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REGULAR ARTICLE

Do environmental and emission disclosure affect firms' performance?

Evidence from sectorial micro data

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Abstract
This study analyzes the relationship between firms' financial performance and their environmental performance, with a particular focus on greenhouse gas-intensive industries. Using financial and environmental data of international listed companies from 2011 to 2017, the financial impact of environmental performances was estimated, measured with multiple indicators that take into account disclosure aspects. The analysis was conducted across different industry aggregation levels, namely the entire group of industries, the Global Industry Classification System (GICS) Industry Group, and the GICS Industry. We found that environmental disclosure indexes are mostly not significant after controlling for environmental performance, suggesting that the effect of environmental disclosure on corporate financial performance is limited, if not altogether absent. In contrast, environmental performance seems to play an important role, and that holds even for high-emitting companies. Overall, our results were consistent with the interpretation that financial markets effectively consider the actual environmental performance of listed companies and, only to a minor extent, the quality of their disclosure.

Keywords Gas emissions · Environmental disclosure · Stock prices · High-emitting sectors

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1 Introduction

Financial economics have recently started to address corporations' capability to self-adjust their environmental performance. One of the potential drivers is the pressure from investors to be compensated for climate change-related policy risks (Bolton & Kacperczyk, 2020). Without evidence of financial performance improvements, the achievement of low-carbon targets could be perceived as costly and economically inefficient. The failure to achieve greenhouse gas (GHG) emission targets unfolds negative uncertainties and risks. The taxonomic definition of this phenomenon is transition risk,[1] as presented by the Task Force on Climate-related Financial Disclosure (TCFD). Missing a smooth transition process might induce a disorderly transformation, which represents the worst scenario for high-emitting corporations (European Central Bank, 2021). Understanding the relationship between corporate financial performance (CFP) and corporate environmental performance (CEP) is, therefore, a key issue in financial studies.

Several studies have attempted to investigate the relationship 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 & Günther, 2017; Xie et al., 2019). This literature has converged on a few indicators to identify the CEP. One is the ESG score, which rates environmental, social and governance performances. This variable incorporates CEOs' corporate decisions and is used as a selection criterion by financial institutions for investments (Berg et al., 2019). According to Kim and Adriaens (2013), disclosure-based measures improved predicting capabilities of mainstream models with respect to CFP. Investigation into the effects of improved CEP offered evidence at the country (Lyon et al., 2013; Qi et al., 2014) and industry levels (Wang et al., 2014), but overall results are too mixed to allow drawing a conclusion in this respect. The main reason is the heterogeneity of environmental indicators used as CEP (Berg et al., 2019; Busch & Hoffmann, 2011). Another approach is to observe CEP directly by looking at GHG emissions. The choice of environmental performance measure depends on the analyzed sector and the country. If a country's economy is heavily reliant on fossil fuels and does not have rigid GHG regulations, the probability that emission levels will negatively affect firms' financial performance is high (Wang et al., 2014). The objective of this paper was to address the differences in effects between indicators of CEP as disclosed performance (ESG) and material (GHG emissions) against CFP. A comprehensive review of studies using the two approaches yields mixed evidence. Thus, a common framework was developed to compare the two measurements using regression models. The dependent variable in this study is Tobin's quotient (TQ) (i.e., a ratio between a physical asset's market value and its replacement value), a standard measure of corporate financial performance (Singh et al., 2017). ESG, ESG Environmental pillar score (E pillar score), and GHG are used as

[1] This type of risk is associated with the costs that can arise when moving towards a less polluting, greener economy (i.e. changes in the regulation, demand shifts, etc.).

independent variables along with standard controls that take into account the other CFP determinants.

The novelty of this study is twofold. First, a direct comparison between CEP indicators is conducted, indicating the limits of ESG scores. Second, the comparison of the estimates allows isolating the capability of CEP indicators to influence CFP. The study provides, in addition, industry and sector specific estimates. This allows assessing the heterogeneity of effects, increasing the results' granularity following the recommendations of ECB and TFCD (European Central Bank, 2021; Task Force on Climate-related Financial Disclosure, 2017). Previous studies suggested that emissions, and therefore policy risk, are concentrated in a few industries (Heede, 2014). Consequently, the relationship between CEP and CFP may structurally differ in these industries compared to the rest of the economy. The analysis focused on the four highest-emitting industries, which identification has been based on total GHG emissions. Industries are classified using codes for industry groups and industries from the Global Industry Classification System (GICS).

The structure of the paper is as follows. Section 2 provides a literature review and describes the research hypotheses. Section 3 describes the dataset and the methodology, alongside the sample and the variables used. Sections 4 and 5 present the results and discussion. Section 6 concludes the study.

