Carbon Intensity and the Cost of Equity Capital

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Abstract

The transition from high- to lower-carbon production systems increasingly creates regulatory and market risks for high-emitting firms. We test to what extent financial investors demand a premium to compensate for such risks and thus might raise firms' cost of equity capital (CoE). Using data for 1,897 firms spanning 50 countries over the years 2008–2016, we find a distinct and robust positive impact of carbon intensity (carbon emissions per unit of output) on CoE: On average, a standard deviation higher (sector-adjusted) carbon intensity is associated with a CoE premium of 6 (9) basis points or 1.7% (2.6%). This effect is primarily explained by systematic risk factors: high-emitting assets are significantly more sensitive to economy-wide fluctuations than low-emitting ones. The CoE impact of carbon intensity is more pronounced in high-emitting sectors, EU countries, and firms subject to carbon pricing regulation. Our results suggest that carbon emission reduction might serve as a valuable risk mitigation strategy.

Keywords: Carbon intensity, cost of capital, regulatory risk, asset pricing

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1. Introduction

The transition from high- to lower-carbon production systems creates substantial uncertainties in firms' regulatory and business environments. Especially the extent to which carbon regulation and market developments will make carbon-intensive production more costly represents a significant risk to future cash flows (Ansar, Caldecott, and Tilbury 2013). In financial markets, this risk has been labeled 'carbon risk' and has become a growing concern for investors (Dyck et al. 2019; Krüger, Sautner, and Starks 2020).[1] Investors increasingly show an interest in reducing exposure to high-emitting firms through divestment (Trinks et al. 2018), carbon-tilting strategies (Andersson, Bolton, and Samama 2016; Krüger, Sautner, and Starks 2020; Amir and Serafeim 2018), or investment in green mutual funds (Ibikunle and Steffen 2017).[2] The banking sector develops policies to reduce the financing of high-emitting businesses (RAN et al., 2019), and credit rating agencies incorporate climate-related financial risks in their assessments (Mathiesen 2018). In the same vein, financial market regulators explore how excessive capital allocation to high-carbon assets might undermine financial stability, and whether additional policy interventions might be required to constrain access to capital for such assets (ESRB, 2016; PDC, 2017; TCFD, 2017).

This paper investigates to what extent financial market investors demand a premium for holding assets of high-emitting firms, thereby raising those firms' cost of equity capital (CoE). We exploit two main sources of carbon emission data for an international sample of 1,897 firms

[1] The market interest in carbon risk is further highlighted by the wide range of investor-backed initiatives fostering corporate disclosure and reduction of carbon emissions, including the Carbon Disclosure Project (CDP), supported by over 515 institutional investors with USD 106 trillion in assets (https://www.cdp.net/en/info/about-us/what-we-do), the United Nations Principles for Responsible Investment (UN PRI), with over 3,000 signatories representing USD 103 trillion in assets (https://www.unpri.org/pri), the United Nations Environment Programme Finance Initiative (UNEP-FI), representing over 300 financial institutions (https://www.unepfi.org/about/), and Climate Action 100, which aims to pressure the world's largest carbon emitters to decarbonize their activities, currently representing over 500 investors with more than USD 47 trillion in assets (http://www.climateaction100.org/) (all accessed: November 18, 2020).

[2] To date, most index providers offer a wide variety of fossil-free or low-carbon indices. The first low-carbon index was launched by S&P in March 2009.

spanning 50 countries over the years 2008–2016. Using a combination of portfolio-level analyses and panel regression techniques, we show how firms' CoE is impacted by carbon intensity (carbon emissions per unit of output), which is a well-known measure of firm-level use of and reliance on carbon sources, and hence carbon risk (Hoffmann and Busch 2008; Krüger, Sautner, and Starks 2020).

Our analysis makes three contributions. Firstly, it adds to the understanding of the impact of firms' carbon emissions on financial risk and asset prices. Financial market investments are crucial to facilitate and stimulate low-carbon activity (IPCC, 2018; UNFCCC, 2015). However, much is still unknown about the extent to which this role is actually being performed and which policy interventions might be required and fruitful to drive low-carbon investment. Thus far, attention has been paid to the theoretical effects of public emission reduction on economy-wide risks and social discount rates (Dietz, Gollier, and Kessler 2018). However, private investment is more directly driven by the discount rate applied to the cash flows of individual firms and projects. This is the rate of return demanded by investors to compensate for investment risk, or—from the perspective of firms—the cost of capital (Albuquerque, Koskinen, and Zhang 2019; Elton et al. 2014; Sharfman and Fernando 2008). We empirically examine the extent to which firms' cost of capital is affected by their carbon intensity, a well-known measure of carbon risk. Given its usefulness to industry practitioners and other areas of academic research, the measure is a valuable contribution to the literature.[3]

Secondly, this paper contributes to the prior empirical literature on direct risk and return effects of corporate sustainability, and environmental performance more specifically (Chava 2014; El Ghoul et al. 2011; Ng and Rezaee 2015; Sharfman and Fernando 2008). To date, no consensus exists about the value relevance of firms' environmental performance (Horváthová

[3] Kleimeier and Viehs (2018) study the effects of carbon intensity on the cost of debt. Carbon intensity has further been used in the modeling of carbon risk exposure of financial firms (Battiston et al. 2017; Dietz, Gollier, and Kessler 2018). Delis, de Greiff, and Ongena (2020) assess whether the risk of stranding of fossil fuel reserves is reflected in corporate loan prices.

2010). It is particularly unclear *which kinds* of such performance are relevant financially and *why* (Albuquerque, Koskinen, and Zhang 2019; Bénabou and Tirole 2010). To a large extent, this is due to the almost exclusive focus on aggregate and indirect ratings of environmental performance in the extant finance literature and practice (cf. Liang and Renneboog, 2017; Ng and Rezaee, 2015; van Duuren, Plantinga, and Scholtens, 2016). Despite the widespread use of such ratings, strong concerns exist about their validity and measurement objective (Chatterji, Levine, and Toffel 2009; Chatterji et al. 2016; Dorfleitner, Halbritter, and Nguyen 2015; Semenova and Hassel 2015). Most ratings tend to focus on firm policy and disclosure levels, which may merely reflect symbolic activities rather than actual impacts and associated risks (Cole et al. 2013; Chatterji et al. 2016; Gonenc and Scholtens 2017).[4] Besides, while covering a broad scope of potentially relevant issues, what is being measured is often ambiguous (ibid.). Environmental performance ratings are also not verified, validated, or replicable based on publicly available information.[5] As a result, robust evidence on effect drivers is lacking, and aggregation bias poses a serious concern. This perpetuates the ambiguity and lack of consensus about the value relevance of firms' environmental performance. Our analysis addresses the issue by focusing on carbon intensity as a single, coherent measure of environmental impact.

Lastly, we combine portfolio-level analyses with robust panel regression techniques to disentangle the pricing implications of carbon intensity. Building on the finance literature on sustainability, we argue that firms that emit less carbon could benefit from lower CoE through reduced regulatory and market risks (Albuquerque, Koskinen, and Zhang 2019; Chava 2014; Grey 2018; Sharfman and Fernando 2008) and a larger investor base (Fama and French 2007;

[4] Remarkably, there is a positive correlation between environmental strengths and concerns (Mattingly and Berman 2006) as well as between environmental performance ratings and levels of toxic releases and poor environmental compliance (Delmas and Blass 2010). Doda et al. (2016) find little evidence that, on average, corporate carbon management policies have led to substantial reductions in carbon emissions (cf. Cole et al., 2013).

[5] Chatterji et al. (2016) compare sustainability ratings from KLD, ASSET4, Innovest, DJSI, FTSE4Good and Calvert and find a lack of convergence; Dorfleitner, Halbritter, and Nguyen (2015) document similar results for KLD, ASSET4, and Bloomberg ESG ratings; Horváthová (2010) and Halbritter and Dorfleitner (2015) show that the sustainability rating and its source strongly determine the estimated financial implications.

Heinkel, Kraus, and Zechner 2001). Our analysis contributes to the literature by examining two mechanisms through which carbon intensity might command a risk premium going forward, specifically, systematic and non-systematic risk factors (Dam and Scholtens 2015). The systematic risk of an asset reflects its sensitivity to economy-wide fluctuations. It is the level of risk in investment portfolios that remains when other, non-systematic risks are eliminated through diversification. As a result, mainstream finance theory holds that only systematic risk requires compensation: investors command a risk premium, raising firms' CoE (Albuquerque, Koskinen, and Zhang 2019; Elton et al. 2014; Sharfman and Fernando 2008).

