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) to make it *transparent* and *reproducible* for the reader. All ressources are available on my Github account. 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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Aknowledgments

I would like to thank some of you . . .

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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 their book *"The limits to growth"*, 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"* (Meadows et al., 1972: p23). In the nineties, Houghton and Change (1996) have also pleaded 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 evidence that mankind was not listening. For the first time in 400 000 years, atmospheric carbon dioxide crossed, in 1950, the level of 300 ppm. (Petit et al., 1999; Pieter Tans et al., 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 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 effetcs.

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. (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) has shown that, in the last century, the global sea level rose about 8 inches. Sabine et al. (2004) demonstrated 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. since the beginning of the Industrial Revolution, the acidity of surface ocean waters has, consequently, increased by about 30 percent (NOAA's Pacific Marine Environmental Laboratory, n.d.) leading, *inter alia*, to harsh repercussions to corals.

Today, humankind has to face consequences of its actions and move forward to ensure a more sustainable future. 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 Nations give hope.

Ecosystem degradation and resources depletion engender a threat to firm's longevity (Dowell et al., 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). The Business and Sustainable Development Commission (2017) (p12) report 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."* In other words, adopting environmental strategies ensure companies' competitiveness and survival in the near future.

Testa et al. (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. 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, providing evidence that green strategies impact the financial health of companies could convince them to incorporate environmental sustainability into their core values and actions.

Using a panel data of 393 US publicly traded companies for the period 2012-2014, this study explores whether Corporate Environmental Performance (i.e. CEP) influences Corporate Financial Performance (i.e. CFP) and observes the time influence (i.e. short-term 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 research.

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). Acording 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 is showing growing evidence that improving a company's environmental performance can lead to better economic or financial performance.

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 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 et al., 2011; Porter and Kramer, 2011). In the same logic, Freeman (1984) calls for a radical rethinking of our firm's model. According to him, 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 a negative contest from non-shareholder groups (e.g. boycotts, lawsuits, and protests). 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 developing profitable business strategies that deliver tangible 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?"*.

As claimed by Lu et al. (2014), in a competitive business world, answering this question is crucial to provide a genuine economic justification to the new paradigm. Although results are mixed, the large number of studies on the nexus between Corporate Environmental Performance and Corporate Financial Performance in the last three decades allowed the appearance of recent meta-analyses [1] (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) 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 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 and 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 and 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,

[1] Initially, the literature focused on the link between Corporate Social Performance (i.e. CSP) and Corporate Financial Performance. 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.

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 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 (Chen et al., 2018), environmental accidents and crises (Blacconiere and Patten, 1994), and environmental investment announcements (Gilley et al., 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 Xie and 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 (Chen et al., 2018; Li et al., 2017).

Although recent meta-analyses (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) have demonstrated the positive link between CEP and CFP, some scholars advanced that the multidimensionality of both 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 et al., 2017).

For instance, Busch and 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 and Crifo (2014) and Muhammad et al. (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 measures are characterized by a stronger relation to CEP than market-based and perceptual indicators (Albertini, 2013; Busch and Friede, 2018; Lu et al., 2014; Orlitzky et al., 2003; Wu, 2006).

1.4 When does it pay to be green?

Griffin and 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 and Mahon (1997) with the following question: *"When does it pay to be green?"* (Manrique and Martí-Ballester, 2017).

Zhang and Chen (2017) have shown that CEP has a negative relationship with short-term financial performance 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) have shown 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 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. 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 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 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 (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) 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 figure 2.1. The latter, inspired by Li Suhong et al. (2017) and 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 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 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 can help to provide a better understanding of the CEP-CFP nexus.

Lastly, Busch and Friede (2018) claimed that, to date and at a meta-research level, the call of Griffin and 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 further meta-analysis.