2 Literature review and hypotheses

Extensive research exists around the link between CFP and CEP. This link is underpinned by best practices and technologies driven by regulation, even when self-imposed (Bitat, 2018; Børing, 2019). Expenditures in abatement and compliance foster innovation and indirectly productivity. Three strands of evidence emerge from previous works. One points out the positive relationship between the requirements of CEP and CFP. Lee et al. (2015) note that in Japan, legislation facilitates research and development (R&D) investment and climate change mitigation capabilities. Delmas et al. (2015) found that a decrease in GHG emissions is positively associated with an increase in TQ, implying that financial markets recognize a long-term value in emission reduction. Firms benefit in different ways from integrating ESG activities into their usual processes. The first channel is reputational improvements. Stakeholders' attention to ESG factors is rising (Riedl & Smeets, 2017; Xie et al., 2019), and ESG disclosure positively impacts CFP at a moderate disclosure level. Narrowing down, each pillar has its own effect, with governance being the most positive one, followed by social and environmental. Fatemi et al. (2018) draw a different conclusion, with the E pillar score having a bigger impact. Assessing the role that ESG disclosure has on a firm's financial performance, they find the following evidence: (i) environmental strengths increase a firm's value, while environmental weaknesses decrease it; (ii) social and governance weaknesses decrease the market value; and (iii) no evidence of the positive impact concerning social and governance strengths. Firms prefer to disclose favorable information and tend to withhold unfavorable information to enhance their evaluation in the market. Investors evaluate undisclosed information as unfavorable information (Xie et al., 2019).

A second strand of literature relates unclear evidence regarding CEP and CFP relation. Lorraine et al. (2004) find no abnormalities in equity prices following announcements of positive CEP. Qiu et al. (2016) find evidence of a positive link between social performance and firms' value, but no indication of a relationship with CEP. Fujii et al. (2013) and Trumpp and Günther (2017) note that there is no clear evidence of the positive or negative relationship between the performances, potentially due to non-linearities in CEP-CFP relations. Iwata and Okada (2011) provide evidence of environmental issues having an impact on Japanese manufacturing firms' CFP. By analyzing the impact that waste management and GHG emissions have on firms' TQ, what emerges is that financial performance responses are different depending on each environmental issue and varying stakeholders' preferences. According to Lee et al. (2015), the relationship between CEP and CFP acquires a new dimension. Stakeholders are more sensitive to negative impacts than to positive ones. Dangelico and Pontradolfo (2015) analyze 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. The results show a positive effect of the implementation capabilities on CFP, specifically regarding energy and pollution.

Finally, the last strand of literature presents opposing evidence. A number of recent studies (Fisher-Vanden & Thorburn, 2011; Garzón-Jiménez & Zorio-Grima, 2021; Lyon et al., 2013; Sohn et al., 2020; Trinks et al., 2020) still find that clear engagement in environmentally responsible activities leads to negative abnormal returns. This suggests that these activities are perceived as simple costs and not as return-generating investments. Fisher-Vanden and Thorburn (2011) note that corporate commitment to reduce GHG emissions appears to conflict with firm value maximization: high-growth firms and firms with a poor corporate governance structure experience the highest price drop. Previous research is not unanimous, neither on the kind of relationship that exists between CEP and CFP, nor on the variables that generate the biggest impact.

As a proxy for CFP, this study employs TQ, the ratio of the market value of assets to their book value. It indicates the growth potential of a company through equity financing (Bolton et al., 2011). If variables are positively related to TQ, they convey growth potential, and negative relations indicate disinvestment potential. Coherently with the evidence provided by the literature, the null hypothesis of this study reflects the indifference of CFP to sustainability factors. The first two alternative hypotheses relate to the positive link between ESG score and total CO_2 emissions and firms' financial performance. The value of the former represents a general perspective of the firm with respect to environmental, social, and governance achievements (Fujii et al., 2013; Riedl & Smeets, 2017; Trumpp & Günther, 2017; Xie et al., 2019).

A second couple of alternative hypotheses relate to a potential negative relation between CEP indicators and CFP. Since our focus is on the environmental side, we regressed models employing the E pillar score and financial performance, in accordance with the literature (Fatemi et al., 2018; Xie et al., 2019). Qiu et al. (2016) state that this variable highlights the quality of environmental disclosure and commitment to sustainability. Finally, following Delmas et al. (2015), we consider the hypothesis of a correlation between GHG emissions and firms' CFP to control the similarity of information conveyed by the indicators.

