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Greenhouse Gas Emissions Intensity and the Cost of Capital

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Abstract

The transition from high- to low-carbon energy sources differentially impacts financial assets. Low-carbon assets may benefit from lower costs of capital through a reduction in perceived risk as well as increased investor preference for such assets relative to high-carbon assets. This paper investigates whether firms' greenhouse gas (GHG) emissions intensity affects their cost of equity. Using an international sample of 1,920 publicly listed firms over the years 2002-2016, we find that industry-adjusted GHG emissions intensity positively and significantly impacts the cost of equity. For every unit increase in GHG emissions intensity, we find that the cost of equity increases by 15 basis points. This suggests that firm-level emissions-reduction efforts enhance firm value through a reduction in the cost of capital.

Keywords: Environmental performance, Greenhouse Gas emissions, cost of capital, Socially Responsible Investing, Corporate Social Responsibility, asset pricing

JEL codes: G11, G23, G32, M14, Q41

1. Introduction

Investors show a growing concern about the impacts of economic activity on climate (Busch and Hoffmann, 2011). Currently, a considerable amount of financial capital is invested in a way that takes account of environmental impacts (GSIA, 2016). Indicators of firms' Environmental Performance (EP) have become a common tool for risk management (Van Duuren et al., 2016). Commitments to avoid investment in the fossil fuel industry, fossil fuel divestment, have skyrocketed (www.gofossilfree.org/). So-called 'low-carbon' indexes have mushroomed, providing investors with a way to reduce the Greenhouse Gas (GHG) emissions associated with portfolio holdings while minimizing tracking error (Andersson et al., 2016; De Jong and Nguyen, 2016). Another example of market interest for GHG emissions information is the Carbon Disclosure Project (CDP), which tracks the GHG emissions of major firms worldwide, and has been called ''the most powerful green NGO you've never heard of'' (Winston, 2010).

Numerous studies have identified EP as a key concern for investors with potentially strong financial impacts (Barnett and Salomon, 2006; Scholtens, 2008; Oikonomou et al., 2012). Reducing GHG emissions is expected to limit exposure to several key perceived financial risks related to the transition from high- to low-carbon sources (Andersson et al., 2016; Busch, 2007). These include the growing public policy-, consumer-, and market pressures to transition from high- to low-carbon energy sources, rendering investments in high-carbon energy sources increasingly risky (e.g., Bauer and Hann, 2010). Good EP might reduce risk by mitigating reputational and image impacts (Minor and Morgan, 2011), financial and operational risks (McGuire et al., 1988), and fostering innovation (Porter and Van der Linde, 1995). Lastly, growing investor preference for low-carbon assets may lower the required rate of return on such assets (Heinkel et al., 2001). This paper analyzes whether firms' reduction of GHG emissions leads to a reduction of their cost of capital.

A key concern in the empirical literature on the effect of EP on financial performance (FP) is adequate measurement of EP. So far, studies have mostly relied on aggregated scores and indicators of EP,[1] which combine large numbers of individual EP indicators. Examples include answers as to whether the firm publishes an environmental report, has policies in place to reduce emissions, or uses product labels that display environmental responsibility. However, the use and validity of those indicators have been criticized repeatedly (Chatterji et al., 2009; Chen and Delmas, 2011; Dorfleitner et al., 2015; Semenova and Hassel, 2015). A key limitation of EP scores is that they primarily measure firm policy, or plain 'greenwashing' activity, rather than actual reductions of environmental impacts, which affects environmental risks (see Chava, 2014; Gonenc and Scholtens, 2017; Nawrocka and Parker, 2009).[2] In addition, absolute EP measures may neglect the relative nature of EP (see Cai et al., 2012). Lastly, even though EP scores capture a broad scope of potentially relevant environmental issues, it is questionable which and how much information EP scores contain (Chava, 2014; Dorfleitner et al., 2015; Nawrocka and Parker, 2009). EP scores are also not verified, validated, or replicable based on public information.[3] In sum, recent studies emphasize the need to ''look beneath the surface'' to better understand the financial impacts of EP (Delmas et al., 2011, p.117).

This paper contributes to the EP-FP literature by introducing a key transparent, quantitative, and relative measure of EP: *industry-adjusted GHG emissions intensity*. We

[1] The literature has generally used MSCI ESG (KLD) Stats (Chava, 2014; Hong and Kacperczyk, 2009) and the Asset4 ESG database (Gonenc and Scholtens, 2017; Gupta, 2015). However, this choice could have been driven by data availability (Chatterji et al., 2009).

[2] Quite strikingly, EP scores have been found to positively correlate with levels of toxic releases and low environmental compliance (Delmas and Blass, 2010), and environmental strengths and concerns are positively related (Delmas et al., 2013; Mattingly and Berman, 2006). Doda et al. (2016) find little evidence that on average corporate carbon management policies have led to substantial reductions in GHG emissions.

[3] Dorfleitner et al. (2015) compare EP scores from different ratings providers (KLD, Asset4, and Bloomberg) and find a lack of convergence; Horváthová (2010) and Halbritter and Dorfleitner (2015) show that empirical findings in the EP-FP literature are sensitive to the type of EP measure and data provider used.

contend that this measure is an important first step to answer the criticisms related to the operationalization and measurement of EP. Together with alternative cost of capital measures, these complement the prior literature (Chava, 2014; El Ghoul et al., 2011; 2016; Gupta, 2015). We use an international dataset for a relatively extensive study period. Lastly, by adopting a panel regression framework we complement the investment portfolio literature (e.g., Ibikunle and Steffen, 2015) and attempt to empirically test the theoretical framework by Heinkel et al. (2001).

Using self-reported GHG emissions data for an international sample of 1,920 publicly listed firms over the years 2002-2016, we find that industry-adjusted GHG emissions intensity positively impacts the cost of equity. The effect is robust to alternative GHG emissions intensity measures, GHG emissions data sources, cost of equity estimations, study periods, and model specifications.

This paper is structured as follows. Section 2 provides a theoretical background on the hypothesized EP-CoC relationship. Sections 3 and 4 outline the methods and data used to test our hypotheses. Results are presented in section 5. Section 6 discusses the results and concludes.

