Does the valuation of listed firms indicate Greenium?

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Abstract

We build a dataset of more than 5,000 corporations since 2002 to analyse the relation between indicators of firms environmental performance and their stock market valuation.

We estimate several models, from dummy regressions to propensity score matching, using several indicators of environmental performance. We find mild evidence of Greenium. Non-linearities do not explain this result, as the effect is not found to be stronger for larger changes in the environmental performance. However, the effect is stronger when firms announce emission targets, thereby reinforcing their commitment to greener processes. This signalling effect has become stronger over time. We also find that the valuation of "greener" firms is less volatile. This could be explained by the fact that "greener" companies attract a longer-term oriented investor base, more stable by definition.

Keywords: Environmental performance, carbon emission targets, firm valuation, stock price volatility, cross-section regression, propensity score matching, time-varying effects, non-linear effects, signalling effects.

JEL classification: G12, G15, Q54

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1 Introduction

In addition to climate policies, changes in investors' preference may severely affect the value of assets. The trend in favor of ESG investing is already massive.

Theoretical asset pricing models (Pastor et al., 2021, and Pedersen et al., 2021) show that green assets should provide a lower expected return because investors enjoy holding these assets and because green assets provide a hedge to climate risk. Görgen et al. (2020a) and Bolton and Kacperczyk (2020) empirically demonstrate that investors already demand a compensation for being exposed to carbon emission risk. Ehlers et al. (2020) discuss the benefits of a firm-level rating based on carbon intensity to complement existing project-based green labels and find that such a rating system could provide a useful signal to investors and encourage firms to reduce their carbon footprint.

A growing number of investors pay attention to environmental concerns in their investment decisions (Fink 2020, Krueger et al. 2020). If investors incorporate factors related to the greenness of a company in asset portfolio allocation, the valuation of greener companies is likely to be higher than that of similar brown ones. Their assets may benefit from a Greenium, a positive green premium and firms with higher environmental score or reduced emissions intensity compared to their sector peers, may have higher stock valuation. Nevertheless, so far, empirical evidence of such Greenium remains relatively scarce.

To test whether firm-level environmental standards affect firm value, we examine a sample of 5,132 international firms over the period from 2002 to 2019. We use three criteria to proxy firms' environmental standards, taken from the Refinitiv Asset4 Database.

We first study the effect of environmental standards on firm value. Our dependent variable of interest is the price-to book ratio of the company relative to that of sector peers. To alleviate concerns that the firm value effect we observe is due to some unobserved factor, we adjust all variables to their industry-year mean. We further, employ propensity score matching. Overall, after controlling for sector and various indicators of firm' performance, we find mild evidence of "greenium".

We then seek to assess the effect of environmental standards on stock-price volatility. We find stronger evidence that firms with higher environmental score or reduced emissions intensity compared to their sector peers have a more stable valuation. This may reflect that higher ESG firms attract institutional investors, more long-term oriented.

We assess the robustness of our results by constructing a control group using propensity score matching. For each green firm, we identify a non-green firm that

has statistically the same profitability, size, and leverage. The results also hold when using propensity score matching suggesting that the initially observed effects are not driven by firm characteristics that are associated to groups.

The rest of the paper consists of four sections and concluding remarks. The second section reviews the literature on the valuation of corporates and the greening of the economy. The third section introduces the firm-level dataset assembled and analyses some of its characteristics. We show that the aggregates obtained from the firm level ESG metrics correlate rather well with countrywide or sector wide official statistics. The fourth section presents the estimation results obtained for stock market valuation and the fifth one reports the estimation results obtained for stock price volatility.

2 Literature review

Over the last decade, the finance literature has made substantial advances in demonstrating that climate change affects the economy and that it is a source of uncertainty for society (see for example Weitzman (2014) and Giglio et al. (2018)). This paper is related to previous studies that analyse how environmental standards or climate risk are priced in financial assets. Market valuation can be negatively affected by environmental standards and climate change through three main channels.

First, physical risks related to climate change have the potential to directly affect firm value as extreme weather events stemming from climate change can impose significant damage to corporate profits (see for example Trenberth et al. (2014), Hong et al. (2019), and Addoum et al. (2020)). Empirically, Hong et al. (2019) show that climate risk, measured by the Palmer drought index, strongly predicts changes in profitability and return of the food industry.

Second, Benabou & Tirole (2010) suggest that corporate social responsibility can be attributed to government failures to control negative externalities. Consequently, an investment in environmentally friendly assets enables firms to increase their reputation, which can contribute to their competitiveness. In this vein, previous studies have examined the value effects of voluntary greenhouse gas emission targets and managerial efforts to mitigate climate risk exposure on firm valuations (see Perez-Gonzales & Yun (2013), Matsumura et al. (2014), and Kleimeier & Viehs (2016)). Ramelli et al. (2018) find evidence of a climate responsibility premium which can in part be attributed to increased demand by long-term institutional investors, anticipating future regulatory changes.

Finally, also a regulatory or transition risk can affect firm value. When the negative externality of emissions is corrected by policy, such as carbon tax or emission trading system, firms with high carbon intensity experience a decline in their net present

value ceteris paribus given permanently increased costs. Empirically, Dowell et al. (2000), Servaes & Tamayo (2013), Dimson et al. (2015), Krueger (2015), and Lins et al. (2017) provide examples of mechanisms through which environmental, social, and governmental (ESG) standards can enhance shareholder wealth. Dimson et al. (2015) demonstrate that ESG activism is associated with improving social welfare, as it increases stakeholder value when engagements are successful and does not destroy firm value when engagements are unsuccessful. Also Hoepner et al. (2018) find that ESG engagements can benefit shareholders by reducting firms' downside risk. Further, Engle et al. (2020) document that stocks of firms with high environmental scores have higher returns during periods with negative news about the future path of climate change. Bolton & Kacperczyk (2020) find that stocks CO2 intensive firms earn higher returns, after controlling for other factors that predict the cross section of returns. Also Alessi et al. (2019) show that the European market prices climate risk in the form of a greenness and environmental transparency factor consistent with the interpretation that investors demand compensation for their exposure to carbon emission risk.

While reputational risk, regulatory risk, and physical climate risk are likely to impact asset market today, the effect of environmental standards on equity prices remains ambiguous. In fact, an alternative view suggests a negative effect of ESG on firm value and suggests that ESG represents private benefits (public image) that managers extract at the expense of shareholders. In this vein Dowell et al. (2000) and Matsumura et al. (2014) find a negative relation between carbon emissions and firm value. Also Hartzmark & Sussman (2019) do not find evidence of an outperformance of high-sustainability funds. Thus, the question of whether environmental friendliness increases firm value remains empirical in nature.

