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Do environmental and emission disclosure affect firms' performance?

Evidence from sectorial micro-data

Abstract The study develops an analysis regarding the relationship between firms' financial performance and their environmental performance, with a particular focus on greenhouse gas-intensive sectors. Using financial and environmental data of international listed companies during the years 2011 to 2017, the financial impact of environmental performances, measured with multiple indicators that take into different account disclosure aspects, was estimated. The analysis was conducted across different sector aggregation levels, namely the whole group of industries, the Global Industry Classification System (GICS) Industry Group, and the GICS Industry. We find that environmental disclosure indexes are mostly not significant after controlling for environmental performance, suggesting that financial markets do not take into consideration these kinds of information in determining companies' stock prices. On the contrary, environmental performance seems to play an important role, and that holds even for high-emitting companies. Overall, our results are consistent with an interpretation that financial markets effectively consider the actual environmental performances of listed companies and only to a minor extent the quality of their disclosure.

1 Introduction

In 2015, three events fostered a decisive action to reduce greenhouse gas (GHG) emissions: the Paris Agreement, the publication of Sustainable Development Goals, and the Special Report of the Intergovernmental Panel on Climate Change (IPCC). The vision that led nations to participate relates to the transition to a low-carbon and climate-resilient economy. The EU has agreed on a set of targets for 2030 regarding GHG emission reductions. Among the means to fulfil such end, there are renewable energy and technologies for energy efficiency. To accelerate the transition, European institutions have approved rules on GHG emissions from land use as well as emissions targets for automotive sector (Commission, 2019). One of the most relevant policy actions that the European Commission has adopted is the launch of the European Green Deal in December 2019. This document tackles different issues such as reaching climate-neutrality by 2050 while abiding to just and inclusive transition principles. However, the main reason for the EU's commitment and actions is to engage the private sector and activate a leverage effect through private investments. To meet the EU's energy and climate 2030 targets, an estimated amount of €180 billion per year is needed. Nevertheless, further funds are necessary to achieve climate neutrality by 2050. Business opportunities are significant, and the private sector involvement appears crucial.
However, without evidence of financial performance improvements, the achievement of low-carbon targets could be perceived as costly and economically inefficient. The failure to achieve GHG emission targets unfolds negative uncertainties. Climate-related risks could severely impact business activities as well as financial institutions. Weather-related disasters caused a record of €283 billion in economic damages in 2017 and could affect up to two-thirds of the European population by 2100 compared with 5% today (Commission, 2019). Physical damages are just one of the climate-related risks that can affect businesses. The Task Force on Climate-related Financial Disclosure (TCFD) identified a second kind of risk: transition risk. This type of risk is associated to the costs that can arise when moving towards a less polluting, greener economy (i.e. changes in the regulation, demand shifts, etc.), and, together with physical risks, imply a risk for companies to see their assets strand. To provide some figures, CDP (ex-Carbon Disclosure Project) estimated that in the world's 500 largest companies, the amount reported which are linked to stranded to assets totals US$252 billion (CDP, 2019). In order to manage this risk, companies need to identify and implement a sound resilience business strategy, made of mitigation and adaptation actions.
However, as stated earlier, corporates expect an improvement in their financial performance following the investments in sustainability. For this reason, scholars begun to study the relationship between corporate environmental performance (CEP) and corporate financial performance (CFP), and several studies have linked the positive relation between CEP and CFP (Berg et al., 2019; Busch & Hoffmann, 2011; Delmas et al., 2015; Fisher-Vanden & Thorburn, 2011; Fujii et al., 2013; Iwata & Okada, 2011; Qi et al., 2014; Trumpp & Guen-

ther, 2017; Xie et al., 2019). This finding reversed the established conception according to which corporate responsibility is limited to financial performance (Friedman, 1970). However, literature has used different indicators to identify the CFP. ESG ratings, in this sense, were considered as a useful variable, as they offered information related to companies' environmental, social and governance indicators. Indexes composing ESG ratings capture implicitly the decision-making choices of the CEOs, as they are used as guidance and benchmarking (Berg et al., 2019). Previous literature (Kim & Adriaens, 2013) notes that disclosure-based measures are better predictors of corporate sustainability performance than performance-based measures. For this reason, some kind of conclusions can be drawn at country (Lyon et al., 2013; Qi et al., 2014) and sector level (Wang et al., 2014), but overall results are too mixed to allow us to draw final conclusions in this respect, mainly because of the heterogeneity of environmental indicators (Berg et al., 2019), and because of the different measurement levels that can be chosen (Busch & Hoffmann, 2011). The above brief discussion allows us to imagine that there is some sort of link that undergoes CFP and CEP proxies as ESG scores, but that another possible strategy to shed light on it could be implemented by considering environmental variables directly related to CEP, such as GHG emissions, waste, water use, etc. The choice of environmental variables depends on the analysed sector and the country. If a country's economy is heavily reliant on fossil fuels and does not have a rigid GHG regulation, the probability that emission levels will not affect firms' financial performance negatively is high (Wang et al., 2014). For this reason, we test three hypothesis. The first one relates to the positive correlation between ESG Score and firms' financial performance. The value of the former represents a general perspective of the firm with respect to environmental, social, and governance achievements. Since our focus is on the environmental side, the second hypothesis we consider concerns the positive correlation between the ESG Environmental Pillar Score and financial performance. According to Qiu et al. (2016), this variable highlights the quality of environmental disclosure and resolution to sustainability. We finally consider the hypothesis of a correlation between GHG emissions and firms' CFP. With respect to other works, our has a sectorial premise. The GHG emission is historically concentrated in few sectors (Heede, 2014). Such sectors could perceive a stronger pressure to increase their CEP. In this article we will test the three hypothesis according to each sector, using one model with ESG scores and one with GHG emissions. The dependent variable we chose is Tobin's Quotient (TQ) (i.e. a ratio between a physical asset's market value and its replacement value), which represents a proxy for capitalization. A set of control variables relating to structural and financial characteristics to regress econometric models will be added. The outcome of the study contributes to the existing empirical literature on the financial effects of environmental performance by comparing the different effects of the ESG Score, the ESG Environmental Pillar Score, and the effective environmental performance. The sectors we will focus on are defined according to two level of deepness. The higher level is the Global Industry Classification System (GICS) Industry Group level and the more specific one is the GICS

Industry level. The structure of the paper is as follows. Section two provides a literature review. Section three describes the data-set and the methodology, alongside with the sample and the variables used. Section four presents the results and discussion. In section five we provide conclusion for this study.

2 Literature review

There is extensive research around the link between firms' financial performance and their environmental performance. This link is underpinned by best practices and technologies driven by regulation, even when self-imposed (Bitat, 2018; Børing, 2019). This causal link might seem counter-intuitive. The regulation defines the cost of adaptation to compliant actors, coherently with what is suggested by the literature referring to the Porter Hypothesis. Expenditures in abatement and compliance would foster innovation and indirectly productivity. The mainstream perspective between the seventies and the eighties suggested the contrary to Porter Hypothesis. Any form of constraint on firm activity was seen as a mere cost, for the sole objective of corporations was profit (Friedman, 1970). Friedman argues that the only responsibility of business, hence managers, is to increase the shareholder's revenues. Thus, the underlying assumption is that the payoffs generated by ESG activities do not exceed their costs. During the last decades, various studies proved that environmental performance is positively related to the firm one. Perception of regulations and firm reputation are strong drivers of environmental improvements. For instance, Bitat (2018) suggested a revised form of Porter Hypothesis. Using a panel on German firms, he found no relation between policy instruments and environmental performance. What appears to be relevant, although is the perception of the policy instruments by firms subject to the regulation (Bitat, 2018). On the other hand, environmental innovation appeared as a burden in the short term for bigger firms. The study of Børing (2019) suggested that small and medium enterprises (SME) do not suffer of productivity burdens from environmental innovation.