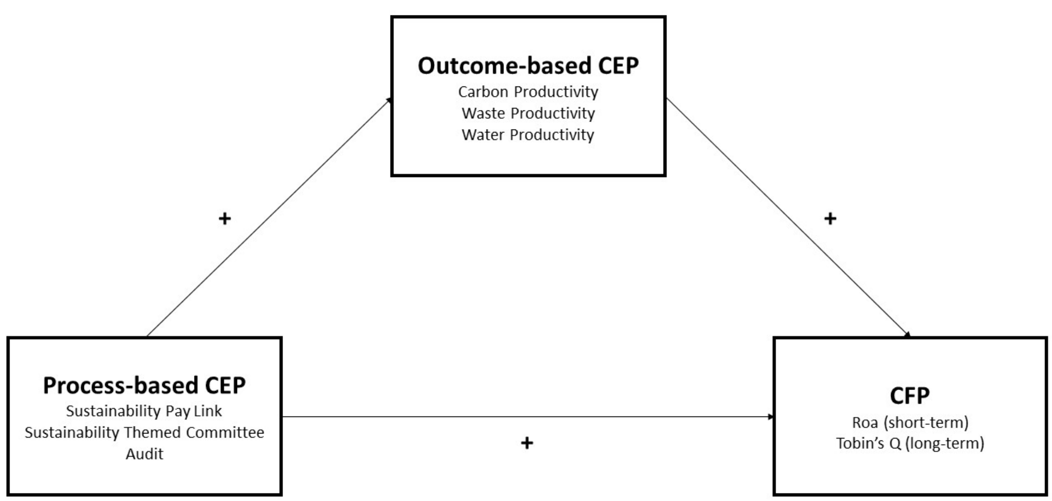


Figure 2.1: Research Framework

3 Data

3.1 Overview

The starting point of the 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 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 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 (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 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. 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). 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 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 seen several attempts to approximate Tobin's Q (Perfect and Wiles, 1994). This study collected Tobin's Q data directly on Ycharts. The latter 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 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

Both process-based and outcome-based CEP had been approached with KPI's of the Newsweek Green Ranking. I use "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 [2]

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. 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 accrues to 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.

[2] Newsweek Green Ranking has another KPI that captures outcome-based CEP (i.e. Energy Productivity). Due to multicollinearity concern (Variance Inflaction Factor superior to 5 for both Energy and Carbon Productivity), I do not consider it into my model.

3.4 Control Variables

Scholars (McWilliams et al., 2006; Surroca et al., 2010; Telle, 2006) 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 and 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) [3].*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). The *growth rate* is approached through the net margin (i.e. the ratio of earnings to revenue).

[3]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 tonnes)–waste recycled/reused (tones)]
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	A	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	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 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 CFP-CEP 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 offers a partial solution to the problem of omitted variables in the 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, α is the intercept, β 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, 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_{it}. In presence of correlation, then μ_i is considered as the *Fixed Effect* (i.e. FE) and the initial equation 5 becomes equation 6. Else, μ_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 imply that the Ordinary Least Square (i.e. OLS) estimators of β 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 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 :

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

The presence of RE model 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 Ho is verified, there is no RE model in the panel data. The presence of FE model 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 Ho is verified, 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 and Millo, 2008). Under FE model, 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 model, 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 and Taylor, 1981). If Ho is verified, scholars should use RE estimator.

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 effect on CFP (short-term and long-term).

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

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, A_{it} is a proxy for a firm's audit score, d_t represents time effect and u_{it} is the error term.

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

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, 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, d_t represents time effect and u_{it} is the error term.

Recent meta-analysis provided evidence of the bidirectional causality of the CFP-CEP 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 lag observations in independent and control variables one year behind the dependent variable. 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.

5 Results

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

5.1 Get a feel of the data

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 = 1176) 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. 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 of the database. 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 my model could suffer from multicollinearity. Table 5.3 reports the variance inflation factor (i.e. 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) defines outliers as observations in the dataset that appear to be unusual and discordant and which could lead to inconsistent results. Osborne and 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, namely observations whose removal causes a different conclusion in the analysis (Cousineau and Chartier, 2010).

The literature has not found common theoretical framework yet for the treatment of influential outliers (Cousineau and Chartier, 2010; Orr John et al., 1991). Tabachnick and Fidell (2007) argue that the imputation with the mean is the best method while Cousineau and 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. Dang et al. (2009) argue that a more elaborate technique involves replacing outliers with possible values (e.g. multiple imputation) while Barnett and Lewis (1994) would prefer to remove or windsorize them. Alternatively, Pollet and Meij (2017) argue 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. Influencial outliers had been identified based on the Cook's distance (Cook, 1977). This test 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 points is deleted, let's say $\hat{\beta}_i$. See Appendix C: Outliers treatment for furthers 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. 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*. Based on the p-value of the F test, the three models have FE model making both the random effect and pooled ols estimators biased.

Except for Model (1) which indicates no significant relation between sustainability pay link and carbon productivity, all models show evidence of a positive and highly statistically significant effect of process-based CEP on outcome-based CEP. These results support findings of Xie and Hayase (2007), Li et al. (2017) and Chen et al. (2018) confirming that implementation of environmental management measures allows companies to significantly increase their performance in carbon productivity, water productivity, and energy productivity which in turn will reduce their environmental impact. 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 pvalue of BPLM and F tests, model (4) had been estimated with the *pooled ols estimation* while model (5) had been estimated with the *fixed effects estimation*.