This paper is concerned with the effects of environmental performance on the investment decisions of institutional investors. There is growing empirical evidence that investors take climate considerations into account, integrating ESG or climate risks into their asset management decision. Krueger et al. (2020) and Gibson Brandon & Krueger (2021) show that investors believe that considerations of climate risk are important in the investment process. Krueger et al. (2020) report that 39% of investors surveyed claim to work to reduce the carbon footprints in their portfolios. Thus, higher ESG ratings (and in particular environmental scores) should help attracting an investor base valuating more long-term and environment issues. The drivers to invest in assets with low environmental impact can be related to financial motives such as the expectation of better financial performance (Hartzmark & Sussman (2019)) or lower risk (Gibson Brandon & Krueger (2021)). These motives can also be attributable to non-pecuniary motives such as pro-social and environmental norms and

attitudes (Hong & Kacperczyk (2009), Riedl & Smeets (2017), Hartzmark & Sussman (2019), Barber et al. (2020)). Empirically, institutional investors have been shown to decrease their their allocation towards sustainable portfolios after climate change induced natural disaster (Dyck et al. (2019)) or to alter their portfolio after the implementation of environmental ratings (Hartzmark & Sussman (2019)).
**********TELL WHAT WE DO **********

3 The dataset assembled

Our dataset assembles information on listed companies, from all around the world. It merges three components: balance sheet and Profit and loss information, stock market information, and environmental performance. We obtain our data for firm characteristics from Compustat and stock return data from Worldscope. Regarding the latter, we gather information from Refinitiv Asset4 database, which contains environmental, social, and governance ratings of publicly traded companies, available since 2002. This database contains yearly ratings, scores, and emission targets on roughly 6,700 companies from more than 70 countries. This source has already been used in previous studies (see for example Dyck et al. (2019) and Flammer (2020)).
Environmental measures are calculated using 61 different categories from publicly available information based on three subcategories: emission reduction, resource use, and product innovation.[2] The emission reduction score measures a firm's efforts towards reducing environmental emission in its operational processes. The resource use score measures a firm's performance to reduce the use of materials, energy, or water and to switch to more environmentally friendly solutions. The product innovation score measures a firm's commitment to reduce the environmental costs for its costumers (Reuters 2018). The ratings, derived from normalized raw scores, range from 0 to 100 and measure the environmental (emission) performance of a company relative to all other companies in a given year.
Our main variable of interest is the emission reduction score, a firm's total CO2 emissions relative to revenue, as well as a variable indicating whether a firm has set targets or objectives to achieve on emissions reduction. The emission score and total emissions are only weakly correlated suggesting that they capture different aspects of environmental standards. While total CO2 emissions capture the current environmental standard of a firm, the emission score is a forward looking measure of climate responsibility. we also consider the binary variable indicating whether a firm has voluntarily adopted an emission target. With these explanatory variables, we evaluate

[2]The information used mainly comes from company annual reports, communications or websites, and NGO websites.

the effect of companies' self-regulatory strategies regarding climate change on firm value.

Table 1 provides a breakdown of ESG ratings by industries and countries. Industries are partitioned using SIC codes. The original ESG dataset includes 6,729 rated companies. The total number of observations for environmental ratings is 58,302, for emissions to revenues 26,874, and the number of observations for the indicator variable for emission reduction targets 52,801.// Table 1 show that ESG ratings are most common in the United States, the European Union, and the United Kingdom. Together, these countries make up around 75% of the entire dataset. One-third of ESG rated firms are domiciled in the United States, 17% in the European Union, followed by firms from the United Kingdom (6.9%), Japan (6.5%), Australia (5.5%), and Canada (4.6%). In terms of sectors, the manufacturing industry is the most populated, with 28.6% of corporations, followed by finance, insurance, and real estate (23%), and services (16.6%). Mining, transportation, and public utilities, retail trade follow, accounting each for 7 to 11% of the number of corporations included in the sample. Together they make up roughly 59% of the entire sample.

Table 1: **Composition of the sample by country and sector**

Countries			**Industry**		
US	2330	34.6%	Manufacturing	1924	28.6%
EU	1158	17.2%	Finance, Insurance, & Real Estate	1549	23.0%
UK	464	6.9%	Services	1120	16.6%
Japan	440	6.5%	Mining	737	10.9%
Australia	369	5.5%	Transportation & Public Utilities	536	8.0%
Canada	306	4.6%	Retail Trade	447	6.6%
South America	282	4.2%	Construction	277	4.1%
Africa	173	2.6%	Agriculture, Forestry, & Fishing	65	1.0%
Taiwan	134	2.0%	Public Administration	58	0.9%
South Korea	133	2.0%	Wholesale Trade	16	0.2%
Switzerland	127	1.9%	**Total**	**6729**	
India	115	1.7%			
Middle East	86	1.3%			
Russia	41	0.6%			
Other	571	8.5%			
Total	**6729**				

This table reports the breakdown of our dataset of E-rated firms by country and sector, using the entire population of rated company from 2002 to 2019. Industries are partitioned using SIC classifications.

After combining the three components of the datasets, we obtain a sample of 5,132 firms over the period from 2002 to 2019. Firms' environmental and financial characteristics for the final sample are summarized in Table 2. The mean (median) emission score is 51.6 (52.4), with substantial dispersion across the sample, as shown by the

elevated standard deviation. The mean (median) Tobin's Q is 5.4 (2.1).[3]

Table 2: **Summary statistics**

	Mean	StDev	p25	p50	p75	N
Emission score	51.63	28.89	26.63	52.43	76.97	41070
Emission reduction targets	27.95	22.54	10.00	21.00	38.00	3951
Environmental pillar score	41.29	26.72	17.15	39.65	63.43	45577
Environmental innovation score	21.54	30.17	0.00	0.00	42.77	58411
Resource use scores	35.91	33.70	0.00	30.21	66.00	58492
CO2 emissions to revenue	399.17	1044.17	13.77	46.98	259.17	26874
Price-to-book ratio	5.45	8.28	0.79	2.14	6.02	95291
ROA	2.44	10.13	0.06	1.99	6.10	113720
Stock returns	5.32	24.70	-4.15	0.06	6.96	110931

This table reports the mean, standard deviation, 25th percentile, median, 75th percentile, and number of observations of firm environmental scores and firm characteristics.

