# Green companies are the future: evidence from US publicly traded companies

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# Abstract

This is an abstract

# Author's Note

This master's thesis has been written in *R Markdown* (Allaire et al., 2016) in order to make it *transparent* and *reproducible* for the reader. All ressources are available on my Github account at the following url path : https://github.com/pkinif/Thesis. The latter is organised following the methodology of Gandrud (2013). Each section of this thesis corresponds to a R Markdown file in the *Child* folder. The *Child/ThesisSkeleton.Rmd* file is the "parent" document which merges all the "child" documents into a consolidated pdf document, namely the one you are reading. The *Child/Analysis* sub-folders contains a list of R script (i.e. Make files) whose outputs are saved into the following sub-folders *Child/Analysis/DataBase*.

The platform I have used is Rstudio which is an open source software for R. Here is the information of my session :

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sessionInfo()
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## Running under: Windows 10 x64 (build 16299)
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## [73] cluster_2.0.6       maxLik_1.3-4
```

## Aknowledgments

I would like to thank some of you . . .

# Contents

## List of Tables

## List of Figures

# Introduction

Over the past decades, humanity is progressively becoming aware of the finiteness of earth's resources and its impact on the current global warming. The club of Rome, with the book *"The limits to growth"*, was pioneers in this awareness. They concluded 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"* (D. H. Meadows, Meadows, Randers, & Behrens, 1972 : p23). In the nineties, Houghton & Change (1996) have also warned human kind. They argued in their report that *"most emission scenarios indicate 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).

In 2018, the current situation provides evidences that humanity was not listening. The global level of carbon dioxide has never been so high (i.e. 407.20 ppm in May 2018). According to the NOAA's Annual Greenhouse Gas Index, the atmospheric abundance of CO2 has increased by an average of 1.80 ppm per year over the past 38 years (i.e. 1979-2016) (Butler & Montzka, 2016). Since the last 19th century, the average temperature of the planet increased by 1.1 degrees Celsius. Most of the warming occurred in the past 35 years, with 16 of the 17 warmest years on record occurring since 2001. (Hansen, Ruedy, Sato, & Lo, 2010, GISTEMP Team (2018)). Data from NASA's Gravity Recovery and Climate Experiment show Greenland lost 150 to 250 cubic kilometers (i.e. 36 to 60 cubic miles) of ice per year between 2002 and 2006, while Antarctica lost about 152 cubic kilometers (i.e. 36 cubic miles) of ice between 2002 and 2005 (GISTEMP Team, 2018). Church & White (2006) has shown that, in the last century, the global sea level rose about 8 inches (i.e. 20.32 cm). Sabine et al. (2004) desmonstrated that oceans have absorbed about the third of the carbon dioxide produced from human activities since 1800 and about the half of the carbon dioxide produced by burning fossil fuels. Consequently, since the beginning of the Industrial Revolution, the acidity of surface ocean waters has increased by about 30 percent (NOAA's Pacific Marine Environmental Laboratory, n.d.) leading, *inter alia*, to harsh repercussions to corals.

Today, we need to open our eyes and face the consequences of our actions in order to move forward and improve the global situation. The statu quo need to be challenged. As argued by Jean Jouzel (2017), *"human beings have to act now if they want to have a chance to reduce effects of climate change"*. The first Global Agreement on global warming during the Paris Conference in 2015 and the 17 Sustainable Development Goals (i.e. SDG) of the United Nation give hope. The Business and Sustainable Development Commission report Better Business, Better World (Business and Sustainable Development Commission, 2017, p12) stated: *"... businesses need to pursue social and environmental sustainability as avidly as they pursue market share and shareholder value. If a critical mass of companies joins us in doing this now, together we will become an unstoppable force. If they don't, the costs and uncertainty of unsustainable development could swell until there is no viable world in which to do business."* Futhermore, ecosystem degradation and resources depletion engender a threat to firm's longevity (Dowell, Hart, & Yeung, 2000). In his speech at Lloyds of London 2015, Mark Carney, Governor of the Bank of England and Chair of the Financial Stability Board , identified climate change as one of the most material threats to financial stability (Elliott, 2015). In other words, adopting environmental strategies ensure companies' competitiveness and survival in the near future.

Testa, Boiral, & Iraldo (2018) have shown that, due to institutional pressure or the influence of stakeholders, a majority of companies have integrated, either substantially or symbolically (i.e. green washing), proactive environmental practises. However, according to Scarpellini, Valero-Gil, & Portillo-Tarragona (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. If we consider that people's actions reflect a variable mix of altruistic motivation, material self-interest, and social or self-image concerns (Bénabou & Tirole, 2006), demonstrating that green strategies implementation has a significant financial interest for companies could convince them to incorporate sustainability into their core values and actions. Consequently, Using a panel data of 393 US publicly-traded companie for the period 2012-2014, this study explores whether Corporate Environmental Performance (i.e. CEP) positively influences Corporate Financial Performance (i.e. CFP) and observes the time influence (i.e. short vs long term) of the relationship.

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

# 1 Literature Review

## 1.1 Two perspectives on Corporate Environmental Performance

Friedman (1970) considers investment in pollution efficient technology as a deviation from the profit maximization goal (i.e. an increase in cost). This paradigm has been widely challenged these last decades. Indeed, the literature is showing growing evidence that improving a company's environmental performance can lead to better economic or financial performance. Ambec & Lanoie (2008) demonstrated that the expenses incurred to reduce pollution can be partly or completely offset by gains made elsewhere. Porter & van der Linde (1995) argued that properly crafted environmental standards can trigger innovation offsets, allowing companies to improve their resource productivity. He also redefined the self-concept of value creation. According to him, companies have to create shared value. Sharing value creation involves building economic value which addresses the current needs and challenges of our society (Porter, Hills, Pfitzer, Patscheke, & Hawkins, 2011, Porter & Kramer (2011)). In the same logic, Freeman (1984) calls to a radical rethinking of our firm's model. According to him, companies have to consider their stakeholders [1] or otherwise face a negative contest from non-shareholder groups. A situation that could lead to diminished shareholder value, through boycotts, lawsuits, and protests, etc. In other words, Freeman (1984) summarizes the idea that companies should consider corporate environmental performance as an undeniable cost of doing business.