2. Theoretical background

The literature has theorized that firms' EP efforts, such as GHG emissions reductions, may impact firm value either positively or negatively. The *trade-off hypothesis*, grounded in agency theory (Preston and O'Bannon, 1997), argues that EP efforts come at the expense of shareholder value, and might be exploited by managers to increase private (reputational) benefits. By contrast, the *risk mitigation hypothesis* holds that emissions reductions can increase firm value by limiting exposure to several key perceived risks. The literature on Socially Responsible Investing (SRI) has so far not reached a consensus on whether EP efforts come with net financial benefits (Endrikat et al., 2014)**.** We contend that the significant policy- and market mechanisms on climate change render the effect of reducing GHG emissions on the *size* of future cash flows ambiguous. Instead, we argue that *risk* is the main channel of interest to assess the value-relevance of GHG emissions reduction efforts.

We follow the microeconomic literature on EP (Dam and Scholtens, 2015; Fama and French, 2007; Heinkel et al., 2001; Mackey and Mackey, 2007), which has theorized that investor preference for low-carbon assets lowers the required rate of return on such assets. By contrast, high-carbon firms see their investor bases reduced, leading investors in them to demand higher returns for the increased risk they bear due to impaired diversification (risk-sharing). The literature has identified three main transmission mechanisms that explain the value-relevance of EP efforts. First, Bollen (2007), Ballestero et al. (2012), and others theorize that the utility function of some investors includes non-financial considerations, such as firms' contribution to climate change. A second way in which EP can increase the investor base is by reducing asymmetric information with the investors (Heinkel et al., 2001 following Merton, 1987). EP information may signal a 'responsible' image (Dhaliwal et al., 2009) and increases media, reporting, and analyst coverage (Hong and Kacperczyk, 2009). Finally, reductions in emissions and exposure to high-carbon assets reduce the perceived risk of assets. As outlined in Section 1, reducing GHG emissions is expected to limit the exposure to several financial risks related to the transition from high- to low-carbon sources (see Andersson et al., 2016; Busch, 2007; De Jong and Nguyen, 2016). Examples are the growing public policy-, consumer-, and market pressures to transition from high- to low-carbon energy sources, which render investments in high-carbon energy sources increasingly risky (e.g., Bauer and Hann, 2010). Good EP might further reduce financial and operational risks

(McGuire et al., 1988), social and environmental risks (Sharfman and Fernando, 2008), and decrease the incidence of (negative) shocks related to future regulation, litigation, and reputational harm through increased stakeholder loyality (Bouslah et al., 2013; Cai et al., 2016; Minor and Morgan, 2011; Boutin-Dufresne and Savaria, 2004; Nofsinger and Varma, 2014). Porter and Van der Linde (1995) have argued that EP enhances competitiveness through innovation.

Based on the microeconomic framework outlined above, we hypothesize that firms with low-GHG emissions intensity benefit from lower costs of capital.[4]

This paper closely relates to recent studies by Chava (2014), El Ghoul et al. (2011; 2016), Gupta (2015), and Sharfman and Fernando (2008), which generally find a negative relationship between EP ratings and the cost of equity (CoE). However, Chava (2014) finds that the CoE is only significantly impacted by environmental weaknesses, while there is no effect of environmental strengths. Boermans and Galema (2017) identify a potential trade-off for pension funds between returns and environmental objectives. With respect to the cost of debt (CoD), Bauer and Hann (2010) show a negative relationship between EP and corporate bond spreads. Chava (2014) and Goss and Roberts (2011) show that environmental concerns relate to higher CoD. Bouslah et al. (2013) and Cai et al. (2016) find that environmental strengths reduce risk. Our study further relates to the literature investigating the return performance of ‘green’ investment portfolios (Ibikunle and Steffen, 2015) and fossil-free portfolios (Trinks et al., 2017). Lastly, a few recent studies specifically use GHG emissions data as well. Liesen et al. (2017) form portfolios based on GHG emissions disclosure and emissions intensity, and Görgen et al. (2017) propose a ‘carbon risk factor’. Another stream of

[4] The hypothesis that GHG emissions information is priced assumes semi-strong market efficiency, implying that investors act on publicly available GHG emissions data. Emissions data have been available to investors for a large number of firms through annual reports, mainstream financial channels (Bloomberg, Thomson Reuters, MSCI/WRDS) and non-financial ones (SRI industry and rating agencies), particularly for the last few years.

literature has focused on the effect of GHG emissions data disclosure on the cost of capital (CoC), and found a positive relationship (Clarkson et al., 2013; Rezec, 2016).

3. Methods

This section outlines the methods used to test our main hypothesis that GHG emissions intensity adversely affects the CoE. To measure the impact of EP on CoE, it is vital to account for omitted variable biases such as unobserved firm heterogeneity (Horváthová, 2010). This motivates our use of panel regression methods[5] instead of two alternative approaches, namely event studies and portfolio studies (see Ambec and Lanoine, 2008). Panel regression also facilitates making reasonable causal inferences based on economic theory. We adopt the following fixed-effects model, which includes year-fixed effects, and estimate it using robust standard errors clustered at the firm level:

$$CoE_{i,t} = \beta_{0i} + \beta_1 GHG\ intensity_{i,t-1} + \beta_2 X_{i,t} + year_i + u_{i,t} \tag{1}$$

$CoE_{i,t}$ is our estimate of the cost of equity (CoE) for firm i at time t (see Section 3.1). $GHG\ intensity_{i,t-1}$ measures the GHG emissions intensity of firm i at time t_{-1} (see Section 3.2). We lag GHG intensity by one year to ensure information on GHG emissions has been fully disseminated to all investors, and to (partially) address potential issues related to reverse causality and simultaneity (Jo and Harjoto, 2014). $X_{i,t}$ is a set of control variables used in the related literature (see Section 3.3). $year_i$ is a year dummy capturing time-varying unobserved

[5] Chava (2014) notes that panel regressions are preferred over Fama and MacBeth (1973) month-by-month cross-sectional regressions because of the short time series available for EP variables.

effects. The error term, $u_{i,t}$, allows for firm heterogeneity and industry and country unobserved effects (Horváthová, 2010).

