Cost of Capital and Climate Change Risk

Abstract

This research examines the question of whether sustainable investing facilitates a transition to a greener future. ESG funds channel capital away from carbon intensive or "brown" firms toward "green" firms which may drive up the cost of equity of firms where green investments matter the most. The implied cost of capital and carbon emissions are compared from firms eligible and those that are not eligible for ESG investment. The annual sample from 2003 through 2023 covers US firms with analyst forecasted earnings. Evidence indicates a carbon premium does exist on brown firms over green firms, but it is unrelated to ESG investment. This paper contributes to a growing literature that finds that the carbon footprint of a firm is related to its climate change risk.

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1. Introduction

Fims wrestle with a crucial decision about what information on climate change risks and costs they should share with the public. The situation presents a clear tension between competing interests. On one side, investors, regulatory bodies, and advocacy groups demand detailed disclosures, standardized reporting methods, and greater transparency overall. However, businesses and their insurers have serious reservations out of concern for the financial burden of extensive reporting, the risk of losing competitive advantages, and potential legal exposure from these disclosures.

This research examines a central question in this debate: Do stock market investors actually factor climate change disclosures into their valuation decisions? In other words, does this information influence how investors adjust stock prices and price forecasts based on all available data? Understanding this question has far-reaching implications. The findings are critical for companies making decisions about what to disclose, regulators considering mandatory climate reporting rules, investors and analysts evaluating how climate data affects stock prices, and courts handling securities law cases related to environmental and climate issues.

The unique scope of this research observes that investors and analysts can preemptively price a carbon change risk factor regardless of a firm's disclosure figures and decision. The decision is one that is founded based on regulatory constraints, industry characteristics, and thorough internal cost-benefit investigations. The findings show that high carbon-emitting firms are priced higher than lower carbon-emitting firms across several years and various industries. The sample covers publicly traded US firms from 2003 through 2023. Wet is important to note that the United States has a voluntary carbon disclosure policy around the annual output of carbon and other greenhouse gas emissions at the time of annual filing.

Relevant literature examines the economic implications of voluntary disclosure, with cost of capital as evidence, are an area of active research interest. Specifically, the study is motivated on the impacts of climate change and question the usefulness of voluntary disclosure regarding carbon performance for investors' decision making (Sullivan and Gouldson, 2012; Depoers et al., 2016; Griffin et al., 2017; Luo, 2017). In this study, we examine the extent to which investors jointly consider carbon disclosure and carbon emissions in the assessment of firms' riskiness for investment decisions as proxied by the firms implied cost of equity capital (ICC). Moreover, the research addresses two issues: (i) whether a firm's ICC is associated with their disclosure decision and/or emission levels and (ii) reason for the existence of a novel climate change factor risk on a firm's cost of capital, to which analyst forecasts are jointly pronounced for.

The study builds upon the sparse empirical evidence directly linking ICC with carbon disclosure and emission figures (Hartzmark and Shue, 2023; Connors and Silva-Gao, 2008; Sharfman and Fernando, 2008; Kim et al., 2015; Plumlee et al., 2015). The main contribution adopts a two-stage econometric technique to examine the relationship between carbon disclosure, carbon emissions, and ICC. Relevant studies have variously considered similar causalities within a single- or multi-country setting, but most papers have maintained their dataset to only reporters. The paper contributes to the extant literature by documenting how carbon emissions can espouse one lens of climate change risk in the cost of equity capital within the voluntary disclosure regulation of the US.

This research aims to explore carbon emissions disclosures among publicly traded companies in the US markets. Given the missing-not-at-random nature of my key variable, realized and reported carbon emissions, finance-relevant emissions literature takes a more selective approach with the data sample to observe only firm-period observations that have reported data. Wen a notable example, a current working paper, "Counterproductive Sustainable Investing: The Impact Elasticity of Brown and Green Firms" (Hartzmark and Shue, 2023), argues that ESG investing has increased the cost of capital for high-emitting firms (brown or upper quintile) in comparison to low-emitting firms (green or lower

quintile). And the raised cost of capital hinders brown firms from partaking in projects to reduce their emission impact elasticity.

This research takes a shot to refute the findings and argues the existence of a novel climate-change risk factor, which better explains the increased cost of capital of brown/carbon-intensive firms. The data includes the full sample of firms (reporters and non-reporters) and imputes synthetic emission figures for non-reporters using an adapted Heckman 2-step bias correction model where the outcome equation is based on a correlated random effects regression and the underlying probit (selection equation) model which finds the inverse mills ratio. The imputed emissions figures find that regardless of reported or imputed emission figures, the implied cost of capital is higher for brown firms over neutral and green (lowest quintile) firms. As firms who choose not to disclose emissions cannot find weightings in ESG funds or given Environmental rating scores, the finding disagrees with Hartzmark and Shue's finding on ESG investing increasing the cost of capital for notable carbon emitters. Wenstead, the results give us reason to believe in this novel climate-change risk factor that exists for firms withstanding their disclosure decisions.