Recent studies by Liesen et al. (2017) and Görgen et al. (2020) have aimed to test whether firms' carbon emissions reflect risks other than the mainstream systematic risk factors. For instance, Görgen et al. (2020) construct a new risk factor that captures the return differential between groups of 'brown' and 'green' firms which are comparable in terms of their size. The factor did not carry a significant risk premium over the period 2010–2017, even though it added explanatory power to conventional systematic risk factors. Our analysis adds the possibility that carbon intensity commands a risk premium through the mechanism put forward by mainstream finance theory, namely by affecting systematic risk. Specifically, we examine the potential role of non-systematic risk in a standard portfolio-level analysis, and then investigate the mechanism of systematic risk using robust panel estimation techniques. By doing so, our empirical findings are not only firmly embedded in mainstream theory and comparable to related studies (Dietz, Gollier, and Kessler 2018; Fisher-Vanden and Thorburn 2011; Monasterolo and de Angelis 2020; Ziegler, Busch, and Hoffmann 2011), but also useful for practitioners, which typically use systematic risk to estimate the CoE (Levi and Welch 2017).

This paper proceeds as follows. Section 2 develops the main hypotheses. Sections 3 and 4 outline the methods and data. Results are presented in Section 5. Section 6 concludes.

2. Carbon emissions and required returns: theory and hypotheses

A hotly debated issue in the financial economics literature and practice is whether capital markets privately reward firms' sustainability (Ferrell, Liang, and Renneboog 2016; Fisher-Vanden and Thorburn 2011). Mainstream finance theory holds that all activities not targeted at creating value for shareholders ultimately destroy firm value (Jensen and Meckling 1976; Preston and O'Bannon 1997). But recent literature suggests that firms' sustainability is positively related to their financial health (Ferrell, Liang, and Renneboog 2016; Liang and Renneboog 2017; Lins, Servaes, and Tamayo 2017). A key underlying mechanism is that firms' sustainability has a cash flow-preserving or insurance-like effect. Specifically, by taking actions that address concerns of a broader set of stakeholders, firms reduce the exposure to and impact of regulations, reputational damages, and litigation events (ibid.). As a result, sustainability may be rewarded in capital markets through a lower discount rate that investors apply to firms' cash flows, i.e. through a reduction of the cost of capital.

We empirically investigate this risk mitigation hypothesis for firm-level carbon emissions. Adopting an investor perspective, we test whether high-carbon assets are being penalized in capital markets through higher required rates of return (CoE) in order to compensate for their associated risk profiles. Finance theory identifies two mechanisms through which carbon intensity might affect CoE, these are screening activity and systematic risk.

2.1. Hypothesis 1: screening

Investors may not only maximize utility over means and variances of returns, but also over non-financial issues such as firms' contribution to climate change (Fama and French 2007; Heinkel, Kraus, and Zechner 2001; Dam and Scholtens 2015). That is, investors concerned about climate change would require lower (higher) risk-adjusted returns if such returns are earned on less (more) environmentally harmful production activities. If high-carbon assets are screened out by a sufficiently large share of the market, this will lead investors in them to require additional returns for the increased risk they bear due to impaired diversification (ibid.). Hence, the screening mechanism predicts a return premium, or higher CoE, for high-carbon assets compared to low-carbon assets, which is not fully explained by common risk factors. As such, this first mechanism departs from the standard asset pricing framework.

The available evidence suggests that screening likely did not induce return premia in our study period (2008–2016). To date, no demonstrable evidence exists for systematic demand differences based on the carbon intensity of assets like those found in some extensively screened controversial industries (Hong and Kacperczyk 2009; Kleimeier and Viehs 2018). In addition, several conceptual reasons make a screening effect of carbon intensity implausible. Firstly, the screening mechanism will create observable pricing effects only when a similar set of assets is screened out by a sufficiently large share of investors, which act in a coordinated fashion (Heinkel, Kraus, and Zechner, 2001). This is unlikely to be the case. Secondly, screening based on carbon emissions has only been gaining traction very recently (PDC, 2017), and thus still represents a small subset of all sustainability-related screening. Investors apply heterogeneous screening practices, based on widely diverging criteria, definitions, and metrics of environmental performance (Eccles and Stroehle 2018; Berg, Kölbel, and Rigobon 2019). Thirdly, environmental screening by powerful institutional investors seems to be risk- rather than screening-related (Krüger, Sautner, and Starks 2020; Fernando, Sharfman, and Uysal 2017; van Duuren, Plantinga, and Scholtens 2016). Lastly, it appears reasonable to assume that information about firms' carbon emission levels is accounted for in capital markets, given its full public availability for nearly two decades through mainstream sources of financial information, such as Bloomberg and Thomson Reuters.

In order to assess whether a screening effect is present during our sample period, we empirically test if high-carbon stocks earn a return premium unexplained by common risk factors. If such a premium is observed, this will create room for a potential influence of non-financial preferences on stock returns; if it is not, this justifies a focus on systematic risk as per the standard asset pricing framework. We therefore hypothesize:

H_1: Carbon intensity is associated with positive risk-adjusted returns

2.2. Hypothesis 2: systematic risk

If no evidence is found in support of H_1, we will test for the impact of carbon intensity on systematic risk. Theoretically, firms' sustainability may reduce systematic risk through a lower incidence and intensity of sustainability-related shocks, as shown by Albuquerque, Koskinen, and Zhang (2019). A complementary theoretical model is provided by Grey (2018), which explains green firm behavior as a competitive strategy that enhances market share and safeguards returns when the firm has strategically lobbied for environmental protection (cf. Ambec and Lanoie, 2008). Empirical studies generally tend to support these predictions. Good environmental performance has been found to reduce systematic risk and CoE (Albuquerque, Koskinen, and Zhang 2019; Bouslah, Kryzanowski, and M'Zali 2013; Salama, Anderson, and Toms 2011; Sharfman and Fernando 2008), corporate bond spreads (Chava 2014), and capital constraints (Cheng, Ioannou, and Serafeim 2014). However, the range of evidence is not univocal. For instance, Becchetti, Ciciretti, and Hasan (2015) document an effect on idiosyncratic risk, and quasi-natural experiments in the US find stock price declines both after negative environmental performance news (Flammer 2013) and firms' voluntary commitment to emission-reduction programs (Fisher-Vanden and Thorburn 2011).

The potential effects on systematic risk are particularly apparent for firms' climate-related performance. This is because climate change poses two direct financial risks (Andersson, Bolton, and Samama 2016; Busch and Hoffmann 2007). Firstly, there are physical climate risks: direct impacts of climate change on physical assets and operations, such as losses from storms, floods, and droughts (Labatt and White 2011). The second risk, on which this paper concentrates, is carbon risk, i.e. the impacts of regulatory and market actions that address the physical climate risks. For instance, carbon pricing regulations may substantially raise the costs of high-emitting production activities (van der Ploeg 2018). Firms that reduce their dependence on high-emitting processes will stay ahead of future regulations and requirements, which reduces future costs of compliance and the risk of premature write-downs of high-emitting assets. Next to regulatory risks, high-emitting firms may be exposed to higher market risks, such as fossil energy price fluctuations (Gregory, Tharyan, and Whittaker 2014; Sharfman and Fernando 2008) and competitive risks due to weak technological innovation and failure to align with growing customer demands for low-carbon operations (Grey 2018; Lash and Wellington 2007; Porter and van der Linde 1995).

We expect that carbon intensity may impact *systematic* risk because the transition away from high-carbon production systems will have economy-wide effects (Battiston et al. 2017; Dietz, Gollier, and Kessler 2018; Monasterolo and de Angelis 2020; TCFD 2017). The interdependence of industries with respect to the use of fossil fuels implies a limited ability to diversify carbon risk, inducing a return premium (Gregory, Tharyan, and Whittaker, 2014; TCFD, 2017). Consequently, we test whether carbon intensity increases CoE:

H_2: Carbon intensity positively impacts the cost of equity capital

3. Model and methods

To test whether carbon intensity relates to required returns runs through the mechanism of screening (H_1) and/or systematic risk (H_2), we apply two distinct empirical strategies.