A number of recent studies (Fisher-Vanden & Thorburn, 2011; Lyon et al., 2013) still find that firms who clearly state their engagement in environmentally responsible activities experience negative abnormal returns, suggesting that these kind of activities are perceived as simple costs and not a return generating investment. Fisher-Vanden and Thorburn (2011) note that corporate commitment to reduce greenhouse gas emissions appears to conflict with firm value-maximisation and that the highest price drop is experienced by high growth firms and firms with a poor corporate governance structure. With respect to the impact of legislation, Lee et al. (2015), note that in Japan, this dynamic produces opposite results by facilitating firms to invest in R&D and develop climate change capabilities and technologies. At the same time, Delmas et al. (2015) found that a decrease in GHG emissions is positively associated to an increase in Tobin's Q, implying that the market recognises a long-term value in emission reduction. It can be noted then that according to the most recent discussions on the topic, firms would benefit in many different ways from integrating ESG activities into their usual business processes. In the first place, firms and management teams would collect significant yields in terms of reputation. In fact, stakeholders' attention towards ESG factors is rising, as Xie et al. (2019) and Riedl and Smeets (2017) note (the latter specifically with respect to the significant increase in socially responsible investment). Xie et al. (2019) note that ESG disclosure has a positive impact on corporate efficiency at moderate disclosure level. Narrowing down, each pillar has its own effect, being Governance the most positive one, followed by Social and Environmental. Nevertheless, Fatemi et al. (2018), draw opposite conclusions, being the ESG Environmental Pillar the one that has a bigger impact. In particular, assessing the role that ESG disclosure has on the firm's financial performance, they find the following evidence: (i) environmental strengths increase firm's value, while environmental weaknesses decrease it; (ii) social and governance weaknesses decrease the market value; (iii) no evidence of positive impact for what concerns social and governance strengths. In fact, firms prefer to disclose favourable information and tend to withhold unfavourable information, in order to enhance their evaluation in the market, but buyers evaluate the undisclosed information as unfavourable information (Xie et al., 2019). Also, the countries' degree of stakeholder orientation, defined as the extent to which management's vision of roles and responsibilities include the interests and claims of non-stock holding groups (Dhaliwal et al., 2014), alongside the degree of transparency of the financial sector, appears to have an important role to play in the discussion. Analysing other market features, Sheikh (2018) states that in highly competitive markets and/or when product fluidity is high, Corporate Social Responsibility (CSR) is a factor that increases firm's value, while no influence can be detected in this sense in case of low competition markets and/or when product fluidity is low. It can then be said that the relationship between CFP and ESG performance is not straightforward. Lorraine et al. (2004) find on one side that, limited to the sample (composed by UK companies), there is no significant relationship between good-news events and abnormal returns, but on the other side, that bad–news events are followed by a significant negative return, while Qiu et al. (2016), although they find evidence on the positive link between social performance and firms' value, perhaps due to the historical importance of social issues in UK's political economy, fail to support their thesis about the positive relationship between environmental disclosure and firms' financial performance.

In this respect, Fujii et al. (2013) and Trumpp and Guenther (2017) note that not only there is no clear evidence of the positive/negative relationship that exists between environmental and financial performance, but also that the link may be non-linear. Another piece of research by Iwata and Okada (2011) provides evidence on which environmental issues have an impact on Japanese manufacturing firms CFP, and the sign of it. By analysing the impact that waste management and GHG emissions have on firm's Tobin's Q, what emerges is that responses of financial performance are different depending on each environmental issue and varying stakeholders' preferences. In Lee

et al. (2015), the relationship between CEP and CFP acquires a new dimension. In fact, investigating the impact that carbon emissions and environmental R&D investments have on Japanese firms' performance, emerges that, alongside the positive impact of CEP on CFP, stakeholders are more sensitive to negative impacts than to positive impacts due to the fact that people assign a higher value to a negative market value than to a positive market value. In this framework, regulatory innovations, such as the Kyoto Protocol, function as an enhancer by stimulating firms to take action and implement environmental R&D investments. Dangelico and Pontradolfo (2015) analyse the issue from a different point of view. Relying on the Resource Based View, they examine the effect that the different environmental managerial capabilities have on firms' performance, namely the capability to implement product and process-related environmental actions and to develop environmental collaborations with both business actors and non-business actors, on the market and from a reputational perspective. The results show a positive effect of the implementation capabilities on firms' market performance, specifically for what regards the energy and pollution topics.
What emerges is that no clear conclusion can be drawn on the relationship between CEP and CFP, being the measurement methodology a key aspect in delivering the results. As a matter of fact, Horvátová (2010) notes that the likelihood of finding a negative relationship rises significantly when using correlation relationships and portfolio analysis while using panel data and multiple regressions produces no significant outcome.

3 Data and Modelling

We used a dataset covering financial and environmental data for international listed companies for the years 2011 to 2017. For variable selection, we started from two-panel datasets. The first relates to the financial variables for all registered firms by Datastream. The latter was Bloomberg. This was a collection of the environmental variables we were interested in using, GHG and ESG scores. We merged the two datasets according to the International Securities Identification Number (ISIN)[1] of each firm. The resulting panel covers a pool of 2,438 international firms from different sectors over the 2011-2017 time range. The vast majority of the firms that we analyse is based in Australia, Europe and the United States. To measure the CEP we use Bloomberg's ESG Score, ESG Environmental Pillar Score and GHG. Financial variables were collected on Datastream. Following the relevant literature, the model considers Tobin's Quotient (TQ) as dependent variable (Smirlock et al., 2016). TQ represents a proxy for capitalization. When this index is above one, the firm's desired capital is higher than the actual capital; collecting capital from markets is productive in this moment. Values below 1 indicate that this firm might be over-capitalised; capital acquisition via markets is costly. According to the TQ, it is possible to predict whether a firm is prone to invest or divest. This theory