Within this research, we also created 2 STATA ado files – which are available upon request – used to (i) derive the cost of equity capital within a Residual Income Model incorporating stated and interpolated future earnings forecasts and (ii) reclassify SIC codes into Fama French industry classifications. The remainder of this paper follows: section 2 provides research background with relevant regulation, existing literature, and the paper's motivation; section 3 delves into the model formulation and sampling process with the inclusion of preliminary statistics; section 4 analyzes regression results; and section 5 discusses concluding remarks and forthcoming steps.

2. Background

2-1. The EPA and US Regulatory Environment

The 1970s marked a turning point in American environmental policy. Wen response to growing environmental concerns, Congress enacted several landmark laws, and notably created the Environmental Protection Agency (EPA) to centralize federal environmental efforts. The EPA became responsible for researching, setting standards, monitoring, and enforcing environmental protection measures. These regulations require companies to take financial responsibility for some of the environmental impact of their operations.

A significant advancement came in 1986 with the Emergency Planning and Community Right-to-Know Act (EPCRA). This law, particularly through its Toxic Release Inventory (TRI) program, requires facilities to report their toxic chemical releases to the EPA annually. The reporting requirements apply to U.S. facilities that meet three criteria: they must have at least ten full-time employees, operate in specific industries, and handle listed chemicals above certain quantities. While the data is self-reported, it's considered reliable and is frequently used by researchers studying pollution and environmental performance.

The EPA also maintains stricter oversight of six particularly dangerous pollutants known as criteria air pollutants: sulfur dioxide, carbon monoxide, nitrogen dioxide, ozone, lead, and particulate matter. Through disclosure requirements and monitoring systems, this regulatory framework has created strong incentives for companies to improve their environmental practices and waste management. Companies that violate air quality standards can face serious penalties under the Clean Air Act, including significant financial consequences.[1]

Over the sample period, several regulatory policies have been enacted to incentivize and require emissions disclosure, while allowing the overall voluntary disclosure for publicly traded firms in their annual filings. Wen 2002, the Carbon Disclosure Project (CDP) established investment pressure on companies to report on their climate performance and

[1] https://www.epa.gov/sites/default/files/documents/1998qa.pdf.

environmental risk mitigation strategies. Starting in 2010, the EPA issued the Final Mandatory Reporting of Greenhouse Gases (GHG) Rule which required mandatory reporting of GHG emissions from manufacturers of vehicles and engines, suppliers of fossil fuels or industrial GHGs, and facilities that emit at least 25,000 metric tons of greenhouse gas emissions per year.[2] The state of California has been requiring GHG emissions reporting (greater than 10,000 metric tons) since 2006, under the California Global Warming Solutions Act.

In 2015, the European Union (EU) announced new guidelines for the Non-Financial Reporting Directive (NFRD), or Directive 2014/95/EU. Of the wide range of topics, it mandated a uniform reporting standard for carbon and greenhouse gas emissions for companies who have at least 500 employees.[3] The EPA followed up with an update, 89 FR31802, which revised emissions measuring implementation and improved data quality.[4] ESG funds have seen increasing popularity, as a sole or significant metric, since 2015. Vanguard's Global ESG fund launched in 2019 and has since paved the way for the largest sustainable funds today.[5] My sample finds post-2015 to be a notable shift in disclosure activity and environmental focus among US firms.

2-2. Literature Review

Investors, regulators, and advocacy media are among powerful stakeholders that constitute analyst forecasts and capital. They often request high-quality information about climate change risks and opportunities from companies (Cotter & Najah, 2012; Kolk et al., 2008). As a result, firms face notable risks in their actions, and this can be founded within valuation models. Ramadorai and Zeni (2023) suggest that firms' beliefs about climate regulation significantly shape their abatement plans and actions, pointing to the influence of regulatory expectations in corporate environmental behavior. Lemma et al. (2021) reveal

[2] https://www.epa.gov/regulations-emissions-vehicles-and-engines/final-rule-mandatory-reporting-greenhouse-gases
[3] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32014L0095
[4] https://www.epa.gov/ghgreporting/rulemaking-notices-ghg-reporting
[5] https://corporate.vanguard.com/content/corporatesite/us/en/corp/who-I-are/pressroom/first-actively-managed-esg-fund-available.html

that firms with a stronger commitment to climate change actions issue a higher proportion of debt with longer terms to maturity, suggesting a reputational benefit and easier access to financial markets. This view is supported by Krueger et al. (2020), who report that long-term, large-scale investors favor engagement over divestment for managing climate risks, indicating a preference for active involvement in shaping corporate environmental strategies. Also, Cenci et al. (2023) find that there is an over-investment in risk mitigation actions as opposed to innovation and cooperation activities, which explains corporate misalignment with the Paris alignment targets. Lastly, Kacperczyk and Peydro (2022) underscore the financial sector's role in driving environmental performance, finding that firms with higher carbon footprints borrowing from environmentally committed banks receive less credit, linking financial incentives directly to environmental performance.