Figure 1: **Environmental performance over time and across industries**

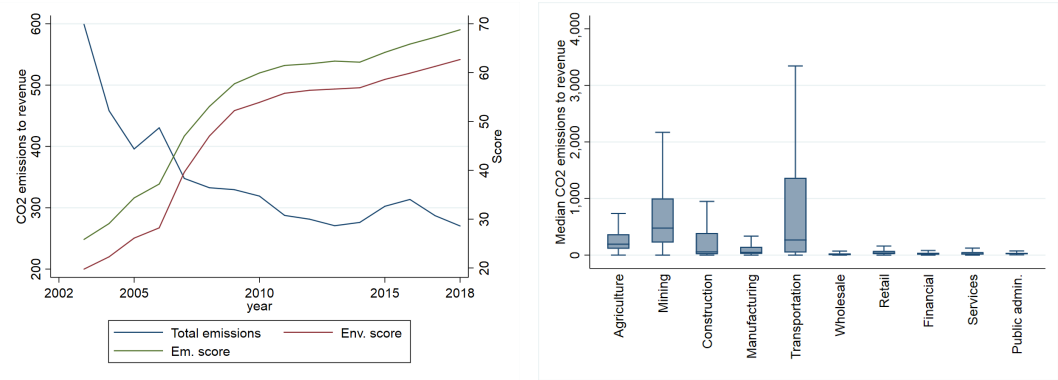


Table 3 shows that the three indicators of environmental performance are correlated. The correlation coefficient between the environmental score and the emission reduction score amounts to 94.2%, while the correlations between CO2 emissions to revenue and the environmental and emission scores is -9.9% and -14.0% respectively.

We next plot mean environmental standards over time in figure 1. We compute this for a constant sample of firms for which data are available in all years between 2002 and 2018. As can be seen, firms have increased their environmental score and reduced their emission rates over time. Panel b of figure 1 also shows the wide diversity across sectors. Transportation and mining are the sectors with the highest emission rate, followed by manufacturing, construction and agriculture. services, wholesale

[3]See Table A.1 in the appendix for more detailed statistics on environmental score, emission score, total emission to revenues, Tobin's Q, cash to assets, return on assets, and leverage ratios at the country level, for the 35 countries with the highest number of E-rated firms. Interestingly, the countries where firms have the highest environmental scores are European (France, Spain, and Finland).

trade, retail trade and financial are the least emitting sectors. For the most polluting sectors, panel b of figure 1 also shows the large within sector diversity.

Table 3: **Correlation between indicators of environmental performance (%)**

	Emission score	Env. score	Emissions	CO2 emissions
Emission score	100			
Env. score	94.2	100		
Emissions	-9.9	-14.0	100	
CO2 emissions	-33.4	-35.8	26.0	100
EPS Index (t-1)	31.5	36.6	-20.0	-40.5

This table reports the correlation coefficient estimates between country year mean firm environmental standards, total country year mean CO2 emissions and the country's environmental policy stringency index.

It is well-known that ESG ratings vary substantially across data providers (see for example Berg et al. (n.d.)). Moreover, it is interesting to assess whether by nature the dataset is not biased, with reporting companies tilted towards the most virtuous ones in terms of environmental performance. It is also important to gauge the degree to which our dataset is representative of the economies as it is constituted from large firms and provide a very incomplete coverage of the economies at stake. For these reasons, we assess the reliability of our dataset along two dimensions.

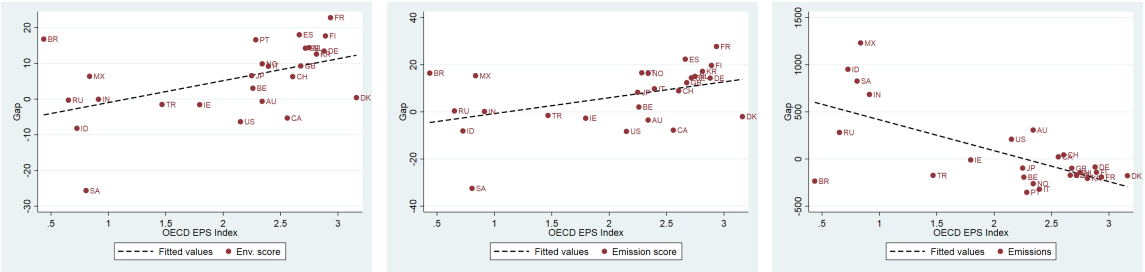
First, we compare our environmental performance variables to the emission rate obtained from macroeconomic statistical sources. We use country's total CO2 emissions (kg per PPP USD of GDP) obtained from the Worldbank. This is to verify that the variables we use in the following analysis are consistent with other variables related to the environment. Figure A1 in the appendix shows the results for each country. It depicts the relation between environmental performance measures at the country level and total country CO2 emissions scaled by GDP. Table 3 in the Appendix reports the correlation the environmental performance scores at each country level obtained by aggregating the emission scores of the local companies included in the dataset and the and CO2 emission ratio to GDP, taken from the Worldbank. The computed country's emission scores, environmental scores are negatively related to CO2 emissions, with a correlation coefficient between 33 and 36%. Moreover, the bottom-up country emission rates are positively correlated to the Worldbank emission rates, with a correlation coefficient between 26%. Further, the average firm emissions to revenue in a country is positively correlated to the country's total CO2 emissions relative to GDP. Overall, the inspection does not suggest major bias in the sample as our environmental performance measures obtained from reporting companies are correlated with macro statistics.

Second, we filter the country environmental performance from the sectoral composition effect and correlate the new measure with Environmental Policy Stringency indicators compiled by the OECD. By nature, some sectors employ a technology that is less green, as shown Panel b of figure 1. To remove the effect of the sector composition, we account for two components. First, for each year and for each of the sector reported in table 1, we compute the average environmental performance scores. We then compute the average score of the country each year, given the sector composition of the reporting companies from this country during this year, assuming its corporates would have been rated as their sector peers at the world level. This component is reported in Figure A2 where the gap between the actual environmental performance and the counterfactual environmental performance reflects the under or over performance compared to the average world economy.

