible to missing values (Delmas et al., 2015). This creates a disparity among the number of observations for each dependent variables. Delmas et al. (2015) encountered the same issue and conducted an identical analysis to check whether this introduces a sample bias. I did the same and the *p-value* of the unpaired two-sample t-test equals 0.365 meaning that there is no significant difference between both samples.

Table 5.2 contains the matrix of correlation. There are highly significant correlations between outcome-based CEP variables (i.e. carbon, water and waste productivity) and process-based CEP variables (i.e. sustainability pay link, sustainable themed commitment and audit score) suggesting that the model could suffer from a high degree of multicollinearity. Multicollinearity inflates the standard errors of the coefficients making some variables statistically insignificant when they should be significant (Akinwande et al., 2015). One common practice in the literature to detect multicollinearity is the computation of the Variance Inflation Factor (i.e. VIF) (Salmerón et al., 2018). VIF indicates how much the estimated variance of the i_{th} regression coefficient is increased above what it would be if R_i^2 equaled zero (O'brien, 2007). Table 5.3 reports VIF of all variables. The maximum VIF is 2,477 meaning that there is no multicollinearity in the model (O'brien, 2007).

5.2 Outliers Treatment

Lyu (2015) has defined outliers as observations in the dataset that appear to be unusual and discordant and which could lead to inconsistent results. Osborne and Overbay (2004) showed that even a small proportion of outliers can significantly affect simple analyses (i.e. t-tests, correlations and ANOVAs). Cousineau and Chartier (2010) claimed that outliers are an issue only and only if they are influential (i.e. any extreme observations whose removal causes a different conclusion in the analysis).

How to treat influential outliers has been a lively debate in the literature (Cousineau and Chartier, 2010; Orr John et al., 1991). Tabachnick and Fidell (2007) argued that the imputation with the mean is the best method while Cousineau and Chartier

(2010) highlighted that it tends to reduce the spread of the population, making the observed distribution more leptokurtic, and possibly increase the likelihood of a type-I error. Dang et al. (2009) advocated that a more elaborate technique involves replacing outliers with possible values (e.g. multiple imputations) while Barnett and Lewis (1994) stressed that the best option is to remove or winsorize them. Alternatively, Pollet and Meij (2017) argued that inclusion or exclusion of outliers depend on the significativity of the results. According to them, if results are more significant without outliers, scholars should remove them.

Following the mindset of Pollet and Meij (2017), I removed outliers from the database. Influential outliers have been identified based on the Cook's distance (Cook, 1977) which is a common statistical tool to assess the influence of outliers (Cousineau and Chartier, 2010; JP Stevens, 1984; Zuur et al., 2010). Cook's Distance observes the difference between the regression parameters of a given model, $\hat{\beta}$, and what they become if the i_{th} data point is deleted, let's say $\hat{\beta}_i$. See *"Appendix C: Outliers Treatment"* for further details on how I proceed.

5.3 The Impact of Process-Based CEP on Outcome-Based CEP

Table 5.4 reports the main results of the analysis of the impact of process-based CEP (i.e. SPL, STC and AS) on outcome-based CEP (i.e. CaP, WatP and WastP). Given the p-value of the F test, all models have FE making the *fixed effects estimation* the most efficient estimator.

Except for Model (1) which indicates no significant relation between SPL and CaP, all models show evidence of a positive and highly statistically significant effect of process-based CEP on outcome-based CEP. Indeed, results demonstrate that companies, which link the remuneration of any member of a company's senior executive team with the achievement of environmental performance targets, have a better WatP (+0.022%) and WastP (+0.025%). The fact of having a sustainability committee on the board of directors level increases the CaP (+0.058%), WatP (+0.067%) and, WastP (+0.046%). Finally, companies having their latest reported environmental metrics audited by a third party have a higher CaP (+0.057%), WatP (+0.068%) and, WastP (+0.071%). Hence, hypothesis 1 is verified.

5.4 The Impact of CEP on CFP

Table 5.5 reports the main results of the analysis of the impact of both process-based CEP (i.e. SPL, STC and AS) and outcome-based CEP (i.e. CaP, WatP and WastP) on short-term CFP (ROA) and long-term CFP (i.e. TobinsQ). Based on the pvalue of BPLM and F tests, model (4) has been estimated with the *pooled OLS estimation* while model (5) has been estimated with the *fixed effects estimation*.

Model (4) shows evidence of a positive and statistically significant effect of SPL, AS, and WaP on *long-term CFP*. Model (5) shows evidence of a positive and statistically significant effect of SPL, STC and CaP on *short-term CFP*.

More precisely, regarding process-based CEP variables, results stress that companies, which link the remuneration of any member of a company's senior executive team with the achievement of environmental performance targets, are characterized by both a higher Tobin's Q (+0.079) and ROA (+0.008). Then, the fact of having a sustainability committee on the board of directors level increases the ROA (+0.012). Finally, companies having their latest reported environmental metrics audited by a third party have a higher Tobin's Q (+0.158). Regarding outcome-based CEP variables, results demonstrate that a 1% increase of carbon productivity increases the ROA (+0.03) and a 1% increase of water productivity increases the Tobin's Q (+0.337). Hence, hypotheses 2, 3, 4 and 5 are verified.

Regarding control variables, firm size and industry sector negatively and significantly influence CFP in both models while growth has a positive impact, with an effect more pronounced in Model (4). These results support previous research (Endrikat et al., 2014; Miroshnychenko et al., 2017). Against all odds, leverage does not have any significant impact.

Table 5.1: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
ROA	1,176	0.06	0.07	−0.62	0.42
TobinsQ	1,038	0.10	0.38	−1.30	1.08
Leverage	1,130	1.51	8.02	0.00	157.90
Growth	1,174	0.12	0.24	−2.04	5.96
FirmSize	1,172	10.35	0.60	8.45	12.51
Industry	1,177	4.59	2.65	1	11
CaP	1,177	0.12	0.18	0.00	0.97
WaP	1,177	0.09	0.18	0.00	0.99
WastP	1,177	0.07	0.17	0.00	0.97
SPL	1,177	0.49	0.50	0	1
STC	1,177	0.48	0.50	0	1
AS	1,177	0.47	0.50	0	1

Table 5.2: Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11
1. ROA											
2. TobinsQ	0.40***										
3. Leverage	-0.02	0.03									
4. Growth	0.19***	-0.02	-0.07**								
5. FirmSize	-0.27***	-0.66***	-0.02	0.09***							
6. Industry	-0.10***	-0.09***	-0.05*	0.00	0.06**						
7. CaP	0.09***	0.02	0.03	0.00	0.07**	0.04					
8. WaP	0.08***	0.03	0.06**	-0.02	0.08***	0.02	0.67***				
9. WastP	0.07**	0.01	0.08***	-0.01	0.07**	0.08***	0.56***	0.69***			
10. SPL	-0.05*	-0.11***	-0.02	-0.02	0.29***	0.09***	0.06**	0.14***	0.15***		
11. STC	0.00	-0.10***	-0.01	-0.04	0.29***	0.06**	0.21***	0.26***	0.24***	0.48***	
12. AS	-0.04	-0.08**	0.01	0.05*	0.26***	0.04	0.21***	0.26***	0.28***	0.50***	0.46***

Note : * $p<0.1$; ** $p<0.05$; *** $p<0.01$

Table 5.3: Variance Inflation Factor

	ROA	Tobin's Q
SPL	1.543	1.487
STC	1.507	1.475
AS	1.527	1.514
CaP	1.862	1.846
WaP	2.477	2.425
WastP	1.966	2.008
Leverage	1.021	1.027
Growth	1.029	1.026
FirmSize	1.155	1.134
Industry	1.025	1.020