3.1. Cost of capital

We estimate the CoE by performing Capital Asset Pricing Model (CAPM) regressions based on prior ten years arithmetic average daily returns.[6] This is in line with Sharfman and Fernando (2008), but contrasts with Chava (2014), El Ghoul et al. (2011; 2016), and Gupta (2015), who use the internal rate of return implied in current stock prices and analyst earnings forecasts to estimate the CoE. This method, however, has various drawbacks, such as the existence of various biases in analyst forecasts, poor data availability (there is only a 30% match between I/B/E/S and GHG emissions data), and the finding by Ioannou and Serafeim (2015) that analyst recommendations interact with CSR. CAPM is common practice (Armitage, 2005; Damodaran, 2016) and theoretically appealing (Perold, 2004). Nevertheless, we recognize that realized historical returns may be an imperfect proxy for expected returns (Elton, 1999; Fama and French, 1997).[7] For robustness, we use different asset pricing models (Fama and French, 1993; Carhart, 1997), a different market factor (MSCI World index), 5-, 2-, and 1-year estimation windows (Carleton and Lakonishok, 1985; Damodaran, 2016), geometric averaging, and weekly and monthly returns (see Section 5.2).

3.2. GHG emissions intensity

GHG intensity is measured as total GHG emissions (measured in metric tonnes of CO2-equivalents) scaled by net sales. GHG intensity has been promoted by Hoffmann and Busch (2008), and used by Görgen et al. (2017), among others, as a straightforward, transparent, and relative indicator of a key environmental impact of business activitiy. As

[6] Arithmetic return averaging is theoretically recommended (Armitage, 2005) and provides plausible CoE estimates. In Section 5.2, we check the robustness of our results against using geometric return averaging.
[7] Note, however, that we analyze the *differences* in CoE, making the precision of estimates less important.

such, the measure should be a key variable determining the environmental risks in firms as well as investor preferences for environmental responsibility. We adjust GHG intensity for the industry market-capitalization-weighted average intensity in the year. This addresses the relative nature of emissions reduction efforts in different industries and years, and aligns with the standard practice of best-in-class selection in SRI. We use the Industry Classification Benchmark (ICB), which divides firms into 10 industries (ICB1), 19 supersectors (ICB2), 41 sectors (ICB3), and 114 subsectors (ICB4).

We acknowledge that relying on GHG intensity may constitute an imperfect measure of the actual efforts taken by firms to reduce GHG emissions. First, intensity ignores trade-offs between GHG emissions and other 'inputs'. Firms may show increased intensity solely due to a substitution between production factors, which can result from modernization, sectoral changes in the economy, and changes in national energy mixes. In addition, intensity generally overstates the extent to which energy efficiency improvements have occurred, particularly during recessions, as energy consumption does not fall as much as production and as consumption is driven by energy input prices. A refined measurement of EP would account for the relative GHG efficiency of the firms based on a Total Factor Productivity (TFP) framework. Addressing these issues is beyond the scope of this paper though. However, we argue that GHG intensity provides a useful, straightforward, and transparent measure of EP that makes an important contribution to the EP-FP literature.

3.3.Control variables

In line with the literature, we control for *Beta*, measured as the factor loading in a CAPM cross-sectional regression of daily excess returns on the global market factor over the previous ten years, *Size*, defined as the natural logarithm of total assets, financial leverage (*Lev*), defined as total debt over total assets, Market-to-Book (*MTB*), defined as the ratio of the market value of equity relative to the book value of equity, Return on Assets (*ROA*), defined as income before extraordinary items divided by total assets, and *Sales growth*, defined as the one-year increase in net sales. Beta (systematic risk) is expected to positively relate to expected stock returns (Sharpe, 1964). Larger firms can be considered less risky (Fama and French, 1993), as they, among other things, may benefit from lower operating and financial risk (Jo and Harjoto, 2014). Size may also proxy for visibility and stakeholder risk (Udayasankar, 2008) and increased analyst coverage and attention, which might reduce information asymmetry and the CoC. Leverage is known to positively relate to the CoC by increasing default risk (Fama and French, 1992; Gonenc and Scholtens, 2017). A low MTB ratio is an indicator of financial distress as well. Consequently, low-MTB firms are expected to earn higher ex post returns (Fama and French, 1992; Galema et al., 2008). Weak profitability (low ROA) may motivate cuts in EP. Improved sales growth signals solvency (Bradley and Chen, 2015).

As a robustness check, we include a battery of additional control variables. We consider return volatility (*RetVol1yr*) to account for total risk, defined as the standard deviation of the daily returns over the previous year (see El Ghoul et al., 2016; Chava, 2014). We further include Research and Development (R&D) intensity (*RDIntTA*), measured as R&D expenses over total assets (cf. Gonenc and Scholtens, 2017; Rezec, 2016). A high R&D intensity could correspond with increased levels of risk. Moreover, EP may proxy for R&D which is linked to FP (Lioui and Sharma, 2012). We do not include R&D intensity in our main regression specification, as it reduces our sample by more than 50% (cf. Rezec, 2016) and does not enter significantly in our regressions. We also control for Capex intensity (*CapexTA*), measured as capital expenditures over total assets, and Capital intensity, measured as Property, Plant, and Equipment (PPE) over total assets, as both have been found to proxy for firms' financial risks (Bauer and Hann, 2010). We control for liquidity effects using Net Working Capital (*NWC*) scaled by total assets (Gonenc and Scholtens, 2017).

4. Data

4.1. GHG emissions

We obtain self-reported data on GHG emissions of publicly listed firms at end-of-June from Thomson Reuters' Asset4 database and Bloomberg ESG data for 2002-2016. Asset4 gathers GHG emissions data for each fiscal year from public sources, mostly annual and CSR reports. Bloomberg additionally provides data on GHG emissions as reported to the Carbon Disclosure Project (CDP)[8] survey. As the data sources represent two different channels which provide different GHG emissions figures, including both data sources increases robustness.

We focus on Scope 1 and 2 emissions. Reporting on Scope 3 emissions is currently poor and not yet widespread, and Scope 3 emissions are largely outside the direct control of the firm. Figure 1 shows the number of firms which report on each of the Scopes over the years. We calculate total GHG emissions as the sum of Scope 1 and Scope 2 emissions *provided that both scopes are reported*[9] (in contrast with other studies (e.g., Liesen et al., 2017; Görgen et al., 2017, which simply take the sum), to ensure comparability in terms of total emissions. Additionally, as a robustness check, we restrict our sample to 2008-2016 because correspondence with Thomson Reuters and Bloomberg underlined the poorer quality of corporate GHG emissions reporting in years before 2008. In addition, the number of reporting firms is very low before 2008 (cf. Görgen et al., 2017), which might be problematic

[8] For a list of studies using CDP data, see: https://www.cdp.net/en-US/Results/Pages/academic-data.aspx (accessed: August 22, 2017).