3.1. Hypothesis 1: screening

If there is evidence of sufficiently large-scale screening of high-carbon assets, we would, theoretically, expect to observe a return premium that cannot be explained by common (systematic) risk factors (Heinkel, Kraus, and Zechner, 2001). We, therefore, test the null hypothesis corresponding to H_1 that risk-adjusted returns are not different among high- and low-carbon intensity firms. Following standard practice, our regressions are specified as:

$$R(High\ carbon\ intensity)_t - R(Low\ carbon\ intensity)_t = \alpha + \beta' Risk\ factors_t + \varepsilon_t \tag{1}$$

Equation (1) tests whether returns on a portfolio long in high-carbon intensity stocks and short in low-carbon intensity stocks in month t are driven by common (systematic) risk factors. $R(High\ carbon\ intensity)_t$ and $R(Low\ carbon\ intensity)_t$ are the market value-weighted returns on portfolios of stocks of high- respectively low-carbon intensity firms (see Ziegler, Busch, and Hoffmann, 2011 for a related long-short portfolio application). We consider both absolute and sector-relative carbon intensity. The latter ensures that we control for sector effects, which may not only influence financial outcomes but also investor preferences. Specifically, we do not know a priori whether investors' preferences are related to absolute carbon intensity (corresponding to the screening of high-emitting industries) or sector-adjusted carbon intensity (corresponding to a best-in-class selection approach). $Risk\ factors_t$ is a vector of common risk factors identified by standard asset pricing models. We follow the standard models, which are the Capital Asset Pricing Model (CAPM) (Sharpe 1966), the Fama-French three-factor model (Fama and French 1993), the Carhart four-factor model (Carhart 1997), and the Fama-French five-factor model (Fama and French 2015).[6] α is the coefficient of interest, capturing the return differential between high- and low-carbon intensity firms unexplained by systematic risk factors. If there is a persistent influence of screening by investors, this should be reflected in a significant positive alpha coefficient in Equation (1) (Heinkel, Kraus, and Zechner 2001). In such a case, the conventional asset pricing models would need to be extended to ensure unbiased estimates of the CoE effects of carbon intensity.

3.2.Hypothesis 2: systematic risk

If there is no evidence supporting a screening effect (H_1), this implies that risk premia are driven only by the conventional mechanism of systematic risk. Hence, it would be justified to focus on systematic risk factors when modeling CoE and the effects carbon intensity. Specifically, we employ the following panel regression to test whether CoE is significantly impacted by carbon intensity, controlling for potential confounding:

$$CoE_{it} = \alpha + \beta \, Carbon\ intensity_{it} + \gamma' X_{it} + \Lambda + u_i + \varepsilon_{it} \quad (2)$$

where CoE_{it} is the measure of firm *i*'s cost of equity at time *t*, which is described in Section 3.2.1; α is a constant term; $Carbon\ intensity_{it}$ is firm *i*'s carbon intensity at time *t*, defined in Section 3.3; X_{it} is a set of observed firm characteristics which are known to affect CoE (see Section 3.2.2); Λ is a vector of year, industry (Industry Classification Benchmark (ICB)

[6] Our conclusions do not change when using different asset pricing factors and carbon intensity measures, or when restricting our analysis to high-emitting sectors or EU countries (see Supplementary materials, Tables SM.1–8).

industries),[7] and country fixed effects to control for time trends and heterogeneity in CoE and emission intensity across industries and due to countries' economic and institutional environments (Fama and French 1997; Cole et al. 2013; Liang and Renneboog 2017); u_i is a vector of firm-specific, time-invariant unobserved variables, which is not included in the OLS estimates; and ε_{it} is an error term.

Since the purpose of our research is to test whether high-emitting firms have higher or lower CoE, and given the persistence and small time dimension of both carbon intensity and CoE measures (T=6, on average), the firm fixed effects estimator is less suited for our analysis (also see related studies by Chava, 2014; Di Giuli and Kostovetsky, 2014). Nevertheless, both a redundant fixed effects test and Breusch-Pagan LM test indicate the presence of significant firm-specific unobserved heterogeneity. Therefore, we estimate Equation (2) using OLS as our main specification, allowing for year, industry, and country fixed effects, and additionally present results using random effects GLS. To further increase confidence in our results, we exploit the panel structure of our data and apply a firm fixed effects estimator to Equation (2) as a robustness check, which allows us to rule out unobserved confounding effects which are time-invariant; our approach follows the state-of-the-art literature (Liang and Renneboog 2017; Salama, Anderson, and Toms 2011). We use robust standard errors clustered at the firm level to account for correlation between multiple observations within firms.[8]

3.2.1. Cost of equity capital

We measure CoE using the CAPM, which is common practice and theoretically appealing. Most importantly, using the CAPM-based CoE, we can identify whether carbon

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[7] https://www.ftserussell.com/financial-data/industry-classification-benchmark-icb (accessed: May 10, 2019).

[8] Results are unaffected when we cluster at sector or country levels (results are available upon request; this holds for all additional analyses we discuss). Note that the small time dimension of our dataset inhibits the use of multidimensional time-interacted clustering or spatial-correlation-consistent standard errors as they violate asymptotic consistency assumptions (Petersen 2009). Similarly, the small time dimension makes Fama-MacBeth (1973) annual cross-sectional regressions an inferior approach (also see Chava, 2014).

intensity impacts theoretically required returns through the conventional mechanism of systematic risk. As such, our approach does not aim to provide the best empirical approximation of CoE and also explicitly differs from recent asset pricing studies focusing on modeling observed stock returns (e.g., Görgen et al., 2020). Instead, the aim is to test whether carbon intensity commands a risk premium and raises CoE through its effect on systematic risk, closely following the approach of Albuquerque, Koskinen, and Zhang (2019) and Sharfman and Fernando (2008). We define firm *i*'s CoE at end-of-June in year *t* as:

$$CoE_{it} = RF_t + \beta_{it} ERP_t \tag{3}$$

where β_{it} is the market beta of firm *i* in year *t*. The market beta represents the level of systematic risk, i.e. the sensitivity of the firm's stock to market-wide fluctuations. As the aim is to test the extent to which carbon intensity affects systematic risk and, hence, the theoretically required returns on equity capital (CoE), we estimate market betas from OLS regressions of individual stock's daily excess returns on the global market factor from end-of-June of year *t* until end-of-June of year *t+1*. Note that, by doing so, we effectively lag the independent variables with respect to the dependent variable, in line with the related literature (Albuquerque, Koskinen, and Zhang 2019).[9, 10] Our approach assumes that the betas represent an equilibrium or consensus estimate of the risk added to a globally diversified portfolio, which, according to

[9] We address outliers by winsorizing excess returns at the 0.5th and 99.5th percentiles before estimating betas, and we require at least 75% of non-missing return observations in the beta regressions. Results are similar without these requirements.
[10] As firms may disclose sustainability and carbon emission information with an unknown period of delay relative to their financial information (correspondence with Thomson Reuters), we also did lag carbon intensity by one additional year and find similar results.

the CAPM, linearly determines CoE.[11] This assumption well aligns with the finance literature (Levi and Welch 2017), specifically with closely related studies by Sharfman and Fernando (2008), Bouslah, Kryzanowski, and M'Zali (2013), and Jo and Na (2012). Importantly, the time-varying nature of beta and its potential causes are best captured using high-frequency short-window CAPM regressions (Fama and French 2006; Lewellen and Nagel 2006). Still, we acknowledge the considerable heterogeneity in beta estimation practices: beta services (e.g., Bloomberg) often apply 2- or 1-year windows, 5-year windows are common in portfolio-level analyses (Fama and MacBeth 1973; Levi and Welch 2017), whereas wider estimation windows (e.g., 10-year) provide more stable and less extreme betas. Moreover, in practice, different asset pricing models may be used to explain returns. Therefore, as robustness analyses, we apply alternative estimation windows, market factors, and asset pricing models.

RF_t is the current risk-free rate (zero-beta return), measured as the US one-month T-bill rate; ERP_t is the equity risk premium based on the mean of the Graham-Harvey survey expected 10-year S&P 500 excess return (Graham and Harvey 2018). We do not use historical average return estimates for ERP due to the prevailing negative return periods in our sample. Again, we want to emphasize that in our model, cross-sectional differences in CoE are solely driven by systematic risk. We closely follow Sharfman and Fernando (2008) and present the main results for CoE (Table 3) as well as market beta (Table 4).