3 Data and modeling

This study used two datasets covering financial and environmental data for listed companies from 2011 to 2017. The first is Datastream and provides financial variables for all registered firms. The second is Bloomberg, which offers a collection of environmental variables in addition to GHG emissions by scope and ESG scores. The two datasets were merged using the International Securities Identification Number (ISIN)[2] of each firm. The resulting panel covers a pool of 2438 international firms operating in different industries over the 2011–2017 time range. The vast majority of firms are based in Australia, Europe and the United States. Three measures of CEP are used, namely the ESG score, the E pillar score and GHG emissions. Following the relevant literature (Smirlock et al., 2016), the model considers TQ as the dependent variable. When this index is above one, the firm's desired capital is higher than the actual capital; collecting capital from markets is productive at this moment. Values below 1 indicate that this firm may be over-capitalized; capital acquisition via markets is costly. Since TQ should not be negative in theory,[3] the dataset has been interpolated so as to have zero whenever it is negative. Its denominator represents the replacement value of installed capital (C^K):

$$Q = \frac{D + d + S^p + E - e}{C^k}.$$

TQ represents a structural approach to evaluating firms' performances. Since it is regarded as an explanatory variable of investment (Blanchard et al., 1993; Hayashi, 1982), it indicates a potential for transition policies, representing the objective function of wealth maximization (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 firm size, financial performance and other structural factors. For the first, the logarithm of employment and turnover ("lnemploy" and "lnturn" on all tables) has been collected. For financial accounts, returns on assets (ROA), earnings before interest, tax, depreciation and amortization (EBITDA), long-term debt and marginal profits ("ROA", "EBITDA", "lnld" and "profmarg" on all tables) are used. According to the hypothesis, the ESG score (esg), E pillar score (esgenv), and the natural logarithm of GHG emissions (lnghg) are added alternatively. The choice of the linear-log model reflected the necessity to aggregate large differences and great quantities for the variables under consideration. Ratios and indexes are kept linear: accordingly, ESG score, E pillar

[2] ISIN Organization: international securities identification numbers organization.

[3] 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 (Sp).

score, and TQ are not logarithms. Once the models for the whole pool of companies are estimated, we identify the highest emitting industries to understand if and how financial markets evaluate the most exposed firms' environmental performances and climate disclosures. We used the Global Industry Classification Standard (GICS) as a classification of various industries. Beginning from the highest level, there are sectors, industry groups, industries and sub-industries with digits 2, 4, 6 and 8, respectively. We chose to work on major polluting industries (GICS at four digits). It is well-known that high-emitting industries are the most exposed to transition risks, in particular three main sources of risk: policy change, liability and technological changes (Task Force on Climate-related Financial Disclosure, 2017). Table 1 reports the descriptive statistics for the four industries (i.e. energy, materials, transportation, utilities). The sample sizes in each group were 889, 1575, 469 and 616, respectively. The lowest TQ on average is registered in the utilities industry, while the highest in materials. Utilities register the highest average emissions. Returns are mostly similar among the four industries. The energy industry has a higher standard deviation. On average, the largest employers are in the transportation sector.

The average firm in the energy industry, unlike the ones in the other three sectors, perceives negative financial accounts despite almost "perfect"[4] capitalization, as the TQ for firms in this sector is almost equal to 1 (1009). The distribution of these financial performances is non-normal and skewed toward the right tail. This indicates the presence of a few high-performing firms among the others. It is common knowledge that within this industry, major actors operate in non-competitive markets. The E pillar score and ESG score seem to be null below the 25th percentile for all industries. The best performers overall are firms within the utilities industry. Since the four industries resemble such heterogeneous distributions, the estimation has been split into four different clusters. Before estimation, regressors were selected for two main reasons. First, TQ drivers, such as firm structure, profitability and then environmental performance, are added, as suggested by the literature. Second, the correlation matrix is used to account for possible correlations among variables and avoid imperfect collinearity. Taking a look at the descriptive statistics, an immediate impact on the hypotheses is noted. Although firms in the utilities industry are the ones with the highest GHG emissions ceteris paribus, these companies report the higher ESG score and E pillar score. They are followed by the materials industry (second most emitting industry), transportation industry (third for GHG emissions), and then by the energy industry. In addition, it is useful to note that, with the exception of the energy industry, all the others show an E pillar score well above the whole panel mean (24.99), suggesting some kind of positive correlation between emission levels and ESG commitment.

The second result that stands out is that, despite the high ESG score, when it comes to financial evaluation, utilities and transportation firms do not appear to perform as well as the other firms. On average, their TQ is 0.81 and 0.99, respectively, while all the others are above 1. In addition, the considered industries all report a TQ lower than the whole panel mean (1.77), which can imply that high-emitting

[4] Meaning the equality of market and book value.

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	(A)
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	
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	1575	1.296	1.972	−0.291	0.641	1.524	54.178	(B)
lnturn	1575	20.618	4.149	0.000	19.774	22.837	25.868	
lnld	1575	5.004	3.191	−5.221	2.509	7.356	10.423	
lnEBITDA	1575	4.741	2.688	−0.208	3.703	6.604	10.011	
lnemploy	1575	6.437	4.037	0.000	2.298	9.536	12.470	
ROA	1575	1.117	22.768	−260.870	0.000	8.515	134.920	
esg	1575	31.810	18.344	0.000	16.116	47.934	75.620	
esgenv	1575	23.256	21.328	0.000	1.550	41.085	82.946	
lnghg	1575	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	(C)
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	
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	(D)
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	
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) utilities