We decompose the reported aggregated performance at the country level into two factors: the first accounting for the sector composition of the reporting companies in each country and the overall energy performance of the economy. Both components are varying over time: as the sample composition changes, the sector composition varies, and as time goes by, energy performance improves, as shown above, in Figure 1. We next correlate the countries environmental outperformance measures with the OECD Environmental Policy Stringency (EPS) index, which is a country-specific and internationally-comparable measure of the stringency of environmental policy. Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behaviour. It covers 28 countries. The correlation coefficients are reported in the last row of Table 3. As expected, the environmental outperformance measures are positively correlated to the OECD's EPS Index, while total emission performance is negatively correlated to the EPS Index indicating that firms in countries with high EPS values outperform in terms of environmental standards relative to firms that are located in countries with low EPS values.

We next run simple ordinary least squares regressions, where environmental outperformance (the gap between the actual environmental performance and the counterfactual performance) is the dependent variable, and where the EPS Index (up to the second lag) is the independent variable. Robust standard errors are clustered at country level, and regressions are weighted by the number of firms having an ESG rating in the country. The estimation results are reported in table A.2. Considering environmental performance with respect to the emission score and environmental performance score we can see that stricter environmental policy stringency are not associated with significantly higher environmental outperformance. Looking at the es-

Figure 2: **Environmental scores and EPS Index**



timation results where total emissions to revenue is the dependent variable we can see however that higher EPS values are associated with lower total emissions. In panel D we use total emissions as dependent variable rather than the gap in total emissions. Here again stricter EPS values are associated with lower total CO2 emissions. While many of our coefficient estimates are only marginally significant, a graphical illustration is instructive. Figure 2 shows the average environmental outperformance of the countries for which EPS values are available. As can be seen France, Finland, and Germany outperform relative to non-European countries.

Overall, the analysis suggest that the indicators obtained from our dataset are consistent with country-based macro indicators as well as measures of environmental policies: The bottom-up estimate of environmental performances correlate with the right sign with emission statistics compiled for the whole economy and more stringer environmental policies tend to be associated with stronger environmental performance of the local corporates.

4 Environmental standards and firm value

In this section, we estimate the effect of environmental standards on firm valuation. We follow the literature in using Tobin's Q as a measure of firm value (see for example Jin & Jorion (2006), Perez-Gonzales & Yun (2013), and Krueger (2015)). We calculate Tobin's Q as the sum of the book value of liabilities plus the market value of common equity divided by the book value of assets. To account for sector effects, we use a firm's industry adjusted Tobin's Q, defined as the ratio between its Tobin's Q and the average Tobin's Q for all firms in the same industry (using two-digit SIC codes). As there are industries that by business model pollute more than other we focus on environmental standards within sectors, to assess the effect of being 'green' within a relevant sector. We first develop dummy regressions, simple or augmented with fundamental determinants. We then implement propensity score matching.

To account for the fundamental determinants of firms' valuation, we control for

firm size (measured by total sales), current and historical profitability (ROA), and firm leverage. To account for bias arising from industry effects we adjust all continuous variables to their industry mean. While the actual CO2 emissions of the financial industry are very small we cannot verify the CO2 intensity of their portfolio. Therefore we exclude the financial industry from our estimations.
To avoid problems of outliers we winsorize all continuous variables at the 1st and 99th percentiles. All independent variables are lagged by one year (with the exception of current profitability), and we cluster standard errors by country.
In order to test for the effect of the environmental performance on firm valuation, we start With a simple static model estimated on the entire dataset using the two proxies of "green" performance, the emission score and total emissions to revenues. As shown in equation 1, the yearly change in firm i's price-to-book ratio ($PtoB$), is projected on a constant, year fixed effects (θ_t), country fixed effects (θ_c), and an indicator variable (D) measuring whether the "green" performance of firm i in year $t-1$ deviates strongly from the industry average. This variable considers symmetrically negative and positive deviations. Deviations from the industry mean are all relative to the standard deviation of the indicator, ranging from 0.5, 1.0, 1.5, and 1.9 standard deviation. For example considering 1.5 standard deviations, the indicator variable is equal to one if environmental standards increase by more than 1.5 standard deviations from the industry mean, it is equal to minus 1 if environmental standards decline by more than 1.5 standard deviations and it is equal to zero otherwise. [4] All estimations include year (θ_t) and country (θ_c) fixed effects.

$$\Delta PtoB_{i,t} = \alpha + \beta D_{i,t-1} + \gamma X'_{i,t-1} + \theta_t + \theta_c + \varepsilon_{i,t} \tag{1}$$

We next use a more sophisticated model to account for the difference in the pricing of corporate equities. In line with simple asset pricing models, we consider indicators of firm performance, firm size, and of firm financing structure ($X'_{i,t-1}$). Firm performance and size are captured by return on assets (ROA) and relative sales respectively. They are expected to exert a positive impact on firm valuation, as it signals higher dividends ceteris paribus - at constant distribution policy -. Firm financing structure is captured by relative leverage ratio. While in a purely efficient financial system, corporate valuation should be independent from the liability structure as stated in the well-know Modigliani-Miller theorem (see Modigliani & Miller (1958)), financial frictions are one of the various reasons for which it is not the case in practice (see for example Myers (1977), Jensen & Meckling (1976) and more recently Holmstrom

[4] Obviously, as shown in the last row of Table A.3, the higher the threshold, the smaller the sample a dummy equals to one.

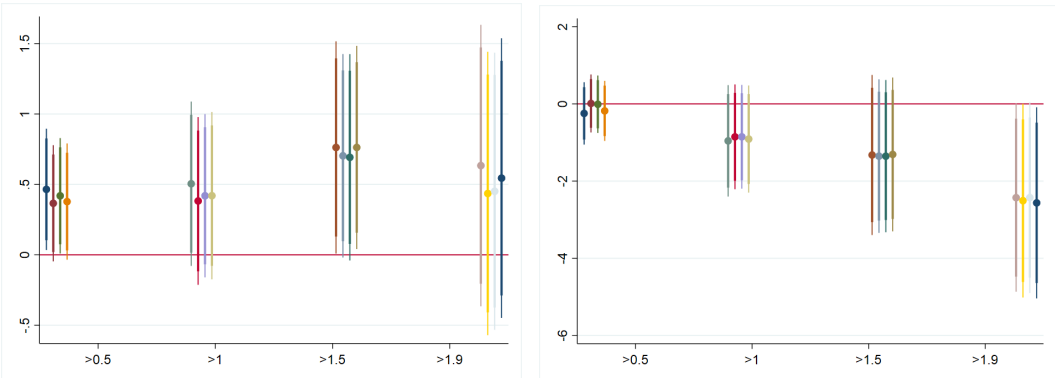
& Tirole (1997)).