3.2.2. Control variables

To isolate the effect of carbon intensity we control for firm characteristics that are known to relate to CoE. We control for *size*, measured as the natural logarithm of total assets,

[11] Our CoE estimate contrasts with some of the related studies which use the rate of return that justifies the observed prices given analyst earnings forecasts (Chava 2014; El Ghoul et al. 2011; Ng and Rezaee 2015). We do not use this method because of the theoretical reasons outlined above as well as due to the very poor (30%) match of our dataset with analyst forecast data, the restrictive assumptions, and possible biases in analyst forecasts, particularly the interaction effects between analyst forecasts and sustainability performance (Adhikari 2016; Ioannou and Serafeim 2015).

as larger firms may incur lower operating and financial risk (Fama and French 1993). Required returns further relate positively to *leverage*, measured as total debt over total assets * 100%, and negatively to the *book-to-market ratio*, defined as book value of common equity divided by its market value; both proxy for default risk (ibid.). This set of controls is in line with related studies (Chava 2014; El Ghoul et al. 2011; Sharfman and Fernando 2008) and with the risk factors included in Equation (1). In additional robustness analyses, we aim to address any potential concerns about confounding events using additional control variables. Appendix A, Table A.1 describes all variables used in this paper.

3.3.Carbon intensity

Carbon intensity is calculated as metric tons of CO_2e per 1,000 USD of net sales. This corresponds to kilograms of CO_2e per 1 USD of net sales. Carbon intensity is a straightforward, coherent, and relative indicator of a key environmental impact of corporate activity (Hoffmann and Busch 2008). It offers a clear conceptual contribution to the environmental performance-cost of capital literature; this contribution is highlighted in Table A.2, where we find a very weak association between carbon intensity and environmental performance ratings which are widely used in research and practice.

Exposure to regulation and business risks naturally increases when emission levels and intensities grow. Nonetheless, carbon regulation often takes into account detailed sector characteristics and benchmarks based on technical possibilities to reduce emissions.[12] Additionally, emission intensity greatly varies due to technical differences in production processes between sectors (cf. Cole et al., 2013). This implies that benchmarking against close sector peers, rather than all firms, may best capture carbon risk exposure (Gupta 2018;

[12] For example, in the EU ETS, there have been clear sector differences regarding inclusion in the scheme, allowances allocation amounts and methods. Since 2013, an important allocation method has become allocation based on a benchmark of the average emission levels of the 10% least carbon-intensive installations, which will be tightened annually.

Kleimeier and Viehs 2018). We account for this possibility by investigating sector-adjusted carbon intensity, which is defined as carbon intensity minus its ICB sector-year average, and divided by its standard deviation. Such standardized measure controls for heterogeneity of carbon intensity levels and variation across as well as within detailed sector groups.

There are some limitations to carbon intensity when used as a measure of carbon risk exposure. Most notably, current firm-level emissions will not be one-on-one with future emissions or firms' abilities for emission reduction. Nonetheless, in our study period (2008–2016), carbon intensity has been highly persistent: the correlation with prior-year carbon intensity is 0.96. This suggests that, although imperfect, carbon intensity is a useful indicator of firm-level dependence on high-emitting production processes. Above all, carbon intensity currently remains an important measure in both research and practice (Cole et al. 2013; Eccles, Serafeim, and Krzus 2011).

4. Data

We obtain annual data on Scopes 1, 2, and 3 carbon emissions[13] for all reporting firms from the two main data sources: Thomson Reuters' ASSET4 (now Refinitiv ESG) and Bloomberg ESG data. These data cover the most important greenhouse gases, represented in metric tons of CO_2-equivalents (CO_2e), including carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulfur hexafluoride (SF_6), and nitrogen trifluoride (NF_3). ASSET4 gathers emission data for each fiscal year from public sources,

[13] Carbon emissions are commonly classified using the three categories or Scopes from the GHG Protocol (WBCSD and WRI, 2004). Scope 1 emissions refer to direct emissions, from sources owned or controlled by the firm, such as those from combusting fossil fuels in power plants, factories, or vehicles. Scope 2 covers the indirect emissions associated with purchased electricity. Scope 3 includes any other indirect emissions associated with production activities within a firm's value chain.

mostly annual and sustainability reports. Bloomberg additionally provides data on emissions as reported to the Carbon Disclosure Project (CDP). According to a recent survey among large institutional investors, both sources are currently being used with no clear preference for one source over the other (Krüger, Sautner, and Starks 2020). Given the public nature of the data from ASSET4, we use these data in our main analysis, while CDP data are employed for robustness. Figure 1 shows the number of firms per year that report on each of the Scopes.[14]

Our main measure of carbon intensity is defined as the sum of Scopes 1 and 2 emissions divided by net sales. Reporting on Scope 3 emissions is currently poor and not yet widespread, and, perhaps more importantly, are largely outside the direct control of the firm. We apply alternative specifications of carbon intensity in robustness analyses.

We acknowledge that the quality and reliability of firm-level emission data might be limited due to the lack of reporting standards or regulations, which makes this type of information qualitatively different from the financial information (Brander, Gillenwater, and Ascui 2018; Sullivan and Gouldson 2012). This shortcoming, however, is shared with virtually all sustainability-related data. Importantly, information on carbon emissions for a large number of firms in all sectors has been publicly available to investors for nearly two decades; it is an empirical issue whether they act on it (also see Ziegler, Busch, and Hoffmann, 2011). In this regard, many institutional investors seem to use carbon emission data for risk management, compare and verify information across firms, and have major shareholdings in the reporting firms, which in turn results in substantial (reputational) costs of misreporting (Krüger, Sautner, and Starks 2020). An indication that the emissions data are of reasonable quality is the high degree of consistency across data providers (Busch, Johnson, and Pioch 2020) and with verified

[14] Note that ASSET4 provides additional data on 'estimated carbon emissions' for firms which have not (yet) publicly reported carbon emission data. We do not use these data due to the lack of comparability between emission estimation models. Also, ASSET4 estimates carbon emissions based on an extrapolation of prior years' carbon intensities, which would artificially inflate the precision of our baseline results. Besides, there is a low level of consistency in estimated emissions across data providers (Busch, Johnson, and Pioch 2020).

mandatory reporting schemes such as the EU ETS (Dechezleprêtre et al., 2019). To address potential remaining concerns about data accuracy and specification, we apply the data checks and requirements outlined below and perform several robustness analyses.

We calculate total carbon emissions as the sum of Scope 1 and Scope 2 CO_2e emissions provided that both Scopes are reported; this procedure differs from Görgen et al. (2020) and Liesen et al. (2017), who take the unconditional sum. We do so to ensure comparability in terms of total emissions;[15] a relevant requirement, given the substantially lower number of emission-reporting firms in Figure 1 (compare the 1st and 4th line).

We restrict our sample to 2008–2016 because, as we learn from our discussions with Bloomberg and Thomson Reuters, the quality of corporate emission reporting is relatively poor in the years before 2008. The data quality issue is, therefore, tempered by focusing on years when a consensus on reporting standards has been developed and emission reporting participation is high. We further require at least two consecutive years of carbon emission data, which ensures the same sample is being used across different panel estimators, and partly handles extreme (unreliable) emission data.

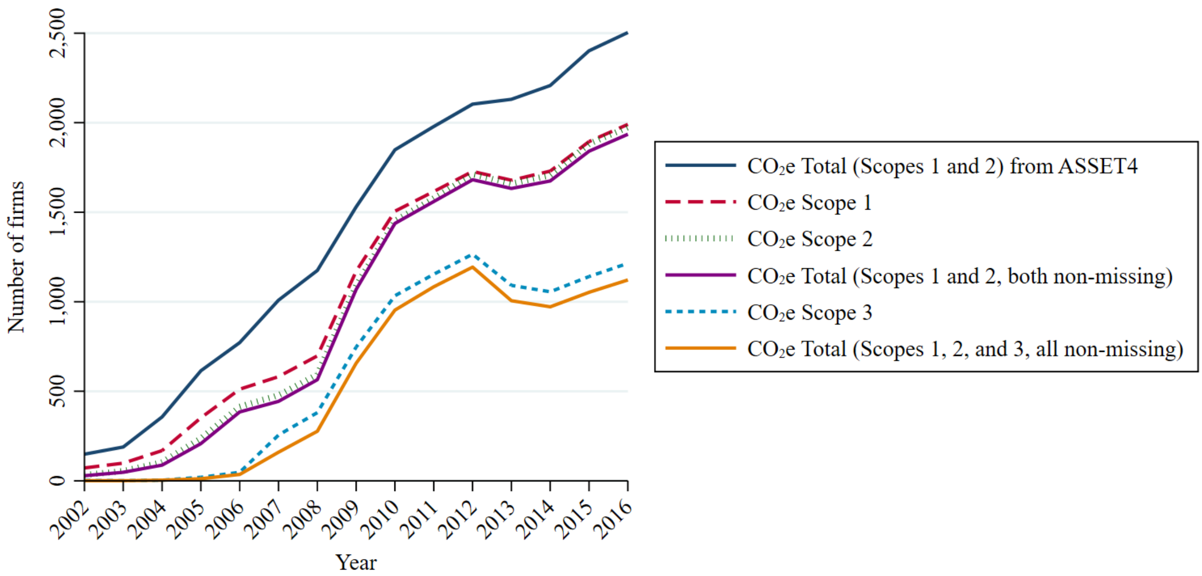
We mitigate any remaining concerns about carbon emission data quality in a systematic and conservative manner, through three additional requirements. First, we exclude firms reporting zero Scope 1 or Scope 2 emissions (57 firms), as this potentially results from data errors or divergent reporting practices (offsetting). Second, we inspect the 99th percentile of carbon intensity and exclude firms for which extreme carbon intensity values result from unconsolidated reporting (5 firms, which form the 99.95th percentile of carbon intensity). Third,