## 1.2 Does it pay to be green?

More and more companies are developping profitable business strategies that deliver tangible social benefits that embrace the new business paradigm of Freeman (1984), Porter & van der Linde (1995) and Ambec & Lanoie (2008). However, others prefer keeping the old fashion way of Friedman (1970). Consequently, this dichotomy has interested scholars and since they have sought to empirically answer the question, *"Does it pay to be green?"*. In a competitive business world, answering this question is crucial to provide a genuine economic justification to the new green way of making business (Lu, Chau, Wang, & Pan, 2014). Although results are mixed, the large number of studies on the nexus between Corporate Environmental Performance (i.e. CEP) and Corporate Financial Performance (i.e. CFP) in

[1] Stakeholders are any group or individual who can affect or is affected by the achievement of an organization's objectives [@Freeman1984, p.25].

the last three decades allowed the appearance of recent meta-analyses [2] (Orlitzky & Benjamin, 2001, Orlitzky, Schmidt, & Rynes (2003), Wu (2006), Albertini (2013), Dixon-Fowler, Slater, Johnson, Ellstrand, & Romi (2013), Endrikat, Guenther, & Hoppe (2014), Lu et al. (2014), Q. Wang, Dou, & Jia (2016), Busch & Friede (2018)) and all suggest that indeed it pays to be green. More precisely, a positive and bidirectional relationship does exist between CEP and CFP meaning that successful firms may have the resources necessary to improve their environmental performance, which in turn increases financial benefits that again can be invested back into further improvements of CEP (Endrikat et al., 2014).

## 1.3 CEP and CFP as a broad meta-construct

CFP is a broad meta-construct. Scholars have adopted three broad subdivisions of CFP: market-based (i.e. investor returns), accounting-based (i.e. accounting returns), and perceptual (i.e. survey) measures. Market-based measures (e.g. price-earning ratio, Tobin's Q, or share price appreciation) consider that returns should be measured from the perspective of the shareholders (Cochran & Wood, 1984). 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 & Wood, 1984, Wu (2006)). Finally, perceptual measures of CFP is a more subjective approach based on the perception of survey respondents (Lu et al., 2014).

CEP is also a broad meta-constructs 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 green performance of companies. Albertini (2013) use 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, Claver-Cortés, López-Gamero, & Tarí, 2009, Schultze & Trommer (2012)). (ii) Environmental Performance Variables (i.e. EPV) which are mostly 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 (F. Chen, Ngniatedema, & Li, 2018), environmental accidents and crises (Blacconiere &

[2] Initially, the literature focused on the link between Corporate Social Performance (i.e. CSP) and Corporate Financial Performance (i.e. CFP). Orlitzky and Benjamin 2001 were the first to consider CEP as apart from CSP. Given that Busch and Friede 2018 could not detect statistically significant differences between the effects of environmental CEP and social-related CSP on CFP and concludes that good CSP pays off, whether social or environmental related, this study considers CSP equals to CEP.

Patten, 1994), and environmental investment announcements (Gilley, Worrell, Davidson III, & El–Jelly, 2000). Endrikat et al. (2014) split up CEP into two sub-dimensions, namely (i) process-based CEP which can be linked to the EMV approach of Albertini (2013) and (ii) outcome-based CEP which can be linked to the EPV dimension. According to S. Xie & Hayase (2007), process-based CEP can be considered as a preliminary step of outcome-based CEP. Besides, scholars demonstrated that the first approach has a positive impact on the second one which in turn has a positive impact on financial performance (Li, Ngniatedema, & Chen, 2017, F. Chen et al. (2018)).

Although recent meta-analyses (Orlitzky & Benjamin, 2001, Orlitzky et al. (2003), Wu (2006), Albertini (2013), Dixon-Fowler et al. (2013), Endrikat et al. (2014), Lu et al. (2014), Q. Wang et al. (2016), Busch & Friede (2018)) have demonstrated the positive link between CEP and CFP, some scholars advanced that the multidimensionality of both CEP and CFP constructs is one reason why the conclusion of the relationship between CEP and CFP have been so mixed (Albertini, 2013, Endrikat et al. (2014), Miroshnychenko, Barontini, & Testa (2017)). For instance, Busch & Hoffmann (2011) found 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. Cavaco & Crifo (2014) and Muhammad, Scrimgeour, Reddy, & Abidin (2015) have used both accounting-based indicators (i.e. ROA) and market-based indicators (i.e. Tobin's Q) as a proxy for CFP and obtained a positive relation between ROA and CEP while no relation between Tobin's Q and CEP. A general consensus has shown that accounting-based CFP are characterized by a stronger relation to CEP than market-based and perceptual indicators (Orlitzky et al., 2003, Wu (2006), Albertini (2013), Lu et al. (2014), Busch & Friede (2018)).

### 1.4 When does it pay to be green?

Griffin & Mahon (1997) were the first to call for researchs that looks at the CEP-CFP relation over time. While scholars had been mainly answering the question: *"Does it pay to be green?"* some have recently tried to move forward and gained interest in answering the call of Griffin & Mahon (1997) with the following question: *"When does it pay to be green?"* (Manrique & Martí-Ballester, 2017).

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

Those empirical results provide pieces of evidences that no common consensus have been found yet to answer the question: *"When does it pay to be green?"*. Busch & 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 & Mahon (1997) remains to date unanswered.

To capture the time dimension in the CFP-CEP nexus, scholars consider accounting-based measures as a proxy for short-term CFP and market-based measures as a proxy for long-term CFP (Endrikat et al., 2014, Delmas et al. (2015), Zhang & Chen (2017), Manrique & Martí-Ballester (2017), Miroshnychenko et al. (2017)). Indeed, Endrikat et al. (2014) highlight that on the one hand, accounting-based measures capture immediate impacts but do not seize long-term effects unlike market-based measures which integrate estimations of a 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 have a positive impact on Outcome-based CEP

**Hypothesis 2.** Outcome-based CEP have a positive impact on short-term CFP

**Hypothesis 3.** Outcome-based CEP have a positive impact on long-term CFP

**Hypothesis 4.** Process-based CEP have a positive impact on short-term CFP

**Hypothesis 5.** Process-based CEP have a positive impact on long-term CFP

# 2 Research Framework

The research framework of this study is summarized in the figure 2.1. The latter, inspired by Li Suhong, Ngniatedema Thomas, & Chen Fang (2017) and F. Chen et al. (2018), aims at answering three calls. Firstly, Endrikat et al. (2014) have highlighted the need for a better understanding of the multidimensionality of both CEP and CFP constructs. To do that, I will examine the combined effects of process-based and output-based CEP on both accounting-based and market-based measures of CFP. Secondly, to the best of my knowledge, Li Suhong et al. (2017) and F. Chen et al. (2018) were the first scholars to use the NewsWeek Green Ranking as a proxy for both process-based and output-based CEP. They performed their analysis with a time frame of one year. Therefore, applying a longitudinal study on this database can help to provide a better understanding of the CEP-CFP nexus. Lastly, Busch & Friede (2018) claimed that to date and at a meta-research level, the call of Griffin & Mahon (1997) regarding the research that looks at the CEP-CFP relation over time remains unanswered and confused. Therefore, capturing the short term vs long term CFP through the use of accounting-based and market-based measures could help to provide a better picture of the time relationship between CEP and CFP. Furthermore, it also provides new data for future meta-analysis.