[1] https://www.isin.org/

is usually called Q-Theory of investment. Since the Q should not be negative in theory, we interpolated the dataset to have result equal to zero whenever it was negative. It can theoretically be negative when short term assets (e) overcome all the other in its numerator: long and short debt value (D, d) plus Market value of equity (E) plus liquidation value of the preferred stock (S^p). Its denominator represents the replacement value of installed capital (C^K):

$$Q = \frac{D + d + S^p + E - e}{C^K} \tag{1}$$

Tobin's Q represents a structural approach to evaluate firms performances. Since it is regarded as explanatory of investment (Blanchard et al., 1993; Hayashi, 1982), it could explain a potential for transition policies, representing the objective function of wealth maximisation (Aggarwal & Dow, 2011). Possible alternatives could be represented by stock returns (Bolton & Kacperczyk, 2020) or distance to default (Kölbel et al., 2020). The control variables account for occupation, financial and other structural factors. For the first we collected the logarithm of employment and turnover ("lnemploy" and "lnturn" on all tables). For financial accounts, we used the returns variables, gross earnings, long term debt and marginal profits. For return variables, we intended the ones on assets (ROA). According to the hypothesis, we add the ESG Score (esg), ESG Environmental Pillar Score (esgenv) and the GHG emissions alternatively. The choice of linear-log model reflected the necessity to aggregate large differences and great quantities for variables under consideration. Ratios and indexes are kept linear. It means that ESG Score, ESG Environmental Pillar Score and TQ are not logarithms. Once we have estimated the models for the whole pool of companies, we identify the highest emitting sectors, being us interested in understanding if and how financial markets evaluate the most exposed firms' environmental performances and climate disclosures. We choose the first four 4 digits GICS sectors according to total GHG emission (not intensity). The highest emitting sectors are Utilities, Energy, Materials and Transportation. It is a well-known fact that high emitting sectors are the most exposed to transition risks. We refer in particular to three main sources of risk: policy change, liability and technological changes. The first relates the emission of new binding regulation, affecting the economic activity of polluting sectors. Liability is relevant for this work and relates to the probability of image damage from GHG emissions. ESG investors are generally interested in reducing the quota of shares from polluting sectors. Finally, technological changes are intended to be paradigmatic shifts that induce obsolescence into a dominant technology. This vulnerability is related to sector dependence on hydrocarbons, both for energy and industrial purposes. In particular, technology is still immature to guarantee a risk-less transition to these sectors. Table 1 reports the descriptive statistics for the four sectors. Sample of firms from each group are respectively 889, 1575, 469 and 616. Lowest TQ on average is registered within the Utilities sector, while the highest within the Materials sector. Utilities register the highest average emission, with a flatter distribution than the others. Therefore it is also more probable to find lesser polluters.

Returns are mostly similar along four sectors. Of them, i.e. the Energy sector, has a higher standard deviation. On average, bigger employers deal in transportation.

[**Insert Table 1 Here**]

On a wider perspective, the average Energy firms perceive negative financial accounts despite almost "perfect" [2] capitalisation. Their Tobin's Q is almost equal to 1 (1,009). The distribution of these financial performances is non-normal with positive skewness. This indicates the presence of a few high performing firms among the others. It is common knowledge that within this sector, major actors operate in non-competitive markets. Therefore, above the 75 percentile firms achieve high ROA. ESG Environmental Pillar Score and ESG Score seem to be null before the 25 percentile for all sectors. It appears so in the occurrence of no disclosure, which seems a rather common practice. The best performers overall are firms within the sectors of utilities. Similar dynamics appears in the material sector. On the other hand, the worst performances are sensibly not as bleak in equity, but worst in assets. Since the four sectors resemble such heterogeneous distributions, we opted for splitting the estimation into four different clusters. Before estimation, we selected regressors according to two main reasons. One is methodological. Following previous studies, we added the Tobin's Q drivers such as firm structure, profitability and then environmental performance. We then used the correlation matrix to address possible interactions.

Taking a look at the descriptive statistics, we can note some immediate impact on our hypothesis. Although firms in the utility industry are the ones which produce the highest greenhouse gas emissions *ceteris paribus*, these companies report the higher ESG Score and ESG Environmental Pillar Score. They are followed by the Materials sector (second most emitting sector), Transportation sector (third for GHG emissions), and then by the Energy sector. In addition, it appears useful to notice that, with the exception of the Energy sector, all the others show an ESG Environmental Pillar Score well above the whole panel mean (24.99), suggesting some sort of positive correlation between emission levels and ESG commitment. The second evidence that stands out is that, despite the high ESG Score, when it comes to financial evaluation utilities and transportation firms appear to perform not as good as the other sector firms. On average, their Tobin's Q is 0.81 and 0.99 respectively, while all the others are above 1. It appears worth to mention that the considered sectors all report Tobin's Q lower than the whole pool mean (1.77), which could imply that high-emitting sectors are generally penalised. These dynamics are reported in figures 1, 2 and 3.

[**Insert Figure 1 Here**]

[2] Meaning the equality of market and book value

The scatter plot in Figure 1 reports the relation between the ESG Environmental Pillar Score and GHG. The colouring is based according to TQ, with darker tones indicating that TQ approaches zero. We highlighted the cloud for each sector we are interested in. It is not possible to evidence a global trend for TQ. In sectors such as Utilities and Transportation there seem to be weak or no relation at all. These evidence leads us to consider two aspects for what concerns Utilities and Transportation sectors. The first one is that financial markets penalise GHG emissions. The second one is that financial markets do not appreciate firms' environmental commitment. Understanding which of these two aspects is relevant is a key factor for comprehending the relationship that exists between financial performance and environmental performance. In order to understand the magnitude of effect variability across sectors, we run a separate model. Furthermore, we assumed linearity of regressors following previous literature (Busch & Hoffmann, 2011; Lorraine et al., 2004). Hypothesis 1 is tested to verify if non-financial information is relevant for pricing the cost of equity capital, while Hypothesis 2 is strictly related to the environmental pillar that composes the aggregated ESG Score.
The analysis will focus on the ESG Environmental Pillar Score, rather than the Social and Governance pillars. In other words, we check if the environment-related information that a firm discloses is of some value for the market. Hypothesis 3, instead, is intended to test if firms' environmental performance can directly influence stock prices. The hypotheses require the operationalization of the relation between variables. We choose to use the to estimate coefficients using linear regression models. In order to avoid biases, we employed a research framework similar to that of cited works. In order to produce innovative results, we added a brief pre-selection procedure regarding possible idiosyncrasies for errors. To control for autocorrelation and cross-sectional dependence, a set of robustness check is applied. The first two hypotheses take into consideration disclosure indexes, being the second one strictly linked to the environmental factors, while the third accounts for environmental performance. ESG Score and the ESG Environmental Pillar Score are correlated at 95%. We used this information to drop the first one. Considering the strong correlation, one explains the other. Therefore, we would use data to two times in the model. We used the Global Industry Classification Standard (GICS) as a classification of various sectors. The classification involves the ordering of sectors according to digits. All firms are grouped according to participation. Beginning from the widest, we have Sectors, Industry Groups, Industries and Sub-Industries with respectively 2, 4, 6 and 8 digits. We chose to work on major polluting sectors (GICS at four digits), and within these, we chose the most polluting industries.
The work resembles a stage analysis. The first step assessed the impact of our variables set for four digits GICS. The second step analysed the most pollutant sectors at six digits level. In this manner, we will test whether our results hold at the micro and or macro level. Furthermore, this methodology contemplates different results for sectors, as they perceive climate change risk differently.