Model (4) shows evidence of a positive and highly statistically significant effect of sustainability pay link, audit score, and water productivity on long-term CEP. Model (5) shows evidence of a positive and highly statistically significant effect of sustainability pay link, sustainable themed commitment and carbon productivity on short-term CEP.

Those results corroborate recent meta-analyses that claim 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 and Benjamin, 2001; Orlitzky et al., 2003; Wang et al., 2016; Wu, 2006) and provides evidence that the relationship stays the same no matter the time horizon. Hypothesis 2, 3, 4 and 5 are verified.

Regarding control variables, firm size and industry sector influence negatively and significantly CFP in both models while growth has a positive impact, with an effect more pronounced in Model (4). These results support previous research (Busch and Hoffmann, 2011; Delmas et al., 2015; 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
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 Model (1)	WaP Model (2)	WastP Model (3)
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 Model (4)	Roa Model (5)
SPL	0.079* (0.044)	0.008** (0.004)
STC	0.063 (0.044)	0.012*** (0.004)
A	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

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 carried out two robustness tests.

First, 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 years behind corporate financial performance variables. 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 confirm findings of the previous section.

Secondly, I 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.

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

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, d_t represents time effect and u_{it} is the error term.

Model (4) had been estimated with the *pooled ols estimators* while Model (5) had been estimated with 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 does have a significant and positive effect on CFP (short-term and long-term).

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	Roa
	Model (4)	Model (5)
SPL	0.102** (0.044)	0.008** (0.004)
STC	0.062 (0.043)	0.011*** (0.004)
A	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: GreenScore - an alternative variable for CEP

	Dependent variable:	
	TobinsQ Model (4)	Roa Model (5)
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

Data of this study comes 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 had been carried out through excel [4]. Among those three rankings and of the 500 US companies, 405 companies were listed for each years.

Second, I obtained some of the financial datas (i.e. Roa, Financial Leverage, Total Assets and Net Margin) on Morningstar. More precisely, 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 download each csv file and bring all data into a tidy database. The R script is available on my Github account in the following Rmarkdown file : *Child/Analysis/MakeFile_WebScrapMorningStars.Rmd*. Outputs of this makefile are in the folder *Child/Analysis/DataBase/MorningStar*.

Due to some missing values, I had to complete Morningstar's data whith data coming from StockPup. The same process had been applied. The R script is available on my Github account 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 make file 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*.

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

Appendix B: Results - R script

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

Packages loading

```r
# 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

```r
# 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", "TotalAssets", "GicsClassification",
    "NetMargin", "CarbonProductivity", "WaterProductivity",
    "WasteProductivity", "SustainabilityPayLink", "SustainableThemedCommitment",
    "AuditScore")
nouveau <- c("Leverage", "FirmSize", "Industry", "Growth",
    "CaP", "WaP", "WastP", "SPL", "STC", "A")
Model1 <- Model %>% setnames(old = vieux, new = nouveau)
```

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
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'. 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 = "DesStat",
    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")
# 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

```
# 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
VifRoa <- car::vif(Roa)
VifTobin <- car::vif(TobinsQ)
# Summary in a nice 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 = "!",
    digits = 3)
```

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)))
# 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 <- 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 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
titre <- "The impact of process-based on outcome-based CEP"
stargazer(CarbonWithin, WaterWithin, WasteWithin, title = titre,
    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.
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("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 <- 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, 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 consolid
titre <- "The impact of process and outcome-based CEP on CFP (lag = 1)"
stargazer(TobinPooling, RoaWithin, title = titre, 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 used to identify and remove outliers from the database. This R scipt is the one contains in the makefile : *Analysis/DataBase/MakeFile_RemoveOutliers_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 GreenScore variables was the only independent variables considered into the econometric model (see section: Sensitivity Analysis).

```r
# 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)
```

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