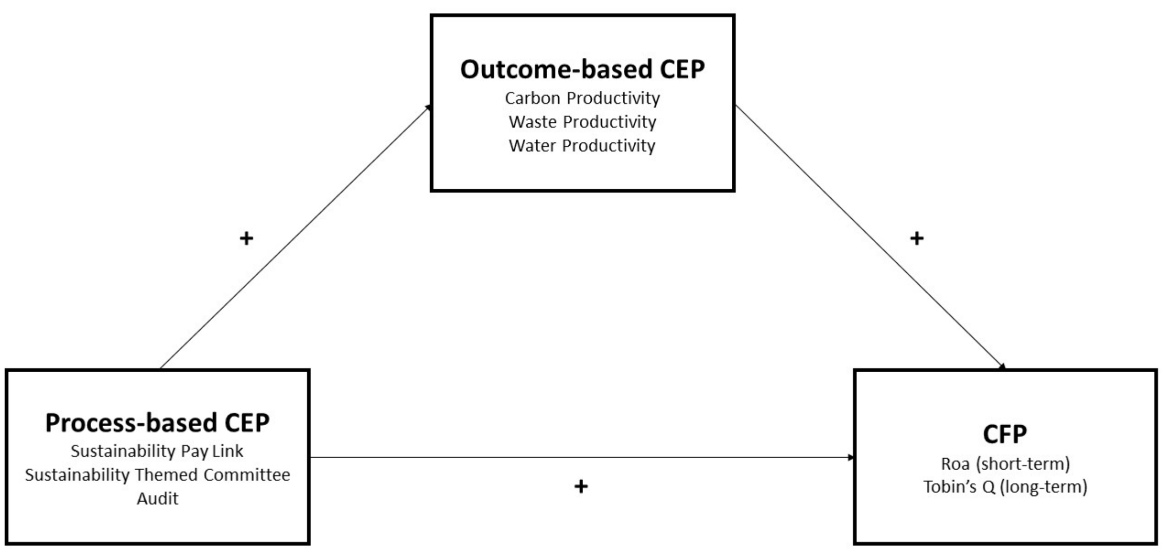



Figure 2.1: Research Framework

# 3 Data

## 3.1 Overview

The starting point of my data collection was the Newsweek Green Ranking. This ranking had assessed the world's largest publicly-traded companies in the US and in the world since 2009. It had been 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 ranking attributes an overall green score to companies. This score is based on a weighted average of key performance indicators (KPI's). This study uses these KPI's to approach both process-based and outcome-based CEP of the 500 largest publicly-traded companies in the United States. As a result of making a transition to a 100% rules-based approach, the methodology for the 2014 Newsweek Green Rankings differs considerably from the framework used in the 2012 Newsweek Green Rankings. Therefore, this study considers only 2014, 2015 and 2016 ranking. Among those three ranking and of the 500 US companies, 405 companies were listed for each year.

Even though green rankings were published in 2014, 2015 and 2016, each company is evaluated based on 2012, 2013 and 2014 data. Therefore, measures for financial performance of companies will be based on 2012, 2013 and 2014 fundamental data. Financial data have been collected on Morningstar, Stockpup and Ycharts using R code. The data collection process is described in the 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 variables of the econometric model. Following sections deeply explain each variable.

## 3.2 Dependent Variables

Regarding dependent variables, Endrikat et al. (2014) claim 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 a firm's future prospects and can be better used as a proxy for long-term CFP. Among scholars which used both measures simultaneously, Return On Asset (i.e. Roa) and Tobin's Q are the most frequent (Lioui & Sharma, 2012, Cavaco & Crifo (2014), Muhammad et al. (2015), Delmas et al. (2015), Semenova & Hassel (2016), Manrique & Martí-Ballester (2017)). Therefore this study uses ROA and Tobin's Q as a proxy for both short 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. Tobin's Q is defined as the ratio of the market value of a firm to the replacement cost of its assets (Chung & Pruitt, 1994). Broadly speaking, 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 & 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 seen several attempts to approximate Tobin's Q (Perfect & Wiles, 1994). Tobin's Q value had been directly collected on Ycharts and this platform uses the simple approximation of Chung & Pruitt (1994) which is summarized in Equation 1. Due to a high right-skew of Tobin's Q (i.e. skew = 2.51), I use a natural logarithm transformation in order to normalize its distribution (Honaker, King, & Blackwell, 2011).

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

where $MVE$ is the product of a firm's shares prices 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 firms.

### 3.3 Independent Variables

Concerning independent variables, both process-based and outcome-based CEP had been approached with KPI's of the Newsweek Green Ranking. More precisely, I have used "Sustainability Pay Link", "Sustainability Themed Committee", and "Audit" as proxies for process-based CEP and "Carbon Productivity", "Water Productivity" and "Waste Productivity" as proxies for outcome-based CEP [3].

*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 is attributed if there is no such link in place.

*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 is attributed if there is no such link in place.

*An Audit Score* (i.e. A) 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 if such an audit has been performed, and a score of 0 is given when such audit was not performed.

*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 US\$, $TGGE_{it}$ 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] Newsweek Green Ranking have an other KPI that capture outcome-based CEP, namely Energy Productivity. Inserting this variable into my models create multicollinearity (Variance Inflaction Factor superior to 5 for both Energy and Carbon Productivity). Consequently, I do not consider this KPI in my econometric model.

## 3.4 Control Variables

Scholars (Telle, 2006, McWilliams, Siegel, & Wright (2006), Surroca, Tribó, & Waddock (2010)) have argued that misspecified models may be the reason for the inconsistency of the empirical results in the CEP-CFP nexus. In order to improve the construct and to avoid the endogeneity issue due to omitted variables (Roberts & Whited, 2013), Endrikat et al. (2014) have highlighted 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 those 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) [4].*Capital structure* is interpreted here as the financial leverage, namely as 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). *Growth rate* is approached through the net margin (i.e. the ratio of earnings to revenue).

[4]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 | Tobins Q | The ratio of a firm's market value to the replacement cost of its assets |
| 3 | Carbon Productivity | Revenue ($US) / Total Greenhouse gas Emissions (CO2) |
| 4 | Water Productivity | Revenue ($US) / Total water (m3) |
| 5 | Waste Productivity | Revenue ($US) / [Total waste generated (metric tonnes)–waste recycled/reused (tones)] |
| 6 | Sustainability Pay Link | 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 | Sustainable Themed Commitment | 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 | Audit Score | 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 evidences exist and 0 otherwise |
| 9 | Financial 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 (GICS) of the firm. The variable take 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 adress the CFP-CEP nexus (Albertini, 2013). Furthermore, 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 & Whited (2013) also argued that using panel data offers a partial solution to the problem of omitted variables in econometric model, namely the most common causes of endogeneity in empirical corporate finance. Panel data takes the following econometric form :

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

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, $X_{it}$ represents a $K$-dimensional row vectors of independent variables, $\alpha$ is the intercept, $\beta$ is a $K$-dimensional column vectors 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, $\mu_i$, represents the individual error components and do not change over time. It can be considered as the unobserved effect model. The second term, $\epsilon_{it}$, is the idiosyncratic error which is assumed well-behaved and independent of $X_{it}$ and $\mu_i$.

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

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

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