Table 5.4: The Impact of Process-Based on Outcome-Based CEP

	Dependent variable:		
	CaP Model (1)	WaP Model (2)	WastP Model (3)
SPL	0.010 (0.011)	0.022* (0.012)	0.025** (0.011)
STC	0.058*** (0.010)	0.067*** (0.011)	0.046*** (0.011)
AS	0.057*** (0.010)	0.068*** (0.011)	0.071*** (0.011)
FirmSize	−0.005 (0.008)	−0.008 (0.008)	−0.010 (0.008)
Leverage	0.0003 (0.001)	0.001* (0.001)	0.001** (0.001)
Growth	0.028 (0.028)	0.001 (0.030)	0.003 (0.028)
Industry	0.002 (0.002)	−0.00001 (0.002)	0.004** (0.002)
BPLM test (pvalue)	0***	0***	0***
F test (pvalue)	0***	0***	0***
Observations	1,123	1,123	1,123
R^2	0.116	0.145	0.139
Adjusted R^2	0.109	0.138	0.132
F Statistic (df = 7; 1113)	20.888***	26.892***	25.632***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5.5: The Impact of Process and Outcome-Based CEP on CFP (Lag = 1)

	Dependent variable:	
	TobinsQ Model (4)	ROA Model (5)
SPL	0.079^{*} (0.044)	0.008^{**} (0.004)
STC	0.063 (0.044)	0.012^{***} (0.004)
AS	0.158^{***} (0.044)	−0.004 (0.004)
CaP	−0.012 (0.135)	0.030^{**} (0.012)
WaP	0.337^{**} (0.155)	0.006 (0.012)
WastP	−0.199 (0.156)	0.010 (0.012)
FirmSize	-0.443^{***} (0.015)	-0.020^{***} (0.001)
Leverage	0.003 (0.003)	−0.00000 (0.0003)
Growth	0.465^{***} (0.152)	0.138^{***} (0.012)
Industry	-0.026^{***} (0.007)	-0.002^{***} (0.001)
Constant	10.701^{***} (0.345)	
BPLM test (pvalue)	0.508	0.024^{**}
F test (pvalue)	0.323	0.012^{**}
Observations	954	1,093
R^2	0.505	0.290
Adjusted R^2	0.500	0.282
F Statistic	96.388^{***} (df = 10; 943)	44.007^{***} (df = 10; 1080)
Note:		*p<0.1; **p<0.05; ***p<0.01

6 Sensitivity Analysis

To ensure the robustness of the main findings of the previous section, I carry out a Sensitivity Analysis (i.e. SA). SA investigates how the variation in the output of equation 10 can be attributed to variations of its input (Pianosi et al., 2016). First, equation 10 has been re-estimated using a lagged variables of two years, such as:

$$\begin{aligned} Y_{it+2} = \quad & \alpha + \beta_1 SPL_{it} + \beta_2 STC_{it} + \beta_3 AS_{it} + \beta_4 CaP_{it} \\ & + \beta_5 WatP_{it} + \beta_6 WastP_{it} + Controls_{it} + d_t + u_{it} \end{aligned} \tag{11}$$

where Y_{it+2} is a proxy of CFP measured as ROA or Tobin's Q, SPL_{it} is a proxy for a firm's sustainability pay link, STC_{it} is a proxy for a firm's sustainability themed commitment, AS_{it} is a proxy for a firm's audit score, CP_{it} is a proxy for a firm's carbon productivity, $WatP_{it}$ is a proxy for a firm's water productivity, $WasP_{it}$ is a proxy for a firm's waste productivity, $Controls_{it}$ is a vector of control variables that includes firm size, industry sector, financial leverage and growth, d_t represents the time effect and u_{it} is the error term.

Estimators of equation 11 are reported in table 6.1. Based on the results of both BPLM and F tests, estimators has been estimated with the *pooled OLS estimation*. Except for the estimator of WaP in Model (4) which loses its significativity, findings stay the same than in section: *"Results"*.

Second, I use the Green Score (i.e. GS) assigned to each company of the NGR as an alternative proxy for CEP. GS is based on a weighted average of the KPI of the ranking. Concretely, it means that equation 10 becomes:

$$Y_{it+1} = \alpha + \beta_1 GS_{it} + ContrOLS_{it} + d_t + u_{it} \tag{12}$$

where Y_{it+1} is a proxy of CFP measured as ROA or Tobin's Q, GS_{it} is a proxy for a firm's green score, $ContrOLS_{it}$ is a vector of control variables that includes firm size, industry sector, financial leverage and growth, d_t represents time effect and u_{it} is the error term.

Given the pvalue of both BPLM and F tests, Model (4) has been estimated with the *pooled OLS estimation* while Model (5) has been estimated with the *fixed effect estimation*. Results are reported in table 6.2 and confirm findings of the section: *"Results"*. More precisely, it shows that a 1% increase of GS increases the long-term CFP (+0.669) and the short-term CFP (+0.051).

Hence, the SA supports that CEP does have a significant and positive effect on CFP, no matter the time horizon (short-term and long-term), and is stronger with a long-term perspective than a short-term perspective. `R` script of this section is available in *"Appendix D: Sensitivity Analysis - R Script"*.

Table 6.1: The Impact of Process and Outcome-Based CEP on CFP (Lag = 2)

	Dependent variable:	
	TobinsQ Model (4)	ROA Model (5)
SPL	0.102** (0.044)	0.008** (0.004)
STC	0.062 (0.043)	0.011*** (0.004)
AS	0.153*** (0.044)	−0.002 (0.004)
CaP	0.112 (0.133)	0.039*** (0.012)
WaP	0.194 (0.155)	−0.001 (0.013)
WastP	0.032 (0.153)	0.011 (0.013)
FirmSize	−0.427*** (0.015)	−0.019*** (0.001)
Leverage	0.003 (0.003)	0.0001 (0.0002)
Growth	0.420*** (0.152)	0.115*** (0.012)
Industry	−0.022*** (0.007)	−0.002*** (0.001)
Constant	10.295*** (0.343)	0.503*** (0.028)
BPLM test (pvalue)	0.56	0.33
F test (pvalue)	0.363	0.598
Observations	946	1,078
R^2	0.488	0.254
Adjusted R^2	0.483	0.247
F Statistic	89.135*** (df = 10; 935)	36.368*** (df = 10; 1067)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6.2: Green Score - an Alternative Variable for CEP

	Dependent variable:	
	TobinsQ Model (4)	ROA Model (5)
GS	0.669*** (0.093)	0.051*** (0.008)
FirmSize	−0.413*** (0.014)	−0.018*** (0.001)
Leverage	0.003 (0.004)	−0.0003 (0.001)
Growth	0.528*** (0.162)	0.134*** (0.013)
Industry	−0.030*** (0.007)	−0.002*** (0.001)
Constant	9.916*** (0.336)	
BPLM test (pvalue)	0.475	0***
F test (pvalue)	0.536	0.002***
Observations	956	1,094
R^2	0.481	0.268
Adjusted R^2	0.479	0.263
F Statistic	176.286*** (df = 5; 950)	79.571*** (df = 5; 1086)

Note: *p<0.1; **p<0.05; ***p<0.01

7 Discussion and Conclusion

Using a panel data of 393 US publicly traded companies for the period 2012-2014, this study first investigates the impact of process-based CEP on outcome-based CEP. Then, it explores whether the combined effect of process-based and outcome-based CEP influences CFP. Finally, it observes the time influence (i.e. short-term vs long-term) on the relationship.