In the expanding finance literature regarding environmental, social, and governance (ESG) ratings, studies have shown that carbon performance impacts firm valuation. Cormier et al. (1993) provide evidence that better pollution records increase the market valuation of firms, attributing this to the potential liability that firms with poor pollution records face. Sharfman and Fernando (2008) found that firms with less risky environmental management strategies attract less expensive debt and lower cost of debt, due to their reduced riskiness of environmentally related penalties. Connors and Silva-Gao (2008) reported that companies with higher toxic chemical emissions have significantly higher cost of capital compared to those with lower emissions. El Ghoul et al. (2011) found a negative association between improved corporate social responsibility (CSR) performance and cost of capital, even after controlling for firm-level corporate governance rating. Gupta (2018) found that an improvement in environmental practices leads to a reduction in the cost of capital in 43 countries. Similarly, Kim et al. (2015) found carbon intensity to be positively associated with the cost of capital.

Gallego-Alvarez et al. (2015) show a positive association between carbon reduction and financial performance, but with no evidence of carbon reduction in operational performance. Based on 1,443 firm-year observations of S&P 500 companies, Matsumura et al. (2014) document that on average each additional thousand metric ton of carbon emitted

is associated with a valuation decrease of $212,000, on average, far exceeding the results by Chapple et al. (2013). Both papers highlight that penalties firms face with disclosing their carbon emissions; yet the penalty is more severe for firms that decline to disclose. Bui et al. (2019) examined the joint impact of carbon disclosure and emissions intensity on cost of capital to conclude that higher emission intensity attracts an additional premium, which can also be moderated with extensive carbon disclosure decisions.

Interestingly, Griffin et al. (2017) found that equity values of 3,460 firm-year observations of US S&P 500 firms are negatively associated with both reported and non-reported (but estimated) GHG emissions. Furthermore, they estimate a $79 penalty for each ton of GHG emission emitted. The contrastive result which doesn't find penalties for firms refusing to not disclose emissions is explained as the investors' ability to assess GHG information relating to non-CDP disclosing firms.

Overall, prior studies indicate an association between a firm's carbon emissions and cost of capital, while leaving ample room for further research and discussion. The ethical investing theory screens investments that meet the definition of responsible corporate behavior (Heinkel et al., 2001; Connors and Silva-Gao, 2008). The growth of ESG funds influences firms of varying emission levels to disclose figures in order to derive environmental scores and apply for weighting in the aforementioned funds. Firms that strive to attain environmental standards put their businesses in an advantageous position, which allows them access to these investors excluded from other (non-environmental performing) firms (Heinkel et al., 2001). Similarly, the market equilibrium theory proposes that firms can expand their investor base by pursuing more environmentally focused initiatives (Wang et al., 2013). Wentuitively, improved risk-sharing, disclosed environmental transparency, and the resultant expanded base of capital providers among prospective investors arguably translates to a reduced cost of capital (Merton, 1987; Dhaliwal et al., 2011; Wang et al., 2013).

Delving into information disclosure research, O'Hara (2004) argues that differences in the composition of information between public and private affect firms' cost of capital, with investors demanding a higher return to hold stocks with greater private information. Cahan et al. (2016) split CSR disclosure into two portions, expected and unexpected. With

the unexpected portion representing the incremental information, they find a positive association between unexpected CSR disclosure and firm value. Traditional agency theory advocates that information asymmetry between the agent (managers) and principal (investors) creates conflict which leads to a higher level of perceived risk by the principal. As such, firms with higher carbon disclosures are seemingly likely to reduce this asymmetry by disclosing information. Yet, a counter expectation here is the non-transferable preparation and proprietary costs associated with the additional disclosure which may discount firms' incentive to disclose (Griffin et al., 2017; Moses et al., 2018).

2-3. Sustainable Investing and Cost Elasticity

Within the expanding popularity of sustainable investing and the dynamic firm selection strategies, funds and investors seek out avenues to be green. Hartzmart and Shue (2023) posit that this growth in sustainable investing has changed the environment, so that green firms are rewarded with lowered implied cost of capital and brown firms are punished with rising cost of capital. This can be counterproductive to green transition goals in economies as brown firms can strictly reduce their carbon output considering their operational environment but face a higher cost to invest in green infrastructure compared to the punishment cost. Gormsen et al. (2023) use quarterly earnings conference call transcripts to show that managers of brown firms perceive that their cost of capital has increased by 2.6 basis points relative to green firms over the period 2016 to 2021. And Cohen et al. (2020) find that brown energy firms tend to be excluded from sustainable portfolios, despite the fact that these firms produce the most highly cited green patents.