For reaching our purpose, we estimate the specifications of a linear model with fixed effects. Such configuration allows for the collection of unexplained but strictly exogenous factors. Among these we could find the geographical location, influencing different policy setting. Another aspect could be public participation, which is relevant in the case of Utilities within European markets. The efficiency over a random-effects model is proven by the results of the Hausman test we performed. Following literature methodology, we set the dependent variable to be Tobin's Q, while the independent variables are the following: turnover, long-term debt, EBITDA, number of employees, the margin of profit, ROA. The second stage of the model is implemented by running a two-stage feasible GLS model to account for possible auto-correlation issues. The equation that defines the model is the following:

$$TQ_{it} = \begin{pmatrix} lnghg_{it} \\ esg_{it} \end{pmatrix} \beta + \begin{pmatrix} lnturn_{it} \\ lnld_{it} \\ lnEBITDA_{it} \\ lnemploy_{it} \\ ROA_{it} \end{pmatrix} \gamma + \alpha_i + u_{it} \tag{2}$$

Estimation will be based according to our panel of N firms along the time span of T. We collected on the left hand the dependent variable y_{it}. The set of independent variables is collected within the matrix X_{it}. Its regressors constitute the vector β of length equal to the number of columns of X_{it}. Since we intend to control for fixed effect on each firm of the panel, we added the vector α_i. The other class of robustness check we employed relates the error term u_{it}. In the first place, we are interested in verifying if environmental disclosure or performance (ESG Score and GHG emissions) had a significant effect on capitalisation *ceteris paribus*. Therefore, we collected the relevant control variables within the vector z_{it}. The hypothesis we defined above will involve a specific two-sided statistical test on β, while γ will control for structural factors and financial ones. We repeated the estimation on six digits GICS. Model and variables do not change. Statistical models do not change for each sector. All were treated to assess relevant biases. We reported the results within Table 2 We treated for auto-correlation of errors, fixed effect, auto-regressive factors and moving averages. We applied the Breusch–Godfrey test for serial correlation. P-value, in this case, was nearly zero. Therefore, we rejected the null hypothesis of no correlation of the error term. The Durbin-Watson and Baltagi-Wu tests show idiosyncratic shocks on TQ. We corrected the bias using a generalised model with time and individual effects. Estimator generalisation corrects for serial correlation of errors. The loss of significance of regressors is risible, and there is no change in signs.

We employed the Lagrange multiplier test to investigate the presence of individual fixed effects with success. This strategy was preferred to time fixed effects as the test results suggested lower statistical significance. We could not control for cross-sectional dependence, due to the limited time/individual ratio. Nevertheless, Feasible Generalised Least Square performs robust results in such conditions. Such regressor is based on a two-stage approach—the first consists of an Ordinary Least Squares estimation. Residuals estimated in this way contain the biases of the standard model. Their covariance matrix is then used as a weight to the second stage "OLS" estimation, changing the structure of data. The cost of this methodology is the loss of sensitivity. This loss might affect the capacity of a model to predict, as uses less information than available. We believed it was the preferred choice as the benefit of unbiased estimates overcame the cost of lower predictability. Next section will investigate the results in two main stages. The first focuses on model estimates over GICS 4 digits sectors, and it follows on GICS 6 digits.

4 Results

Following the research framework, we tested our hypotheses on two GICS industry classification. As reported in Table 3, the environmental score and ESG one are strongly related. Therefore, the first two hypotheses are necessarily entangled. We could not test them jointly without incurring in selection bias. Furthermore, we see that correlation is minimal for returns on equity and assets. In this case, socio-environmental performances reported had no impact on the market allocation of polluting firms.

[**Insert Table 3 Here**]

The following tables report the results of our fixed-effect model. Being the data we have used for this research differentiated by GICS Industry Group, and at a narrower level, by industry, we run a regression for each of the variables of interest, namely ESG Environmental Score and greenhouse gas emissions differentiating. For the former, we decided to select are the first four groups for greenhouse gas emissions, i.e. Energy, Materials, Transportation, and Utilities. Since the model relates continuous variables and in some cases a natural logarithm, a clarification is needed. When considering emissions and structural variables, we are talking about semi-elasticity. Therefore, each β represents the result of an absolute change of GHG to a percentage of Y. We transformed similarly structural variables such as long term debt and EBITDA in logarithms, with the exception of ROA. Table 4 reports the estimates for the two-step feasible GLS models by GICS Industry Group. The first column reports the variables included in each model, while columns from two to nine report coefficients and standard errors (between brackets) of each GICS Industry Group. The stars indicate the level of significance.

[**Insert Table 4 Here**]

Structural variables affect each sector's capitalisation similarly. For instance, turnover has similar impacts. It always resembles a positive sign, and in terms of magnitude, it is the biggest factor among all structural variables. Long term debt is negatively correlated to Tobin's Q, as it is contained within the denom-

inator. EBITDA is positively sloped unless we add GHG to the model (only for the Materials sector). Marginal Profits are significant, but risible compared to the other factors. Employment dimension has no impact on capitalisation, except for Transportation, Utilities and Materials (when GHG emissions are taken into account). ROA resembles negligible, but mostly positive values. The impact from high correlation to structural variables might induce a loss of significance. Overall, this does not change the sign of results. It is important to recall that the ESG Score is less correlated. ESG Environmental Pillar Score is positive and statistically significant for Materials and Transportation. However, emissions register for these sectors a negative impact for the first and a positive one for the latter. This is probably due to the necessary input that affects value structure for Transportation firms. TQ for Energy and Utilities is not affected by ESG ratings. Although it is affected negatively from GHG emissions. Therefore, the percentage increase of GHG emission reduces TQ in unitary terms. It is a generally negative but relatively greater reduction for Energy. This is a relevant result as TQ from these sectors does not register a much greater variance than other sectors. Therefore, this semi-elastic relation is a particular case. One particular difference concerns the Transportation sector, for which evidence suggests ESG and GHG emissions positively affects TQ. Table 4 shows that GHG emissions affect capitalization despite the size of emissions. Only firms within the sector of Transportation and the industry of Electric Utilities display positive but limited semi-elastic impact. Looking at subsystems, we find different results.
Table 5 summarises the estimates of the GLS Models sorted by GICS 6 digits Industry, meaning that we took a deeper look into the composition of each GICS Industry Group. In fact, maintaining the GHG emission levels as a selection criterion for the analysed sectors, we break down each GICS Industry Group at industrial level. We chose to report only the GICS Industries, for each GICS Industry Group, above a certain threshold of observations, namely Energy Equipment and Services, and Oil, Gas and Consumable Fuels for the Energy Industry Group, Chemicals for the Materials Industry Group, and Electric Utilities for the Utilities Industry Group.

[**Insert Table 5 Here**]

In this case, we see that structural variables's coefficients are coherent with the previous case, except for Energy Equipment and Services' TQ which is negatively affected by turnover. For others, this industry's TQ is negatively affected by long term debt and profit margins. This last variable affects similarly all industries analysed. On the other hand, ROA has a positive impact on the dependent variable. Oil and gas firms register low significance for ESG and structural variables. In addition, their TQ is negatively affected by GHG emissions. Chemicals related firms register significant results for structural variables and ESG. We did not find here relevant effects from GHG. Finally, we estimated the models for Electric Utilities. This industry does not differ from the others for the impact of structural variables and ROA. For structural

variables, Energy Equipment and Services capitalization is mainly affected by EBITDA and number of employees. On the other hand, this is the only sector among these four to be damaged by turnover. Moreover, gross profit has a positive effect also on Chemicals and Electric Utilities.
Both sets of regressions have been fitting. All R^2 are over 70%. All models have passed the F test, with all P-values near zero. Models treating GICS 6 digits data did not lose significance while using less data. However, it is complex to evaluate the magnitude of effect that CEP has on CFP: GHG and ESG Environmental Pillar Score have different distributions. In the next section, we commented the outcome of the regressions.