Table A.3 report the regression results. We are mostly interested in the coefficient estimates β associated with the dummy variable indicating a large deviation in environmental performance. If there is a greenium, we should observe a positive coefficient estimate for the dummy built based on the emission score and a negative coefficient for that built on the emission to revenues. A company recording a high increase in environmental performance relative to its peers in the same sector should be relatively more valued, recording an increase in relative $PtoB$, and conversely for emission rates.

We plot coefficient estimates regarding the variable indicating a large change in emission scores and total emissions to revenue in figure 3, regression results relating to the three measures of environmental performance are reported in table A.3 in the Appendix.

Considering large changes in emission scores we observe the expected positive relation between scores and firm value. Regarding the relation between large changes in CO2 emissions to revenue and firm value we observe a negative relation. Nevertheless the effect of changes in CO2 emissions is significant only for changes in CO2 emissions above 1.9 standard deviations. Indication the existence of non-linear effects. Logically, a stronger deviation tend to be associated with a larger impact of the dummy, as the significance increases with the deviation. Larger deviations are not more significantly priced in.

Figure 3: textbfChange in environmental performance and firm value



When studying how environmental performance affects firm value, we are confronted with an empirical challenge, which is that environmental performance is possibly endogenous with respect to firm value. To disentangle the direction of the two effects, we construct a control group using a propensity score matching approach, which allows us to minimize observable differences between green and brown firms. In the year preceding the ESG rating, we match green firms defined as those who have seen a large increase in environmental standards to non-green firms. Similarly,

we match brown firms (those that have seen a large decline in environmental standards) to non-brown firms. We then select the nearest neighbour based on covariates capturing firm characteristics, industry, and year fixed effects. This procdure ensures that the treatment group - green or brown firms - is as similar as possible to the control group, except for the "greenness" or brownness.

Additionally to verifying the robustness of our previous results considering large positive and negative changes in environmental standards enables us to check whether the effect we observe is caused by a green premium or a negative brown premium. We use firm size, profitability, and leverage as firm covariates. Using firm size and leverage rules out concerns that treated firms have better access to capital markets, while firm profitability, addresses concerns that treated firms may be more profitable than control firms.

We compare the change in firm value between treatment (green or brown) firms and matched control firms. Table 4 shows the average effect of the treatment. The results show that increases in environmental scores are associated with an increase in firm value. Further, we find that large declines in environmental scores are not associated with a statistically significant decline in firm value.

Table 4: **Environmental standards and firm value**

Positive change

		0.5σ	1σ	1.5σ	1.9σ
Emission score$_{t-1}$	ATE	1.16***	0.89	1.43*	0.78
		(2.77)	(1.48)	(1.80)	(0.86)
	N	33319	33319	33319	33319
Environmental score $_{t-1}$	ATE	1.23***	1.19*	1.10	1.16
		(2.83)	(1.83)	(1.37)	(1.25)
	N	33217	33217	33217	33217

Negative change

		0.5σ	1σ	1.5σ	1.9σ
Emission score $_{t-1}$	ATE	0.21	0.92	-0.80	0.23
		(0.33)	(0.77)	(-0.47)	(0.16)
	N	33319	33319	33319	33319
Environmental score $_{t-1}$	ATE	0.92	1.89	3.47	1.70
		(1.12)	(1.49)	(1.57)	(0.91)
	N	33217	33217	33217	33217

5 Signalling emission reduction and firm value

Next, we consider the effect of voluntary emission reduction targets on firm value.[5] We specify the relation between having an emission target and firm value for a given firm i as the linear regression:

$$\Delta PtoB_{i,t} = \alpha + \beta Target_{i,t-1} + \gamma X'_{i,t-1} + \theta_t + \theta_c + \varepsilon_{i,t} \tag{2}$$

where $\Delta PtoB_{i,t}$ is the change in the price-to-book ratio for firm i in year t, $Target_{i,t-1}$ is a binary variable indicating if a firm has set an emission reduction target in the previous year, and $X'_{i,t-1}$ is a set of control variables lagged by one year. As before we control for firm profitability (ROA), firm leverage, and size. All estimations include country (θ_c) and year fixed-effects (θ_t). Regression results are reported in table 5.
We first estimate the model on the whole time sample (columns (1) to (4)) and then on sub-periods: earlier, from 2002 until 2015 and more lately from 2016 to 2020. The starting year for the second period corresponds to that of the Paris climate agreement and of Carney (2015)'s famous speech, "Breaking the tragedy of the horizon". For an illustration of the dramatic increase in attention to the topic of ESG in the recent period we show in figure A3 in the appendix an index of the worldwide volume of Google searches for the topic "ESG investing".
Considering the entire sample period we find strong evidence that firms that have set an emission reduction target have increasing firm value. Splitting the sample over time, we find that the significance of the impact has increased in the most recent period. While it is not statistically significant in the period from 2002 to 2015, its significance has increased in the later period. This finding suggests that investors are becoming more and more concerned about the environmental impact of the companies invested in. This is consistent with the fact that citizens become more concerned about the issue (see EIB, Investment Report), and governments actually design, and in some cases, start implementing policies to reduce the environmental footprint of production activity. This partly explains why part of the empirical literature, conducted using dataset starting long ago, fail to find a significant impact.

To check the robustness of our results we match firms that have an emission target to firms that do not have an emission target. We then select the nearest neighbour based on covariates capturing firm characteristics, industry, and year. This ensures that the treatment group - green firms - is as similar as possible to the control group, except for having and emission target. We use firm size, profitability, and leverage as firm covariates. Using firm size and leverage rules out concerns that treated firms

[5] In some cases, the target is reported in terms of reduction. However, the reporting intensity of such information limits too much the population sample.

Table 5: **Emission reduction target and firm value**

	(1)	(2)	(3)	(4)	2002-2015	2016-2018
Target dummy (t-1)	2.15***	1.19***	1.85***	1.23***	1.01	1.37**
	(5.309)	(2.872)	(4.569)	(3.033)	(1.315)	(2.354)
Relative ROA (t-1)		0.005	0.007		0.035	-0.026
		(0.364)	(0.533)		(1.553)	(-0.840)
Relative leverage ratio (t-1)		0.081***	0.087***	0.077***	0.088***	0.076***
		(4.919)	(5.324)	(4.532)	(4.165)	(4.922)
Relative sales (t-1)		0.001***		0.001***	0.001***	0.001***
		(4.791)		(4.823)	(3.864)	(3.886)
R-sqr	2.2	2.8	2.7	2.6	2.6	3.7
N	36371	34599	35351	35204	17274	17325
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Change in the Price-to-Book ratio of the company to that of the sector

have better access to capital markets, while firm profitability, addresses concerns that treated firms may be more profitable than control firms.