15 Correspondence with Thomson Reuters and Bloomberg assured this method maximizes consistency as firms may report a total carbon emissions figure for which it is unknown which emission Scopes are included. We indeed find that in 90% of the cases where either Scope 1 or Scope 2 emissions are not reported, the total carbon emission figure by ASSET4 captures only Scope 1 or only Scope 2 emissions. These cases are observed in all industries. In addition, in 4% of the cases there is a difference between the sum of Scope 1 and Scope 2 emissions and the total emissions figure from ASSET4, allowing for a margin of error of 1 $ktCO_2e$ to accommodate a reasonable degree of rounding, with a mean difference of 75,578 tCO_2e (0.08 $MtCO_2e$).

we exclude firms in the 99th percentile of year-on-year changes in carbon intensity (17 firms). These additional quality checks lead to a notably lower mean and standard deviation of carbon intensity. Still, our results uphold when ignoring them.

Finally, we employ robust regression and log-transformation as a tool to diagnose potentially influential outliers that could be caused by data issues. Doing so also allows us to evaluate whether our results are influenced by the skewness of our carbon intensity measure. We find that estimates are virtually identical to our ordinary regression specification. This further ensures the reliability of our main model and variable measurement.

Figure 1: Non-financial firms reporting CO_2 emission data



Source: ASSET4, own calculations

We obtain financial variables from Thomson Reuters Datastream and Bloomberg, consistent with the data source used for carbon emissions. In line with the international outlook of our sample, we use the Fama-French global return data.[16] After removing firms belonging to

[16] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (accessed: March 29, 2019).

the financial services industry and those which report on an unconsolidated basis, we end up with a sample of about 10,000 firm-year observations (N), covering 1,897 firms, spanning 50 countries. Our sample is unequally distributed over time (Figure 1), industries (Figure 2), and countries (Table A.3). We winsorize all financial variables at the 1st and 99th percentile to mitigate the effects of extreme values and/or data errors on our estimates.[17]

The summary statistics in Table 1 show that there is a large amount of variation in carbon intensity. Most of this variation comes from heterogeneity between firms (column (5)), whereas there is little variation in carbon intensity within firms over time (column (6)). An important source of between-firm heterogeneity is industry affiliation. High carbon intensities are observed in utilities (mean = 1.54), basic materials (0.80), oil and gas (0.62), and industrials (0.39). However, there is still substantial variation in carbon intensities even within detailed sector groups, as shown in Figure 2. This is consistent with the emission data used by Cole et al. (2013). We address this sector-heterogeneity by expanding our main analysis with a measure of standardized sector-adjusted carbon intensity (Section 3.3). Furthermore, there is a substantial difference in the mean and median emissions, which indicates that the sample includes a few big emitters and a majority of much lower-emitting firms. A result of this skewness is that the standard deviation of carbon intensity exceeds the mean value (see Table 1 and Figure 2). We evaluate whether the skewness affects our main results in additional robustness analyses, including log-transformation (described above) and truncation of the carbon intensity measure (Section 5.3.5). Regarding the dependent variables, we observe relatively precise estimates that are well in line with those reported in related studies using unadjusted betas (Levi and Welch 2017; Salama, Anderson, and Toms 2011).

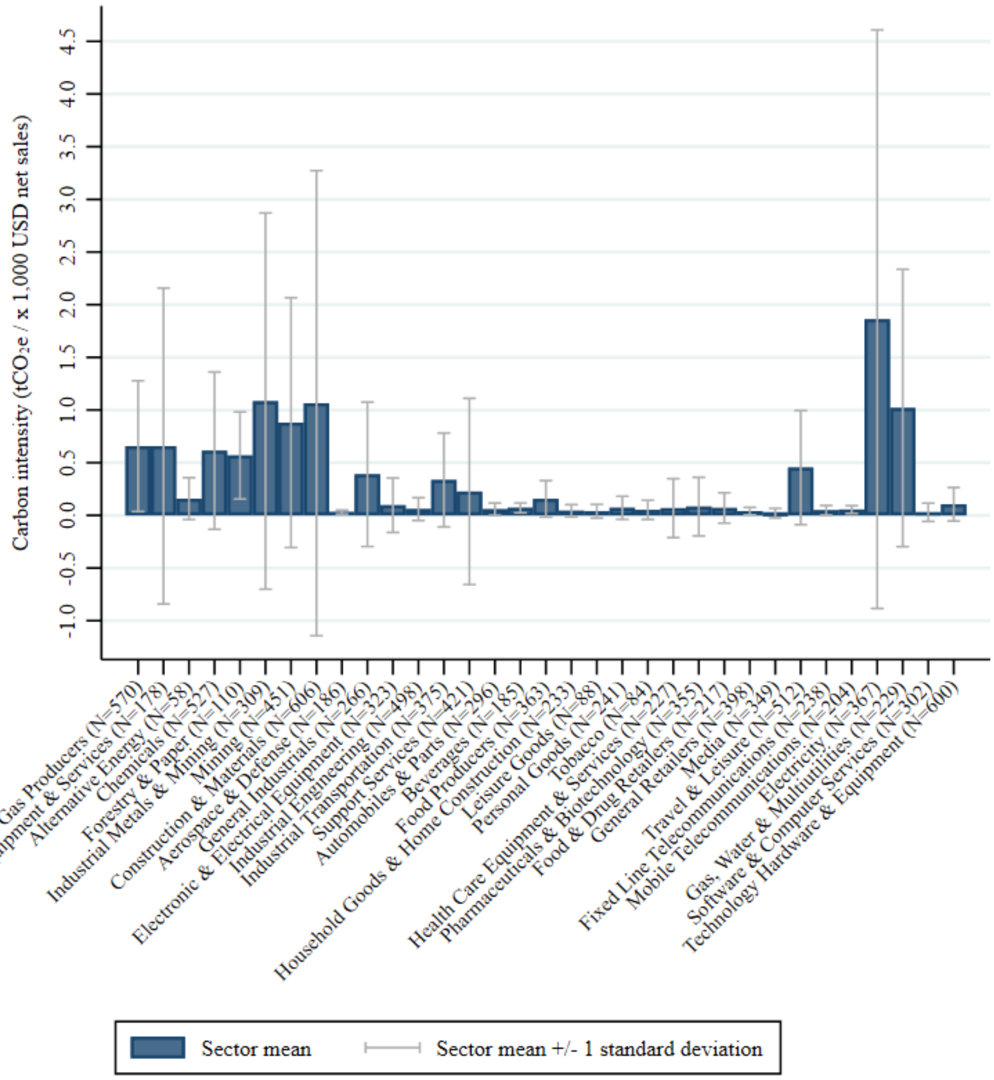
[17] Results are unaffected when using the raw data.

Table 1
Summary statistics of carbon emissions and financial variables (2008–2016). Variable definitions are included in Appendix A, Table A.1.