Fixed (i.e. Equation 6) and Random (i.e. Equation 7) Effect Model implies that the Ordinary Least Square (i.e. OLS) estimator of $\beta$ are inconsistent. Five assumptions are required to produce consistent estimators with OLS : (i) a random sample of observations on $y$ and

$(x_1, ..., x_n)$, (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 & Millo, 2008).

While OLS is not consistent to estimate panel data model, the R package *plm* provides pertinent estimation methods. (i) *The pooled ols estimation* ignores the panel structure of the data and apply the same cofficients to each individual (Schmidheiny, 2015). (ii) *The random effects estimation* is the feasible Generalized Least Squares (i.e. GLS) estimator. (iii) *The fixed effects estimation*, also called *within estimation*, transforms the original equation 5 in substracting the time averages to every variables, such as :

$$Y_{it} - \bar{Y}_i = \beta(X_{itk} - \bar{X}_{ik}) + (u_{it} - \bar{u}_i) \tag{8}$$

The presence of RE model in a panel data can be tested using the Breusch-Pagan Lagrange Multiplier (i.e. BPLM) test (Breusch & Pagan, 1980). This test is represented by the *plmtest* function in *R*. It examines if time and/or individual specific variance components equal zero (Park, 2011). If Ho is verified, then there is no RE model in the panel data. The presence of FE model is tested by a 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 & Millo, 2008). If Ho is verified, then there is no FE model in the panel data.

In case of the absence of both RE and FE model, namely $\mu_i = 0$, pooled ols estimation is the most efficient estimator (Croissant & Millo, 2008). Under the assumption of the FE model, the random effects estimators are biased and inconsistent given that $\mu_i$ is omitted and potentially correlated with other regressors. Therefore, the fixed effects estimation need to be used. Under the assumption of the RE model, both FE and RE estimators are unbiased and consistent. According to Schmidheiny (2015), scholars should prefer the RE estimator only and only if $E[\mu_i, X_i] = 0$. This precondition is tested by the Hausman test (Hausman & Taylor, 1981). If Ho is verified, then scholars should use RE estimator.

### 4.2 Econometric Model

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

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

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, $A_{it}$ is a proxy for a firm's audit score and $u_{it}$ which is the error term.

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

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, $A_{it}$ 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 and lastly $u_{it}$ which is the error term.

Recent meta-analysis provided evidences that the CFP-CEP nexus is characterized by a bidirectional causality (Orlitzky & Benjamin, 2001, Orlitzky et al. (2003), Wu (2006), Albertini (2013), Dixon-Fowler et al. (2013), Endrikat et al. (2014), Lu et al. (2014), Q. Wang et al. (2016), Busch & Friede (2018)). This could cause simultaneous causality between the dependent and the independent variable and lead to endogeneity concern in my model (Sánchez-Ballesta & García-Meca, 2007, Biørn & Krishnakumar (2008), Roberts & Whited (2013)). In order to adress this issue I have lagged observations in independent and control variables one year behind financial performance. This increases the confidence of the direction of the relationship (S. L. Hart & Ahuja, 1996, Delmas et al. (2015), Miroshnychenko et al. (2017)) and *in fine* reduce the potential simultaneity bias.

# 5 Results

## 5.1 Get a feel of the data

This section gives an overview of the database. Table 5.1 presents the main descriptive statistics of each variables. The sample size of Roa (i.e. N = 1176) is superior to the sample size of TobinsQ (i.e. N = 1038). Indeed, compared to ROA, calculating Tobin's Q requires a relatively high number of financial variables and is more susceptible to missing values. 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 sample bias. I did the same and the p-value of the unpaired two-samples t-test equals 0.365 meaning that they is not significant difference between both samples.

Table 5.2 contains the matrix of correlation of my database. There are statistically significant correlations between outcome-based CEP variables (i.e. carbon, water and waste productivity) suggesting that my model could suffer from multicollinearity. Table 5.3 reports the variance inflation factor (i.e. VIF) of all the variables. The maximum VIF is 2,477 meaning that there is no multicollinearity in the model (O'brien, 2007).

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

## 5.2 Outliers treatment

Lyu (2015) defines outliers as observations in the dataset that appear to be unusual and discordant and which could lead to inconsistent results. Osborne & Overbay (2004) have shown that even a small proportion of outliers can significantly affect simple analyses (i.e. t-tests, correlations and ANOVAs). Outliers are an issue only and only if they are influential [5] (Cousineau & Chartier, 2010). I have used the Cook's distance (Cook, 1977) test which is a common statistical tool to assess the influence of outliers (JP Stevens, 1984, Cousineau & Chartier (2010), Zuur, Ieno, & Elphick (2010)). Cook's Distance observes the difference between the regression paramater of a given model, $\hat{\beta}$ and what they become if the $i_{th}$ data points is deleted, let's say $\hat{\beta}_i$. One difficulty with treatment of outliers is that the literature have not found common theoretical framework yet for the treatment of influential outliers (Orr John, Sackett Paul, & Dubois Cathy, 1991, Cousineau & Chartier (2010)). Tabachnick & Fidell (2007) argues that the imputation with the mean is the best method while Cousineau & Chartier (2010) highlight 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.

[5] Influential obervations are observations whose removal causes a different conclusion in the analysis

Dang, Serfling, & Zhou (2009) argue that more elaborate technique involves replacing outliers with possible values while Barnett & Lewis (1994) would prefer to remove or windsorized them. Alternatively, Pollet & Meij (2017) propose an other route to handle outliers and argue that inclusion or exclusion of outliers depend on the significativity of the results, meaning that if results are more significant without outliers, scholars should remove them and vice versa. Following the mindset of Pollet & Meij (2017), I have removed outliers from my database. See Appendix C : Outliers treatment for furthers details.

## 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. sustainability pay link, sustainable themed commitment and audit score) on outcome-based CEP (i.e. carbon, water and waste productivity). Estimators of the three models had been estimated with the *fixed effects estimation*. Indeed, based on the p-value of the F test, the three models have FE model making both the random effects and pooled ols estimators biased.

Except for Model 1 which indicates no significant relation between sustainability pay link and carbon productivity, all models show evidences of a positive and highly statistically significant effect of process-based CEP variables on outcome-based CEP. Consequently, 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. sustainability pay link, sustainable themed commitment and audit score) and outcome-based CEP (i.e. carbon, water and waste productivity) on short-term CFP (i.e. Roa) and long-term CFP (i.e. TobinsQ). Based on the results of BPLM and F tests, estimators of the TobinsQ model had been estimated with the *pooled ols estimation* and the estimators of the Roa model with the *fixed effects estimation*.