Recent research has supported that sustainable investing have raised the cost of capital for brown firms relative to green firms (Chava (2014), Van Der Beck (2021), Kacperczyk and Peydro (2022), Pastor et al. (2022), Aron-Dine et al. (2023), Green and Vallee (2022), and Gormsen et al. (2023)). Wen their paper, Hartzmart and Shue (2023) posit that sustainable investing ($35 trillion in committed assets) supports the existent literature. They show that creating a wedge in the cost of capital between brown and green firms may actually be counterproductive for sustainable investors who seek to transition firms to be

more environmentally conscious. Their findings show that sustainable investors normally overweight green industries and underweight brown industries. Weighting is measured as $\frac{w_{SF}-w_{MKT}}{w_{MKT}}$, where w_{SF} is the stock's weight in the aggregate sustainable portfolio and w_{MKT} is the stock's weight in a value-weighted market portfolio.

In theory, an increase in the ICC implies that cash in the present becomes more attractive relative to cash in the future. The higher rate makes all investment projects less attractive, but more so for investments with back-loaded cash flows, e.g.,, projects with higher growth rates. For example, the high-emitting agriculture industry sees that its higher ICC makes green investments too costly to undercut the cost for food production. As such, reducing the ICC out of green incentives and effective policy would reduce the green costs.

2–4. Motivation and Hypotheses

We agree that higher cost of capital can deter brown firms from investing in projects to solve their emissions outputs, while also supporting climate change policy and initiatives. However, we posit that ICC is driven beyond sustainable investing when we observe the sample between 2003 and 2023. Given that earlier portions of the sample see fewer disclosures of carbon emissions where, (i) the Environmental component of an ESG rating cannot be established without disclosing emissions and (ii) sustainable funds saw significant growth after 2015 and notably 2019 with the Vanguard Global ESG fund. As such, we determine the existence of a climate change risk factor that is implied within investors ascribed discount rates on firms and industries that are generally higher carbon emitters regardless of disclosure decision.

We support my key hypothesis and extend Hartzmark and Shue (2023) by imputing emissions data for non-disclosure firm-year observations. We estimate my imputations with an expansion on the prediction regressions by Berg et al. (2024) and Thomas et al. (2022). Firms who do not disclose emissions figures, cannot be scored an environmental ration – and are therefore unable to find weighting in sustainable funds. We find that the relationship between cost of capital and carbon emissions is consistent when I change between reported

and actual emission figures and the imputed figures I calculate for my sample. Ultimately, we find that climate change (measured in emissions) is a priced risk factor in my cost of capital model because brown firms consistently show higher betas.

The imputation methodology – described in detail in section, 3 – allows for the consideration of missing-not-at-random (MNAR) bias while accounting for correlated unobserved factors that may influence both the selection and outcome equations within the sample. The bias stems from a firm's decision to disclose emissions in a given year. The process is meticulously designed to read firm size and operational expenditures as well as industry characteristics to impute emission figures for all reporting and non-reporting firms in my sample. The first hypothesis deals with the imputed figures where we posit (i) its higher predicting accuracy when compared to predictions based on a typical fixed effects regression, and (ii) the yearly correlations, ρ – ranging from 35% to 79% within the sample – shows that firms with unexpectedly higher emissions are more likely to be reporters.

H1: Imputed emissions adequately fit the reported emissions and do so better than the predictions out of a fixed-effects regression.

Intuitively speaking, there must be a bias in the variable emissions as firms voluntarily choose to disclose in a given year. Wen theory, firms – who are not subject to mandating reporting standards under EPA regulations – will disclose if they are within a threshold to which they may benefit from reporting. Additional disclosure decision drivers are industry peer disclosing activity and marginal discrepancy expectations between earnings forecasts and announcements in the short-term.

The threshold constraint presumably changes after 2015 as disclosure decisions are prompted with the surge in sustainable investing and green monitoring. The Heckman correction model and the inverse mills ratios will highlight the yearly selection bias and given the pattern in disclosure over the time sample, the bias should decrease in more recent years.

H2: There is a significant bias in the sample selection but decreases after 2015.

In agreement with relevant literature, brown firms, based on reported and imputed emissions figures, see higher costs of equity capital than green firms. The ICC estimates are derived from analyst forecasts and coverage; as such, brown firms see higher analyst coverage. Larger firms in many industries would be higher emitters, and a bulk of previous literature shows that large firms have lower ICCs compared to small firms. Finding that brown firms – based on imputed and reported carbon emissions – have higher ICCs after 2015 and across varying size quintiles further supports that brown firms are punished for their carbon footprint and points to the pricing factor that climate change has in the market.