	(1) N	(2) Mean	(3) Median	(4) StDev (overall)	(5) StDev (between)	(6) StDev (within)	(7) Min	(8) Max
Carbon emissions and carbon intensity								
Carbon emissions total (tCO_2e)	10,366	4,412,162	445,938	14,162,865	13,805,220	2,050,017	81.40	251,318,704
Carbon intensity (tCO_2e/ x1000 USD net sales)	10,366	0.40	0.06	1.05	1.18	0.24	0.00*	22.89
Sector-adjusted carbon intensity	10,366	-0.00	-0.29	1.00	0.98	0.33	-2.17	6.92
Financial variables								
Cost of equity (CoE) (%)	10,130	3.32	3.13	1.78	1.56	0.99	-0.24	8.89
Market beta	10,130	0.85	0.80	0.45	0.39	0.22	-0.09	2.29
Size	10,364	15.90	15.91	1.38	1.38	0.20	10.82	18.58
Book-to-Market ratio	9,930	0.71	0.56	0.65	0.55	0.39	-0.26	6.85
Leverage (%)	10,364	26.12	24.76	16.08	15.79	5.89	0.00	96.13

* Note: Carbon intensity is never precisely zero, but for conciseness it is rounded to two digits.

Figure 2: Carbon intensity by ICB sector



Source: ASSET4, own calculations

5. Results

This section presents and discusses our results regarding the return premia associated with carbon intensity due to screening (Section 5.1) and investment risk (Section 5.2). We further assess the robustness of these results in Section 5.3.

5.1. High- vs. low-carbon portfolios

To test if carbon intensity is associated with a return premium due to screening (H_1), we apply a standard long-short portfolio approach. That is, we examine whether a significant return differential exists between high- and low-carbon stock portfolios, which is left unexplained by common risk factors. As reported in Table 2, we find no significant return premium that common risk factors cannot explain (alpha). Instead, portfolios of high-carbon stocks even earn slightly lower risk-adjusted returns than low-carbon stocks. This result is observed for both absolute (Panel A) and sector-relative carbon intensity (Panel B). The results for absolute carbon intensity could, however, be explained by generic differences between sectors. In Panel B, we control these sector-effects by focusing on variation in carbon intensity within sectors. Here, we find that consistent with our theoretical expectations, market betas primarily drive returns. In all, we find no evidence for a return premium induced by a potential large-scale screening of high-carbon assets (Fama and French 2007; Heinkel, Kraus, and Zechner 2001). These empirical findings validate the conceptual arguments against such an effect made in Section 2.1. Therefore, it is appropriate to evaluate the impact of carbon intensity on CoE using conventional asset pricing models that focus on systematic risk.

Table 2

Risk-adjusted returns of high- vs. low-carbon intensity stock portfolios (2009–2017, N=108).

The estimated equation is: $R(High\ carbon\ intensity)_t - R(Low\ carbon\ intensity)_t = \alpha + \beta' Risk\ factors_t + \varepsilon_t$ (Equation (1)). The dependent variable is the monthly return on a portfolio long in stocks of firms with high one-year lagged carbon intensity and short in low-carbon intensity firms. Carbon intensity is measured as Scopes 1 and 2 CO_2e emissions divided by net sales. High and low carbon intensity are defined by their 10th/90th percentile values. Portfolios are formed based on absolute carbon intensity in Panel A or sector-adjusted carbon intensity in Panel B. Sector-adjusted carbon intensity is defined as carbon intensity minus the average carbon intensity in the associated sector and year, and scaled by the standard deviation of carbon intensity. The coefficients of the MktRF, SMB, HML, WML, RMW, and CMA are the loadings on the global market, size, book-to-market, momentum, profitability, and investment factors respectively (Sharpe, 1966; Fama and French, 1993; Carhart, 1997; Fama and French, 2015). Alpha captures the return differential between high- and low-carbon assets unexplained by the systematic risk factors. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1) CAPM	(2) FF3	(3) Carhart	(4) FF5
Panel A: Carbon intensity				
Alpha	-0.0050*	-0.0040*	-0.0015	-0.0053*
	(0.0026)	(0.0024)	(0.0047)	(0.0029)
MktRF	-0.0140	-0.0994	-0.0980	-0.0922
	(0.0696)	(0.0738)	(0.0731)	(0.0731)
SMB		0.2791	0.2823	0.3706*
		(0.1933)	(0.1933)	(0.2194)
HML		0.6428***	0.6511***	0.8585***
		(0.1598)	(0.1556)	(0.2291)
WML			-0.1187	
			(0.2313)	
RMW				0.4082
				(0.3148)
CMA				-0.2689
				(0.3965)
Adj. R^2	0.0004	0.1684	0.1731	0.1941
Panel B: Sector-adjusted carbon intensity				
Alpha	-0.0022	-0.0022	-0.0053*	-0.0028
	(0.0018)	(0.0018)	(0.0028)	(0.0021)
MktRF	0.0845*	0.0861*	0.0843*	0.0887*
	(0.0447)	(0.0483)	(0.0472)	(0.0514)
SMB		0.0031	-0.0008	0.0416
		(0.1317)	(0.1326)	(0.1393)
HML		-0.0112	-0.0214	0.0830
		(0.1033)	(0.1057)	(0.1446)
WML			0.1470	
			(0.0936)	
RMW				0.1745
				(0.2392)
CMA				-0.1207
				(0.1510)
Adj. R^2	0.0416	0.0417	0.0605	0.0544

5.2. Cost of equity regressions

We test if carbon intensity impacts CoE through the channel of systematic risk (H_2) by estimating the effect of carbon intensity on the CAPM-based CoE by Equation (2). We present the effects of absolute and sector-relative carbon intensity on CoE (Table 3) and—to facilitate a more detailed interpretation—market beta (Table 4). Both measures and estimators show a consistent positive effect of carbon intensity on CoE. We find that for each standard deviation (1.05) higher carbon intensity, ceteris paribus, CoE increases by 6 basis points (Table 3, column (1)) and the market beta increases by 0.01 (Table 4, column (1)), which is a 1.7% increase relative to the average CoE and market beta. Regarding sector-relative carbon intensity, we find that firms with a carbon intensity of one standard deviation above the sector average have a 9 basis points higher CoE (Table 3, column (3)) or 0.02 higher market beta (Table 4, column (3)), corresponding to a 2.6% increase.

The effect of carbon intensity we document seems modest, considering the substantial operational changes required for reducing emissions by the amounts just discussed. Hence, although investors penalize high-emitting firms by demanding higher returns, this CoE penalty on its own provides a relatively weak market incentive for emission reductions. While our estimates are close to those by Kleimeier and Viehs (2018) on the effects of carbon emissions on loan spreads, they are small when compared to the literature on sustainability ratings. Chava (2014) finds that each ‘environmental concern’ flagged in four environmental performance categories is associated with a 4.4% higher CoE relative to the median firm. Gupta (2018) finds a 5.0% rise in CoE for each standard deviation increase in the environmental performance score. Albuquerque, Koskinen, and Zhang (2019) report a 1.1% rise in market betas for each standard deviation higher sustainability score. Possible explanations for the difference in effect size compared to these prior studies include the differences in the sampling procedure as well as the fact that carbon intensity is a single element of environmental performance that is conceptually different from generic sustainability ratings.

In all, our findings lend support to the risk mitigation hypothesis, which holds that improvements in environmental performance can be valuable as it reduces stakeholder risks. Specifically, by focusing on the carbon intensity, we find that low-emitting production tends to be rewarded in capital markets in the form of a (slightly) lower CoE. Our two-stage analysis further shows that the relationship is driven by differences in systematic risk among high- and low-carbon assets rather than by investors' non-financial preferences for low-carbon assets.

Table 3
Carbon intensity and the cost of equity (2008–2016, N=9,802).