5 Discussion

The results presented the estimates of the relation between CEP and CFP. The variables indicating the former were GHG and ESG Environmental Pillar Score. The interpretation of the results is bounded to the definition of TQ. It is a ratio between market value and book value. Therefore, CEP-CFP coefficients might be interpreted as effects on the numerator (market value) or denominator (book value). On the condition of an increase in CEP with a positive coefficient, the TQ might increase due to a market value appreciation (assuming book-value constant). For similar conditions, the TQ could also rise as as consequence of a reduction of book-value with respect to market value (Delmas et al., 2015; Hennessy, 2004; Kim & Adriaens, 2013; Lee et al., 2015). We found non-negative signs in the coefficient of ESG Environmental Pillar Score to TQ across all sectors. This probably suggests that market value is positively affected by better-measured performances, and this kind of relationship is stronger in more stakeholder-oriented countries (Dhaliwal et al., 2014; Xie et al., 2019). Interestingly, where the disclosure was significant, pollution was too. In this case, it seems reasonable that carbon policies affected structural dynamics in a firm. Qi et al. (2014) argue that under certain conditions (i.e. resource slack), environmental improvements can benefit corporate financial performance. In fact, financial markets appear to value positively firms environmental commitment, which needs continuous investment without an immediate payoff, supported by slack resources which provide assurance for scarcity problems in allocating resources for environmental improvement. Neither of those comprehends a negative downturn. For the first, market value comes at constant corporate net worth. For the other, corporate net worth reduction comes at no loss of market value. For instance, Lee et al. (2015) note that compliance to regulatory legislation oriented at reducing GHG emissions, may trigger environmental R&D investment, which will contribute to environmental innovation and ultimately to better financial performance.

In order to plain the differences according to the scale, we interpreted the effects according to the standard deviation (σ) per variable within the sector. For instance, it is possible that the independent variable (GHG or ESG Environmental Pillar Score) affects with similar β TQ. We can measure the impact of one $\sigma(X)$ with respect to $\sigma(TQ)$.

[Insert Table 6 Here]

In Table 6 we collected the results at digits 4 GICS cluster. In the case of firms within the Materials cluster (B), the effect of one $\sigma(X)$ variation of disclosure quality affects 5.3% of $\sigma(TQ)$ variation. It represents a minimal effect if we compare it to GHG emissions. For the same sector one $\sigma(X)$ of emissions is translated to -46% reduction of a $\sigma(TQ)$. We repeated the approach for Energy (A), Transportation (C) and Utilities (D). Overall, standardised variations of emissions register greater impact on TQ value. By recalling the level of interaction among disclosure quality and emissions, it is evident that the former cannot substitute the second in evaluating environmental performances. It would require great disclosure effort to substitute a limited absolute reduction of GHG. The only GICS 4 digits sector where this does not work is Transportation. Here we see that disclosure affects TQ (8.5%) better than emission increases (4.2%). According to these outcomes, improvements in composite indicators presents limited results in terms of increased TQ if compared to total GHG abatement. Abatement is strongly correlated to structural variables, suggesting that abatement policies could imply disruptive changes. Market to book value would be positively affected in GICS sectors such as Energy, Materials and Utilities. The Transportation sector is vulnerable to abatement policies, as the coefficient is positive: reduction in GHG will negatively affect TQ at current conditions. However, the expected impact of abatment in one standard deviation of GHG (equivalent to 51.93 mt) to one standard deviation of TQ (equivalent to 0.640) is small (0.042). This indicates that abatement policies might have limited effects on the financial structure of Transportation related firms.
The second group of estimation relates GICS digits 6 cluster. We reported the relative impact of $\sigma(X)$ within Table 7.

[Insert Table 7 Here]

It emerges here that better environmental disclosure almost cover the impact of emissions on TQ. There are two sub-sectorial clusters that register positive effect of disclosure. These are Energy Equipment and Services (a) and Chemicals (c). The interesting dynamics we found was that for the first sub-sector, TQ increases or decreases, in terms of standard deviation, of the same amount when, respectively, the ESG Environmental Pillar Score or the GHG Emissions increase. For these sectors, we register an indifference between abatement policies and disclosure ones with respect to TQ. This might sound dire for climate change mitigation, but another hypothesis has recently arose. Market value dependence from carbon emission might be affected by the dynamic of carbon premium (Bolton & Kacperczyk, 2020). Firms must guarantee higher market performances for carbon emissions. In our study, we found greatest polluters are structurally affected by emissions. Even more interestingly, Transportation (GICS 4) and Electric Utilities (GICS 6) register positive effects on both ESG and emission. Nevertheless, semi-elasticity from the second are always greater in terms of absolute dimension. In case of both positive signs, ESG Score requires marginally more to affect TQ than GHG emissions. Among our results, we have to report the strange case of Chemicals (c). This panel register no impact of emissions on TQ. It has registered that improvements of ESG Environmental Pillar Score positively affect TQ (0.145). The positive relation between market value and GHG emissions could be determined by a carbon premium dynamic: investors are compensated for potential cost of GHG with higher returns. The requirement of higher stock returns is negatively reflected on abatement costs according to our results. When GHG emissions are positively related to TQ, their abatement negatively affects TQ. If the coefficient that captures such relation contains *ceteris paribus* a premium, then the coefficient is higher. Abatements reduce market value but may increase the CEP outlook of firms via ESG Environmental Pillar Score, hence TQ. However, the difference in slope of CEP coefficients indicates that better composite indicators may not compensate abatement costs for Electric Utilites. In other words, sectors with negative abatement cost but positive composite indicator impact may underperform with better CEP. Alternatively, as Busch and Hoffmann (2011) state, capital market participants may consider superior corporate carbon performance as a virtue. It is also possible that we were not able to measure impact due to low quality of disclosure in this class. Low quality might undermine the comprehended role of GHG in firm structural value and therefore no impact is registered. Great polluters tend to present stricter policies for corporate social responsibility (Cooper et al., 2018). Thus, no impact of ESG Environmental Pillar Score to Tobin's Q might indicate green-washing practices.

Further aspects could be highlighted according to the recent literature regarding transition risks. We refer to liability risk for GHG emission. It might be reasonable that we find no significant relation for three possible reasons. The first relates the risk aversion that ESG investors have for polluting firms. Their strategy would then be to avoid them, sorting no effect on market value. Therefore, TQ is not affected by liable energy use above the 75 percentile for GHG emissions. The second possible explanation relates to our data. Biggest polluters are generally better in terms of disclosure quality; emissions and ESG Environmental (E) Pillar are positively correlated. Thus, better acknowledgement might simply "sterilise" the negative effects of GHG emissions on TQ. As a result, the use of ESG Score and its interpretation is counter-intuitive if compared to GHG. The third explanation that could be given is that, as Riedl and Smeets (2017) state, socially responsible companies' asset prices might be affected only in the long run. Overall, abatement policies might have greater positive effects on TQ than high quality environmental disclosure.

