This is the title of my thesis

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Abstract

This is an abstract

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. On the one hand, Houghton and Change (1996) anticipated in their first report an average global warming between +1° and +3.5° C until 2100 relative to the temperature of 1990. They also warned that an increase of temperatures superior to +2° C could have some harsh climatic repercussions. On the other hand the Kyoto Protocol had been written in 1997, enforced in 2005 and led to the first Global Agreement on global warming during the Paris Conference in 2015. Those different solutions implemented over the past decades did not have any significant impacts on the fight against global warming. Greenhouse Gas Emissions (GGE) have still increased considerably across years. Although the environmental consciousness-raising had already gained ground, according to Jean Jouzel (2017) human being have to act now if he wants to have a chance to reduce effects of climate change.

For the last several decades, companies have been more and more considered as entities responsible for stewardship of the natural environment (Majumdar and Marcus 2001; J. Przychodzen and Przychodzen 2015). Ecosystem degradation and resources depletion engender a threat to firm's longevity (Dowell, Hart, and Yeung 2000), and as a reaction, firms have to pro-actively adopt an environmental strategy (S. L. Hart 1995). In his speech at Lloyds of London 2015, Mark Carney, Governor of the Bank of England and Chair of the Financial Stability Board (FSB), identified climate change as one of the most material threats to financial stability (Elliott 2015). Companies facing higher risks associated to climate change are the ones subject to greater incentives to develop green strategies (Hoffman 2005). However, both economic benefits and strategic opportunities deriving from sustainable development are usually underestimated by managers and still too many companies do not feel concerned about global warming (Berchicci and King 2007; S. L. Hart 1995). Moreover, according to Scarpellini, Valero-Gil, and Portillo-Tarragona (2016), green projects are 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 and Tirole 2006), demonstrating that green development is a significant interest for firms could be a serious step forward in the fight against global warming.

Prendre en compte les remarques de Prof. Béreau 050418, see pdf dans dropbox

To be continued...

1 Literature Review

1.1 Two perspectives on Corporate Environmental Performance

The paradigm of profit maximization of Friedman (1970) have been widely challenged these last decades. Whereas Friedman (1970) considers investment in pollution efficient technology as deviation from the wealth maximization goal, the literature is showing growing evidences that improving a company's environmental performance can lead to better economic or financial performance, and not necessarily to an increase in cost. Ambec and Lanoie (2008) have 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 rather than simply adding to cost, properly crafted environmental standards can trigger innovation offsets, allowing companies to improve their resource productivity. He even redefined the self concept of value creation in advocating that the solution lies in the principle of shared value which involves creating economic value in a way that also creates value for society by addressing its needs and challenges (Porter et al. 2011, Porter and Kramer (2011)). Freeman (1984) call to a radical rethinking of our model of the firm. According to him, companies have to consider their stakeholder, namely *"any group or individual who can affect or is affected by the achievement of an organisation's objectives"* (p.25) or else face negative confrontation from non-shareholder groups, which can 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 unavoidable cost of doing business.

1.2 Does it pay to be green?

While more and more companies are embracing this new paradigm and develop profitable business strategies that deliver tangible social benefits, others keep the old fashion way of Friedman (1970). This dichotomy have 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 paradigm (Lu et al. 2014). Although results are mixed, the large quantity of studies on the nexus between Corporate Environmental Performance (i.e. CEP) and Corporate Financial Performance (i.e. CFP) in the last two decades allowed the appearance of recent meta-analyses [1] (Orlitzky and Benjamin 2001, Orlitzky, Schmidt, and Rynes (2003), Wu (2006), Albertini

[1] 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.

(2013), Dixon-Fowler et al. (2013), Endrikat, Guenther, and Hoppe (2014), Lu et al. (2014), Q. Wang, Dou, and Jia (2016), Busch and 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, Guenther, and Hoppe 2014).

1.3 CEP and CFP as a broad meta-construct

CFP is a broad meta-constructs and the current literature have shown that each construct play a moderator role in the relationship between CEP and CFP (Orlitzky, Schmidt, and Rynes 2003, Lu et al. (2014), Busch and Friede (2018)).Scholars have mainly adopted three broad subdivisions of CFP: market-based (investor returns), accounting-based (accounting returns), and perceptual (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, Guenther, and Hoppe (2014)). Scholars have used a wide variety of indicators as proxies for approaching the 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 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 (F. Chen, Ngniatedema, and Li 2018), environmental accidents and crises (Blacconiere and Patten 1994), and environmental investment announcements (Gilley et al. 2000). Endrikat, Guenther, and Hoppe (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. Scholars demonstrated that the first approach have a positive impact on the second one which in turn has a positive impact on financial performance (Li, Ngniatedema, and Chen 2017, F. Chen, Ngniatedema, and Li (2018)).