The estimated equation is: $CoE_{it} = \alpha + \beta\ Carbon\ intensity_{it} + \gamma' X_{it} + \Lambda + u_i + \varepsilon_{it}$ (Equation (2)). CoE_{it} is the measure of firm *i*'s cost of equity at time *t*, which is based on the CAPM, using one-year betas, the one-month US Treasury bill rate as risk-free rate, and the Graham-Harvey survey expected 10-year S&P 500 excess return as proxy for the equity risk premium. $Carbon\ intensity_{it}$ is firm *i*'s carbon intensity at time *t*. Carbon intensity is measured as Scopes 1 and 2 CO_2e emissions divided by net sales. Sector-adjusted carbon intensity is defined as carbon intensity minus the average carbon intensity in the associated sector and year, and scaled by the standard deviation of carbon intensity. X_{it} is a set of time-varying firm-level controls described in Section 3.2.2. Variable definitions are included in Appendix A, Table A.1. Λ is a vector of year, industry, and country fixed effects. u_i is a vector of firm-specific, time-invariant unobserved variables (included in columns (2) and (4)). ε_{it} is an error term. Robust standard errors clustered at the firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1) OLS	(2) RE – GLS	(3) OLS	(4) RE – GLS
Carbon intensity	0.0551**	0.0728***		
	(0.0239)	(0.0231)		
Sector-adjusted carbon intensity			0.0856***	0.0852***
			(0.0231)	(0.0208)
Size	0.0599***	0.0418*	0.0624***	0.0445**
	(0.0213)	(0.0220)	(0.0212)	(0.0219)
Book-to-Market ratio	0.1117***	-0.0031	0.1084**	-0.0022
	(0.0431)	(0.0330)	(0.0434)	(0.0330)
Leverage	0.0032*	0.0052***	0.0030*	0.0053***
	(0.0017)	(0.0016)	(0.0017)	(0.0016)
Adj. R^2	0.4819	0.4782	0.4831	0.4795

Table 4
Carbon intensity and market beta (2008–2016, N=9,802).

The estimated equation is: $Beta_{it} = \alpha + \beta\ Carbon\ intensity_{it} + \gamma' X_{it} + \Lambda + u_i + \varepsilon_{it}$ (Equation (2) replacing CoE_{it} with $Beta_{it}$). $Beta_{it}$ is the measure of firm i's market beta at time t, obtained from one-year ahead CAPM regressions using daily excess returns. $Carbon\ intensity_{it}$ is firm i's carbon intensity at time *t.* Carbon intensity is measured as Scopes 1 and 2 CO_2e emissions divided by net sales. Sector-adjusted carbon intensity is defined as carbon intensity minus the average carbon intensity in the associated sector and year, and scaled by the standard deviation of carbon intensity. X_{it} is a set of time-varying firm-level controls described in Section 3.2.2. Variable definitions are included in Appendix A, Table A.1. Λ is a vector of year, industry, and country fixed effects. u_i is a vector of firm-specific, time-invariant unobserved variables (included in columns (2) and (4)). ε_{it} is an error term. Robust standard errors clustered at the firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1) OLS	(2) RE – GLS	(3) OLS	(4) RE – GLS
Carbon intensity	0.0141**	0.0185***		
	(0.0063)	(0.0060)		
Sector-adjusted carbon intensity			0.0228***	0.0222***
			(0.0061)	(0.0055)
Size	0.0152***	0.0115*	0.0158***	0.0122**
	(0.0057)	(0.0059)	(0.0057)	(0.0059)
Book-to-Market ratio	0.0285**	-0.0064	0.0276**	-0.0062
	(0.0112)	(0.0083)	(0.0113)	(0.0083)
Leverage	0.0008*	0.0012***	0.0007*	0.0012***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Adj. R^2	0.4440	0.4396	0.4454	0.4411

5.3.Robustness

Our analysis thus far suggests that high-emitting firms incur a penalty deriving from investors' perception of the effects of carbon constraints on those firms' performance. However, there could be alternative explanations for our results, which we will evaluate below. Taken together, the additional analyses described below and presented in Appendix B indicate that our main results (Table 3) are not driven by potential confounding events or data and model specification issues. They further suggest that the effect of carbon intensity is stronger in sectors and policy environments in which carbon risk tends to be a more salient issue.

5.3.1. Confounding factors

Carbon intensity might be related to generic sustainability performance, and its effects could, therefore, stem from risk reduction associated with superior stakeholder management (Becchetti, Ciciretti, and Hasan 2015; Lins, Servaes, and Tamayo 2017) rather than reduction of carbon risk specifically. Another possibility is that energy price exposures or other omitted variables drive our main results. In Table B.1, we address potential confounding by saturating our model (Equation (2)) with an extensive set of additional control variables[18] and fixed effects which control for sector-specific shocks and unobserved heterogeneity at the firm level (Gormley and Matsa 2014). Results in Table B.1 indicate that the effect of carbon intensity on CoE is independent of an extensive set of potential confounders. Note that in the firm fixed effects regressions, presented in columns (3) and (4), the estimates are consistently positive but more uncertain. This is due to the fact that a restrictive focus on the limited time variation in carbon intensity, as shown in Table 1, column (6), considerably reduces power (also see Di Giuli and Kostovetsky, 2014) and might amplify noise (Gormley and Matsa 2014).

5.3.2. Sample selection

A second potential concern is that firms' disclosure of carbon emission data is a voluntary decision and, therefore, unlikely to be random. Disclosure might correlate with firms' sustainability policies more generally and could be driven by strategic financial considerations. To control for the potentially resulting sample selection bias (e.g., Broadstock et al., 2018), we

[18] We control for *momentum*, given the persistence found in average stock returns (Carhart 1997; Chava 2014); *profitability*, since weak profitability may motivate cuts in environmental performance (increasing carbon intensity) and/or affect required returns (Fama and French 2015; Kubik, Scheinkman, and Hong 2012); liquidity effects, measured by *stock liquidity* and *working capital* (Bouslah, Kryzanowski, and M'Zali 2013; Gonenc and Scholtens 2017); investment opportunities, measured by *cash flow* (Kaplan and Zingales 1997); *sales growth* (Lins, Servaes, and Tamayo 2017); *capital intensity* (Cole et al. 2013); *Research and Development (R&D) intensity* (ibid.), all of which might relate to financial risk and/or carbon intensity; *environmental performance*, which measures the relative strength of stakeholder management and potentially acts as a generic risk reduction variable (Becchetti, Ciciretti, and Hasan 2015; Lins, Servaes, and Tamayo 2017); and *energy price index*, given that generic energy price risk might drive stock returns (Degiannakis, Filis, and Arora 2018; Driesprong, Jacobsen, and Maat 2008). All variables are defined in Appendix A, Table A.1.

employ the two-stage Heckman (1979) selection procedure.[19] We find in Table B.2 that sample selection does not induce an economically meaningful bias in our main estimates.

5.3.3. Simultaneity

Because both environmental performance and CoE are the result of corporate choices, there might be simultaneity in the main relationship we study (Ferrell, Liang, and Renneboog 2016; Kubik, Scheinkman, and Hong 2012). Even though lowering carbon emission levels naturally requires long-term investments and changes in the production process, and notwithstanding our use of lagged independent variables, poor financial performance (high CoE) could nevertheless motivate cuts in emission-reduction efforts (higher carbon intensity), while good financial performance (low CoE) could give managers additional flexibility to lower emissions (lower carbon intensity).

To help address these concerns, we apply a two-stage least squares (2SLS) regression in Table B.3 using the mean carbon intensity of the focal firm's sector-year peers as an instrument for carbon intensity, closely following related studies by Cheng, Ioannou, and Serafeim (2014) and Ferrell, Liang, and Renneboog (2016). The significant F-statistic in the first stage confirms that the instrument is a strong determinant of the focal firm's carbon intensity (Stock, Wright, and Yogo 2002; also see Cole et al. 2013). Yet, theoretically, it can be expected to be exogenous to the firm's decisions, and it is unlikely that there is an influence on (variables impacting) CoE through channels other than those for which we control. To be conservative regarding any remaining endogeneity, we extend the 2SLS regressions with firm

[19] The first stage uses a probit model to estimate the selection hazard, which is disclosure of Scopes 1 and 2 carbon emission data. We use the ASSET4 ESG database of about 6,100 non-financial firms to obtain a comprehensive sample of disclosers (37%) and non-disclosers (63%). The first-stage model includes the variables from Equation (2) and an additional variable that helps identify disclosure, namely the fraction of ICB sector peer firms disclosing carbon emission data. This additional variable closely relates to a focal firm's disclosure decision through peer effects (Cao, Liang, and Zhan 2019), but it is theoretically unlikely to influence CoE. Our results do not change when the exclusion restriction is excluded or when it is augmented with the ASSET4 environmental performance rating. In the second stage, Equation (2) is estimated including the selection hazard as a control for selection bias.

fixed effects. In the second stage, we use the fitted values of the instrument in place of carbon intensity and continue to find a robust positive relationship.

5.3.4. Cost of equity estimation

Realized historical returns are an imperfect proxy for expected returns (Elton 1999; Fama and French 1997), and investors might apply different models when estimating CoE. Therefore, we assess robustness against the use of different market factors, asset pricing models, and estimation windows. As reported in Table B.4, results are consistent across a wide range of CoE estimates. Hence, we are confident that our main results are not driven by the measurement of beta and CoE.