industries are generally penalized. These dynamics are reported in Figs. 1, 2 and 3 and commented in the appendix. Separate models are run to understand the magnitude of effect variability across industries. 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. Hypothesis 3, instead, is intended to test if firms' environmental performance can directly influence stock prices. The selection approach previously described reduced the potential for collinearity and correlation. It abides by the findings of the literature and previously constructed model. In order to produce innovative results, a brief pre-selection procedure regarding possible idiosyncrasies for errors was added, while to control for autocorrelation and cross-sectional dependence, a set of robustness checks was applied. The first two hypotheses take into consideration disclosure indexes, the second being strictly linked to environmental factors, while the third accounts for environmental performance. The ESG and E pillar scores are correlated at 95% (see Table 3). As a result of this correlation, the ESG score has been dropped. The work resembles a stage analysis. The first step assessed the impact of the variables set for the four-digit GICS. The second step analyzed the most pollutant industries at the six-digit level. In this manner, we tested whether our results hold for both levels of aggregation. Furthermore, this methodology contemplates different results for industries, as they perceive climate change risk differently. To reach our goal, a linear model with fixed effects was estimated. Such configuration allows for the collection of unexplained but strictly exogenous factors. Among these could be found the geographical location, influencing different policy settings. 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. We employed the Lagrange multiplier test to investigate the significance of fixed effects. According to the results, individual effects were significant, while time effects were not. The dependent variable was set as TQ, while the independent variables were the following: turnover, long-term debt, EBITDA, number of employees, profit margin and ROA. The second stage of the model was 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:

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

The estimation is based on our panel of N firms along the time span of T. On the left hand, we collected the dependent variable TQ. The set of independent variables is collected within the matrix X_{it}. Its coefficients constitute the vector β of length equal to the number of columns of X_{it}. Since we intend to control for fixed effects on each firm on the panel, we added the vector α_i. The other class of robustness checks we employed relates to the error term unit. First, we are interested in verifying whether environmental disclosure or performance (ESG score and GHG emissions) have 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 industries, keeping the same set of control variables.

Table 2 reports the robustness check results. We treated for auto-correlation of errors, fixed effect, auto-regressive factors and moving averages. The Breusch-Godfrey test for serial correlation allows rejecting the null hypothesis of no error correlation. The Durbin-Watson and Baltagi-Wu tests show idiosyncratic shocks on TQ. We corrected for serial correlation using a generalised least squares estimator with individual effects. We could not control for cross-sectional dependence due to the limited time or individual ratio. Feasible generalised least square (FGLS) performs robust results in such conditions. Such a regression is based on a two-stage approach; the first consists of an ordinary least squares (OLS) 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

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) utilities; 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

structure of the data. The use of an FGLS is motivated by the presence of both heteroskedasticity and autocorrelation; the estimator is asymptotically more efficient in large sample conditions (Ullah & Huang, 2006).

4 Results

In Table 3, correlations between variables are reported. The independent variables present high cross-correlation. The ESG score and the E pillar score are highly correlated (95.2%). Therefore, the first two hypotheses are necessarily entangled. The logarithm of GHG emissions presents a correlation with both variables (around 42% for both). Furthermore, we see that the correlation is minimal for returns on equity and assets.

The following tables report the results of our fixed-effect model. 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.

Structural variables affect each industry's TQ similarly. For instance, turnover has a similar impact across industries, it always resembles a positive sign, and in terms of magnitude, it has the largest effect among all structural variables. Long-term debt is negatively correlated to TQ, which is expected, considering that it is part of the TQ denominator. EBITDA is positively sloped unless we add GHG emissions to the model (only for the materials industry). Marginal profits show a positive and significant sign, but are risible compared with the other factors. The employment dimension has no impact on capitalization, except for the transportation, utilities and materials industries (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 the results. The E pillar score is positive and statistically significant for materials and transportation. However, for these industries, the logarithm of total GHG emissions registers a negative impact for the former and a positive impact for the latter.

TQ is not affected by ESG scores in the energy and utilities industries, while it is negatively affected by GHG emissions. Moreover, the impact of GHG emissions is greater in the energy industry compared to the utilities industry. This is a relevant result, as these industries' TQs do not register a much greater variance than other industries. Therefore, this semi-elastic relation is a specific case. One particular difference concerns the transportation industry, for which evidence suggests ESG score and GHG emissions positively affect TQ. Table 4 shows that GHG emissions affect capitalization despite the size of emissions.