[9] Correspondence with Thomson Reuters and Bloomberg assured this method maximizes consistency as firms may report a total figure for which it is unknown which scopes are included. A further benefit of manual summation of Scopes 1 and 2 is that it eliminates any errors in the total emissions data entries.

for obtaining plausible industry-average intensities. For robustness, we also extend our sample using Scopes 1-3 emissions as well as focusing on Scope 1 only. Additionally, from Bloomberg, we obtain information on the proportion of the emissions that have been externally verified, indicating whether reported emissions are consistent with the reporting guidelines (GHG protocol), and the level of uncertainty reported by the firm, indicating the level of estimation or extrapolation used to determine the reported total emissions. Results of the above robustness analyses are in Tables A.4, A.5, and A.7.

Self-reported GHG emissions data have several limitations. Most notably, there is no standard or regulation for reporting on GHG emissions. This reduces the quality and reliability of GHG emissions data, which in turn limits their value to investors (see Adamsson et al., 2016; Schaltegger et al., 2016; Sullivan and Gouldson, 2012). However, reporting has become more standardized in recent years. Also, ‘’looking at emissions over longer time frames and for a large group of businesses gives a reasonable actionable level of information on how firms’ GHG emissions are evolving’’.[10] Relatedly, the GHG emissions figure from Asset4 and Bloomberg does not guarantee that all GHGs are included, as firms may differ in terms of which GHGs they report about. Still, the reported GHG emissions figure is the information that investors have and might or might not act on, which is an empirical issue.

4.2. Environmental performance scores and institutional shareownership

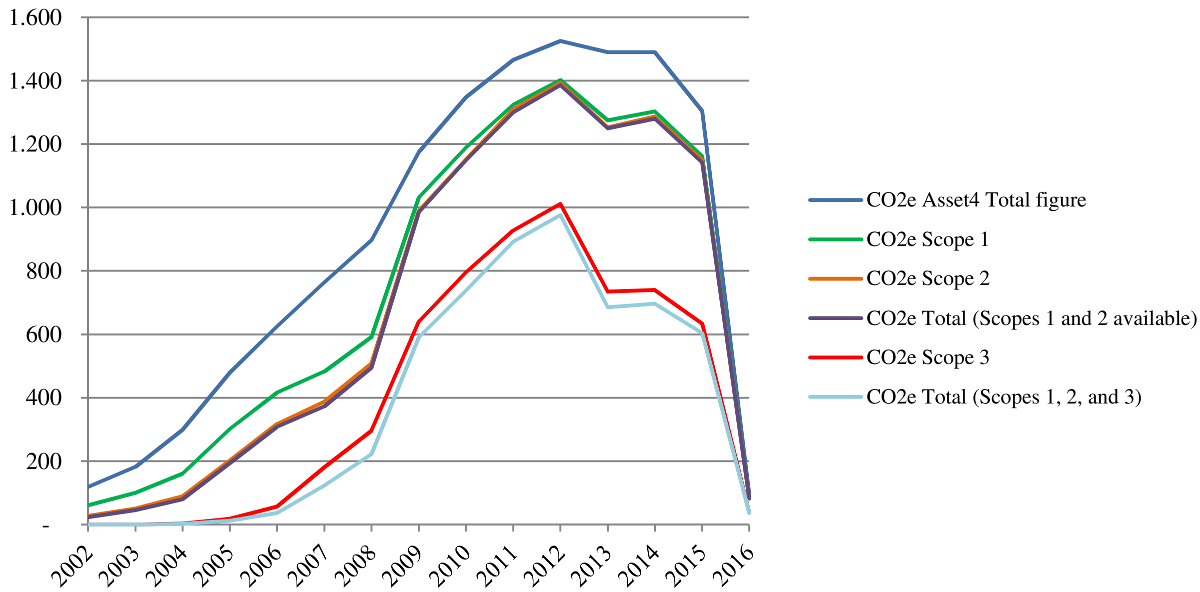
We further obtain EP scores from Asset4 to relate our GHG intensity with the EP-CoC literature using EP scores (in Section 4.5) (Chava, 2014; El Ghoul et al., 2011; 2016; Gupta, 2015). ENVSCORE is the overall EP rating from Asset4, which is based on three EP subcategories. ENVPILLAR1-3 represent the subcategory ratings for *emissions reduction, product innovation, and resource reduction* respectively. A4IR is the overall sustainability

[10] https://www.thomsonreuters.com/content/dam/openweb/documents/pdf/corporate/Reports/global-500-greenhouse-gases-performance-trends-2010-2013.pdf (accessed: August 29, 2017).

rating from Asset4, which is comprised of environmental, social, governance, and economic performance.

In addition, the literature has identified that sustainable or high-EP firms benefit from a larger institutional investor base, possibly due to their visibility and greater sensitivity to social norms (Chava, 2014; Hong and Kacperczyk, 2009). Therefore, we compare (in Section 4.5) high- and low-GHG intensity firms in terms of their average percentage of shares outstanding held by institutional investors, excluding investment firms, which can include less visible mutual funds, etc. (as in Bouslah et al., 2013; Hong and Kacperczyk, 2009).

Figure 1: Number of non-financial firms reporting GHG emissions



** Note that for 2016, GHG emissions data will be fully processed End of 2017.*

4.3.Financial variables

We obtain financial variables from Thomson Reuters Datastream and Bloomberg, consistent with the data source used for GHG emission data. In line with the international outlook of our sample, we use the Global factors from Kenneth French' website (http://mba.tuck.dartmouth.edu/pages/ faculty/ken.french/data_library.html). We winsorize all variables at the 1st and 99th percentile.