Testing employs correlated random effects model since it allows for flexibility in modeling panel data while acknowledging the potential correlation between unobserved individual effects and observed covariates (Semykina and Wooldridge, 2010). We interchange the main independent variable to show that the ICC is priced higher for high carbon emitters whether carbon emissions are reported or not.

H3: Brown firms have higher costs of capital compared to green firms.

How poorly are firms affected for failing to keep within pollution targets? If a firm is characterized as brown, in line with the scope of this research, it already has a climate change risk. Many brown industries have fewer voluntary restrictions, and the effect of disclosing may continue to become less significant in capital pricing models. Thus, firms can find that reporting extraordinary emissions may not hurt their cost of capital as much, and the act of disclosure can be more of a hedging decision. This also coincides with the change and increase in the threshold for disclosure selection.

H4: Firms with unexpected higher emissions are likely to disclose voluntarily.

The findings on brown firms' carbon risk premium, the sample selection bias every year, and disclosing trend point that disclosure decision should be insignificant. Voluntary regulations are inconsistent with all industries, and carbon emissions pricing is representative of this. While disclosure decisions can be significant with sustainable fund

weighting, as shown in previous literature, it and the impact of sustainable investing on cost of capital are weak. The bias becoming weaker and insignificant in recent years also corresponds to the weak evidence of disclosure impact on cost of capital after 2016. The tests run on disclosure will espouse this.

H5: The significance of disclosure decision on cost of capital is nuanced and weak at best; and most certainly becomes weaker from 2016 on.

3. Sampling and Methodology

3–1. Data Sampling

My data sample covers June-calendar firm-year observations between 2003 and 2023. Carbon emissions data is computed as carbon dioxide emissions plus carbon-equivalent scaling of other greenhouse gas emissions.[6] This data is found in Thomson Reuters Datastream. We convert raw emission figures (in metric tons of emissions) to a unit of the natural log of emissions in cars and require a firm to emit at least one car's worth of carbon emissions, to be counted as a valid disclosure in a given year.[7] As such, we require firms to emit at least a car's annual worth of metric tons to be counted as a valid report of emissions in that year. Emissions are reported annually, around the fiscal reporting timeline.

We use data on scopes 1 and 2 emissions. Scope 1 emissions are direct emissions from equipment that the firm owns and resultant pollution of direct materials. Scope 2 emissions are the indirect emissions associated with the purchase of electricity, steam, and heating, so they occur at a location not controlled by the firm but are directly tied to firm actions. We do

[6] According to the United States Environmental Policy Agency (EPA), the primary greenhouse gases emitted in the U.S. are carbon dioxide (79%), methane (11%), nitrous oxide (7%), and fluorinated gases (3%) such as hydrofluorocarbons and perfluorocarbons.
[7] The EPA estimates that a typical passenger vehicle emits about 4.6 metric tons of carbon dioxide per year; a gasoline vehicle that gets 22.2 miles per gallon and is driven 11,500 miles per year.

not utilize scope 3 emissions (all other indirect emissions that occur in the firm's upstream and downstream activities), because reporting of scope 3 emissions is very noisy and involves double-counting. Additionally, current political lobbying on carbon disclosure revolves around scope 3 measurements and reporting. As noted above, disclosure of scope 1 and 2 emissions determines a firm's applicability to sustainable investing weighting.

Datastream's coverage of total firm emissions – which sums scope 1 and scope 2 emissions – incorporates a firm's self-reported disclosed metric as well as their proprietary model-based estimates of emissions from supplement environmental data regarding the firm. While there is noise and arguable bias in this metric, the total estimated emissions ultimately permit a firm to receive environmental scores and present itself as a potential investment for sustainable investment. Most carbon data providers have to impute some portion of their sample (others common providers are S&P TruCost and Clarity AI). Furthermore, any firm's measurement process is likely closer to being a multiplier of consumption units than exact. As other researchers do, we will use the estimated metrics from Datastream. *Supplement robustness will examine the substitution of the estimated figure with only firm-reported total figures as well as scope 1 and scope 2 individual figures.* Data relating to ESG ratings comes from MSCI ESG Ratings, found within Datastream as well. Lastly, we pool all reporting firm year observations into carbon quintiles. Brown firms are the highest 20% of emitters in a given year, while green firms are the lowest 20% of emitters in a given year. While firms in the three neutral quintiles are still observed in further testing, the key emphasis is the distinctive differences between the brown and green firms. Additionally, new quintile classifications are done with the imputed emissions data.