Table 6: **ATE of greening on firm valuation**

	(1)	2002-2015	2016-2018
ATE	1.34***	1.38**	1.66***
	(2.97)	(2.29)	(2.59)
N	34398	17300	17098

Note: Change Price-to-Book ratio

In line with our previous results from Table 5, our results suggest that setting an emission reduction target is strongly associated with increases in firm value. Further the effect has become stronger in the more recent period.

6 Environmental performance and stock volatility

In this section, we consider the effect of environmental standards on stock volatility. We measure stock price volatility ($HtoL$) by dividing the highest price of a stock in a year by its lowest price in the same year. We specify the relation between having environmental standards and stock price volatility for a given firm i as the linear regression:

$$\Delta HtoL_{i,t} = \alpha + \beta Score_{i,t-1} + \gamma X'_{i,t-1} + \theta_t + \theta_c + \varepsilon_{i,t} \tag{3}$$

Table 7: **Stock price volatility and environmental standards**

	HtoL											
	Emission score$_{t-1}$				Environmental score$_{t-1}$				Emissions per revenue$_{t-1}$			
Score$_{t-1}$	-0.09***	-0.07***	-0.07***	-0.07***	-0.11***	-0.09***	-0.09***	-0.09***	0.73*	0.69*	0.72*	0.50
	(-3.886)	(-3.688)	(-3.576)	(-4.167)	(-3.405)	(-3.132)	(-3.084)	(-3.679)	(1.886)	(1.777)	(1.868)	(1.315)
Sales$_{t-1}$		-0.002***	-0.002***	-0.002***		-0.002***	-0.002***	-0.002***		-0.002***	-0.002***	-0.002***
		(-5.109)	(-5.303)	(-7.432)		(-5.437)	(-5.632)	(-7.732)		(-4.386)	(-4.407)	(-6.554)
Sales growth$_{t-1}$			0.017	0.028**			0.016	0.027**			-0.006	0.004
			(1.452)	(2.093)			(1.416)	(2.073)			(-0.298)	(0.170)
B-to-M$_{t-1}$				0.047***				0.047***				0.063***
				(7.019)				(6.954)				(5.775)
R-sqr	14.3	14.4	14.9	17.1	14.3	14.4	14.9	17.1	14.5	14.8	14.7	18.3
N	51644	50576	49780	40793	51662	50594	49798	40810	24221	23508	23418	19129
	Volatility											
	Emission score$_{t-1}$				Environmental score$_{t-1}$				Emissions per revenue$_{t-1}$			
Score$_{t-1}$	-0.06**	-0.05*	-0.04*	-0.06**	-0.06	-0.05	-0.05	-0.05	0.69	0.56	0.57	0.67
	(-2.066)	(-1.927)	(-1.721)	(-2.274)	(-1.615)	(-1.387)	(-1.288)	(-1.569)	(1.411)	(1.147)	(1.143)	(1.551)
Sales$_{t-1}$		-0.003**	-0.003**	-0.003***		-0.003**	-0.003**	-0.003***		-0.002***	-0.002**	-0.002***
		(-2.498)	(-2.515)	(-3.041)		(-2.507)	(-2.520)	(-3.047)		(-2.601)	(-2.565)	(-3.281)
Sales growth$_{t-1}$			-0.003	0.005			-0.003	0.006			-0.008	0.002
			(-0.293)	(0.541)			(-0.285)	(0.570)			(-0.583)	(0.123)
B-to-M$_{t-1}$				0.039***				0.039***				0.056***
				(3.930)				(3.863)				(4.810)
R-sqr	70.88	71.03	71.54	72.22	70.83	70.98	71.49	72.15	74.88	75.27	75.39	75.71
N	49971	48966	48277	39516	49989	48984	48295	39533	23778	23081	23006	18779
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

where $Score_{i,t-1}$ represents emission, environmental scores, or total CO2 emissions per revenue of firm i in year $t-1$. Additional to including country and year fixed effects and we control for standard characteristics that have been found to explain stock returns, namely firm size (Banz (1981)), book-to-market (Fama & French (1995)), and gross profitability (Novy-Marx (2013)). The results are reported in Table 7.

To assess the robustness of our results we proceed with matching firms that have above median environmental scores to firms that have below median environmental scores and then select the nearest neighbour based the covariates from the regressions before. This ensures that the treatment group - green firms - is as similar as possible to the control group, except for the "greenness". Results are reported in table 8.

Table 8: **Stock price volatility and environmental standards**

	HtoL								
	Emission score			Emissions to revenue			Environmental score		
		2002-2015	2016-2018		2002-2015	2016-2018		2002-2015	2016-2018
ATE	-3.36***	-3.34***	-3.62***	1.82**	1.69*	1.62	-3.44***	-3.20***	-3.64***
	(-8.52)	(-6.39)	(-5.43)	(2.20)	(1.75)	(1.18)	(-7.79)	(-5.51)	(-5.57)
N	40920	23062	17858	19200	10575	8625	40937	23074	17863
	Volatility								
	Emission score			Emissions to revenue			Environmental score		
		2002-2015	2016-2018		2002-2015	2016-2018		2002-2015	2016-2018
ATE	-4.16***	-2.99***	-4.95***	10.02***	9.43***	11.40***	-5.40***	-4.07***	-5.88***
	(-7.62)	(-3.93)	(-6.71)	(9.74)	(6.92)	(6.96)	(-9.19)	(-4.96)	(-7.47)
N	39615	22396	17219	18836	10378	8458	39632	22408	17224

7 Concluding remarks

We build a dataset of more than 5,000 corporations since 2002 to analyse the relation between indicators of firms environmental performance and their stock market valuation. We estimate several models, from dummy regressions to propensity score matching, using several indicators of environmental performance. We find mild evidence of Greenium. Non-linearities do not explain this result, as the effect is not found to be stronger for larger changes in the environmental performance. However, the effect is stronger when firms announce emission targets, thereby reinforcing their commitment to greener processes. This signalling effect has become stronger over time. We also find that the valuation of "greener" firms is less volatile. This could be explained by the fact that "greener" companies attract a longer-term oriented investor base, more stable by definition.