TobinsQ model shows evidences of a positive and highly statistically significant effect of sustainability pay link, audit score and water productivity on long-term CEP. Roa model shows evidences of a positive and highly statistically significant effect of sustainability pay link, sustainable themed commitment and carbon productivity on short-term CEP. Consequently hypothesis 2, 3, 4 and 5 are verified.

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 |
| A | 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. A | -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 |
| A | 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 | WaP | WastP |
| SPL | 0.010 | 0.022** | 0.026** |
| | (0.011) | (0.011) | (0.011) |
| STC | 0.054*** | 0.062*** | 0.042*** |
| | (0.010) | (0.011) | (0.010) |
| A | 0.062*** | 0.070*** | 0.072*** |
| | (0.010) | (0.011) | (0.010) |
| BPLM test (pvalue) | 0*** | 0*** | 0*** |
| F test (pvalue) | 0*** | 0*** | 0*** |
| Observations | 1,177 | 1,177 | 1,177 |
| $R^2$ | 0.117 | 0.144 | 0.131 |
| Adjusted $R^2$ | 0.113 | 0.140 | 0.128 |
| F Statistic (df = 3; 1171) | 51.709*** | 65.539*** | 59.054*** |
| *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 | Roa |
| SPL | 0.079* | 0.008** |
| | (0.044) | (0.004) |
| STC | 0.063 | 0.012*** |
| | (0.044) | (0.004) |
| A | 0.158*** | −0.004 |
| | (0.044) | (0.004) |
| CaP | −0.012 | 0.030** |
| | (0.135) | (0.012) |
| WaP | 0.337** | 0.006 |
| | (0.155) | (0.012) |
| WastP | −0.199 | 0.010 |
| | (0.156) | (0.012) |
| FirmSize | −0.443*** | −0.020*** |
| | (0.015) | (0.001) |
| Leverage | 0.003 | −0.00000 |
| | (0.003) | (0.0003) |
| Growth | 0.465*** | 0.138*** |
| | (0.152) | (0.012) |
| Industry | −0.026*** | −0.002*** |
| | (0.007) | (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

Sensitivity Analysis investigates how the variation in the output of a numerical model can be attributed to variations of its input factors (Pianosi et al., 2016). To ensure the robustness of the main findings of the previous section I have carried out two robustness tests.

Firstly the equation 10 had been re-estimated using dependent variables accelerated by one year in a sense that observations in independent and control variables are now lagged two year behind corporate financial performance. Based on the results of both Breusch Pagan Multiplier and F tests, estimators had been estimated with the *pooled ols estimation*. Results are reported in table 6.1 and confirms results of the previous section.

Secondly, I have used an alternative proxy for approaching corporate environmental performance, namely the Green Score assigned to each company of the NewsWeek Green Ranking. The score is based on a weighted average of the key performance indicators of the ranking. Concretely, it means that equation 10 becomes the following equation.

$$Y_{it+1} = \alpha + \beta_1 GS_{it} + Controls_{it} + u_{it} \tag{11}$$

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 and lastly $u_{it}$ which is the error term.

The model using TobinsQ as a proxy for CFP had been estimated with the *pooled ols estimators* while the model using Roa uses the *fixed effect estimation*. Results are reported in table 6.2 and confirms findings of the previous section. Consequently, the sensitivity analysis supports that CEP do have a significant and positive effect on CFP (short and long-term).

R script of this section is in the Appendix D : Sensitivity Analysis - R script.

Table 6.1: The impact of process and outcome-based CEP on CFP (lag = 2)

| | *Dependent variable:* | |
|---|---|---|
| | TobinsQ | Roa |
| SPL | 0.102** | 0.008** |
| | (0.044) | (0.004) |
| STC | 0.062 | 0.011*** |
| | (0.043) | (0.004) |
| A | 0.153*** | −0.002 |
| | (0.044) | (0.004) |
| CaP | 0.112 | 0.039*** |
| | (0.133) | (0.012) |
| WaP | 0.194 | −0.001 |
| | (0.155) | (0.013) |
| WastP | 0.032 | 0.011 |
| | (0.153) | (0.013) |
| FirmSize | −0.427*** | −0.019*** |
| | (0.015) | (0.001) |
| Leverage | 0.003 | 0.0001 |
| | (0.003) | (0.0002) |
| Growth | 0.420*** | 0.115*** |
| | (0.152) | (0.012) |
| Industry | −0.022*** | −0.002*** |
| | (0.007) | (0.001) |
| Constant | 10.295*** | 0.503*** |
| | (0.343) | (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: GreenScore - an alternative variable for CEP

| | *Dependent variable:* | |
|---|---|---|
| | TobinsQ | Roa |
| GreenScore | 0.669*** | 0.051*** |
| | (0.093) | (0.008) |
| FirmSize | −0.413*** | −0.018*** |
| | (0.014) | (0.001) |
| Leverage | 0.003 | −0.0003 |
| | (0.004) | (0.001) |
| Growth | 0.528*** | 0.134*** |
| | (0.162) | (0.013) |
| Industry | −0.030*** | −0.002*** |
| | (0.007) | (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

Let's speak…

# Conclusion

This is my conclusion. . .

# Appendix

## Appendix A : Database construction

The data of this study comes from several platforms and the final database is the result of a long step process.

First, I have downloaded the green data from NewsWeek for each years ranking (i.e. 2014 to 2016). All companies were not automatically listed in the three rankings. Consequently, I had to look after companies that were listed in each ranking. This step had been carried out through excel (see the file *Child/Analysis/DataBase/NewsWeekGreenRankin/RechercheMatch 14-16.xlsx* ) using some *vlookup*. Among those three rankings and of the 500 US companies, 405 companies were listed for each years.

Second, I have used Morningstar to get the financial data. More precisely, I have used its API. The platform have saved key ratios data in csv format for each company. The common csv path is: *http://financials.morningstar.com/ajax/exportKR2CSV.html?t=FB*. You can observe that the ticker of the company stands at the end of the path. Consequently I have written an R code which download each csv file and bring all data into a tidy database. The R code is available in the following file :* Child/Analysis/MakeFile_WebScrapMorningStars.Rmd* and the outputs of this make file are in the folder *Child/Analysis/DataBase/MorningStar*.

Third, I have downloaded all financial data on StockPup. I have used the same process than for Morningstar. The website have saved financial data for each company in a csv file (e.g. http://www.stockpup.com/data/A_quarterly_financial_data.csv). Consequently I have written an R code to make a loop on each companies to dowload the csv file. Then all data had been compiled into a tidy database. The make file is available ath the folowing path : *Child/Analysis/MakeFile_WebScrapStockPup.Rmd*. Outputs of this make file are in this folder *Child/Analysis/DataBase/StockPup*.

Fourth, I have completed my database with data coming from Ycharts. On this platform I have collected the Tobin's Q. At the date of collect, Ycharts offered a 7-day free trial. I have also used R to bring all data into a tidy database. The make file path is : *Child/Analysis/MakeFile_WebScrapYcharts.Rmd*. Outputs of this make file are in this folder *Child/Analysis/DataBase/Ycharts*.

Fifth, I have synchronized all data into one tidy database. The make file is *Child/Analysis/MakeFile_DataSynchronization.Rmd* and outputs are saved in the following folder : *Child/Analysis/DataBase/DataSynchronization*.

## Appendix B : Results - R script

The following R script is the R code used to produce the section : Results.

### 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)
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**