The methodology to impute emissions in this research follows the empirical findings within relevant carbon finance literature as well as industrial focuses of EPA policies. Limited research in this niche has undertaken imputing emissions data. Berg et al. (2024) derive a solid baseline framework for imputation, using the training and machine learning capabilities of Clarity AI. Thomas et al. (2022) find that U.S. firms will likely disclose regardless of emission output or improvement when they are close to meeting or just beating

recent EPS forecasts; interestingly, this relation is stronger for firms with higher environmental ratings who may hedge the ratings against increased pollution costs.

Figure 1 *and*

Figure 2 *depict the trend in emissions within my data sample.*

Figure 1 shows that firms have been reducing their emissions since 2003, and this case holds for green and brown firms. After 2015, green firms see a notable decline in the cumulative average carbon reduction that outpaces the decline of brown firms. Wet is noteworthy that much of the earlier environmental disclosure policy affected brown industries, and a significant proportion of new firms who began disclosing emissions in 2016 or after were in greener industries (e.g., business services, depository institutions).

Figure 2 displays the proportion of firms who report each year; the shift after 2015 further supports that environmental policy has reduced the green costs of already greener industries.

At the firm level, earnings per share (realized-fiscal) and monthly, upcoming fiscal forecasts for the two upcoming fiscal year end periods, relative to a calendar month, are pulled from IBES. The predictions are the mean FY1 and FY2 forecast as well as median Long-term Growth estimates. CRSP and COMPUSTAT are used to download firm accounting and stock price data. The implied cost of capital estimation requires the book value of equity per share and monthly price to be greater than $1.00, requires a market capitalization of at least $50 million, and restricts the dividend payout ratio between 0 and 1. The terminal valuation is the median of historical industry return on equity computation, constraining that firms in the same Fama-French 49 Industry Class have anywhere from 5-10 ROEs previous at each fiscal year. Observations are dropped if missing any of the required variables needed to compute the ICC.

The sample ultimately selects firm-years by the June calendar months, between 2003 and 2023. We meticulously connect my CRSP and IBES monthly data to relevant COMPUSTAT and Datastream fiscal annual data with fiscal year-ends by March 31st of the respective calendar year. Firms are given a 3-month lag to compile and release their data. With this adjustment to the matchup by COMPUSTAT convention, EPS forecasts timely match up with upcoming fiscal periods and the recent, actual earnings are known by June of each firm-year. Likewise, the accounting variables are matched up already within the lag of being readily known at a certain calendar month. Other papers utilize a different method which endorses a synthetic book value per share to account for reporting timeline constraints; *this is another task for upcoming robustness*. Lastly, missing observations within key estimation and control variables such as those listed in the following section are dropped. Ratios, used as control variables, are winsorized at the 1% and 99% levels.

3–2. Implied Cost of Equity Capital

Gebhardt et al. (2001) computes the cost of equity capital from forecasted eps valuations within a Residual Income Model (RIM). The model seeks to understand the market's perception of a common stock's risk, and its systematic variation across firms and industries. The model results were found to incorporate systematic relations between the implied cost-of-capital and ex ante firm or industry characteristics. In other words, if the market tends to consistently assign a higher (or lower) discount rate to certain firms and industries, such relations should be exploited in deriving a cost-of-capital estimate for valuation and investment purposes. The model computes, r_e, the cost of equity capital.

$$P_t = B_t + \frac{FROE_{t+1} - r_e}{(1+r_e)} B_t + \frac{FROE_{t+2} - r_e}{(1+r_e)^2} B_{t+1} + TV \qquad \textit{Equation 1a}$$

P_t is the calendar month ending stock price. B_t is the book value of equity from the most recent 10K divided by number of shares outstanding in the current calendar month. $FROE_t$ is the forecasted ROE in select period computed as $FROE_t = \frac{forecastEPS_{t+i}}{B_{t+i-1}}$. TV is the terminal valuation computed within the 3rd and final time (T) horizon, $T = 12$. $B_{t+i} = B_{t+i-1} + \big(FROE_{t+1} \times B_{t+i-1} \times (1 - DP)\big)$ is the periodic book value estimation and DP is the dividend payout ratio.

$$TV = \sum_{i=3}^{T-1} \frac{FROE_{t+i} - r_e}{(1+r_e)^i} B_{t+i-1} + \frac{FROE_{t+T} - r_e}{r_e(1+r_e)^{T-1}} B_{t+T-1} \qquad \textit{Equation 1b}$$

$FROE_t$ uses analyst mean EPS forecast measures for the next two upcoming fiscal years as well as the median long-term growth rate forecast measure. These forecasts are made each calendar month. $forecastEPS_1$, $forecastEPS_2$, and $forecastLTG$ are given. $forecastEPS_3 = forecastEPS_2 * (1 + forecastLTG)$. $forecastEPS_T$ is the median of the last 5-10 ROEs within Fama French 49 Industry Classes. $forecastEPS_t$ with $4 \leq t \leq T - 1$ is the linear interpolation to industry median ROE. $FROE_t$ reversion property captures the long-term erosion of abnormal ROE as individual firms tend to become more like their industry peers in the long run (Fama and French, 1997).