After removing firms belonging to the financial sector and those which report on an unconsolidated basis, we end up with a sample of 1,920 firms. Our sample has a highly international outlook and is unequally distributed over years, industries, and countries, as shown in Tables A.1-A.3. Our sample is larger than that of El Ghoul et al. (2016) and Sharfman and Fernando (2008), but smaller than Chava (2014), El Ghoul et al. (2011), and Gupta (2015), as coverage of GHG emissions data is relatively low compared to EP ratings.

4.4.Summary statistics and correlations

GHG emissions vary strongly across firms, as shown by the substantial standard deviation of the total GHG emissions figure (see Table 1). The strong variation in total GHG emissions and GHG emissions intensity underlines the importance of controlling for industry differences in carbon intensity. Moreover, we find a substantial difference in the mean and median total GHG emissions. This indicates that there are a few big emitters and a majority of much less-emitting firms.[11] We performed several cross checks to verify the cross-sectional and time variation in the carbon intensity. We confirm that these are plausible, in the sense that they are consistent with the (publicly) reported values of emissions and sales.

Against expectations, we do not find GHG intensity to be strongly correlated with the CoE (see Table 2). Also, contrary to the literature using EP scores (e.g., Chava, 2014), we find that GHG intensity is only weakly negatively correlated with the percentage of institutional investors. Interestingly, we find that GHG intensity only weakly negatively correlates with the EP scores from Asset4. ENVPILLAR1, which measures the firm's policy on emissions reductions, does not seem to relate strongly to the firm's actual reductions in

[11] As a robustness check, we check and confirm that removing the 10th and 90th percentile total GHG emissions does not qualitatively change the results.

GHG intensity levels. The weak correlation between GHG intensity and EP scores highlights the conceptual differences of both indicators.

Table 1: Summary statistics of key EP variables (Panel A) and financial variables (Panel B)

Panel A: EP variables

	N	Mean	Median	SD	Min	Max	Skewness	Kurtosis
GHG emissions total (tCO2e)	10,091	4,602,107	495,730	12,240,216	2,566	81,000,000	4.35	23.65
GHG intensity (tCO2e/net sales)	10,047	0.39	0.06	0.90	0.00	5.94	4.24	23.08
GHG intensity, industry-adjusted	10,047	0.14	-0.02	0.82	-0.97	5.35	4.31	24.74

Panel B: Financial variables

	N	Mean	Median	SD	Min	Max	Skewness	Kurtosis
CoE	21,744	0.06	0.06	0.02	0.02	0.12	0.56	3.01
Beta	21,744	0.61	0.55	0.33	0.05	1.48	0.58	2.71
Size (ln, USD thousands)	25,852	15.43	15.48	1.56	11.10	18.99	-0.20	2.99
MTB	24,666	1.67	1.38	0.91	0.67	5.91	2.29	9.35
Lev	25,822	0.26	0.24	0.17	0.00	0.74	0.52	2.96
ROA	25,407	0.07	0.06	0.08	-0.23	0.33	-0.15	6.50
Salesgrowth	23,896	0.08	0.07	0.22	-0.59	0.88	0.44	5.62
% Institutional shareholdings	26,044	0.05	0.00	0.23	0.00	1.65	5.70	36.77

Table 2: pairwise correlations between key variables

Panel A: GHG intensity and financial variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CoE (1)	1.00								
GHG intensity, industry-adjusted (2)	0.01	1.00							
Beta (3)	0.72	-0.04	1.00						
Size (4)	-0.20	0.04	0.28	1.00					
MTB (5)	0.04	-0.07	-0.02	-0.27	1.00				
Lev (6)	0.04	0.09	0.01	0.21	-0.14	1.00			
ROA (7)	-0.09	-0.06	-0.08	-0.09	0.55	-0.18	1.00		
Salesgrowth (8)	-0.02	-0.05	-0.07	-0.02	0.15	-0.04	0.24	1.00	
% Institutional shareholdings (9)	-0.05	-0.02	-0.08	0.11	-0.04	0.04	0.01	-0.01	1.00

Panel B: GHG intensity and Asset EP ratings

	(1)	(2)	(3)	(4)	(5)	(6)
GHG intensity, industry-adjusted (1)	1.00					
ENVSCORE (2)	-0.06	1.00				
ENVPILLAR1 (3)	-0.01	0.87	1.00			
ENVPILLAR2 (4)	-0.07	0.80	0.52	1.00		
ENVPILLAR3 (5)	-0.09	0.86	0.73	0.50	1.00	
A4IR (6)	-0.04	0.75	0.69	0.50	0.71	1.00

4.5. Univariate tests

To compare the GHG intensity measure with commonly used EP scores (El Ghoul et al., 2011; Gupta, 2015), we divide the sample into high (above median) and low (below median) industry-adjusted GHG intensity firms.[12] Interesting, we find that low-GHG intensity firms have significantly lower EP scores; even the ENVPILLAR1 score, which represents firms' emissions reduction policies, is significantly lower for low-GHG intensity firms. This further supports the concerns that commonly used EP scores are an imperfect measure of actual GHG emissions reductions made by firms. We further test whether institutional shareownership is higher for low-GHG intensity firms (cf. Chava, 2014; Hong and Kacperczyk, 2009). We do not find institutional shareownership to be significantly higher for low-GHG intensity firms. Finally, with respect to the CoE we find that low-GHG intensity firms on average have 0.1% lower CoE than firms with high GHG intensity. However, it is likely that other factors (e.g., leverage and firm size), more than low-GHG intensity, are the main drivers of the lower CoE. To test our hypothesis that GHG intensity positively affects the CoE, we must disentangle these effects through multivariate regressions, which we will present in the next section.

Table 3: Univariate test of means

	(1) Low-GHG intensity (N = 5,023)	(2) High-GHG intensity (N = 5,024)	(1) - (2) Difference t-test
CoE	0.0560	0.0570	-0.0010*
% Institutional shareholdings	0.0585	0.0608	-0.0022
ENVSCORE	75.9815	77.4515	-1.4700***
ENVPILLAR1	76.2624	78.7934	-2.5310***
ENVPILLAR2	66.6649	65.6134	-1.0515*
ENVPILLAR3	75.2460	77.3061	-2.0601***
A4IR	76.0377	77.1953	-1.1576***

This table reports mean difference tests for low-GHG intensity (below-median GHG intensity) and high-GHG intensity (above-median GHG intensity) subsamples. GHG intensity is the one-year lagged GHG intensity (GHG emissions/net sales) minus the industry- (ICB1) market-capitalization-weighted average GHG intensity in the corresponding year. CoE is estimated using the CAPM using prior ten years daily excess returns. % Institutional shareholdings is the percentage of shares outstanding held by institutional investors, excluding investment firms. ENVSCORE is the overall EP rating from Asset4, and ENVPILLAR1-3 represent the subcategory ratings for *emissions reduction, product innovation, and resource reduction* respectively. A4IR is the overall sustainability rating from Asset4. *** p<0.01, ** p<0.05, * p<0.1.