This study shows that process-based CEP positively influences outcome-based CEP. More precisely, it stresses that (i) companies which link the remuneration of any member of a company's senior executive team with the achievement of environmental performance targets, have a better WatP and WastP. Then, (ii) the fact of having a sustainability committee on the board of directors level increases the CaP, WatP and, WastP. Finally, (iii) companies having their latest reported environmental metrics audited by a third party have a higher CaP, WatP and, WastP.

The results support findings of previous studies that demonstrated the implementation of environmental management measures allows companies to significantly increase their environmental performance (Chen et al., 2018; Li et al., 2017; Melnyk et al., 2003; Xie and Hayase, 2007). One possible explanation for this relationship could be the employees' engagement. The latter would allow individuals to gain awareness of the environmental footprint of their companies, making them strongly involved in the process of change towards greener companies. Moreover, companies having their latest reported environmental metrics audited by a third party could be driven by the willingness of real improvements. Engagement in process-based CEP could also make companies be more concerned about the whole process and not only on its outputs.

Furthermore, this study provides evidence that both process and outcome-based CEP have a positive impact on CFP. This relationship is always positive, no matter the time horizon, and is stronger with a long-term perspective than a short-term perspective. Regarding the process-based CEP, the empirical results show that (iv) companies which link the remuneration of any member of a company's senior executive team with the achievement of environmental performance targets are characterized by both a higher short-term and long-term CFP. Then, (v) the fact of having a sustainability committee on the board of directors level increases the short-term CFP. Lastly, (vi) companies having their latest reported environmental metrics audited by a third party have a higher long-term CFP. Regarding outcome-based CEP variables, results demonstrate that (vii) companies which have a higher CaP and CatP have respectively a higher short-term and long-term CFP.

These results corroborate recent meta-analyses that claimed a positive influence between CEP and CFP (Albertini, 2013; Busch and Friede, 2018; Dixon-Fowler et al., 2013; Endrikat et al., 2014; Lu et al., 2014; Orlitzky et al., 2003; Wang et al., 2016; Wu, 2006). Furthermore, findings support the general consensus that accounting-based measures are characterized by a stronger relation to CEP than market-based indicators (Albertini, 2013; Busch and Friede, 2018; Lu et al., 2014; Orlitzky et al., 2003; Wu, 2006).

This study also proves that Ambec and Lanoie (2008) were right in affirming that expenses incurred to reduce pollution can be offset by gains made elsewhere. The positive influence of CEP on CFP could be partly explained by the increasing awareness of citizens on environmental degradation who impact the demand for green products and services (Kotler, 2011; Leonidou et al., 2013). Thus, results of this study provide a genuine economic justification to the new paradigm which mediates business and respect of the environment. Lastly, this study emphasizes strong incentives for companies to invest in environmental strategies.

The contributions of this empirical study are twofold. First, I provide an initial answer to the research call of Endrikat et al. (2014) who highlighted the need for a better understanding of the multidimensionality of both CEP and CFP constructs. Second, I give a first overview of the call of Griffin and Mahon (1997) and Busch and Friede (2018) who called for studies that look at the CEP-CFP relationship over time.

This study has some limitation and consequently, highlights potential future research. First, the time horizon is relatively small (i.e. 3 years) and may consequently not totally capture how changes in CEP affect changes in CFP. Furthermore, it implies that I could not consider a lagged variables in equation 9. Therefore, the econometric model could suffer from a simultaneity bias. One feasible approach for future research is to expect for latter NGR and reproduce this study by considering a larger time horizon. To deal with the endogeneity concern in equation 9, a future approach could also consider adding an instrumental variable to uncover the causal effect of process-based CEP on outcome-based CEP.

Second, market-based indicators are imperfect proxies for long-term CFP. Considering Tobin's Q as a measure of long-term performance gives too much credit to the Efficient Market Hypothesis. As claimed by Malkiel (2003), the market cannot be perfectly efficient, or there would be no incentive for professionals to uncover the information that gets so quickly reflected in market prices. Future research should investigate a better approach to measure long-term CFP.

Third, CEP is a large construct and a lot of methodologies have been developed to assess this concept. Due to data limitation, no robustness test considering alternative CEP data sources has been performed. However, reproduce this study by considering other CEP data source could potentially provide different results. Indeed, Delmas and Blass (2010) demonstrated that the rating of companies varies significantly according to whether the screening methodology is based on toxic releases and regulatory compliance or on the quality of environmental policy and disclosure. Future research could reproduce this study in taking into account other CEP data sources (e.g. Asset4 ESG data from Thomson Reuters) and compare the results with the ones of this study. Future research should also refine current methodologies to measure CEP.

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Appendices

Appendix A: Database Construction

Data of this study come from several platforms. Consequently, the final database is the result of a long step process. First, I downloaded green metrics from NewsWeek for each year's ranking (i.e. 2014 to 2016). All companies were not automatically listed in the three rankings. Thus, I had to match companies that were listed in each ranking. This step has been carried out through excel [6]. Among those three rankings and of the 500 US companies, 405 companies were listed for each year.

Second, I obtained some of the financial data (i.e. ROA, Financial Leverage, Total Assets and Net Margin) on Morningstar. To do that, I have used its API. The platform has saved key ratios data in `csv` format for each company. Consequently, I have written an `R` script which downloads each `csv` files and bring all data into a tidy database. The `R` script is available on my `GitHub` account `https://github.com/pkinif/Thesis` in `Child/Analysis/MakeFile_WebScrapMorningStars.Rmd`. Outputs of this makefile are in the folder `Child/Analysis/DataBase/MorningStar`.

Due to missing values regarding previous financial variables, I had to complete the database with data coming from StockPup. The same process than for `Morningstar` has been applied. The `R` script is available on my `GitHub` account `https://github.com/pkinif/Thesis` in the file `Child/Analysis/MakeFile_WebScrapStockPup.Rmd`. Outputs are in the folder `Child/Analysis/DataBase/StockPup`.

Third, I completed my database with data coming from Ycharts. On this platform, I collected the Tobin's Q. At the date of collect, `Ycharts` offered a 7-day free trial. The makefile path is `Child/Analysis/MakeFile_WebScrapYcharts.Rmd`. Outputs of this makefile are in the folder `Child/Analysis/DataBase/Ycharts`.

Finally, I have synchronized all data into a tidy database. The makefile is `Child/Analysis/MakeFile_DataSynchronization.Rmd`. Outputs are saved into the folder `Child/Analysis/DataBase/DataSynchronization`.

[6] see the file `Child/Analysis/DataBase/NewsWeekGreenRankin/RechercheMatch 14-16.xlsx`

Appendix B: Results - R Script

The following `R` script is the one used to produce the section *"Results"*.

Packages Loading

```
# Removes all items in the R environment
rm(list = ls())
# Packages loading
if (!require("plm")) install.packages("plm")
library(plm)
if (!require("dplyr")) install.packages("dplyr")
library(dplyr)
if (!require("data.table")) install.packages("data.table")
library(data.table)
if (!require("stargazer")) install.packages("stargazer")
library(stargazer)
if (!require("Hmisc")) install.packages("Hmisc")
library(Hmisc)
if (!require("lattice")) install.packages("lattice")
library(lattice)
if (!require("survival")) install.packages("survival")
library(survival)
if (!require("ggplot2")) install.packages("ggplot2")
library(ggplot2)
if (!require("car")) install.packages("car")
library(car)
if (!require("ggpubr")) install.packages("ggpubr")
library(ggpubr)
if (!require("xtable")) install.packages("xtable")
library(xtable)
```