Table 5 summarizes the estimates of the GLS models sorted by GICS six-digit industries, showing a deeper look into the composition of each GICS industry group. In fact, maintaining the GHG emission levels as a selection criterion for the analyzed industries, we break down each GICS industry group at the industrial

Table 3 Correlation matrix

Variable	TQ	Lnturn	lnld	profmarg	lnEBITDA	lnemploy	ROA	ROE	esg	esgenv	lnghg
TQ	1										
lnturn	0.183	1									
lnld	−0.212	0.600	1								
profmarg	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

Variable	ESG				GHG			
	(A)	(B)	(C)	(D)	(A)	(B)	(C)	(D)
E pillar	−0.002	0.006***	0.003***	0.001				
	(0.002)	(0.002)	(0.001)	(0.001)				
lnghg					−0.090**	−0.482***	0.148*	−0.065***
					(0.044)	(0.030)	(0.079)	(0.008)
lnturn	0.090***	0.244***	0.242***	0.100***	0.187***	0.288***	0.106***	0.118***
	(0.023)	(0.015)	(0.009)	(0.012)	(0.040)	(0.020)	(0.026)	(0.008)
lnld	−0.090***	−0.046***	−0.052***	−0.046***	−0.031	−0.112***	−0.132***	−0.038**
	(0.014)	(0.011)	(0.005)	(0.015)	(0.021)	(0.015)	(0.031)	(0.019)
lnE-BITDA	0.042***	0.053***	0.047***	0.038***	0.094***	−0.029	0.023	0.113***
	(0.012)	(0.018)	(0.013)	(0.012)	(0.020)	(0.021)	(0.031)	(0.006)
profmarg	0.001	0.0002	0.001***	−0.0004	0.0002	−0.005***	0.006***	0.001**
	(0.001)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.002)	(0.0003)
lnemploy	−0.055	−0.033	0.030^**	−0.058**	0.067	0.285***	−0.018	−0.019
	(0.038)	(0.032)	(0.013)	(0.023)	(0.056)	(0.032)	(0.072)	(0.019)
ROA	0.002	0.010***	0.011***	0.007***	0.003	0.026***	0.009***	−0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(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***	18.680***	23.200***	17.559***	9.258***	17.990***	26.900***	11.932***

(A) energy, (B) materials, (C) transportation, (D) utilities

*p < 0.1; **p < 0.05; ***p < 0.01

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. In this case, it appears that structural variables' 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 similarly affects all industries that were analyzed. On the other hand, ROA has a positive impact on the dependent variable.

Oil and gas firms register low significance for ESG score and structural variables. In addition, their TQ is negatively affected by GHG emissions. Chemicals-related firms register significant results for structural variables and ESG. No relevant effects from GHG emissions were found in this case. 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 are mainly affected by EBITDA and the number of employees. On the other hand, this is the only industry among these four to be negatively affected by turnover. Moreover, gross profit also has a positive effect on chemicals and electric utilities. Both sets of regressions have been fitting. All R^2 values are over 70%. All models have passed the F test, with all p-values near zero. Models treating GICS six-digit data did not lose significance while using less observations. However, it is complex to evaluate the magnitude of the effect that CEP has on CFP: GHG emissions and E pillar score have different distributions.

5 Discussion

The results presented the estimates of the relation between CEP and CFP. The variables indicating the former were GHG emissions and E pillar score. The interpretation of the results is bound 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 increase as a consequence of a reduction of book value with respect to market value (Delmas et al., 2015; Hennessy, 2004;

Table 5 Regression results, GICS 6 digits

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

(a) Energy equipment and services, (b) oil gas and consumable fuels, (c) chemicals, (d) electric utilities; *p < 0.1; **p < 0.05; ***p < 0.01

Kim & Adriaens, 2013; Lee et al., 2015). We found non-negative signs in the coefficient of the E pillar score to TQ across all industries. This could suggest 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 positively value firms' environmental commitment, which needs continuous investment without an immediate payoff supported by slack resources, which provides assurance for scarcity problems in allocating resources for environmental improvement. Neither of those explains 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 with 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.

Since the E pillar score and GHG variable have very different scales, their marginal effect on TQ based on coefficient estimates are not directly comparable. We decided, hence, to compute the marginal effect of a standard deviation (σ) increase in E pillar score and GHG and to compare this with a standard deviation increase in TQ.

In Table 6, we collected the results for four digit GICS clusters. In the case of firms within the materials industry (B), the effect of one (*X*) variation of disclosure quality impacts 5.3% of the σ (*TQ*) variation. It represents a minimal effect if we compare it to GHG emissions. For the same industry, one σ (*X*) of emissions is translated to a −46% reduction of σ (*TQ*). We repeated the approach for energy (A), transportation (C) and utilities (D). Overall, standardized variations of emissions register greater impact on the TQ value. By recalling the level of interaction between disclosure quality and emissions, it is evident that the former cannot substitute the second in evaluating environmental performance. It would require a great disclosure effort to substitute a limited absolute reduction of GHG. The only GICS four-digit industry where this does not work is transportation. Here, we see that disclosure affects TQ (8.5%) more than emissions (4.2%).