Although recent recent meta-analyses (Orlitzky and Benjamin 2001, Orlitzky, Schmidt, and Rynes (2003), Wu (2006), Albertini (2013), Dixon-Fowler et al. (2013), Endrikat, Guenther, and Hoppe (2014), Lu et al. (2014), Q. Wang, Dou, and Jia (2016), Busch and Friede (2018)) have demonstrated the positive link between CEP and CFP, some scholars advanced that the multidimensionality of both CEP and CFP constructs are one reason why the conclusion of the relationship between CEP and CFP have been so mixed (Albertini 2013, Endrikat, Guenther, and Hoppe (2014), Miroshnychenko, Barontini, and Testa (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 got a positive relation between ROA and CEP while no relation between Tobin's Q and CEP. A general consensus have shown that accounting-based CFP are characterized by a stronger relation to CEP than market-based and perceptual indicators (Orlitzky, Schmidt, and Rynes 2003, Wu (2006), Albertini (2013), Lu et al. (2014), Busch and Friede (2018)).

1.4 When does it pay to be green?

Griffin and Mahon (1997) was the first to call for research 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, Nairn-Birch, and 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, and 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 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. F. Chen, Ngniatedema, and Li (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 evidences that no common consensus have be 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 (Endrikat, Guenther, and Hoppe 2014, Delmas, Nairn-Birch, and Lim (2015), Zhang and Chen (2017), Manrique and Martí-Ballester (2017), Miroshnychenko, Barontini, and Testa (2017)). Indeed Endrikat, Guenther, and Hoppe (2014) highlitht 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

My research framework is summarized in the figure 2.1. The latter, inspired by Li Suhong, Ngniatedema Thomas, and Chen Fang (2017) and F. Chen, Ngniatedema, and Li (2018), aims at answering three calls. Firstly Endrikat, Guenther, and Hoppe (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, Ngniatedema Thomas, and Chen Fang (2017) and F. Chen, Ngniatedema, and Li (2018) were the first scholars to use the NewsWeek Green Ranking as a proxy for both process-based and output-based CEP and performed their analysis with a time frame of one year. Therefore applying a longitudinal study on this new database 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 and also provides new data for future meta-analysis.

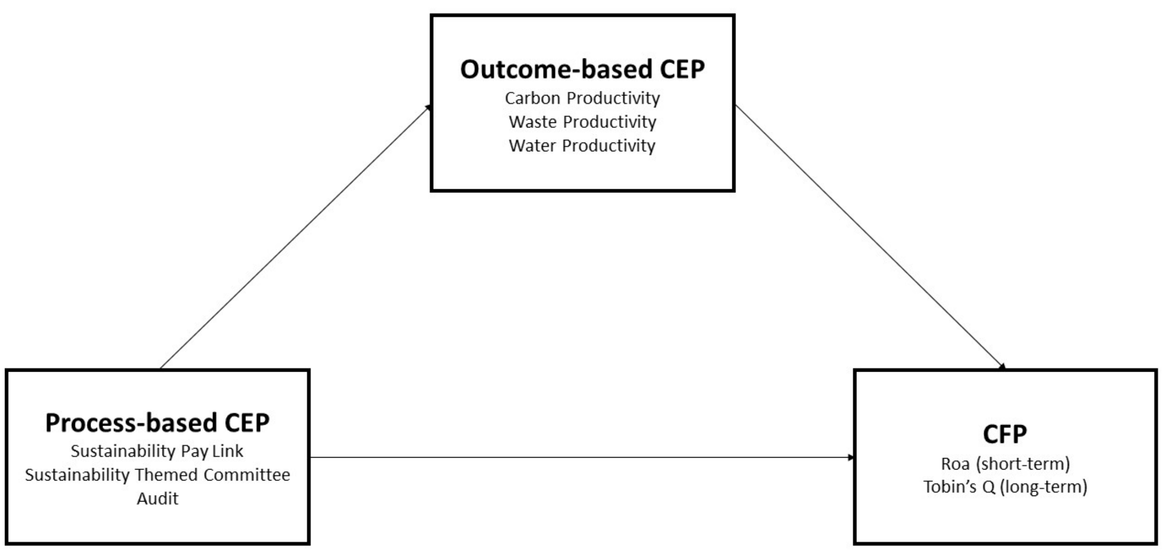


Figure 2.1: Research Framework

3 Data

3.1 Overview

The starting point of my data collection was the Newsweek Green Ranking which had assessed the world's largest publicly-traded companies in the US and in the world since 2009. This ranking 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 attribute an overall green score to companies. The score is based on a weighted average of key performance indicators (KPI's). This study uses these KPI's to measure both process-based and outcome-based of the 500 largest publicly-traded companies in the United States. Due to a methodology change in the 2014 Newsweek Green Rankings\footnote{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 ranking results prior to 2014 and ones subsequent can not be compared}, only the 2014, 2015 and 2016 ranking were considered. Among those three ranking and of the 500 US companies, 405 companies were listed for each years.