5.3.5. Carbon intensity specification

Given that carbon emission data do not have the same quality as data on financial variables, we apply various robustness analyses to alleviate potential concerns about data accuracy and specification issues. We expect that the value relevance of carbon intensity data to investors is higher when there is less uncertainty about their consistency and accuracy, when reported values are less extreme, and when there is a long track-record of emission reporting. In Table B.5, we find evidence consistent with this expectation. In addition, we alter the business metric by which carbon emissions are scaled and investigate the effect of different emission Scopes (Hoffmann and Busch 2008). For instance, focusing solely on Scope 1 emissions provides insights into the emissions that are directly attributable to firms' own production technology, which tends to be more stable over time than the combination of all three emission Scopes, which in turn gives a more comprehensive measure of firms' full carbon footprint. Finally, it should be noted that when carbon emissions are scaled for size, as we do when we measure carbon intensity, this provides a production-relative measure. However, for ecological purposes, it is not so much the intensity that matters as the absolute amount of emissions produced by firms. Therefore, we also consider the absolute amount of carbon emissions as the main independent variable. In Table B.5, we find our main result holds for alternative carbon (intensity) specifications.

5.3.6. Emission data source, uncertainty, and verification

To further explore the role of emission data accuracy, we use an alternative main source of emission data, namely the CDP survey. The dataset from CDP also enables us to evaluate the potential influence of consistency and accuracy of the reported emission data using two additional variables. First, we retrieve data on the proportion of firms' emissions that has been externally verified, i.e., whether reported emissions are consistent with reporting guidelines (GHG protocol). This issue has attracted a relatively high investor interest (Eccles, Serafeim, and Krzus 2011). Secondly, we retrieve an indicator that reflects the degree of uncertainty which firms report having around the reported emission figures. This indicator ultimately captures the extent to which estimation or extrapolation is used by the firm in determining its total emissions. In Table B.6, we find a consistent positive effect of carbon intensity on CoE, while the effect is significantly attenuated by emission data uncertainty and slightly amplified by verification. These findings show the robustness of our main estimates to data specification and underscore the importance of reliable carbon emission reporting to investors.

5.3.7. Salience of carbon risk

If exposure to carbon risk is the driver of our main results, we would expect to see larger implications of carbon intensity in sectors and policy environments in which firms would be most strongly affected by carbon regulation. We examine this issue by interacting carbon intensity with a dummy variable that indicates a carbon risk salient environment. We employ three specifications of the salience dummy: being a member of a high-carbon sector, an EU country, or being subject to direct carbon pricing regulation (i.e., a carbon tax or ETS). The interaction term thus measures the additional effect of carbon intensity on CoE for firms in high-carbon sectors as compared to those in low-carbon sectors, in the EU vs. those outside the EU, and for firms subject to carbon pricing regulation vs. firms that are not.

Results, in Table B.7, generally support our expectation that carbon intensity affects risk especially in carbon regulation-prone sectors (Jo and Na 2012; Gonenc and Scholtens 2017). We further find notably stronger effects in EU countries as compared to countries outside the EU, where the carbon regulation environment is substantively different (also see Delis, de Greiff, and Ongena, 2020; Ziegler, Busch, and Hoffmann, 2011). We confirm these results by showing stronger effects for firms that report being subject to the EU ETS or other carbon pricing regulations compared to those that do not.

Even so, the effect is less evident for sector-adjusted carbon intensity. We posit that this is an indication that, while carbon intensity matters especially in regulation-prone environments, the sector-adjusted performance remains relevant across all sectors and regions. Still, our results should be interpreted with caution, as they could potentially be driven by several unexplored factors. For instance, some sectors and firms might be better equipped to mitigate carbon risk by passing through additional costs to customers, substituting production inputs, or by moving their operations to less-regulated areas (Fell, Hintermann, and Vollebergh 2015; Ganapati, Shapiro, and Walker 2020; Sato et al. 2015). More research would be needed to shed light on the determinants and implications of carbon risk, considering mitigating factors like these.

6. Conclusion

The transition from high- to lower-carbon production systems increasingly creates regulatory and market risks for high-emitting firms. In this paper, we investigate the implications of such risks for firms' cost of equity capital (CoE). We do so by focusing on carbon intensity (carbon emissions per unit of output), which is a well-known measure of firm-level use of and reliance on carbon sources, and hence carbon risk. We test whether financial investors demand a premium on high-emitting assets and whether systematic or non-systematic risk factors primarily drive this premium.

Using two main sources of carbon emission data for an international sample of 1,897 firms spanning 50 countries over the years 2008–2016, we find a robust positive impact of carbon intensity on CoE. On average, a one standard deviation higher (sector-adjusted) carbon intensity is associated with a CoE premium of 6 (9) basis points or 1.7% (2.6%). The effect primarily relates to systematic risk factors: stock returns of high-emitting firms are significantly more sensitive to economy-wide fluctuations than those of low-emitting firms. The transition to low-carbon production systems thus appears to be a source of financial risk across all industries, and as such requires a return premium. This relationship upholds when controlling for a multitude of factors, such as the common determinants of risk as well as year, industry, and country unobserved factors. The CoE premium for carbon intensity is more pronounced in contexts in which carbon risk poses a salient issue, such as in high-emitting industries, EU countries, and firms subject to carbon pricing regulation.

These findings show that emission reduction might be a valuable risk mitigation strategy, and hence constitute a source of intangible value rather than a mere drain on corporate resources. Specifically, our analysis suggests that consistent with the risk mitigation hypothesis, a lower carbon intensity helps reduce exposure to key stakeholder risks, such as regulatory and market risks stemming from a global transition towards a low-carbon economy.

Our analysis offers a solid microeconomic understanding of the growing interest of firms, investors, and regulators in corporate emission disclosure and reduction (Bénabou and Tirole 2010; Cole et al. 2013). From a macroeconomic perspective, our findings show how climate-related factors influence investment behavior through risk premia (Cochrane 2017; Dietz, Gollier, and Kessler 2018). By implication, effective environmental management should account for the interplay between climate policy and market behavior. The risk-mitigation effect of carbon intensity is relevant for policymakers as this shows that capital markets give additional incentives to reduce carbon intensity. The strength of this incentive, however, appears to be low and ultimately depends on the strength of future carbon regulation. Besides, the role of capital markets to incentivize emission reduction further depends on the availability of reliable emission data. As we find that uncertainty about carbon emissions data suppresses the risk-mitigation effect of carbon intensity, policymakers could impose regulatory measures directed at standardization and transparency of data on climate-related factors.

Our finding that emission reduction is, to some extent, privately rewarded in financial markets offers new insights into the value relevance of environmental performance, which can be used to guide both firms and investors. Investors could use our analysis to guide their security selection, sector allocation, and portfolio decarbonization strategies (PDC, 2017; TCFD, 2017). The results inform firm managers by showing the benefits of carbon management for CoE, which is a key driver of business and project decisions. This adds to prior studies that have mostly examined the effects of generic ratings of environmental performance (e.g., Chava, 2014; Sharfman and Fernando, 2008). We demonstrate that a much more direct, disaggregated, and coherent measure of environmental performance, namely carbon intensity, has similar, albeit somewhat weaker, risk-reduction effects. Moreover, our empirical strategy shows that carbon intensity commands a risk premium through its impact on systematic risks (Albuquerque, Koskinen, and Zhang 2019; Lins, Servaes, and Tamayo 2017) and not through large-scale screening of carbon-intensive assets (Heinkel, Kraus, and Zechner 2001).

In all, this paper reveals important effects of firm-level carbon intensity on equity pricing and firm risk. Future research could improve our understanding of these effects in several ways. For instance, longer-term impacts could be assessed. Especially when a large share of the market starts to avoid high-carbon assets, this may create an important additional driver of the CoE premium. The CoE premium might become more salient over time especially in countries and regions which plan to intensify their current climate policies. At the same time, future climate policies might, depending on their design, offer long-term competitive benefits as well (see Porter and Van der Linde, 1995).

Furthermore, it could be useful to validate our results for other forms of firm capital. Finally, this paper has focused on carbon intensity, which is an imperfect measure of carbon risk exposure. Most importantly, it focuses on current firm-level emissions, which will not be one-on-one with future emissions or firms' abilities for emission reduction. It would be promising to develop and analyze new measures, for instance at the level of carbon costs of individual production plants, that allow for a more detailed understanding of carbon risk.

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