[12] When defining high- and low-GHG intensity by the $30^{th}/70^{th}$, $20^{th}/80^{th}$, or $10^{th}/90^{th}$ percentiles, results are similar but differences are more pronounced.

5. Results

5.1. Multivariate regressions

We perform fixed-effects regressions (Eq.1) to test the effect of GHG intensity on the CoE (see Table 5). We find a positive effect of lagged industry-adjusted GHG intensity on the CoE, which is significant at the 5% level. We find that every unit increase in the industry-adjusted GHG intensity, ceteris paribus, increases next year's CoE by 15bps. Conversely, reducing the GHG intensity by, for example, 0.3 per year, which are frequently observed in our sample, has a modest CoE-reducing impact of 5bps. The control variables' coefficients all have the expected sign and are also mostly statistically significant in our regressions.

Our findings support the risk mitigation hypothesis, which holds that emissions reductions can increase firm value by limiting exposure to several key perceived risks. Firms with low relative GHG emissions tend to benefit from a lower required rate of return (cost of capital). This might result from growing investor preference for low- instead of high-carbon assets as well as the increased perceived riskiness of high-carbon assets.

5.2. Robustness

We assess the robustness of our results to 1) alternative GHG intensity measures, 2) alternative GHG emissions data source (CDP survey), 3) CoE estimation (asset pricing model, market factor, estimation window, averaging method, and data frequency), 4) subperiods, 5) and omitted variables and reverse causality concerns.

First, we consider the robustness of our results to alternative scaling of GHG emissions (by total assets or market capitalization), correcting GHG intensity for sector- as well as country-average GHG intensity, and focusing on Scope 1 only and Scopes 1, 2, and 3 combined. Results are qualitatively similar across GHG intensity measures, but are not significant anymore when considering Scope 1 only or Scopes 1, 2, and 3 combined (see Table A.4).

Table 4: Cost of equity regression

L.GHG intensity	0.0015***
	(0.0005)
Beta	0.0628***
	(0.0020)
Size	-0.0013
	(0.0009)
MTB	0.0011***
	(0.0004)
Lev	0.0087***
	(0.0027)
ROA	0.0007
	(0.0027)
Salesgrowth	0.0003
	(0.0009)
Constant	0.0355***
	(0.0135)
Observations	8,365
R-squared	0.8316
Number of id	1,694
Firm fixed effects	Yes
Year fixed effects	Yes

This table shows the fixed-effects regressions of the CoE on our relative GHG intensity measure and control variables. CoE is estimated using the CAPM using prior ten years daily excess returns. L.GHG intensity is the one-year lagged GHG intensity (GHG emissions/net sales) minus the industry- (ICB1) market-capitalization-weighted average GHG intensity in the corresponding year. Beta is the factor loading in a CAPM regression of prior ten years daily excess returns on the global market factor. Size is the natural logarithm of market capitalization. MTB is market value of equity to book value of equity. Lev is total debt over total assets. ROA is return on assets. Sales growth is the % one-year growth in net sales. Robust standard errors clustered at the firm level are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Second, we we rerun our analyses replacing GHG emissions data from publicly available sources (Asset4) with data from the CDP survey (Bloomberg). We find that the EP-CoE relationship is generally stronger compared to our main analysis (see Table A.5). Differences might result from sample differences between the two data providers. An alternative explanation is our finding that emissions figures reported to the CDP survey tend to be somewhat higher than those being reported in annual reports. We include the CDP variable indicating the firm's level of uncertainty about the reported emissions figure. Interestingly, we find that uncertainty about Scope 1 emissions reduces the effect of GHG intensity on the CoE. This finding seems to emphasize the importance to investors of reliable GHG emissions reporting (consistent with Rezec, 2016).

Results on CoE estimation, reported in Table A.6, show that our results are generally robust to different CoE estimation procedures (asset pricing model, market factor, estimation window, averaging method, and data frequency). The only exception is the weaker effect when using a 5-year estimation window.

In Table A.7, we find that the effect of GHG emissions intensity on the CoE is stable across three-year subperiods. The effect size tends to be somewhat larger in more recent time frames, which is suggestive of the growing investor preference for low-carbon assets.

To address concerns about potential omitted variable biases, we add additional control variables to our main model, described in section 3.3, and compare our findings with the model specifications of related studies (Chava, 2014; El Ghoul et al., 2011; 2016). From Table A.8, we find that results are somewhat different across model specifications. However, potentially important variables, such as R&D intensity and liquidity, do not enter significantly in the regression. This contrasts with the finding by Lioui and Sharma (2012), who emphasize the potential moderating role of R&D intensity in a CSR-FP framework. Also, note that differences might be driven by the restricted sample size due to poor data availability.

Lastly, a potential concern raised in the literature (e.g., Scholtens, 2008) is reverse causality in the EP-CoC relationship. However, we find little theoretical reasons why CoE might drive GHG intensity. Table A.9 further alleviates the concerns that might subsist as only three-, two-, and one-year lagged GHG intensity significantly positively relates to CoE, while there are no significant loadings on current and one-year lead GHG intensity.

6. Discussion and conclusion

Climate-related risks have become a growing concern in capital markets. This study is among the first to investigate whether a key indicator of environmental impact, GHG emissions intensity, lowers the returns required by investors. Our main finding is that firms' industry-adjusted GHG intensity positively relates to their cost of equity (CoE). This finding is robust to using alternative GHG emissions intensity measures, GHG emissions data sources, and CoE estimation. We do find a weaker CoE effect for earlier periods as well as when adopting alternative model specifications. We do not find any evidence of potential edogeneity concerns. In all, we find strong support for the hypothesis that reducing the impact on climate can increase firm value by lowering the returns required by investors. This might result from growing investor preference for low- instead of high-carbon assets as well as the increased perceived riskiness of high-carbon assets.