```r
# Database Loading. Here I consider the database with
# outliers.
path <- "Analysis/DataBase/DataSynchronization/Lag1.csv"
DataBase <- read.csv(file = path, header = TRUE, stringsAsFactors = FALSE)
# I create a new df called 'model' which contains only
# variables that I need
Model <- DataBase %>% 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$TotalAssets <- log(Model$TotalAssets)
# I use the natural log for TobinsQ
Model$TobinsQ <- log(Model$TobinsQ)
# I rename some columns
Model1 <- Model %>% setnames(old = c("DebtToEquityRatio",
    "TotalAssets", "GicsClassification", "NetMargin", "CarbonProductivity",
    "WaterProductivity", "WasteProductivity", "SustainabilityPayLink",
    "SustainableThemedCommitment", "AuditScore"), new = c("Leverage",
    "FirmSize", "Industry", "Growth", "CaP", "WaP", "WastP",
    "SPL", "STC", "A"))
```

### Unpaired two sample t-test

```
# unpaired two-samples 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
IdenticalAnalyses <- round(t.test(Sample1, Sample2, alternative = "two.sided",
    var.equal = FALSE)$p.value, digits = 4)
# I print the pvalue
IdenticalAnalyses
```

### Descriptive statistics

```
# Descriptive statistics
# I remove the column 'GreenScore', 'CompaniesIndex' and
# 'YearIndex'. Right now I do not need it.
Model2 <- Model1 %>% select(-c(GreenScore, YearIndex, CompaniesIndex))
# I use stargazer to create a table containing
# descriptive statistics for each variables
stargazer(Model2, title = "Descriptive statistics", label = "DescriptiveStatistics",
    header = FALSE, type = "latex", align = FALSE, table.placement = "b",
    digits = 2, digits.extra = 2)
```

**Matrix of correlation**