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Appendix - Supplementary figures and tables

Figure A1: **Environmental performance measures and country CO2 emission levels**

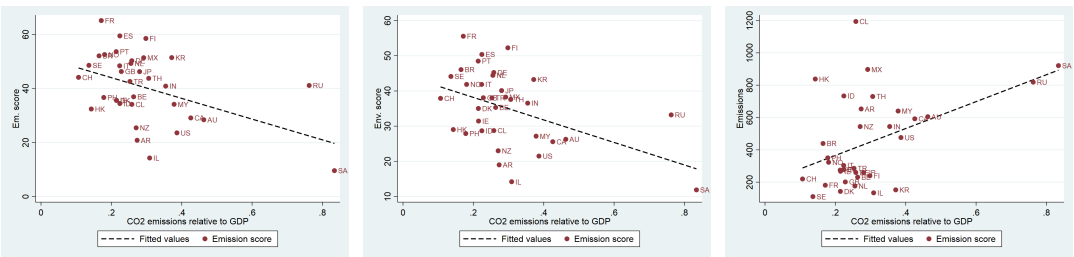

Table A.1: **Environmental performance and Tobin's Q by country**

	Env. Score	Em. Score	CO2 emissions	PtoB	Cash	ROA	Leverage	N
Argentina	36.85	43.99	1628.71	8.54	3.19	1.33	14.58	52
Australia	60.98	68.52	455.47	6.46	4.54	3.87	16.50	369
Belgium	55.35	58.68	243.56	2.07	4.47	4.30	22.23	48
Brazil	64.43	73.61	364.29	2.84	4.84	2.12	23.01	94
Canada	51.17	60.78	656.49	1.90	4.36	2.89	17.74	306
Switzerland	64.87	75.74	190.66	2.60	6.85	4.38	9.87	127
Chile	42.71	51.85	1013.75	0.86	2.88	0.01	22.43	42
Germany	69.96	77.05	258.44	1.59	6.02	3.59	16.99	175
Denmark	56.71	65.79	154.25	4.05	7.40	0.99	18.69	43
Spain	73.04	80.21	259.95	3.42	6.06	4.25	24.34	70
Finland	64.96	72.10	247.91	3.79	5.94	5.05	14.98	37
France	70.77	81.88	184.23	1.53	6.15	3.20	16.00	155
United Kingdom	64.71	76.18	213.69	7.29	5.44	7.28	15.01	424
Hong Kong	51.71	57.31	960.88	2.68	9.01	0.62	3.57	67
Indonesia	33.52	44.54	2110.28	2.83	5.42	0.00	10.42	43
Ireland	58.06	67.59	263.17	4.63	9.33	7.03	13.23	44
Israel	38.30	42.22	99.43	1.46	5.15	0.86	17.04	24
India	55.17	65.54	1317.34	2.83	2.91	0.11	17.53	115
Italy	69.41	80.12	251.54	2.92	4.71	2.75	20.28	92
Japan	60.61	69.36	265.26	1.07	9.65	0.02	15.55	440
South Korea	63.87	74.22	172.83	1.05	6.03	0.00	16.43	133
Malaysia	38.87	43.20	69.20	1.85	5.62	1.47	10.72	60
Mexico	55.56	69.39	561.85	4.23	6.09	0.51	18.90	51
Netherlands	65.99	71.79	172.94	2.44	7.26	4.82	16.42	74
Norway	65.24	78.47	280.50	1.42	5.86	0.67	12.99	53
New Zealand	35.91	46.00	427.60	11.96	3.35	3.78	22.82	55
Philippines	34.07	42.26	395.44	1.95	5.35	0.10	19.50	25
Russia	47.57	58.97	1344.51	2.38	5.16	0.20	14.37	41
South Africa	45.08	40.47	821.56	2.65	6.85	1.03	8.32	154
Sweden	64.96	71.54	114.87	2.68	6.50	0.74	14.91	132
Singapore	38.37	47.33	315.15	5.90	8.02	2.64	12.21	41
Thailand	63.18	73.92	625.12	2.95	7.80	0.17	21.41	41
Turkey	51.27	57.77	367.68	4.77	6.41	2.93	15.40	57
Taiwan	51.92	60.14	440.85	2.19	10.89	0.23	3.62	134
US	53.24	62.23	506.66	3.72	7.38	5.35	17.58	2330

Table A.2: **Environmental outperformance and Environmental Policy Stringency**

	Panel A: Gap emission score		Panel B: Gap Env. score	
EPS (t-1)	0.1638	-0.0005	0.0547	-0.0474
	(0.1087)	(-0.0007)	(0.0324)	(-0.0664)
EPS (t-2)		0.7913		0.8426
		(0.8623)		(1.3059)
Intercept	0.7510	-1.7807	2.4472	0.3370
	(0.1781)	(-0.4821)	(0.5172)	(0.1027)
R-squared	0.7671	0.8162	0.6925	0.8075
N	342	318	342	318
	Panel C: Gap total emissions		**Panel D: Total emissions**	
EPS (t-1)	-36.7252	35.9580	-144.1224***	-18.2344
	(-1.1929)	(1.2211)	(-3.9806)	(-0.6903)
EPS (t-2)		-64.9343*		-88.6469*
		(-1.8887)		(-2.0272)
Intercept	-362.4036***	-388.2837***	743.6767***	630.9653***
	(-4.0561)	(-5.5907)	(7.0774)	(7.5595)
R-squared (%)	47.6	48.5	50.5	52.0
N	326	309	326	309

This table reports coefficient estimates and t-statistics of weighted ordinary least squares regressions, where a country's environmental outperformance is the dependent variable. EPS is the OECD's environmental policy stringency index. Regressions are weighted by the number of firms having an ESG rating in the country. *, **, and *** indicate significance at the 90, 95, and 99% level.