Table 6 Comparing E pillar to GHG impacts, GICS 4 digits

X	E pillar				ln(GHG)			
	(A)	(B)	(C)	(D)	(A)	(B)	(C)	(D)
β		0.006	0.003		−0.09	−0.482	0.148	−0.065
σ (TQ)		2.009	0.624		0.952	2.009	2.196	0.413
σ (X)		17.132	15.686		2.526	1.92	0.624	2.405
		0.053	0.085		−0.239	−0.46	0.042	−0.378

(A) energy, (B) materials, (C) transportation, (D) utilities

According to these outcomes, improvements in composite indicators present limited results in terms of increased TQ compared with 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 industries such as energy, materials and utilities. The transportation industry 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 abatement 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 a limited effect on the financial structure of transport-related firms. The second group of estimations relates to GICS six-digit industries. We have reported the relative impact of σ (*X*) in Table 7.

It emerges that better environmental disclosure almost covers the impact of emissions on TQ. There are two sub-sectorial clusters that register positive effects of disclosure. These are energy equipment and services (a) and chemicals (c). Interesting dynamics that were found were that for the first sub-sector, TQ increases or decreases, in terms of standard deviation of the same amount when, respectively, the E pillar score or the GHG emissions increases. For these industries, we register an indifference between abatement and disclosure policies with respect to TQ. This might sound ominous for climate change mitigation, but another hypothesis has recently arisen. Market value dependence on carbon emissions might be affected by the dynamic of carbon premium (Bolton & Kacperczyk, 2020). Firms must guarantee higher market performance for carbon emissions. In our study, we found that the greatest polluters are structurally affected by emissions. Even more interestingly, transportation (GICS 4) register positive effects on both ESG and emissions.

Among our results, we have to report the unexpected results for the chemical industry (c). This panel registered no impact of emissions on TQ. It registered that improvements in the E 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 the potential cost of GHG with higher returns. The requirement of higher stock returns is negatively reflected in abatement costs, according to our results. When GHG emissions are positively related to TQ, their abatement negatively affects TQ. For such industries, the transition to a low-carbon society will necessarily implicate changes in capital structure. Recent

Table 7 Comparing E pillar to GHG impacts, GICS 6 digits

X	E pillar				ln(GHG)			
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
β	0.008		0.013		−0.077	−0.187		0.026
σ (TQ)	0.435		1.485		0.435	0.435		0.275
σ (X)	12.847		16.532		1.872	1.872		1.682
	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 developments in Q-theory indicate that highly capitalized corporations tend to function in a different manner with respect to the market-to-book ratio (Lee et al., 2021); our results would open a gap with respect to the relationship between abatement policies and highly capitalized corporations. Abatements reduce market value but may increase the CEP outlook of firms via the E pillar score, hence TQ. However, the difference in slope of CEP coefficients indicates that better composite indicators may not compensate abatement costs for electric utilities. In other words, industries with negative abatement cost but positive composite indicator impact may underperform with better CEP. 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 the 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 the E pillar score on TQ 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 emissions.

It might be reasonable that we find no significant relation for three possible reasons. The first relates to the risk aversion that ESG investors have for polluting firms. Their strategy would then be to avoid them, having no effect on market value. Therefore, TQ is not affected by liable energy use above the 75th percentile for GHG emissions. The second possible explanation relates to our data. Larger polluters are generally better in terms of disclosure quality; emissions and the E pillar score are positively correlated. Thus, better acknowledgement might simply "sterilise" the negative effects of GHG emissions on TQ. As a result, the use of the ESG score and its interpretation is counterintuitive when compared with 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 firms' involvement in sustainable activities is reflected in their CFP. In particular, the paper's focus is on firms' CEP proxied by the E pillar score and total GHG emissions. Using a dataset that covers a panel of international firms over seven years, we ran a linear regression model oriented at shedding some light on this relationship. The objective was to focus on the industries that could be the most affected by the transition to a low-carbon society and, in some cases, have the highest historical emission background (European Central Bank, 2021; Heede, 2014). The innovation presented in this paper is in the comparison of two different indicators, often used as alternatives to measure the same variable. We found novel evidence in the sense that these indicators often convey different information. First, for some polluters, the ESG and the E pillar scores are mainly not significant. In other cases, it might reflect effective policies of decarbonization. One of the possible explanations is that financial operators may not take into consideration this kind of information when it comes to investment choices. It is also relevant that on average, the highest emitting macro industries are also the ones that report ESG scores that are well above average. This is inconsistent with the definition of environmental performance. Second, GHG total emissions seem to play an important role in defining capital structure. Observing the statistical relevance of the variable and it's sign, it does seem reasonable to state that the emission levels contribute substantially to the pricing process.

Furthermore, it can be stated that the paradigm that, for high-emitting industries, emissions are associated with production, hence revenue, and consequentially positive financial performance, does not hold anymore. As a matter of fact, the considered industries report poor CFPs when confronted with the average. Part of the explanation can be attributed to the fact that, at least for European firms, the EU regulatory framework intends to discourage GHG emissions growth to pursue climate neutrality by 2050. The evidence presented indicates that there is a potential theoretical gap emerging from this study. While the relation between investment and TQ is still debated (Lee et al., 2021; Puopolo, 2017), the link with energy and transition pathways is not similarly discussed (Lin & Huang, 2011). Furthermore, the innovation of this paper consists in clearly separating (at least for carbon intensive industries) CEP as ESG and total carbon footprint, which are more related to climate pledges.