Database Loading

```
# Database Loading. I consider the database with
# outliers.
path <- "Analysis/DataBase/DataSynchronization/Lag1.csv"
Db <- read.csv(file = path, header = TRUE, stringsAsFactors = FALSE)
# I create a new df called 'model' which contains only
```

```
# variables that I need
Model <- Db %>% select(c(YearIndex, CompaniesIndex, Roa,
    TobinsQ, DebtToEquityRatio, NetMargin, TotalAssets,
    GicsClassification, CarbonProductivity, WaterProductivity,
    WasteProductivity, SustainabilityPayLink, SustainableThemedCommitment,
    AuditScore, GreenScore))
# I transform the 'TotalAssets' column into 'FirmSize'
# using the log of TotalAssets
Model$TotalAssets <- log10(Model$TotalAssets)
# I use the natural log for TobinsQ
Model$TobinsQ <- log10(Model$TobinsQ)
# I rename some columns
vieux <- c("DebtToEquityRatio", "Roa", "TotalAssets", "GicsClassification",
    "NetMargin", "CarbonProductivity", "WaterProductivity",
    "WasteProductivity", "SustainabilityPayLink", "SustainableThemedCommitment",
    "AuditScore")
nouveau <- c("Leverage", "ROA", "FirmSize", "Industry",
    "Growth", "CaP", "WaP", "WastP", "SPL", "STC", "AS")
Model1 <- Model %>% setnames(old = vieux, new = nouveau)
```

Unpaired Two Sample T-Test

```
# I create two vectors.
Sample1 <- Model1 %>% subset(subset = !is.na(ROA)) %>% select(ROA)
Sample2 <- Model1 %>% subset(subset = !is.na(TobinsQ)) %>%
    select(ROA)
# I carry out the t-test and save the pvalue into IdAnal
IdAnal <- round(t.test(Sample1, Sample2, alternative = "two.sided",
    var.equal = FALSE)$p.value, digits = 4)
```

Descriptive Statistics

```
# Descriptive statistics
# I remove the column 'GreenScore', 'CompaniesIndex' and
# 'YearIndex' as I do not need it.
Model2 <- Model1 %>% select(-c(GreenScore, YearIndex, CompaniesIndex))
# I use stargazer to create a table containing
# descriptive statistics for each variable
```

```
stargazer(Model2, title = "Descriptive statistics", label = "DesStat",
    header = FALSE, type = "latex", align = FALSE, table.placement = "b",
    digits = 2, digits.extra = 2)
```

Correlation Matrix

```
# The following corstars function creates the matrix of correlation.
corstars <-function(x,
                    method=c("pearson", "spearman"),
                    removeTriangle=c("upper", "lower"),
                    result=c("none", "html", "latex"))
  {
    # Compute correlation matrix
    require(Hmisc)
    x <- as.matrix(x)
    correlation_matrix<-rcorr(x, type=method[1])
    # Matrix of correlation coeficients
    R <- correlation_matrix$r
    # Matrix of p-value
    p <- correlation_matrix$P
    # Define notions for significance levels; spacing is important.
    mystars <- ifelse(p < .01, "*** ",
                      ifelse(p < .05, "**  ",
                             ifelse(p < .1, "*   ", "    ")))
    # trunctuate the correlation matrix to two decimal
    R <- format(round(cbind(rep(-1.11, ncol(x)), R), 2))[,-1]
    # build a new matrix that includes the correlations
    # with apropriate stars
    Rnew <- matrix(paste(R, mystars, sep=""), ncol=ncol(x))
    diag(Rnew) <- paste(diag(R), " ", sep="")
    rownames(Rnew) <- colnames(x)
    colnames(Rnew) <- paste(colnames(x), "", sep="")
    # remove upper triangle of correlation matrix
    if(removeTriangle[1]=="upper")
      {
      Rnew <- as.matrix(Rnew)
      Rnew[upper.tri(Rnew, diag = TRUE)] <- ""
```

```
      Rnew <- as.data.frame(Rnew)
      }
    # remove lower triangle of correlation matrix
    else if(removeTriangle[1]=="lower")
      {
      Rnew <- as.matrix(Rnew)
      Rnew[lower.tri(Rnew, diag = TRUE)] <- ""
      Rnew <- as.data.frame(Rnew)
      }
    # remove last column and return the correlation matrix
    Rnew <- cbind(Rnew[1:length(Rnew)-1])
    if (result[1]=="none") return(Rnew)
    else{
    if(result[1]=="html") print(xtable(Rnew), type="html")
    else print(xtable(Rnew), type="latex")
    }
  # end of the function
  }
# I use the function on my database (i.e. Model2)
CorMatrix <- corstars(Model2,
                      method = "pearson",
                      removeTriangle = "upper",
                      result = "none")
# Now, names of each variable stand as row names and column names.
# I do not need to have dupplicates.
# So I keep the names of the variables as names of the row,
# and I use a number as the names of the column.
number <- c( 1 : (ncol(Model2) - 1)) #number of variables
colnames(CorMatrix) <- number
NewRowNames <- paste(c( 1 : ncol(Model2)),
                     rownames(CorMatrix),
                     sep = ". ")
rownames(CorMatrix) <- NewRowNames
# I use stargazer to make a table
table <- stargazer(CorMatrix,
                   summary = FALSE,
                   type = "latex",
```

```
                   title = "Correlation Matrix",
                   label = "Matrix",
                   float=TRUE,
                   float.env = "sidewaystable",
                   header = FALSE,
                   table.placement = "h",
                   column.sep.width = "2pt",
                   font.size = "small",
                   notes = "Note : * p<0.1; ** p<0.05; *** p<0.01",
                   notes.align = "r",
                   align = TRUE)
```

Variance Inflation Factor

```
# I make Model1 a plm database
Model1 <- pdata.frame(Model1, index = c("CompaniesIndex",
    "YearIndex"))
# The vif function can not be used with within model. I
# need to estimate my models with the pooling model.
Roa <- plm(ROA ~ SPL + STC + AS + CaP + WaP + WastP + Leverage +
    Growth + FirmSize + Industry, model = "pooling", data = Model1,
    index = c("YearIndex", "CompaniesIndex"))
TobinsQ <- plm(TobinsQ ~ SPL + STC + AS + CaP + WaP + WastP +
    Leverage + Growth + FirmSize + Industry, model = "pooling",
    data = Model1, index = c("YearIndex", "CompaniesIndex"))
# VIF Calculation
VifRoa <- car::vif(Roa)
VifTobin <- car::vif(TobinsQ)
# Summary in a stargazer table
VifTable <- cbind(VifRoa, VifTobin)
colnames(VifTable) <- c("ROA", "Tobin's Q")
titre <- "Variance Inflation Factor"
stargazer(VifTable, summary = FALSE, title = titre, label = "VIF",
    header = FALSE, type = "latex", align = TRUE, table.placement = "!")
```