Our findings are consistent with and complement the closely related studies by Chava (2014), El Ghoul et al. (2011), El Ghoul et al. (2016), Gupta (2015), and Sharfman and Fernando (2008), which have identified a negative relationship between Environmental Performance (EP) scores and the CoE. Our finding that GHG emissions intensity lowers the required rate of return is also in line with Bouslah et al. (2013) and Cai et al. (2016) who specifically show the risk-reducing effects of EP. Our results are furthermore in line with portfolio studies by Ibikunle and Steffen (2015) and Boermans and Galema (2017), but contrast with Liesen et al. (2017) and Görgen et al. (2017). As the latter two studies focus on realized returns instead of expected returns, they do not directly test the risk mitigation hypothesis. Moreover, Liesen et al. (2017) use a limited sample size and study period and report only weakly significant results. Additionally, while Görgen et al. (2017) find negative returns on a 'Brown-minus-Green' carbon risk mimicking factor, the authors do not capture industry-adjusted carbon intensity and their results show a significant carbon risk premium for 2012-onwards. Finally, our results are consistent with the findings of Clarkson et al. (2013) and Rezec (2016), which underline the CoE-reducing impacts of GHG emissions disclosure.

These findings have important implications for managers, investors, and regulators. First, our results indicate that managers should consider the value-relevance of GHG emissions reductions and disclosure. Growing investor preferences for low- instead of high-carbon assets fuels this mechanism. For investors, low-carbon investing may reduce exposure to climate-related risks, but our findings underline its costs in terms of lower expected returns. Our findings further underline the important role of capital markets in providing a promising (partial) solution to market and regulatory failures in the area of climate change by effectively rewarding emissions-reduction efforts through a reduction in the cost of capital.

We feel that the main limitation of our study is the currently limited and non-standardized way of GHG emissions reporting. However, we contend that the proposed measures are an important first step to quantifying and understanding the EP-CoC relationship.

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Appendix A

Table A.1: GHG emissions data coverage by data source: Number of observations per year

	Public reports (Asset4)	CDP survey (Bloomberg)
2002	27	-
2003	50	-
2004	89	-
2005	202	-
2006	317	55
2007	388	265
2008	508	443
2009	990	625
2010	1,152	824
2011	1,310	980
2012	1,393	1,041
2013	1,253	1,107
2014	1,287	1,162
2015	1,150	1,204
2016	82*	1,174*
Total	10,092	8,880

* Incomplete sample: GHG emissions data will be fully processed End of 2017.

Table A.2: Firm-year observations by country

Country	Freq.	Percent
US	6,240	21.68
GB	4,470	15.53
JP	2,850	9.90
CA	1,605	5.58
AU	1,515	5.26
FR	1,185	4.12
ZA	1,170	4.06
KR	915	3.18
DE	870	3.02
TW	825	2.87
BR	690	2.40
SE	555	1.93
CH	525	1.82
ES	510	1.77
IN	495	1.72
HK	390	1.35
NL	375	1.30
Other	3,600	12.51
Total	32,592	100

Table A.3: Firm-year observations by industry (ICB level 1)

ICB1	Industry name	Firm-year obs	Percent
1	Oil & Gas	2,205	7.66
1000	Basic Materials	4,020	13.97
2000	Industrials	7,125	24.75
3000	Consumer Goods	4,110	14.28
4000	Health Care	1,620	5.63
5000	Consumer Services	4,320	15.01
6000	Telecommunications	1,170	4.06
7000	Utilities	1,800	6.25
9000	Technology	2,415	8.39
Total		**28,785**	**100.00**

Table A.4: Cost of equity regressions with different GHG intensity measures

	(1) GHG intensity sales	(2) GHG intensity total assets	(3) GHG intensity market cap	(4) GHG intensity sales, sector-adjusted	(5) GHG intensity Scope 1	(6) GHG intensity Scope 1+2+3
L.GHG intensity	0.0015***	0.0027**	-0.0002	0.0023**	0.0006	0.0007
	(0.0005)	(0.0012)	(0.0003)	(0.0010)	(0.0005)	(0.0004)
Observations	8,365	8,365	8,365	7,437	9,026	4,759
R-squared	0.8316	0.8315	0.8313	0.7478	0.8343	0.8288
Number of id	1,694	1,694	1,694	1,655	1,700	1,189
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table shows the fixed-effects regressions of the CoE on different GHG intensity measures and control variables. CoE is estimated using the CAPM using prior ten years daily excess returns. L.GHG intensity is the one-year lagged GHG intensity, measured as GHG emissions/net sales (1), GHG emissions/total assets (2), GHG emissions/market cap (3), GHG emissions Scope 1/net sales (5), GHG emissions Scopes 1+2+3/net sales (6), minus the industry- (ICB1) market-capitalization-weighted average GHG intensity in the corresponding year. Specification (4) replaces the industry-average with the sector- (ICB3) average intensity. All regression include the control variables described in section 3.3. Robust standard errors clustered at the firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Cost of equity regressions with GHG emissions data from CDP survey

L.GHG intensity	0.0029**	0.0110***
	(0.0013)	(0.0035)
L.GHG intensity x L(uncertainty Scope 1)		-0.0441*
		(0.0231)
L.GHG intensity x L(uncertainty Scope 2)		-0.0001
		(0.0205)
Observations	7,383	5,007
R-squared	0.7745	0.7738
Number of id	1,177	1,128
Controls	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes

This table shows the fixed-effects regressions of the CoE on our relative GHG intensity measure and control variables. CoE is estimated using the CAPM using prior ten years daily excess returns. L.GHG intensity is the one-year lagged GHG intensity (GHG emissions/net sales) minus the industry- (ICB1) market-capitalization-weighted average GHG intensity in the corresponding year. L.GHG intensity x L(uncertainty Scope 1) and L.GHG intensity x L(uncertainty Scope 2) are interaction terms capturing the moderating effect of uncertainty about reported emissions data. All regression include the control variables described in section 3.3. Robust standard errors clustered at the firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: Cost of equity regressions with different CoE specifications