3–3. Adapted Heckman 2-Stage Equation

The imputation methodology allows for the consideration of missing-not-at-random (MNAR) bias while accounting for correlated unobserved factors that may influence both the selection and outcome equations within the sample. The decision to disclose is up to the firm in a given year, and therefore missing emission figures are missing by selection. The Heckman two-step model obtains unbiased and consistent estimates of the relationships of interest (Heckman, 1979), often in the context of a selection bias in the panel data. The adapted model utilizes a correlated random effects model to identify coefficients of the model endogenous variables based on the deviations in the instrumental variables from their within-individual average values. This is very similar to traditional fixed-effects estimation, where the unobserved heterogeneity is assumed to be time-invariant (Semykina and Wooldridge, 2010). To account for sample selection, the command uses the interaction of inverse mills ratios with the time variable in the model specification. Standard errors of the model are obtained using a panel bootstrap procedure, using the *gvkey* as the cluster.

The selection equation (first stage) focuses on the selection binary variable which will populate a value for the main outcome variable if it equals 1; the outcome variable will have a missing observation if the selection variable equals 0. The equation is a probit model with correlated random effects, thus incorporating time averages of time-varying variables. Specifically, we want to allow coefficients in the selection equations for different time periods to be entirely unrestricted. For each year, the probit model's obtained Inverse Mills Ratios (IMRs) interact with time dummies to allow for different correlations between idiosyncratic errors and allow correlation to differ across each year.

The outcome equation (second stage) is a correlated random effects model where the covariates are shared between the stages; however, the probit (first stage) has additional endogenous variables which would trigger a selection. The testing employs the Correlated Random Effects (CRE) model, instead of the fixed effects model, due to its flexibility when modeling heterogeneity, particularly when there are correlations between different sources of variation. Wen its hybrid functionality, the model can capture trends and individual-level deviations to account for both within-group and between-group variability. By incorporating

explanatory means into the model, testing can separate out the average trend from the individual deviations and gauge the general effect of the explanatory variables. This is critical for my methodology as we am imputing un-disclosed data from a collection of firm, industry, and investment variables.

The imputation was done using the XTHECKMANFE command in STATA (Rios-Avila, Fernando) who credits the model to Semykina and Wooldridge (2010). The imputation methodology is detailed below.

(1) The selection equation models the likelihood of being selected into the sample:

$$D_i^* = \gamma' Z_i + u_i + v_i \; where \; D_i = \begin{cases} 1 \; if \; D_i^* > 0 \\ 0 \; otherwise \end{cases} \qquad \textit{Equation 2a}$$

D_i^* is a latent variable determining selection. γ' is vector of parameters to estimate from vector of selection covariates. Z_i are observed covariates affecting selection (endogenous selection variables **included here**). u_i is the error term for the selection process. v_i is the random effect, capturing unobserved heterogeneity.

(2) The (Inverse Mills Ratio) IMR from the selection model is calculated as:

$$IMR(Z_i) = \frac{\phi(\gamma' Z_i)}{\Phi(\gamma' Z_i)} \qquad \textit{Equation 2b}$$

ϕ is the standard normal probability density function (PDF). Φ is the standard normal cumulative distribution function (CDF). Z_i are observed covariates affecting selection.

(3) The outcome equation that includes the random effects and the IMR is given by:

$$\widehat{Y}_i = \beta' X_i + \lambda \cdot IMR(Z_i) + \epsilon_i + v_i \qquad \textit{Equation 3}$$

$\widehat{Y}_i$ is the imputed outcome variable for which Y_i is only observed when $D_i = 1$, a firm decides to disclose in a given year. β' is vector of parameters to estimate from vector of outcome

covariates. X_i are observed covariates affecting outcome. ϵ_i is the error term for the outcome. v_i is the random effect from the selection equation.

3–4. Variable Selection for Imputation

Table *1* below details the variables used for the imputation; note that the common covariates in both stages are the in the top panel. The 2-Stage imputation model uses $report_{i,t}$ as the binary selection variable which takes a value of 1 if a firm discloses its carbon emissions in a given year; and 0 otherwise. The outcome variable, $CO2_{i,t}$, which is the natural log of carbon emissions in cars for a reporting firm in a given year, is studied in the second stage. The imputed value of carbon emissions, enacted on all observations, is labeled as, $HeckCO2_{i,t}$, which shares the same units as the actual figure. The endogenous selection covariates are $suspect_{i,t}$ and $disclose_{i,t}$.