The Impact of Process-Based CEP on Outcome-Based CEP

```
# I select only CEP variables in model2 which is already
# a pdataframe.
Model3 <- Model1 %>% select(c(YearIndex, CompaniesIndex,
    CaP, WaP, WastP, SPL, STC, AS, Leverage, FirmSize, Industry,
    Growth))
# I test for Random Effect Model using the Lagrange
# Multiplier Test Pooling Model
CarbonPooling <- plm(CaP ~ SPL + STC + AS + FirmSize + Leverage +
    Growth + Industry, data = Model3, model = "pooling")
WaterPooling <- plm(WaP ~ SPL + STC + AS + FirmSize + Leverage +
    Growth + Industry, data = Model3, model = "pooling")
WastePooling <- plm(WastP ~ SPL + STC + AS + FirmSize +
    Leverage + Growth + Industry, data = Model3, model = "pooling")
# Plmtest
PlmtestCarbon <- as.numeric(round(plmtest(CarbonPooling,
    effect = "time", type = "bp")$p.value, digits = 3))
PlmtestWater <- as.numeric(round(plmtest(WaterPooling, effect = "time",
    type = "bp")$p.value, digits = 3))
PlmtestWaste <- as.numeric(round(plmtest(WastePooling, effect = "time",
    type = "bp")$p.value, digits = 3))
# Improve p-value understanding
PlmtestCarbon <- ifelse(PlmtestCarbon < 0.01, paste(PlmtestCarbon,
    "***", sep = ""), ifelse(PlmtestCarbon < 0.05, paste(PlmtestCarbon,
    "**", sep = ""), ifelse(PlmtestCarbon < 0.1, paste(PlmtestCarbon,
    "*", sep = ""), PlmtestCarbon)))
PlmtestWater <- ifelse(PlmtestWater < 0.01, paste(PlmtestWater,
    "***", sep = ""), ifelse(PlmtestWater < 0.05, paste(PlmtestWater,
    "**", sep = ""), ifelse(PlmtestWater < 0.1, paste(PlmtestWater,
    "*", sep = ""), PlmtestWater)))
PlmtestWaste <- ifelse(PlmtestWaste < 0.01, paste(PlmtestWaste,
    "***", sep = ""), ifelse(PlmtestWaste < 0.05, paste(PlmtestWaste,
    "**", sep = ""), ifelse(PlmtestWaste < 0.1, paste(PlmtestWaste,
    "*", sep = ""), PlmtestWaste)))
# I test for Fixed Effect Model using pFtest which is a
# test of individual and/or time effects based on the
```

```
# comparison of the within and the pooling model.
# Within Model with time effect
CarbonWithin <- plm(CaP ~ SPL + STC + AS + FirmSize + Leverage +
    Growth + Industry, data = Model3, model = "within",
    effect = "time")
WaterWithin <- plm(WaP ~ SPL + STC + AS + FirmSize + Leverage +
    Growth + Industry, data = Model3, model = "within",
    effect = "time")
WasteWithin <- plm(WastP ~ SPL + STC + AS + FirmSize + Leverage +
    Growth + Industry, data = Model3, model = "within",
    effect = "time")
# pFtest
pFtestCarbon <- round(pFtest(CarbonWithin, CarbonPooling)$p.value,
    digits = 3)
pFtestWater <- round(pFtest(WaterWithin, WaterPooling)$p.value,
    digits = 3)
pFtestWaste <- round(pFtest(WasteWithin, WastePooling)$p.value,
    digits = 3)
# Improve p-value understanding
pFtestCarbon <- ifelse(pFtestCarbon < 0.01, paste(pFtestCarbon,
    "***", sep = ""), ifelse(pFtestCarbon < 0.05, paste(pFtestCarbon,
    "**", sep = ""), ifelse(pFtestCarbon < 0.1, paste(pFtestCarbon,
    "*", sep = ""), pFtestCarbon)))
pFtestWater <- ifelse(pFtestWater < 0.01, paste(pFtestWater,
    "***", sep = ""), ifelse(pFtestWater < 0.05, paste(pFtestWater,
    "**", sep = ""), ifelse(pFtestWater < 0.1, paste(pFtestWater,
    "*", sep = ""), pFtestWater)))
pFtestWaste <- ifelse(pFtestWaste < 0.01, paste(pFtestWaste,
    "***", sep = ""), ifelse(pFtestWaste < 0.05, paste(pFtestWaste,
    "**", sep = ""), ifelse(pFtestWaste < 0.1, paste(pFtestWaste,
    "*", sep = ""), pFtestWaste)))
# Based on results of both tests, the three models need
# to be estimated with the fixed effects estimations
# (i.e. model = 'within' in plm). Let's consolidate into
# a stargazer table
titre <- "The impact of process-based on outcome-based CEP"
stargazer(CarbonWithin, WaterWithin, WasteWithin, title = titre,
```

```
    label = "CepResults", header = FALSE, type = "latex",
    align = FALSE, single.row = TRUE, model.numbers = FALSE,
    table.placement = "!", add.lines = list(c("BPLM test (pvalue)",
        PlmtestCarbon, PlmtestWater, PlmtestWaste), c("F test (pvalue)",
        pFtestCarbon, pFtestWater, pFtestWaste)))
```

The Impact of CEP on CFP

```
# I have already removed outliers from both models (i.e.
# Roa and TobinsQ) via the file =
# 'Analysis/MakeFile_RemoveOutliers_Lag1.rmd'.
# Consequently, I load the two following databases.
p <- "Analysis/DataBase/DataSynchronization/NoOutliersLag1/Roa.csv"
RoaNoOut <- read.csv(file = p, header = TRUE, stringsAsFactors = FALSE)
p <- "Analysis/DataBase/DataSynchronization/NoOutliersLag1/TobinsQ.csv"
TobinNoOut <- read.csv(file = p, header = TRUE, stringsAsFactors = FALSE)
# I change names
RoaNoOut <- RoaNoOut %>% setnames(old = c("Roa", "FinancialLeverage",
    "CarbonProductivity", "WaterProductivity", "WasteProductivity",
    "SustainabilityPayLink", "SustainableThemedCommitment",
    "AuditScore"), new = c("ROA", "Leverage", "CaP", "WaP",
    "WastP", "SPL", "STC", "AS"))
TobinNoOut <- TobinNoOut %>% setnames(old = c("Roa", "FinancialLeverage",
    "CarbonProductivity", "WaterProductivity", "WasteProductivity",
    "SustainabilityPayLink", "SustainableThemedCommitment",
    "AuditScore"), new = c("ROA", "Leverage", "CaP", "WaP",
    "WastP", "SPL", "STC", "AS"))
# I make both df a plm dataframe
RoaNoOut <- RoaNoOut %>% pdata.frame(index = c("CompaniesIndex",
    "YearIndex"))
TobinNoOut <- TobinNoOut %>% pdata.frame(index = c("CompaniesIndex",
    "YearIndex"))
# I test for Random Effect Model using the Lagrange
# Multiplier Tests for Panel Models.
# Pooling Model
RoaPooling <- plm(ROA ~ SPL + STC + AS + CaP + WaP + WastP +
    FirmSize + Leverage + Growth + Industry, data = RoaNoOut,
```

```
    model = "pooling")
TobinPooling <- plm(TobinsQ ~ SPL + STC + AS + CaP + WaP +
    WastP + FirmSize + Leverage + Growth + Industry, data = TobinNoOut,
    model = "pooling")
# Plmtest
PlmtestRoa <- as.numeric(round(plmtest(RoaPooling, effect = "time",
    type = "bp")$p.value, digits = 3))
PlmtestTobin <- as.numeric(round(plmtest(TobinPooling, effect = "time",
    type = "bp")$p.value, digits = 3))
# Improve p-value understanding
PlmtestRoa <- ifelse(PlmtestRoa < 0.01, paste(PlmtestRoa,
    "***", sep = ""), ifelse(PlmtestRoa < 0.05, paste(PlmtestRoa,
    "**", sep = ""), ifelse(PlmtestRoa < 0.1, paste(PlmtestRoa,
    "*", sep = ""), PlmtestRoa)))
PlmtestTobin <- ifelse(PlmtestTobin < 0.01, paste(PlmtestTobin,
    "***", sep = ""), ifelse(PlmtestTobin < 0.05, paste(PlmtestTobin,
    "**", sep = ""), ifelse(PlmtestTobin < 0.1, paste(PlmtestTobin,
    "*", sep = ""), PlmtestTobin)))
# I test for Fixed Effect Model using pFtest which is a
# test of individual and/or time effects based on the
# comparison of the within and the pooling model.
# Within Model with time effect
RoaWithin <- plm(ROA ~ SPL + STC + AS + CaP + WaP + WastP +
    FirmSize + Leverage + Growth + Industry, data = RoaNoOut,
    model = "within", effect = "time")
TobinWithin <- plm(TobinsQ ~ SPL + STC + AS + CaP + WaP +
    WastP + FirmSize + Leverage + Growth + Industry, data = TobinNoOut,
    model = "within", effect = "time")
# pFtest
pFtestRoa <- round(pFtest(RoaWithin, RoaPooling)$p.value,
    digits = 3)
pFtestTobin <- round(pFtest(TobinWithin, TobinPooling)$p.value,
    digits = 3)
# Improve p-value understanding
pFtestRoa <- ifelse(pFtestRoa < 0.01, paste(pFtestRoa, "***",
    sep = ""), ifelse(pFtestRoa < 0.05, paste(pFtestRoa,
    "**", sep = ""), ifelse(pFtestRoa < 0.1, paste(pFtestRoa,
```

```
    "*", sep = ""), pFtestRoa)))
pFtestTobin <- ifelse(pFtestTobin < 0.01, paste(pFtestTobin,
    "***", sep = ""), ifelse(pFtestTobin < 0.05, paste(pFtestTobin,
    "**", sep = ""), ifelse(pFtestTobin < 0.1, paste(pFtestTobin,
    "*", sep = ""), pFtestTobin)))
# Let's consolidate into a stargazer table
titre <- "The impact of process and outcome-based CEP on CFP (lag = 1)"
stargazer(TobinPooling, RoaWithin, title = titre, label = "Lag1",
    header = FALSE, type = "latex", single.row = TRUE, align = FALSE,
    model.numbers = FALSE, table.placement = "!", add.lines = list(c("BPLM test (pvalue)",
        PlmtestTobin, PlmtestRoa), c("F test (pvalue)",
        pFtestTobin, pFtestRoa)))
```