Even though green rankings were published in 2014, 2015 and 2016, each company is evaluated based on the 2012, 2013 and 2014 data. Therefore, measures for financial performance of companies will be based on the 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 describes my variables and following sections deeply explaine each variables.

3.2 Dependent Variables

Regarding dependent variables, Endrikat, Guenther, and Hoppe (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 and Sharma 2012, Cavaco and Crifo (2014), Muhammad et al. (2015), Delmas, Nairn-Birch, and Lim (2015), Semenova and Hassel (2016), Manrique and 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 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 prefers companies with Tobin's Q superior to one. Due to the complexity of calculating the replacement cost of a firm, the literature have seen several attempts to approximate Tobin's Q (Perfect and Wiles 1994). Tobin's Q value had been directly collected on Ycharts and this platform use the simple approximation of Chung and 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, and 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 the KPI's of the Newsweek Green Ranking. More precisely, I have used "Sustainability Pay Link", "Sustainability Themed Committee", and "Audit" as a proxies for process-based CEP and "Carbon Productivity", "Water Productivity" and "Waste Productivity" as a 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 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.

[2] 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 models.

3.4 Control Variables

Several scholars (Telle 2006, McWilliams, Siegel, and Wright (2006), Surroca, Tribó, and 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 and Whited 2013), Endrikat, Guenther, and Hoppe (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, Nairn-Birch, and Lim 2015, Miroshnychenko, Barontini, and Testa (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 or more precisely as the debt to equity ratio, namely 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).

[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	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 which is a common approach to adress the CFP-CEP nexus (Albertini 2013). Panel data analysis 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, Hsiao (2014)). Roberts and Whited (2013) also argued that using panel data offers a partial, but by no means complete and costless, 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, 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 components and do not change over time. 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 case it is correlated, then μ_i is considered as the *Fixed Effect* (i.e. FE) and the initial equation 5 is now described as the 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 implies that the Ordinary Least Square (i.e. OLS) estimator 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).

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 and Pagan 1980). This test is represented by the *plmtest* function in *R* and 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 and 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 and Millo 2008). Under the assumptions of the FE model, the random effects estimators are biased and inconsistent as μ_i is omitted and potentially correlated with the other regressors. Consequently, 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 is tested by the Hausman test (Hausman and 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 and Benjamin 2001, Orlitzky, Schmidt, and Rynes (2003), Wu (2006), Albertini (2013), Dixon-Fowler et al. (2013), Endrikat, Guenther, and Hoppe (2014), Lu et al. (2014), Q. Wang, Dou, and Jia (2016), Busch and Friede (2018)). This could cause simultaneous causality between the dependent and the independent variable and lead to endogeneity concern in my model (Sánchez-Ballesta and García-Meca 2007, Biørn and Krishnakumar (2008), Roberts and 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 and Ahuja 1996, Delmas, Nairn-Birch, and Lim (2015), Miroshnychenko, Barontini, and Testa (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, Nairn-Birch, and Lim (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 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 [4] (Cousineau and 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 and Chartier (2010), Zuur, Ieno, and 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, and Dubois Cathy 1991, Cousineau and Chartier (2010)). Tabachnick and Fidell (2007) argues 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

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

the observed distribution more leptokurtic, and possibly increase the likelihood of a type-I error. Dang, Serfling, and Zhou (2009) argue that more elaborate technique involves replacing outliers with possible values while Barnett and Lewis (1994) would prefer to remove or windsorized them. Alternatively, Pollet and 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 and 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	0.22	0.87	−3.00	2.50
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	23.83	1.39	19.45	28.82
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).

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

```
# 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