	(1) Main specification CAPM	(2) Fama-French model	(3) Carhart model	(4) MSCI World market factor	(5) Geometric returns	(6) Monthly returns	(7) 5-year estimation window	(8) 2-year estimation window
L.GHG intensity	0.0015***	0.0038**	0.0040**	0.0013**	0.0013***	0.0018***	0.0032**	0.0056***
	(0.0005)	(0.0016)	(0.0016)	(0.0005)	(0.0005)	(0.0007)	(0.0015)	(0.0019)
Observations	8,365	8,365	8,365	8,365	8,365	8,335	8,962	9,149
R-squared	0.8316	0.2299	0.2281	0.8310	0.8310	0.7821	0.8330	0.8528
Number of id	1,694	1,694	1,694	1,694	1,694	1,690	1,779	1,816
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table shows the fixed-effects regressions of various CoE estimates on our main relative GHG intensity measure and control variables. In our main specification (1), the CoE is estimated using the CAPM using prior ten years daily excess returns. The main estimation results are shown when replacing the CAPM with the Fama-French model (2) or Carhart model (3), replacing the Global market factors with the MSCI World index (4), geometric averaging of daily returns instead of arithmetic averaging (5), relying on monthly return data instead of daily return data (6), and employing an estimation window of 5 years (7) or 2 years (8). L.GHG intensity is the one-year lagged GHG intensity (GHG emissions/net sales) minus the industry- (ICB1) market-capitalization-weighted average GHG intensity in the corresponding year. All regression include the control variables described in section 3.3. Robust standard errors clustered at the firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.7: Cost of equity regressions for subperiods

	(1) Full period	(2) 2008-2016	(3) 2008-2011	(4) 2009-2012	(5) 2010-2013	(6) 2011-2014	(7) 2012-2015	(8) 2013-2016
L.GHG intensity	0.0015***	0.0016**	0.0008	0.0034***	0.0034**	0.0005	0.0001	0.0008**
	(0.0005)	(0.0007)	(0.0009)	(0.0011)	(0.0016)	(0.0006)	(0.0003)	(0.0004)
Observations	8,365	7,801	2,655	3,461	4,241	4,486	4,634	4,006
R-squared	0.8316	0.8208	0.8339	0.8061	0.8259	0.8559	0.8566	0.8899
Number of id	1,694	1,676	1,126	1,271	1,407	1,490	1,549	1,510
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table shows the fixed-effects regressions of the CoE on our main relative GHG intensity measure and control variables for various subperiods. CoE is estimated using the CAPM using prior ten years daily excess returns. L.GHG intensity is the one-year lagged GHG intensity (GHG emissions/net sales) minus the industry-(ICB1) market-capitalization-weighted average GHG intensity in the corresponding year. All regression include the control variables described in section 3.3. Robust standard errors clustered at the firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.8: Cost of equity regressions with alternative model specifications

	(1) Main specification	(2) Full model	(3) Chava (2014)	(4) El Ghoul et al. (2016)	(5) El Ghoul et al. (2011)
L.GHG intensity	0.0015***	0.0011	-0.0007	-0.0007	-0.0006
	(0.0005)	(0.0007)	(0.0008)	(0.0008)	(0.0008)
Beta	0.0628***	0.0622***			
	(0.0020)	(0.0030)			
Size	-0.0013	-0.0018	-0.0017	-0.0017	-0.0009
	(0.0009)	(0.0015)	(0.0012)	(0.0012)	(0.0012)
MTB	0.0011***	0.0004	-0.0003	-0.0003	0.0003
	(0.0004)	(0.0007)	(0.0006)	(0.0006)	(0.0006)
Lev	0.0087***	0.0110**	0.0038	0.0042	0.0046
	(0.0027)	(0.0043)	(0.0033)	(0.0033)	(0.0033)
ROA	0.0007	-0.0065			
	(0.0027)	(0.0050)			
Salesgrowth	0.0003	0.0008			
	(0.0009)	(0.0014)			
RetVol1yr		-0.3370***	-0.3235***	-0.3207***	
		(0.0450)	(0.0305)	(0.0302)	
L.m_ExcessRet		0.0040	0.0042**		
		(0.0028)	(0.0020)		
RDIntTA		-0.0211			
		(0.0317)			
NWC		0.0000			
		(0.0000)			
Constant	0.0355***	0.0538**	0.0881***	0.0883***	0.0689***
	(0.0135)	(0.0233)	(0.0193)	(0.0192)	(0.0190)
Observations	8,365	3,597	8,381	8,437	8,443
R-squared	0.8316	0.8409	0.7651	0.7653	0.7565
Number of id	1,694	811	1,689	1,700	1,700
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes

This table shows the fixed-effects regressions of various model specifications, following closely related studies. L.GHG intensity is the one-year lagged GHG intensity (GHG emissions/net sales) minus the industry- (ICB1) market-capitalization-weighted average GHG intensity in the corresponding year. All control variables are described in section 3.3. Robust standard errors clustered at the firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.9: Main specification using different lag orders for GHG intensity

	(1) 5-year lag	(2) 4-year lag	(3) 3-year lag	(4) 2-year lag	(5) 1-year lag	(6) no lag	(7) 1-year lead	(8) 2-year lead	(9) 3-year lead	(10) 4-year lead	(11) 5-year lead
L.GHG intensity	0.0000	0.0009	0.0019***	0.0027***	0.0015***	0.0004	-0.0008	-0.0014**	-0.0014***	0.0000	0.0008
	(0.0005)	(0.0006)	(0.0007)	(0.0007)	(0.0005)	(0.0007)	(0.0007)	(0.0006)	(0.0005)	(0.0004)	(0.0005)
Obs	3,853	5,051	6,213	7,307	8,365	8,778	8,496	8,187	7,795	7,323	6,810
R^2	0.8626	0.8615	0.8563	0.8436	0.8316	0.8244	0.8272	0.8338	0.8437	0.8598	0.8717
Firms	1,243	1,397	1,526	1,630	1,694	1,711	1,648	1,601	1,545	1,479	1,435
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table shows the fixed-effects regressions of our main specification using different lag orders for GHG intensity. L.GHG intensity is the GHG intensity (GHG emissions/net sales) minus the industry- (ICB1) market-capitalization-weighted average GHG intensity in the corresponding year. All regression include the control variables described in section 3.3. Robust standard errors clustered at the firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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