```
# 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")
# Right 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 for 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 nice 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

```
# 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 + A + CaP + WaP + WastP + Leverage +
    Growth + FirmSize + Industry, model = "pooling", data = Model1,
    index = c("YearIndex", "CompaniesIndex"))
TobinsQ <- plm(TobinsQ ~ SPL + STC + A + CaP + WaP + WastP +
    Leverage + Growth + FirmSize + Industry, model = "pooling",
    data = Model1, index = c("YearIndex", "CompaniesIndex"))
# VIF Calculation summary in a nice stargazer table
VifRoa <- car::vif(Roa)
VifTobin <- car::vif(TobinsQ)
VifTable <- cbind(VifRoa, VifTobin)
colnames(VifTable) <- c("Roa", "Tobin's Q")
# summary in a nice stargazer table
stargazer(VifTable, summary = FALSE, title = "Variance Inflation Factor",
    label = "VIF", header = FALSE, type = "latex", align = TRUE,
    table.placement = "!", digits = 3)
```

**The impact of process-based CEP on outcome-based CEP**

```
# The impact of process-based CEP on outcome-based CEP
# I select only CEP variables in model2. As Model2 is
# already a pdata.frame, I do not need to reproduce this
# function on Model3.
Model3 <- Model1 %>% select(c(YearIndex, CompaniesIndex,
    CaP, WaP, WastP, SPL, STC, A))
# I test for Random Effect Model using the Lagrange
# Multiplier Tests for Panel Models.
# Pooling Model
CarbonPooling <- plm(CaP ~ SPL + STC + A, data = Model3,
    model = "pooling")
WaterPooling <- plm(WaP ~ SPL + STC + A, data = Model3,
    model = "pooling")
WastePooling <- plm(WastP ~ SPL + STC + A, 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)))
```

```r
# 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 + A, data = Model3,
    model = "within", effect = "time")
WaterWithin <- plm(WaP ~ SPL + STC + A, data = Model3, model = "within",
    effect = "time")
WasteWithin <- plm(WastP ~ SPL + STC + A, data = Model3,
    model = "within", effect = "time")
# pFtest
pFtestCarbon <- as.numeric(round(pFtest(CarbonWithin, CarbonPooling)$p.value,
    digits = 3))
pFtestWater <- as.numeric(round(pFtest(WaterWithin, WaterPooling)$p.value,
    digits = 3))
pFtestWaste <- as.numeric(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 the results of the tests, the three models
# need to be estimated with the fixed effects
# estimations (i.e. model = 'within' in plm). Let's
# consolidate into a nice stargazer table
stargazer(CarbonWithin, WaterWithin, WasteWithin, title = "The impact of process-based on ou
    label = "CepResults", header = FALSE, type = "latex",
    align = FALSE, 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.
path <- "Analysis/DataBase/DataSynchronization/NoOutliersLag1/Roa.csv"
RoaNoOut <- read.csv(file = path, header = TRUE, stringsAsFactors = FALSE)
path <- "Analysis/DataBase/DataSynchronization/NoOutliersLag1/TobinsQ.csv"
TobinNoOut <- read.csv(file = path, header = TRUE, stringsAsFactors = FALSE)
# I change names
RoaNoOut <- RoaNoOut %>% setnames(old = c("FinancialLeverage",
    "CarbonProductivity", "WaterProductivity", "WasteProductivity",
    "SustainabilityPayLink", "SustainableThemedCommitment",
    "AuditScore"), new = c("Leverage", "CaP", "WaP", "WastP",
    "SPL", "STC", "A"))
TobinNoOut <- TobinNoOut %>% setnames(old = c("FinancialLeverage",
    "CarbonProductivity", "WaterProductivity", "WasteProductivity",
    "SustainabilityPayLink", "SustainableThemedCommitment",
    "AuditScore"), new = c("Leverage", "CaP", "WaP", "WastP",
    "SPL", "STC", "A"))
# 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 + A + CaP + WaP + WastP +
    FirmSize + Leverage + Growth + Industry, data = RoaNoOut,
    model = "pooling")
```

```
TobinPooling <- plm(TobinsQ ~ SPL + STC + A + 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 + A + CaP + WaP + WastP +
    FirmSize + Leverage + Growth + Industry, data = RoaNoOut,
    model = "within", effect = "time")
TobinWithin <- plm(TobinsQ ~ SPL + STC + A + CaP + WaP +
    WastP + FirmSize + Leverage + Growth + Industry, data = TobinNoOut,
    model = "within", effect = "time")
# pFtest
pFtestRoa <- as.numeric(round(pFtest(RoaWithin, RoaPooling)$p.value,
    digits = 3))
pFtestTobin <- as.numeric(round(pFtest(TobinWithin, TobinPooling)$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, TobinsQ need to be
# estimated with the pooling ols estimations (i.e. model
# = 'pooling' in plm) while Roa with the within effect
# estimation.. Let's consolidate into a nice stargazer
# table
stargazer(TobinPooling, RoaWithin, title = "The impact of process and outcome-based CEP on C
    label = "Lag1", 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)))
```

### Appendix C : Outliers treatment

This appendix presents the R code I have used to identify and remove outliers from my database. This R scipt is the one contains in the following make file : *Analysis/DataBase/MakeFile_RemoveOutliers_Lag1.Rmd*. I have repeated this process three times, namely when dependent variables were lagged one year (see section : The impact of CEP on CFP) and two years behind others variables and also when the GreenScore variables was the only independent variables 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 models
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$TotalAssets <- log(ModelLag1$TotalAssets)
# I use the natural log for TobinsQ
ModelLag1$TobinsQ <- log(ModelLag1$TobinsQ)
# I rename some columns
ModelLag1 <- ModelLag1 %>% setnames(old = c("DebtToEquityRatio",
    "TotalAssets", "GicsClassification", "NetMargin"), new = c("Leverage",
    "FirmSize", "Industry", "Growth"))
```

```r
# I define my models in lm as cooks.distance do not
# 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
```

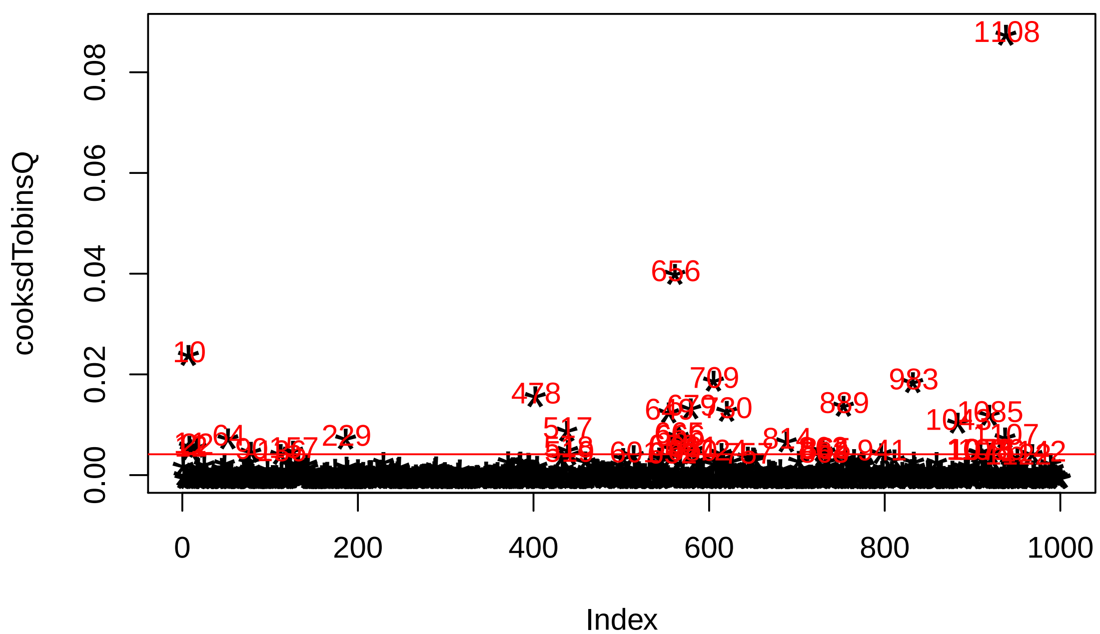
[1] 10 12 25 55 96 244 245 246 381 413 479 480 645 656 [15] 679 684 718 730 777 794 948 949 1106 1107 1108 1122 1123 1156 [29] 1171

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

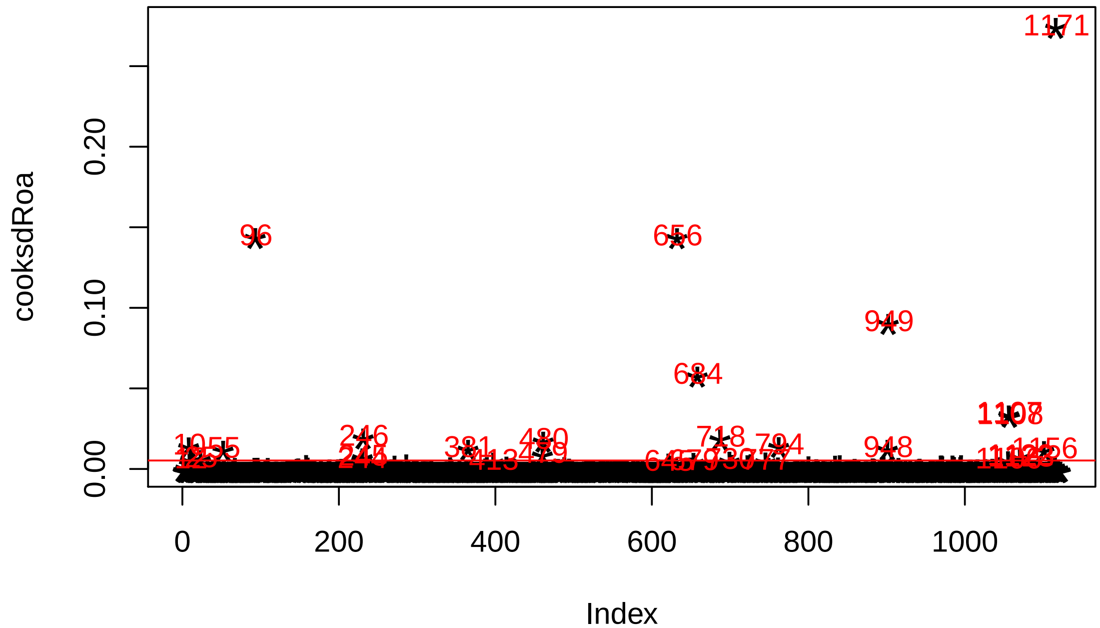
[1] 10 11 12 22 64 90 136 157 229 478 517 518 519 601 [15] 649 652 653 654 656 665 666 679 680 681 709 724 730 757 [29] 814 862 863 864 865 889 941 983 1043 1073 1074 1075 1085 1086 [43] 1107 1108 1122 1142

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