Appendix C: Outliers Treatment

This appendix presents the `R` code used to identify and remove outliers from the database. This R script is the one contains in the makefile `Analysis/DataBase/MakeFile_RmvOut_Lag1.Rmd`. This step had been repeated three times : (i) when dependent variables were lagged one year (see section: *"The Impact of CEP on CFP"*) and (ii) two years behind others variables and (iii) when the Green Score variable was the only independent variable considered into the econometric model (see section: *"Sensitivity Analysis"*).

```
# Packages loading
if (!require("dplyr")) install.packages("dplyr")
library(dplyr)
if (!require("data.table")) install.packages("data.table")
library(data.table)
if (!require("formatR")) install.packages("formatR")
library(formatR)
if (!require("highlight")) install.packages("highlight")
library(highlight)

# Database Loading
path <- "Analysis/DataBase/DataSynchronization/Lag1.csv"
Lag1 <- read.csv(file = path, header = TRUE, stringsAsFactors = FALSE)

# Select only variables that I need for my model
ModelLag1 <- Lag1 %>% select(c(YearIndex, CompaniesIndex,
    Roa, TobinsQ, DebtToEquityRatio, NetMargin, TotalAssets,
    GicsClassification, CarbonProductivity, WaterProductivity,
    WasteProductivity, SustainabilityPayLink, SustainableThemedCommitment,
    AuditScore))
# I transform the 'TotalAssets' column into FirmSize
# using the log of TotalAssets
ModelLag1$TotalAssets <- log10(ModelLag1$TotalAssets)
# I use the natural log for TobinsQ
ModelLag1$TobinsQ <- log10(ModelLag1$TobinsQ)
# I rename some columns
ModelLag1 <- ModelLag1 %>% setnames(old = c("DebtToEquityRatio",
    "TotalAssets", "GicsClassification", "NetMargin"), new = c("Leverage",
    "FirmSize", "Industry", "Growth"))
# I define my models in lm as cooks.distance do not
```

```r
# support plm object
Roa <- lm(Roa ~ SustainabilityPayLink + SustainableThemedCommitment +
    AuditScore + CarbonProductivity + WaterProductivity +
    WasteProductivity + FirmSize + Growth + Leverage + Industry,
    data = ModelLag1)
TobinsQ <- lm(TobinsQ ~ SustainabilityPayLink + SustainableThemedCommitment +
    AuditScore + CarbonProductivity + WaterProductivity +
    WasteProductivity + FirmSize + Growth + Leverage + Industry,
    data = ModelLag1)
# I calculate my cooks distance (i.e. D)
cooksdRoa <- cooks.distance(Roa)
cooksdTobinsQ <- cooks.distance(TobinsQ)
# I extract rows considered as influential (i.e.
# observations whose D > 4 * means) and I print them for
# the reader.
influentialRoa <- as.numeric(names(cooksdRoa)[(cooksdRoa >
    4 * mean(cooksdRoa, na.rm = T))])
influentialRoa
```

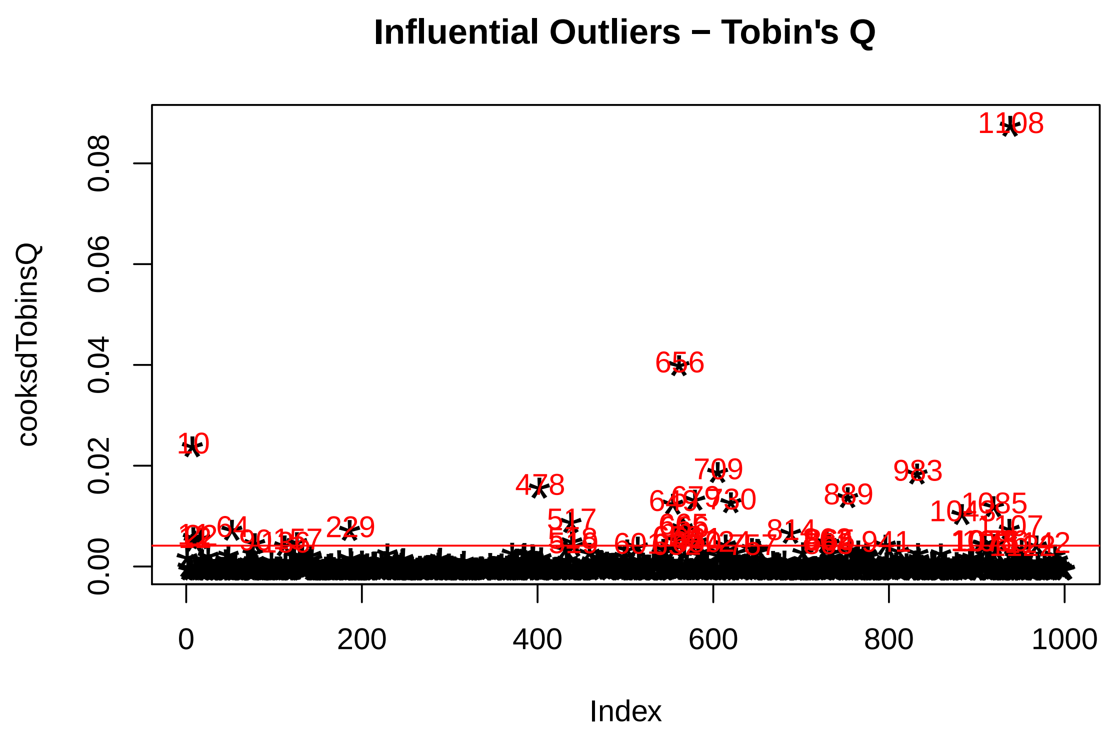
[1] 10 12 25 55 96 244 245 246 381 413 479 480 645 656 [15] 679 684 718 730 777 794 948 949 1106 1107 1108 1122 1123 1156 [29] 1171

```r
influentialTobin <- as.numeric(names(cooksdTobinsQ)[(cooksdTobinsQ >
    4 * mean(cooksdTobinsQ, na.rm = T))])
influentialTobin
```