```r
# 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)))
```

```
# 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 model (i.e.
# Roa and TobinsQ) through the file =
# 'Analysis/MakeFile_RemoveOutliers_Lag1.rmd'.
# Consequently I just need to download them in this
# file.
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
```

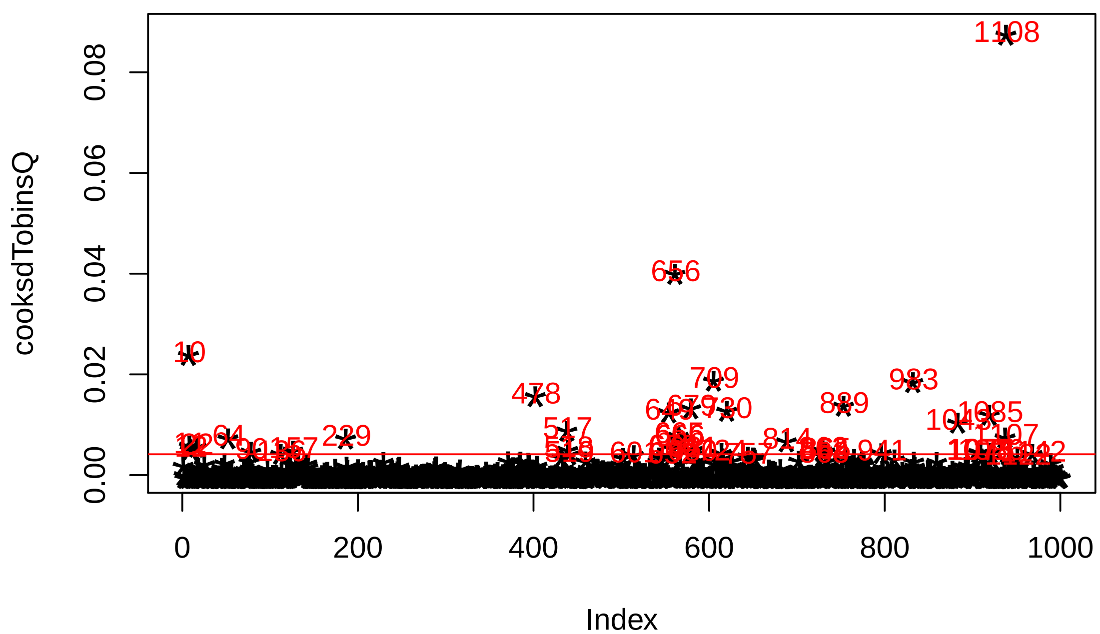
[1] 10 12 25 55 96 244 245 246 381 413 479 480 645 656 [15] 679 684 718 730 777 794 948 949 1106 1107 1108 1122 1123 1156 [29] 1171

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

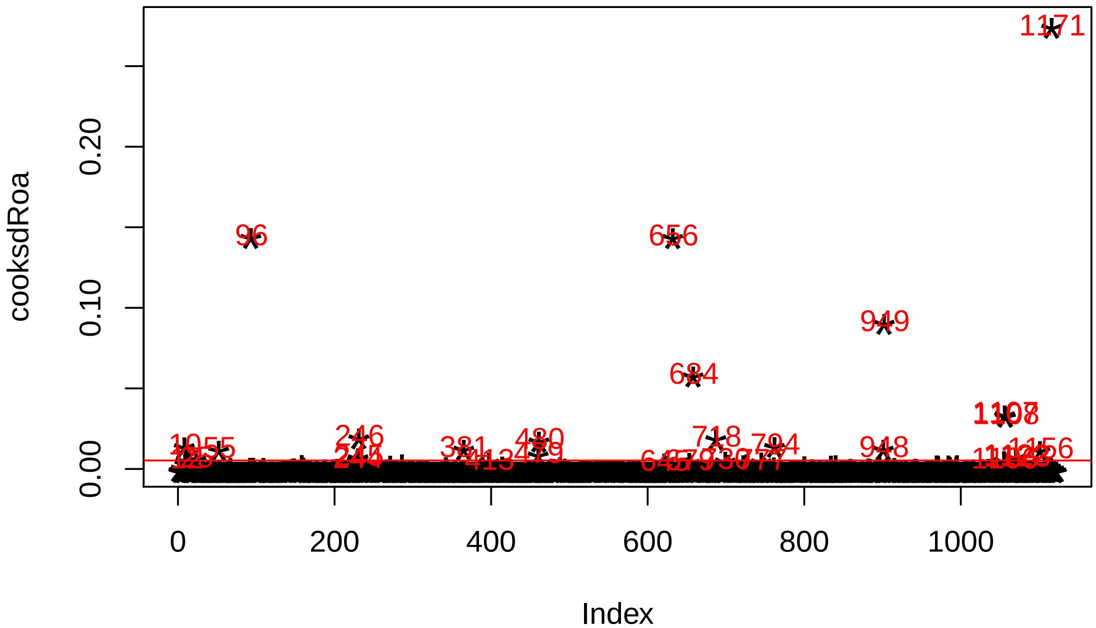
[1] 10 11 12 22 64 90 136 157 229 478 517 518 519 601 [15] 649 652 653 654 656 665 666 679 680 681 709 724 730 757 [29] 814 862 863 864 865 889 941 983 1043 1073 1074 1075 1085 1086 [43] 1107 1108 1122 1142

```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")
```



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