From a managerial point of view, a key takeaway is that for high-emitting industries, CEP does count in defining firms' capitalization level, and that disclosing data on specific environmental performance indicators can generate positive impacts on market-to-book value. For this reason, the reporting obligations imposed by national and international authorities should be embraced as an opportunity to improve the company's financial position and not performed as a mere compliance exercise. On the policy side instead, following the example of the most recent initiatives launched by the European Commission, authorities might consider updating and integrating the reporting framework. Increasing the number of KPIs required might be useful as it would guide companies in collecting data. Naturally, this growth of data required should be accompanied by an increase in the degree of standardization. Heterogeneous frameworks, in fact, would impede the comparability between different firms or different datasets.

Finally, widening the scope of the reporting obligations to SMEs should be carefully considered. An ad hoc approach seems to be necessary in this case, as SMEs typically lack the resources or knowledge to comply with the "standard" set of requirements. However, these conclusions may apply only to a determined number of industries, as our research focuses on the highest emitting ones. This, in fact, represents the major limitation of our study. Moreover, as previously stated, more research in this field is still necessary. In particular, it would be useful to understand more deeply the role that EU regulation has on the behavior of firms and stock markets. Alongside this field of research, the application of non-linear models to test the contribution of GHG emission dynamics could provide further insights into the role of this variable.

Appendix

Table 3 represents the correlation matrix among variables. The calculations were made according to the complete pool of firms, without industry clustering. Therefore, it represents a general point of view. We see that variables such as the ESG score, E pillar score and GHG emissions are negatively correlated to the TQ. On the other hand, they positively affect each other. This is consistent with the cited literature (Kim & Adriaens, 2013; Siew et al., 2013). The dimension of occupation is negatively correlated with the liquidity of firms, but positively related to environmental variables in this panel. Lastly, "profmarg" is negatively correlated to other variables except for financial ones. Curiously, their relationship with environmental variables is negative.

The scatter plot in Fig. 1 reports the relation between the E pillar score and GHG emissions. The coloring is based according to TQ, with the darker tones indicating that TQ approaches zero. It is not possible to point out a global trend for TQ. In industries such as utilities and transportation, there seems to be a weak or no relation at all. This evidence leads us to consider two aspects that concern the utilities and transportation industries. The first is that financial markets seem to penalize GHG emissions. The second is that financial markets may weigh relatively more actual environmental performance than disclosure scores in these industries. Understanding which of these two aspects is relevant is a key factor for comprehending the relationship between CFP and CEP.

The positive relation between the ESG score and GHG emissions is reported in Fig. 2, while Fig. 3 represents the relation between the ESG and E pillar scores. As previously reported, we focused on the average values between 2011 and 2017

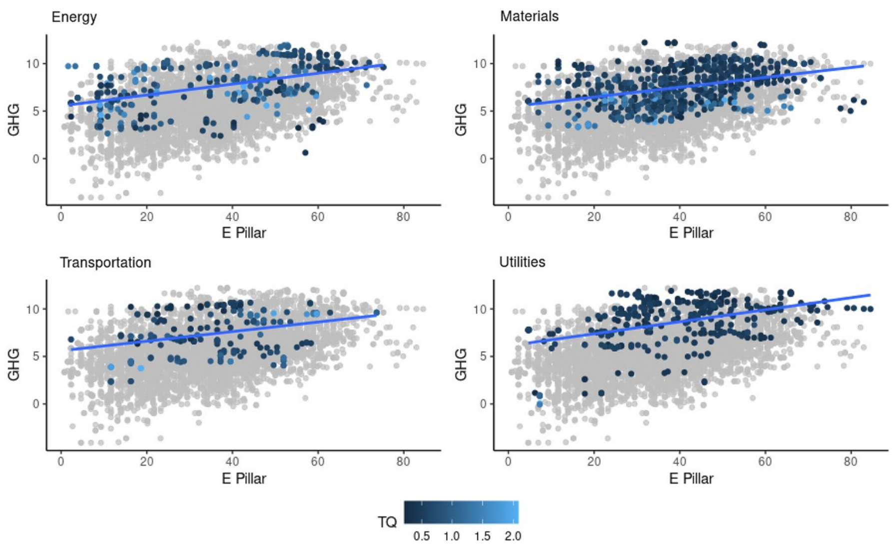

Fig. 1 Scatter plot with highlighted sectors, GHG logarithmic scale Vs Environmental pillar score