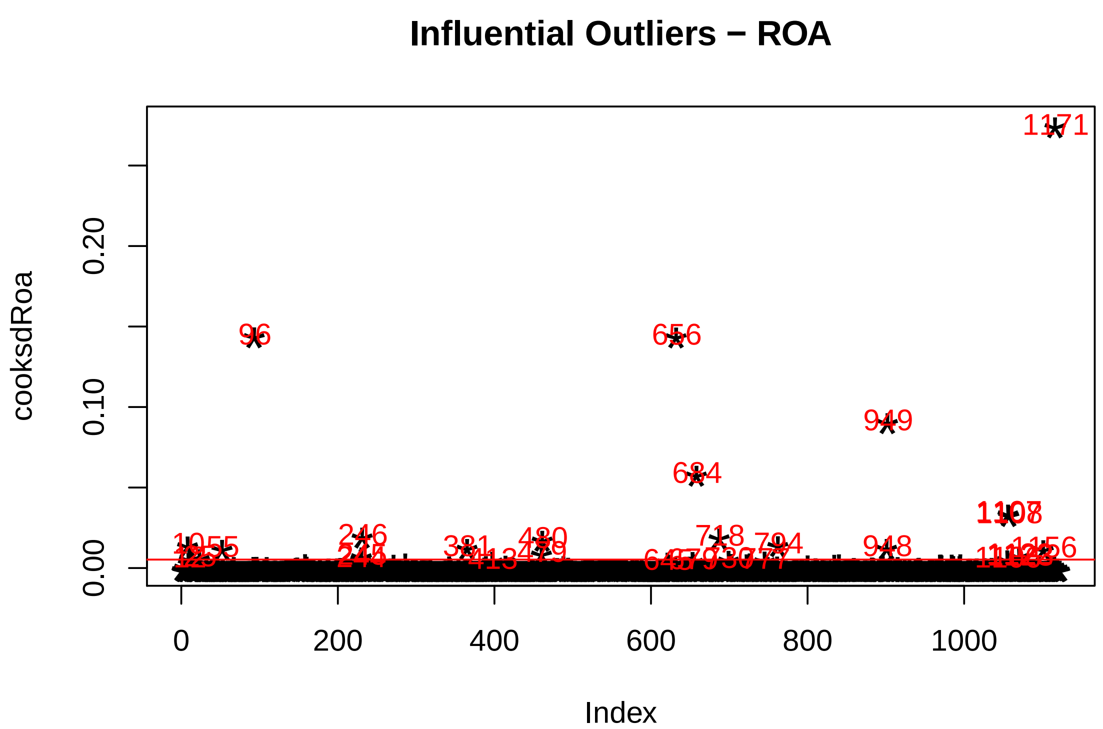
[1] 10 11 12 22 64 90 136 157 229 478 517 518 519 601 [15] 649 652 653 654 656 665 666 679 680 681 709 724 730 757 [29] 814 862 863 864 865 889 941 983 1043 1073 1074 1075 1085 1086 [43] 1107 1108 1122 1142

```r
# I remove outliers and create two new dataframes that I
# write in my folders
TobinsQ_Db <- ModelLag1[-c(influentialTobin), ]
p <- "Analysis/DataBase/DataSynchronization/NoOutliersLag1/TobinsQ.csv"
write.csv(TobinsQ_Db, file = p)
p <- "Analysis/DataBase/DataSynchronization/NoOutliersLag1/Roa.csv"
Roa_Db <- ModelLag1[-c(influentialRoa), ]
write.csv(Roa_Db, file = p)
```

```
# I report influencial obervations on a graph
## TobinsQ plot cook's distance
plot(cooksdTobinsQ, pch = "*", cex = 2, main = "Influential Outliers - Tobin's Q")
### add cutoff line
abline(h = 4 * mean(cooksdTobinsQ, na.rm = T), col = "red")
### add labels
text(x = 1:length(cooksdTobinsQ) + 1, y = cooksdTobinsQ,
    labels = ifelse(cooksdTobinsQ > 4 * mean(cooksdTobinsQ,
        na.rm = T), names(cooksdTobinsQ), ""), col = "red")
```



```
## Roa plot cook's distance
plot(cooksdRoa, pch = "*", cex = 2, main = "Influential Outliers - ROA")
### add cutoff line
abline(h = 4 * mean(cooksdRoa, na.rm = T), col = "red")
### add labels
text(x = 1:length(cooksdRoa) + 1, y = cooksdRoa, labels = ifelse(cooksdRoa >
    4 * mean(cooksdRoa, na.rm = T), names(cooksdRoa), ""),
    col = "red")
```



Appendix D: Sensitivity Analysis - R Script

The following R script is the one used to produce the section : *"Sensitivity Analysis"*.

Packages Loading

```
# Packages loading
rm(list = ls())  #Removes all items in the R environment
if (!require("plm")) install.packages("plm")
library(plm)
if (!require("dplyr")) install.packages("dplyr")
library(dplyr)
if (!require("data.table")) install.packages("data.table")
library(data.table)
if (!require("stargazer")) install.packages("stargazer")
library(stargazer)
```