```r
# 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
# 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
```

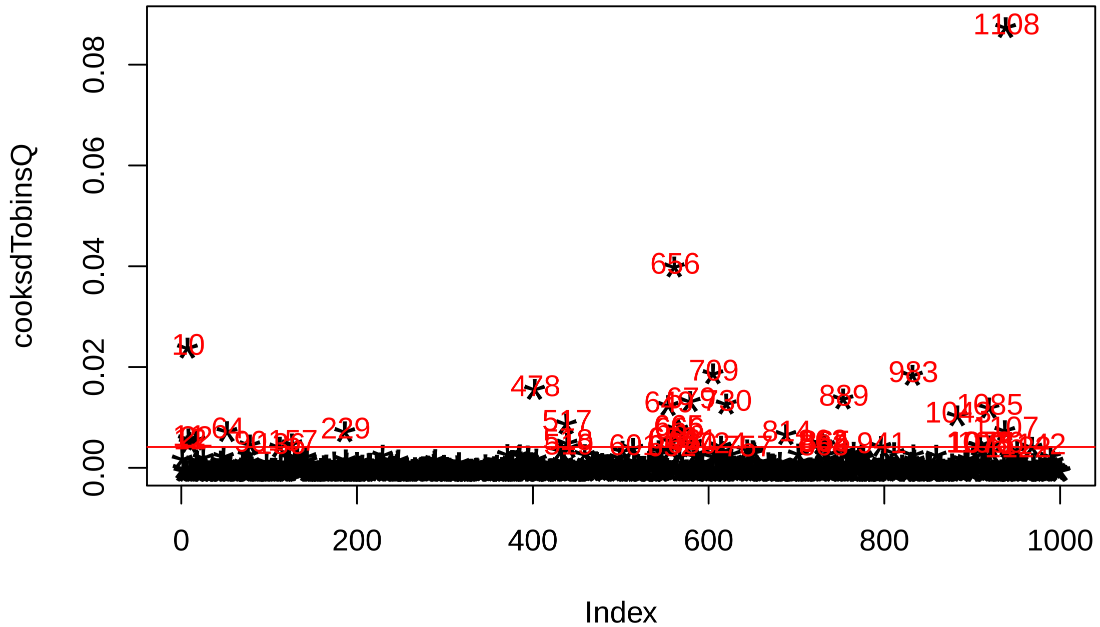
[1] 10 12 25 55 96 244 245 246 381 413 479 480 645 656 [15] 679 684 718 730 777 794 948 949 1106 1107 1108 1122 1123 1156 [29] 1171

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

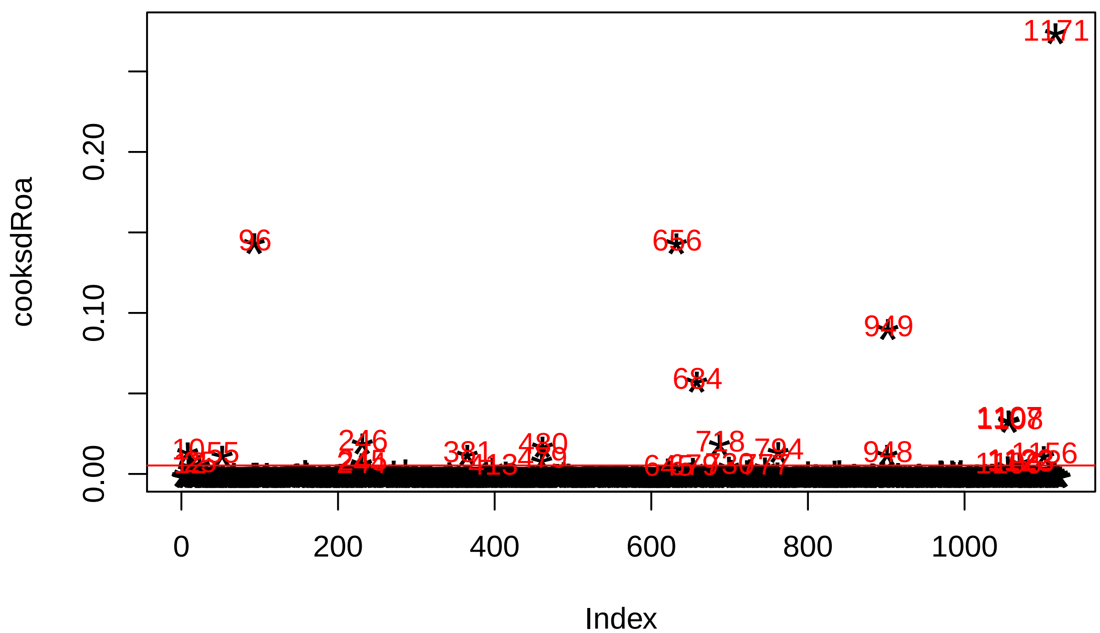
[1] 10 11 12 22 64 90 136 157 229 478 517 518 519 601 [15] 649 652 653 654 656 665 666 679 680 681 709 724 730 757 [29] 814 862 863 864 865 889 941 983 1043 1073 1074 1075 1085 1086 [43] 1107 1108 1122 1142

```
# 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)
### 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")
```


1108
656
10
709
478
983
829
1085
517
cooksdTobinsQ
Index
0.00
0.02
0.04
0.06
0.08
0
200
400
600
800
1000

```
## 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.
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("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
```

```r
# 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 <- 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, 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 = "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 <- 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 <- "GreenScore - an alternative variable for CEP"
stargazer(TobinPooling, RoaWithin, title = titre, 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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