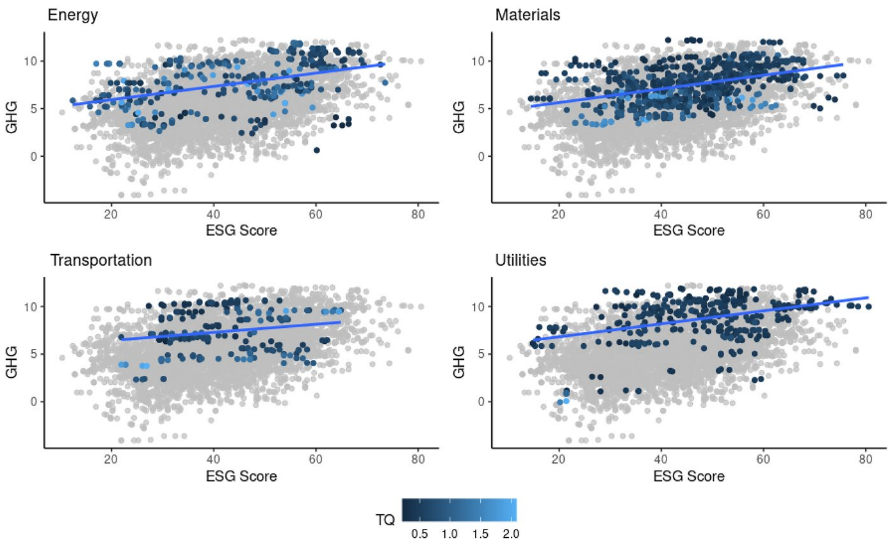

Fig. 2 Scatter plot with highlighted sectors, GHG logarithmic scale Vs ESG score

in order to counter time effects and simplify the cross-sectional plotting. All macro-industries reported positive correlations.

It is possible to point out the difference in slope that may arise from utilities and materials. In this case, the E pillar score and GHG emissions are at least positively related. A less striking correlation is evident for ESG score vs GHG emissions. We highlighted such a relationship in Fig. 2. The transportation industry has the lowest correlation among all four. Nevertheless, the ESG score is positively correlated to GHG emissions with possible fixed effects. The strong correlation between the ESG score and the E pillar is plotted in Fig. 3. The difference from the previous is that we could not find signs indicative of fixed effects between firms. The relation is positive and has low residuals. In this case, we could see that transportation is the only industry to have a narrower interval with respect to the other firms.

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

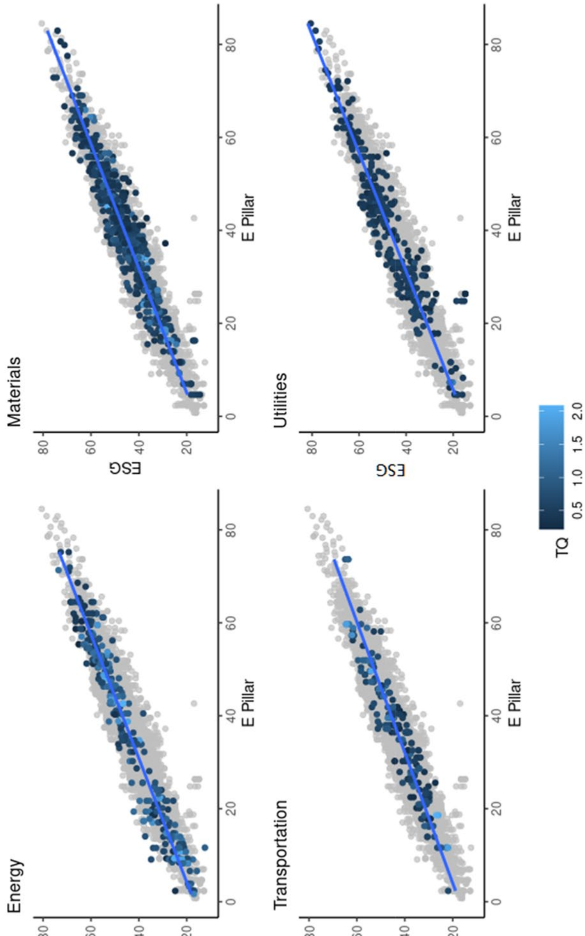

Fig. 3 Scatter plot with highlighted sectors, ESG score Vs Environmental pillar score

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
Adj. 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)

(A) Energy, (B) materials, (C) transportation, (D) utilities

*p < 0.1; **p < 0.05; ***p < 0.01

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
Adj. 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)

(A) Energy, (B) materials, (C) transportation, (D) utilities

*p < 0.1; **p < 0.05; ***p < 0.01

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
Adj. R^2	0.950	0.915	0.904	0.890
Residual Std. Error	4.367	4.230	4.277	5.379
F Statistic	6118.400***	7198.397***	1910.217***	2672.520***
	(df = 319)	(df = 670)	(df = 202)	(df = 330)

(A) Energy, (B) materials, (C) transportation, (D) utilities

*p < 0.1; **p < 0.05; ***p < 0.01

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