The Impact of CEP on CFP

```
# I have already removed outliers from both models (i.e.
# Roa and TobinsQ) via the file =
# 'Analysis/MakeFile_RemoveOutliers_Lag2.rmd'.
# Consequently I just need to load folowing databases.
p <- "Analysis/DataBase/DataSynchronization/NoOutliersLag2/Roa.csv"
RoaNoOut <- read.csv(file = p, header = TRUE, stringsAsFactors = FALSE)
p <- "Analysis/DataBase/DataSynchronization/NoOutliersLag2/TobinsQ.csv"
TobinNoOut <- read.csv(file = p, header = TRUE, stringsAsFactors = FALSE)
# I change names
RoaNoOut <- RoaNoOut %>% setnames(old = c("Roa", "FinancialLeverage",
    "CarbonProductivity", "WaterProductivity", "WasteProductivity",
    "SustainabilityPayLink", "SustainableThemedCommitment",
    "AuditScore"), new = c("ROA", "Leverage", "CaP", "WaP",
    "WastP", "SPL", "STC", "AS"))
TobinNoOut <- TobinNoOut %>% setnames(old = c("Roa", "FinancialLeverage",
    "CarbonProductivity", "WaterProductivity", "WasteProductivity",
    "SustainabilityPayLink", "SustainableThemedCommitment",
    "AuditScore"), new = c("ROA", "Leverage", "CaP", "WaP",
    "WastP", "SPL", "STC", "AS"))
# I make both df a plm dataframe
```

```
RoaNoOut <- RoaNoOut %>% pdata.frame(index = c("CompaniesIndex",
    "YearIndex"))
TobinNoOut <- TobinNoOut %>% pdata.frame(index = c("CompaniesIndex",
    "YearIndex"))
# I test for Random Effect Model using the Lagrange
# Multiplier Tests for Panel Models.
# Pooling Model
RoaPooling <- plm(ROA ~ SPL + STC + AS + CaP + WaP + WastP +
    FirmSize + Leverage + Growth + Industry, data = RoaNoOut,
    model = "pooling")
TobinPooling <- plm(TobinsQ ~ SPL + STC + AS + CaP + WaP +
    WastP + FirmSize + Leverage + Growth + Industry, data = TobinNoOut,
    model = "pooling")
# Plmtest
PlmtestRoa <- as.numeric(round(plmtest(RoaPooling, effect = "time",
    type = "bp")$p.value, digits = 3))
PlmtestTobin <- as.numeric(round(plmtest(TobinPooling, effect = "time",
    type = "bp")$p.value, digits = 3))
# Improve p-value understanding
PlmtestRoa <- ifelse(PlmtestRoa < 0.01, paste(PlmtestRoa,
    "***", sep = ""), ifelse(PlmtestRoa < 0.05, paste(PlmtestRoa,
    "**", sep = ""), ifelse(PlmtestRoa < 0.1, paste(PlmtestRoa,
    "*", sep = ""), PlmtestRoa)))
PlmtestTobin <- ifelse(PlmtestTobin < 0.01, paste(PlmtestTobin,
    "***", sep = ""), ifelse(PlmtestTobin < 0.05, paste(PlmtestTobin,
    "**", sep = ""), ifelse(PlmtestTobin < 0.1, paste(PlmtestTobin,
    "*", sep = ""), PlmtestTobin)))
# I test for Fixed Effect Model using pFtest which is a
# test of individual and/or time effects based on the
# comparison of the within and the pooling model.
## Within Model with time effect
RoaWithin <- plm(ROA ~ SPL + STC + AS + CaP + WaP + WastP +
    FirmSize + Leverage + Growth + Industry, data = RoaNoOut,
    model = "within", effect = "time")
TobinWithin <- plm(TobinsQ ~ SPL + STC + AS + CaP + WaP +
    WastP + FirmSize + Leverage + Growth + Industry, data = TobinNoOut,
    model = "within", effect = "time")
```

```
# pFtest
pFtestRoa <- round(pFtest(RoaWithin, RoaPooling)$p.value,
    digits = 3)
pFtestTobin <- round(pFtest(TobinWithin, TobinPooling)$p.value,
    digits = 3)
# Improve p-value understanding
pFtestRoa <- ifelse(pFtestRoa < 0.01, paste(pFtestRoa, "***",
    sep = ""), ifelse(pFtestRoa < 0.05, paste(pFtestRoa,
    "**", sep = ""), ifelse(pFtestRoa < 0.1, paste(pFtestRoa,
    "*", sep = ""), pFtestRoa)))
pFtestTobin <- ifelse(pFtestTobin < 0.01, paste(pFtestTobin,
    "***", sep = ""), ifelse(pFtestTobin < 0.05, paste(pFtestTobin,
    "**", sep = ""), ifelse(pFtestTobin < 0.1, paste(pFtestTobin,
    "*", sep = ""), pFtestTobin)))
# Based on the results of the tests, the two models need
# to be estimated with the pooling ols estimations (i.e.
# model = 'pooling' in plm). Let's consolidate into a
# nice stargazer table
titre <- "The impact of process and outcome-based CEP on CFP (lag = 2)"
stargazer(TobinPooling, RoaPooling, title = titre, label = "Lag2",
    header = FALSE, single.row = TRUE, type = "latex", align = FALSE,
    model.numbers = FALSE, table.placement = "!", add.lines = list(c("BPLM test (pvalue)",
        PlmtestTobin, PlmtestRoa), c("F test (pvalue)",
        pFtestTobin, pFtestRoa)))
```

Green Score as an Alternative

```
# I have already removed outliers from both models (i.e.
# Roa and TobinsQ) via the file =
# 'Analysis/MakeFile_RemoveOutliers_Lag1.rmd'.
# Consequently I just need to load folowing databases.
p <- "Analysis/DataBase/DataSynchronization/NoOutliersLag1/GreenScore/Roa.csv"
RoaNoOut <- read.csv(file = p, header = TRUE, stringsAsFactors = FALSE)
p <- "Analysis/DataBase/DataSynchronization/NoOutliersLag1/GreenScore/TobinsQ.csv"
TobinNoOut <- read.csv(file = p, header = TRUE, stringsAsFactors = FALSE)
# I change names
RoaNoOut <- RoaNoOut %>% setnames(old = c("GreenScore",
```

```
    "FinancialLeverage", "Roa"), new = c("GS", "Leverage",
    "ROA"))
TobinNoOut <- TobinNoOut %>% setnames(old = c("GreenScore",
    "FinancialLeverage", "Roa"), new = c("GS", "Leverage",
    "ROA"))
# I make both df a plm dataframe
RoaNoOut <- RoaNoOut %>% pdata.frame(index = c("CompaniesIndex",
    "YearIndex"))
TobinNoOut <- TobinNoOut %>% pdata.frame(index = c("CompaniesIndex",
    "YearIndex"))
# I test for Random Effect Model using the Lagrange
# Multiplier Tests for Panel Models.
# Pooling Model
RoaPooling <- plm(ROA ~ GS + FirmSize + Leverage + Growth +
    Industry, data = RoaNoOut, model = "pooling")
TobinPooling <- plm(TobinsQ ~ GS + FirmSize + Leverage +
    Growth + Industry, data = TobinNoOut, model = "pooling")
# Plmtest
PlmtestRoa <- as.numeric(round(plmtest(RoaPooling, effect = "time",
    type = "bp")$p.value, digits = 3))
PlmtestTobin <- as.numeric(round(plmtest(TobinPooling, effect = "time",
    type = "bp")$p.value, digits = 3))
# Improve p-value understanding
PlmtestRoa <- ifelse(PlmtestRoa < 0.01, paste(PlmtestRoa,
    "***", sep = ""), ifelse(PlmtestRoa < 0.05, paste(PlmtestRoa,
    "**", sep = ""), ifelse(PlmtestRoa < 0.1, paste(PlmtestRoa,
    "*", sep = ""), PlmtestRoa)))
PlmtestTobin <- ifelse(PlmtestTobin < 0.01, paste(PlmtestTobin,
    "***", sep = ""), ifelse(PlmtestTobin < 0.05, paste(PlmtestTobin,
    "**", sep = ""), ifelse(PlmtestTobin < 0.1, paste(PlmtestTobin,
    "*", sep = ""), PlmtestTobin)))
# I test for Fixed Effect Model using pFtest which is a
# test of individual and/or time effects based on the
# comparison of the within and the pooling model.
# Within Model with time effect
RoaWithin <- plm(ROA ~ GS + FirmSize + Leverage + Growth +
    Industry, data = RoaNoOut, model = "within", effect = "time")
```

```
TobinWithin <- plm(TobinsQ ~ GS + FirmSize + Leverage +
    Growth + Industry, data = TobinNoOut, model = "within",
    effect = "time")
# pFtest
pFtestRoa <- round(pFtest(RoaWithin, RoaPooling)$p.value,
    digits = 3)
pFtestTobin <- round(pFtest(TobinWithin, TobinPooling)$p.value,
    digits = 3)
# Improve p-value understanding
pFtestRoa <- ifelse(pFtestRoa < 0.01, paste(pFtestRoa, "***",
    sep = ""), ifelse(pFtestRoa < 0.05, paste(pFtestRoa,
    "**", sep = ""), ifelse(pFtestRoa < 0.1, paste(pFtestRoa,
    "*", sep = ""), pFtestRoa)))
pFtestTobin <- ifelse(pFtestTobin < 0.01, paste(pFtestTobin,
    "***", sep = ""), ifelse(pFtestTobin < 0.05, paste(pFtestTobin,
    "**", sep = ""), ifelse(pFtestTobin < 0.1, paste(pFtestTobin,
    "*", sep = ""), pFtestTobin)))
# Let's consolidate into a stargazer table
titre <- "Green Score - an alternative variable for CEP"
stargazer(TobinPooling, RoaWithin, title = titre, label = "GreenScoreResults",
    single.row = TRUE, header = FALSE, type = "latex", align = FALSE,
    model.numbers = FALSE, table.placement = "!", add.lines = list(c("BPLM test (pvalue)",
        PlmtestTobin, PlmtestRoa), c("F test (pvalue)",
        pFtestTobin, pFtestRoa)))
```