```
# I report influencial obervations on a graph
## TobinsQ plot cook's distance
plot(cooksdTobinsQ, pch = "*", cex = 2)
### 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)
### 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 R code 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.
path <- "Analysis/DataBase/DataSynchronization/NoOutliersLag2/Roa.csv"
RoaNoOut <- read.csv(file = path, header = TRUE, stringsAsFactors = FALSE)
path <- "Analysis/DataBase/DataSynchronization/NoOutliersLag2/TobinsQ.csv"
TobinNoOut <- read.csv(file = path, header = TRUE, stringsAsFactors = FALSE)
# I change names
RoaNoOut <- RoaNoOut %>% setnames(old = c("FinancialLeverage",
    "CarbonProductivity", "WaterProductivity", "WasteProductivity",
    "SustainabilityPayLink", "SustainableThemedCommitment",
    "AuditScore"), new = c("Leverage", "CaP", "WaP", "WastP",
    "SPL", "STC", "A"))
TobinNoOut <- TobinNoOut %>% setnames(old = c("FinancialLeverage",
    "CarbonProductivity", "WaterProductivity", "WasteProductivity",
    "SustainabilityPayLink", "SustainableThemedCommitment",
```

```
    "AuditScore"), new = c("Leverage", "CaP", "WaP", "WastP",
    "SPL", "STC", "A"))
# 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 + A + CaP + WaP + WastP +
    FirmSize + Leverage + Growth + Industry, data = RoaNoOut,
    model = "pooling")
TobinPooling <- plm(TobinsQ ~ SPL + STC + A + 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 + A + CaP + WaP + WastP +
    FirmSize + Leverage + Growth + Industry, data = RoaNoOut,
    model = "within", effect = "time")
```

```
TobinWithin <- plm(TobinsQ ~ SPL + STC + A + CaP + WaP +
    WastP + FirmSize + Leverage + Growth + Industry, data = TobinNoOut,
    model = "within", effect = "time")
# pFtest
pFtestRoa <- as.numeric(round(pFtest(RoaWithin, RoaPooling)$p.value,
    digits = 3))
pFtestTobin <- as.numeric(round(pFtest(TobinWithin, TobinPooling)$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
stargazer(TobinPooling, RoaPooling, title = "The impact of process and outcome-based CEP on
    label = "Lag2", 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)))
```

### 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.
path <- "Analysis/DataBase/DataSynchronization/NoOutliersLag1/GreenScore/Roa.csv"
RoaNoOut <- read.csv(file = path, header = TRUE, stringsAsFactors = FALSE)
path <- "Analysis/DataBase/DataSynchronization/NoOutliersLag1/GreenScore/TobinsQ.csv"
```

```
TobinNoOut <- read.csv(file = path, header = TRUE, stringsAsFactors = FALSE)
# I change names
RoaNoOut <- RoaNoOut %>% setnames(old = "FinancialLeverage",
    new = "Leverage")
TobinNoOut <- TobinNoOut %>% setnames(old = "FinancialLeverage",
    new = "Leverage")
# 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 ~ GreenScore + FirmSize + Leverage +
    Growth + Industry, data = RoaNoOut, model = "pooling")
TobinPooling <- plm(TobinsQ ~ GreenScore + 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 ~ GreenScore + FirmSize + Leverage +
```

```
    Growth + Industry, data = RoaNoOut, model = "within",
    effect = "time")
TobinWithin <- plm(TobinsQ ~ GreenScore + FirmSize + Leverage +
    Growth + Industry, data = TobinNoOut, model = "within",
    effect = "time")
# pFtest
pFtestRoa <- as.numeric(round(pFtest(RoaWithin, RoaPooling)$p.value,
    digits = 3))
pFtestTobin <- as.numeric(round(pFtest(TobinWithin, TobinPooling)$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
stargazer(TobinPooling, RoaWithin, title = "GreenScore - an alternative variable for CEP",
    label = "GreenScoreResults", 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)))
```

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