Figure A2: **Environmental performance measures and country CO2 emission levels**

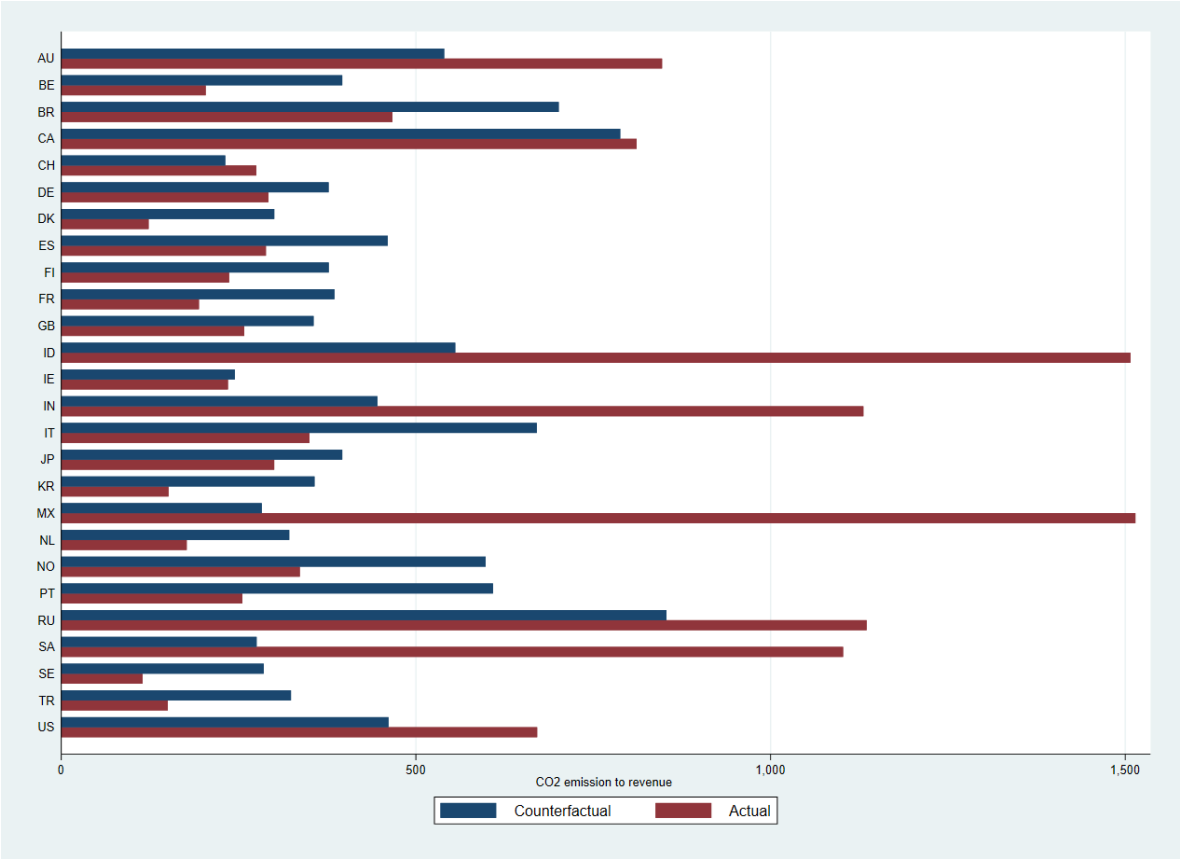

Figure A3: **Google searches for 'ESG investing'**

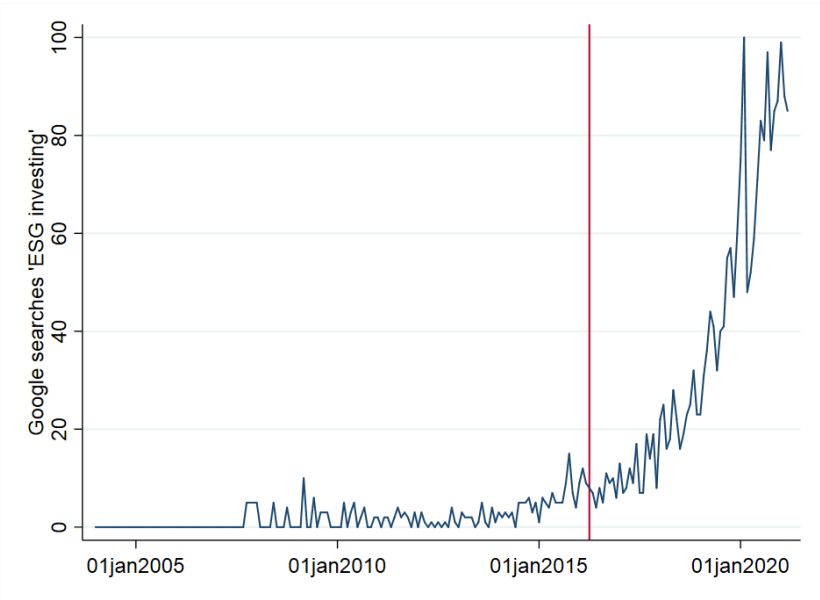

Table A.3: **Environmental standards and firm value**

	0.5σ				**1σ**				**1.5σ**				**1.9σ**			
Emission score																
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
D_{t-1}	0.46**	0.37*	0.42**	0.38*	0.50*	0.38	0.42	0.42	0.76**	0.70*	0.69*	0.76**	0.63	0.44	0.45	0.54
	(2.116)	(1.739)	(2.005)	(1.795)	(1.696)	(1.259)	(1.418)	(1.386)	(1.983)	(1.907)	(1.853)	(2.072)	(1.243)	(0.849)	(0.899)	(1.075)
R-sqr	2.3	3.0	2.9	2.9	2.3	3.0	2.9	2.9	2.3	3.0	2.9	2.9	2.3	3.0	2.9	2.9
N	35882	34291	35047	34778	35882	34291	35047	34778	35882	34291	35047	34778	35882	34291	35047	34778
Emissions per revenue																
	0.5σ				**1σ**				**1.5σ**				**1.9σ**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
D_{t-1}	-0.25	0.01	-0.01	-0.18	-0.96	-0.85	-0.85	-0.91	-1.32	-1.35	-1.35	-1.31	-2.24*	-2.51*	-2.43*	-2.56**
	(-0.596)	(0.031)	(-0.023)	(-0.453)	(-1.299)	(-1.231)	(-1.242)	(-1.286)	(-1.252)	(-1.333)	(-1.346)	(-1.288)	(-1.953)	(-1.958)	(-1.925)	(-2.029)
R-sqr	3.0	3.5	3.3	3.4	3.0	3.5	3.3	3.4	3.0	3.5	3.3	3.4	3.0	3.5	3.3	3.4
N	15103	15103	15103	15103	15103	15103	15103	15103	15662	14949	15426	15103	15662	14949	15426	15103
ROA_{t-1}		x	x	x		x	x	x		x	x	x		x	x	x
$Leverage_{t-1}$		x	x			x	x			x	x			x	x	
$Sales_{t-1}$		x		x		x		x		x		x		x		x

This table reports coefficient estimates and t-statistics of ordinary least squares regressions.