6 Conclusions

In this study we addressed the still open issue of if and how financial operators evaluate firms' involvement in sustainable activities. In particular, the paper's focus is on firms' CEP, climate disclosure and CFP. Using a panel dataset that covers a pool of international firms over seven years, we run a linear regression model oriented at shedding some light on this relationship. We found some interesting evidences. In the first place, that for some polluters the ESG Score and the ESG Environmental Pillar Score are mainly not significant. In other cases might reflect effective policies of decarbonisation. One of the possible explanations is that financial markets may not take into consideration these kinds of information when it comes to price firms' stock. This kind of behaviour could stem from the belief that climate disclosures do not report relevant information, being used only as a compliance instrument from firms that are obliged to publish it, or by the confusion that these indicators generate, being an aggregation of qualitative and quantitative information, that varies even across different data providers. This statement is also suggested by the fact that, on average, the highest emitting macro-sectors are also the ones that report ESG Scores well above the average. On the other hand, greater emitters are not. In the second place, GHG emissions seem to play an important role in defining stock market prices. Observing the statistical relevance of the variable, the sign, it does seem reasonable to state that the emission levels contribute substantially in the pricing process. Furthermore, it can be stated that the paradigm that, for high-emitting sectors, associates emissions to production, hence revenue, and consequentially positive financial performance, does not hold anymore. As a matter of fact, the considered sectors report poor CFP if confronted with the average. Part of the explanation can be attributed to the fact that, at least for what concerns European firms, EU's regulatory framework intends to discourage GHG emissions growth, if not to pursue climate neutrality by 2050. As previously stated, research in this field is still necessary. In particular, it would be useful to understand more deeply the role that EU's regulation has on firms' and stock markets behaviour. Alongside this field of research, the application of non-linear models to test the contribution of GHG emission dynamics could provide further insights on the role that this variable has.

7 Appendix

Table 3 represents the correlation matrix among variables. The calculations were made according to the whole pool of firms, without sector clustering. Therefore it represents a general point of view. We see that variables such ESG Score, ESG Environmental Pillar Score and Greenhouse gasses emissions are negatively correlated to the Tobin's Q. On the other hand, they positively affect each other. This is consistent to cited literature (Kim & Adriaens, 2013; Siew et al., 2013). Dimension of occupation is negatively correlated with liquidity of firms, but positively related to environmental variables in this panel. Lastly, "prof_marg" are negatively correlated to other variables except for financial ones. Curiously enough, their sign with environmental variable is negative.

[**Insert Table 3 Here**]

We reported this correlation using Figures 1, 2, and 3. Positive relation between ESG Environmental Pillar Score and GHG emissions is reported in Figure 2, while Figure 3 represents the relation between ESG score and ESG Environmental Pillar Score. As previously reported, we focused on the average values between 2011 and 2017, in order to counter time effects and simplify the cross-sectional plotting. All macro-sectors reported positive correlations.

[**Insert Figure 2 Here**]

It is possible to point out the difference in slope that may arise from Utilities and Materials. In this case, ESG Environmental Pillar and GHG emissions are at least positively related. Less striking correlation is evident for ESG score vs GHG emissions. We highlighted such relationship in Figure 2. Transportation sector has the lowest correlation among all four. Nevertheless, ESG score is positively correlated to GHG emissions with possible fixed effects. The strong correlation between ESG score and ESG Environmental Pillar is plotted on Figure 3. The difference with the previous is that we could not find sings indicative of fixed effects between firms. The relation is positive and with low residuals. In this case we could see that Transportation is the only sector to have a narrower interval with respect to the other firms.

[**Insert Figure 3 Here**]

We reported the results of the fitting line in Tables 8, 9, and 10. These are simply reporting the estimates of those regression line. The most interesting results are probably collected within the last one. The other two predict between 4% to 20% the endogenous variable. ESG Score represents ESG Environmental Pillar Score at 90%. The results show that after a certain disclosure quality index (it varies for each sector) each ESG Score is equivalent to 1.2, 1.3 points of ESG Environmental Pillar Score.

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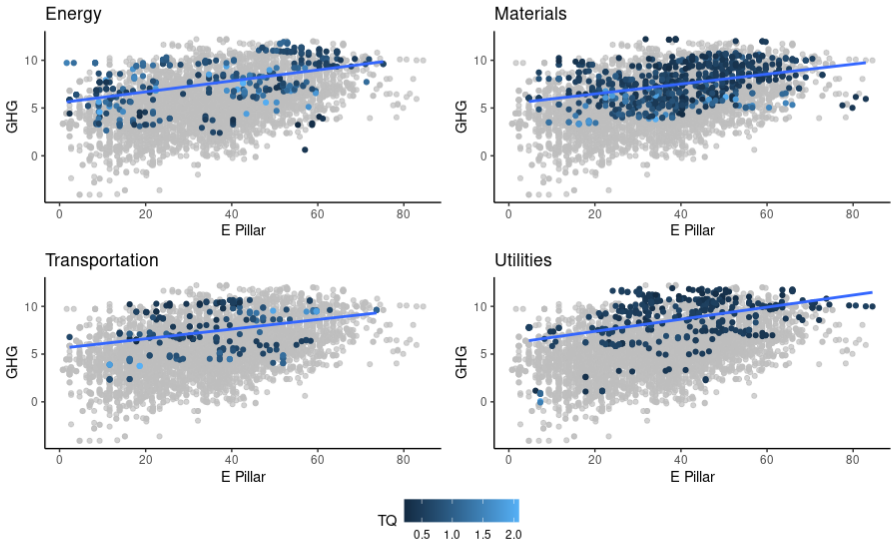

Fig. 1: Scatter plot with highlighted sectors, GHG logarithmic scale Vs Environmental Pillar

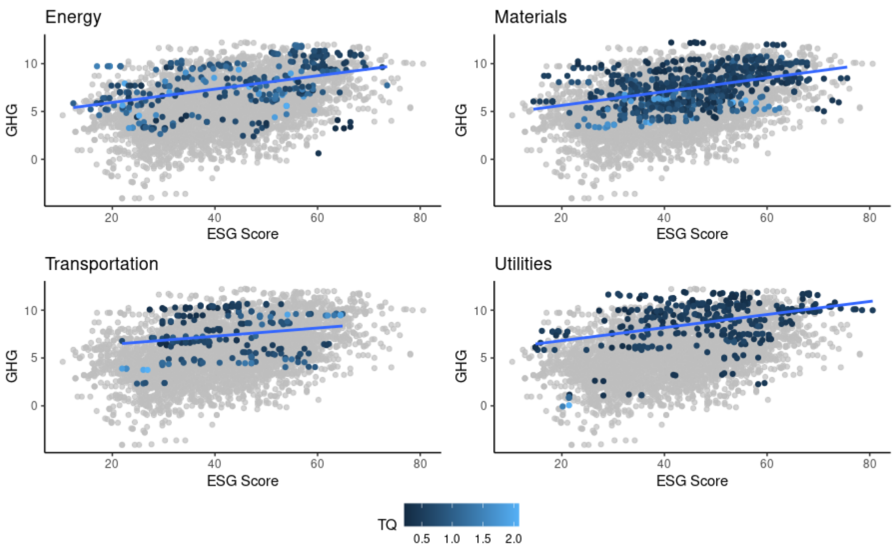

Fig. 2: Scatter plot with highlighted sectors, GHG logarithmic scale Vs ESG Score

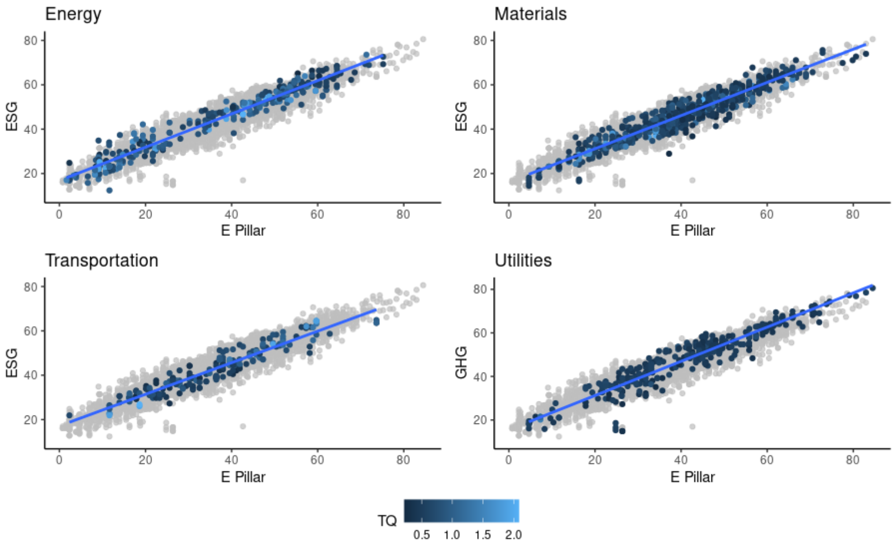

Fig. 3: Scatter plot with highlighted sectors, ESG Score Vs Environmental Pillar

Table 1: Summary table for variables within sectors

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max	Sector
TQ	889	1.009	0.958	-0.180	0.604	1.206	17.484	
lnturn	889	20.593	5.653	0.000	20.043	23.682	26.472	
lnld	889	5.660	3.327	-7.131	4.151	8.079	11.273	
lnEBITDA	889	4.814	3.068	-3	2.9	6.9	11	
lnemploy	889	6.347	3.416	0.000	4.625	8.711	11.534	(A)
ROA	889	-0.893	17.237	-142.700	-2.250	6.220	66.950	
esg	889	26.665	17.777	0.000	14.523	39.004	73.554	
esgenv	889	16.256	20.438	0	0	28.7	75	
lnghg	889	2.740	3.935	-1	0	6.6	12	
TQ	1,575	1.296	1.972	-0.291	0.641	1.524	54.178	
lnturn	1,575	20.618	4.149	0.000	19.774	22.837	25.868	
lnld	1,575	5.004	3.191	-5.221	2.509	7.356	10.423	
lnEBITDA	1,575	4.741	2.688	-0.208	3.703	6.604	10.011	
lnemploy	1,575	6.437	4.037	0.000	2.298	9.536	12.470	(B)
ROA	1,575	1.117	22.768	-260.870	0.000	8.515	134.920	
esg	1,575	31.810	18.344	0.000	16.116	47.934	75.620	
esgenv	1,575	23.256	21.328	0.000	1.550	41.085	82.946	
lnghg	1,575	3.417	3.948	0.000	0.000	7.178	12.236	
TQ	469	0.983	0.640	0.000	0.595	1.211	3.654	
lnturn	469	20.298	5.081	0	19.8	22.9	26	
lnld	469	6.470	2.539	-6.119	5.749	8.261	9.968	
lnEBITDA	469	5.692	2.140	0.000	4.840	6.962	9.303	
lnemploy	469	8.069	3.509	0	7.2	10.3	13	(C)
ROA	469	5.051	8.759	-55	2.7	7.3	115	
esg	469	28.951	16.350	0.000	15.289	42.149	64.876	
esgenv	469	20.139	19.017	0.000	2.326	37.209	73.643	
lnghg	469	3.273	3.950	0.000	0.000	6.759	10.652	
TQ	616	0.818	0.436	-0.042	0.626	0.984	4.898	
lnturn	616	20.899	4.601	0.000	20.328	23.311	24.849	
lnld	616	7.771	2.100	-0.514	7.006	9.033	10.932	
lnEBITDA	616	6.341	2.107	0.000	5.488	7.718	9.774	
lnemploy	616	7.599	3.143	0.000	6.867	9.618	12.462	(D)
ROA	616	3.304	3.935	-25.590	2.145	4.540	24.100	
esg	616	35.629	18.977	0.000	18.182	52.453	80.579	
esgenv	616	27.123	21.636	0.000	4.959	45.517	84.496	
lnghg	616	4.779	4.665	-0.064	0.000	9.489	11.896	

(A) Energy, (B) Materials, (C) Transportation, (D) Utilites

Table 2: Results tests for GICS Industry Group

	ESG				GHG			
	(A)	(B)	(C)	(D)	(A)	(B)	(C)	(D)
Breusch–Godfrey	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Baltagi & Li	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LBI	1.491	1.616	1.402	1.143	1.492	1.616	1.398	1.144
Bera LM	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Durbin–Watson	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
FE test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hausman	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LM FE Individual	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LM FE Time	0.005	0.005	0.156	0.022	0.004	0.009	0.134	0.033
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
Breusch–Godfrey	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Baltagi & Li	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LBI	1.616	1.532	1.416	1.459	1.617	1.535	1.408	1.428
Bera LM	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Durbin–Watson	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
FE test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hausman	0.998	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LM FE Individual	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LM FE Time	0.014	0.401	0.000	0.611	0.024	0.407	0.000	0.564

Digits 4: (A) Energy, (B) Materials, (C) Transportation, (D) Utilites; Digits 6: (a) Energy Equipment and Services, (b) Oil Gas and Consumable Fuels, (c) Chemicals, (d) Electric Utilities; P-Values, Locally Best Invariant (LBI) Additivity Test is in critical values

Table 3: Correlation Matrix

Variable	TQ	lnturn	lnld	prof_marg	lnEBITDA	lnemploy	ROA	ROE	esg	esgenv	lnghg
TQ	1										
lnturn	0.183	1									
lnld	-0.212	0.600	1								
prof_marg	0.054	-0.050	-0.029	1							
lnEBITDA	0.019	0.789	0.738	0.007	1						
lnemploy	-0.017	0.533	0.438	-0.361	0.628	1					
ROA	0.555	0.139	-0.174	0.337	0.132	0.002	1				
esg	-0.085	0.287	0.372	-0.009	0.463	0.295	-0.040	-0.004	1		
esgenv	-0.068	0.297	0.354	-0.016	0.460	0.297	-0.027	-0.003	0.952	1	
lnghg	-0.212	0.487	0.562	-0.241	0.620	0.534	-0.156	-0.017	0.419	0.426	1

Table 4: Regression results, GICS 4 digits

	Dependent variable: TQ							
	ESG				GHG			
Variable	(A)	(B)	(C)	(D)	(A)	(B)	(C)	(D)
E Pillar	-0.002 (0.002)	0.006*** (0.002)	0.003*** (0.001)	0.001 (0.001)				
lnghg					-0.090** (0.044)	-0.482*** (0.030)	0.148* (0.079)	-0.065*** (0.008)
lnturn	0.090*** (0.023)	0.244*** (0.015)	0.242*** (0.009)	0.100*** (0.012)	0.187*** (0.040)	0.288*** (0.020)	0.106*** (0.026)	0.118*** (0.008)
lnld	-0.090*** (0.014)	-0.046*** (0.011)	-0.052*** (0.005)	-0.046*** (0.015)	-0.031 (0.021)	-0.112*** (0.015)	-0.132*** (0.031)	-0.038** (0.019)
lnEBITDA	0.042*** (0.012)	0.053*** (0.018)	0.047*** (0.013)	0.038*** (0.012)	0.094*** (0.020)	-0.029 (0.021)	0.023 (0.031)	0.113*** (0.006)
profmarg	0.001 (0.001)	0.0002 (0.001)	0.001*** (0.0004)	-0.0004 (0.001)	0.0002 (0.001)	-0.005*** (0.001)	0.006*** (0.002)	0.001** (0.0003)
lnemploy	-0.055 (0.038)	-0.033 (0.032)	0.030** (0.013)	-0.058** (0.023)	0.067 (0.056)	0.285*** (0.032)	-0.018 (0.072)	-0.019 (0.019)
ROA	0.002 (0.002)	0.010*** (0.002)	0.011*** (0.001)	0.007*** (0.002)	0.003 (0.003)	0.026*** (0.002)	0.009*** (0.003)	-0.001 (0.001)
adj. R^2	0.761	0.852	0.866	0.856	0.768	0.878	0.902	0.855
F test	9.221 (0.000)	18.680 (0.000)	23.200 (0.000)	17.559 (0.000)	9.258 (0.000)	17.990 (0.000)	26.900 (0.000)	11.932 (0.000)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

(A) Energy, (B) Materials, (C) Transportation, (D) Utilites

Table 5: Regression results, GICS 6 digits

	Dependent variable: TQ							
	ESG				GHG			
Variable	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
E Pillar	0.008*** (0.001)	0.003 (0.002)	0.013*** (0.003)	0.013*** (0.003)				
lnghg					-0.077*** (0.010)	-0.187*** (0.064)	-0.048 (0.052)	0.026* (0.015)
lnturn	-0.035*** (0.012)	0.168*** (0.021)	0.328*** (0.045)	0.328*** (0.045)	0.065 (0.042)	0.122** (0.047)	0.290*** (0.060)	0.097*** (0.017)
lnld	-0.069*** (0.007)	-0.228*** (0.017)	-0.076*** (0.023)	-0.076*** (0.023)	-0.033** (0.015)	-0.060 (0.040)	-0.003 (0.032)	-0.041 (0.035)
lnEBITDA	0.190*** (0.008)	-0.007 (0.012)	0.010 (0.051)	0.010 (0.051)	0.154*** (0.021)	0.046** (0.022)	0.155* (0.087)	0.124*** (0.024)
profmarg	-0.002*** (0.0005)	-0.001* (0.001)	-0.046*** (0.005)	-0.046*** (0.005)	0.0004 (0.001)	0.001 (0.001)	-0.023*** (0.008)	0.001 (0.001)
lnemploy	0.230*** (0.021)	-0.002 (0.035)	-0.170** (0.074)	-0.170** (0.074)	0.031 (0.030)	0.162** (0.077)	-0.429*** (0.127)	-0.195*** (0.052)
ROA	0.003** (0.001)	0.007*** (0.002)	0.079*** (0.008)	0.079*** (0.008)	0.013*** (0.003)	0.001 (0.003)	0.042*** (0.011)	-0.003 (0.005)
adj. R^2	0.752	0.748	0.852	0.852	0.719	0.815	0.915	0.919
F test	7.231 (0.000)	10.548 (0.000)	8.947 (0.000)	9.223 (0.000)	9.532 (0.000)	12.385 (0.000)	13.090 (0.000)	11.932 (0.000)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

(a) Energy Equipment and Services, (b) Oil Gas and Consumable Fuels, (c) Chemicals, (d) Electric Utilities;

Table 6: Comparing E Pillar to GHG impacts, GICS 4 digits

	(A)	(B)	(C)	(D)	(A)	(B)	(C)	(D)
X	E Pillar				ln(GHG)			
β		0.006	0.003		-0.09	-0.482	0.148	-0.065
$\sigma(TQ)$		2.009	0.624		0.952	2.009	2.196	0.413
$\sigma(X)$		17.132	15.686		2.526	1.92	0.624	2.405
$\beta\frac{\sigma(X)}{\sigma(TQ)}$		0.053	0.085		-0.239	-0.46	0.042	-0.378

(A) Energy, (B) Materials, (C) Transportation, (D) Utilites

Table 7: Comparing E Pillar to GHG impacts, GICS 6 digits

	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
X	E Pillar				ln(GHG)			
β	0.008		0.013		-0.077	-0.187		0.026
$\sigma(TQ)$	0.435		1.485		0.435	0.435		0.275
$\sigma(X)$	12.847		16.532		1.872	1.872		1.682
$\beta\frac{\sigma(X)}{\sigma(TQ)}$	0.236		0.145		-0.331	-0.805		0.159

(a) Energy Equipment and Services, (b) Oil Gas and Consumable Fuels, (c) Chemicals, (d) Electric Utilities;

Table 8: Regression Parameters from Fig.1

	Dependent variable:			
	lnghg			
	(A)	(B)	(C)	(D)
esg	0.070***	0.072***	0.043***	0.068***
	(0.008)	(0.006)	(0.015)	(0.009)
Constant	4.542***	4.192***	5.573***	5.445***
	(0.376)	(0.281)	(0.642)	(0.448)
Observations	321	672	204	332
R^2	0.188	0.180	0.040	0.145
Adjusted R^2	0.185	0.179	0.035	0.143
Residual Std. Error	2.194	1.744	2.167	2.236
F Statistic	73.828***	146.956***	8.378***	56.179***
	(df = 1; 319)	(df = 1; 670)	(df = 1; 202)	(df = 1; 330)
Note:				*p<0.1; **p<0.05; ***p<0.01

(A) Energy, (B) Materials, (C) Transportation, (D) Utilites

Table 9: Regression Parameters from Fig.2

	Dependent variable:			
	lnghg			
	(A)	(B)	(C)	(D)
esgenv	0.057***	0.052***	0.050***	0.063***
	(0.006)	(0.005)	(0.011)	(0.007)
Constant	5.547***	5.439***	5.596***	6.115***
	(0.252)	(0.200)	(0.406)	(0.324)
Observations	321	672	204	332
R^2	0.213	0.153	0.099	0.180
Adjusted R^2	0.210	0.151	0.095	0.178
Residual Std. Error	2.160	1.772	2.099	2.190
F Statistic	86.262***	120.583***	22.239***	72.489***
	(df = 1; 319)	(df = 1; 670)	(df = 1; 202)	(df = 1; 330)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
(A) Energy, (B) Materials, (C) Transportation, (D) Utilites

Table 10: Regression Parameters from Fig.3

	Dependent variable:			
	esgenv			
	(A)	(B)	(C)	(D)
esg	1.266***	1.223***	1.271***	1.133***
	(0.016)	(0.014)	(0.029)	(0.022)
Constant	−19.545***	−16.434***	−18.420***	−13.125***
	(0.748)	(0.681)	(1.268)	(1.077)
Observations	321	672	204	332
R^2	0.950	0.915	0.904	0.890
Adjusted R^2	0.950	0.915	0.904	0.890
Residual Std. Error	4.367	4.230	4.277	5.379
F Statistic	6,118.400***	7,198.397***	1,910.217***	2,672.520***
	(df = 319)	(df = 670)	(df = 202)	(df = 330)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
(A) Energy, (B) Materials, (C) Transportation, (D) Utilites