The first stage probit model (equation 2a) will ultimately compute the inverse mills ratio for all observations by taking the ratio of the probability density function to the cumulative distribution function of a normal distribution. The IMR (equation 2b) will capture selection bias and when interacted with the year effect in the second stage (equation 3), it is reflective of the time-varying correlation of unobserved error terms between the two equations. The resultant IMR shows a downward trend which points that selection bias is decreasing over time. Given that firms may voluntarily disclose in order to attain ESG scores as a possible incentive, as well as the vast majority of firms disclosing post-2015, the disclosure decision does not hold as much weight.

Figure 3 *shows the trend of the average annual IMR across the sample.*

Table *2* shares a portion of the correlated random effects model in the second stage of the Heckman correction (outcome equation). The interaction between year and IMR is significant and growing through much of the sample. Specifically, we find that the coefficient jumps after 2015 and continues its trajectory up until 2020, showing that selection bias was notably prevalent during this period. Post-2020, the bias falls and becomes insignificant. As such, the effect of selection bias on the outcome becomes stronger until it shows itself to no longer be a key driver of the outcome in later periods.

Next, we compare the imputed carbon emissions figures against reported emissions. Additionally, we introduce the predictions that a fixed effects regression would produce and compare the fitting nature of the two. A fixed effects regression is widely used due to its applicability in panel data structure and time-varying data; this research's imputations have fixed effects as a component, as mentioned earlier. **Table *3*** compares yearly ρ and R^2. The imputed values show better fitting except when it comes to the within R^2. Specifically, the imputed values show better fitting across the full sample, except for green quintiles after 2019.

Table *3* shares the fitting nature of the imputed values (Heckman) and predicted values from a fixed effects regression adapted from the outcome equation (FE). Panel A shares the yearly correlations. Panel B runs a fixed effects regression with reported emission values as the dependent; the regression includes time fixed effects. The second and third columns observe firm-years in brown and green quintiles. Panel B also sheds light onto the Heckman performance from 2016 on, which is where voluntary disclosure really picks up,

and the selection bias wanes after 2019. The results coincide with the findings of sample selection in **Table *2*** as well as disclosure trends in **Figure *2***.

Figure *4* depicts a distribution box plot of the firm-year differences between imputed and reported emissions. Wet is separated by the reported emissions quintile and 2016 as a time break. The imputations seemingly overestimate browner firm's emissions output and underestimate greener firms. The lines on the box show the 75^{th}, 50^{th}, and 25^{th} percentiles, top to bottom; the whiskers give the full range. The post 2016-time sample shows an uptick in overestimation in firms' emissions output from the earlier time sample, for green and brown reporting firms.

3–5. Incidentally Truncated Moments

The theory behind the imputation follows Theorem 19.5, Moments of the Incidentally Truncated Bivariate Normal Distribution.[8] The theory references the statistical properties (mean, variance, covariance, etc.) of a bivariate normal distribution when one or both variables are subject to incidental truncation. Wencidental truncation occurs when observations are excluded from the sample based on conditions involving one of the variables, which affects the statistical moments of the distribution.

First, consider the joint distribution of two normally distributed variables, X_1 and X_2, characterized by their means (μ_1, μ_2), variances (σ_1^2, σ_2^2), and covariance $\sigma_{1,2}$. Truncation is incidental when it is based on a condition involving one variable, X_2, but affects the observed sample of X_1 and X_2. For example, data might only be observed if $X_2 < c$, where c is some threshold. Logically, firms with voluntary participation in carbon disclosure would theoretically disclose if their emissions were below a specific threshold. Truncation alters the distribution by excluding a portion of the data, resulting in a sample that is not representative of the original population. This changes the moments (mean, variance, covariance) of the observed distribution compared to the untruncated distribution. As such,

[8] Greene's textbook, *Econometric Analysis*, Theorem 19.5, pg. 873

for a truncation condition $X_2 < c$, the mean of X_1 and X_2 are adjusted using the inverse mills ratio, the ratio of the PDF to the CDF of the standard normal distribution. **The derivation below explains the process.**

There is no doubt that any firm emits greenhouse gas each year. While the imputation method systematically assesses a figure to each firm-year, the baseline theory is to fully comprehend the true mean in the sample (mean of every firm's actual carbon emissions for the year disregarding disclosure decision). When there is a positive correlation between two variables, X_1 (imputed or actual) and X_2 (reported or disclosed), the observed sample is truncated such that $X_2 < c$, the relationship between the true mean and the conditional mean depends on the nature of the truncation and the correlation. Positive correlation means that as X_2 increases, X_1 tends to increase on average. Wen fact, the imputations do display an increasing and positive ρ with reported data across the time sample. When truncation occurs at $X_2 < c$, the observed sample includes only values of X_2 below c. This alters the distribution of X_1 because the truncated sample is no longer representative of the full population, especially when X_1 depends on X_2. Because of the positive correlation, lower X_2 values are associated with lower X_1 values on average, **thus skewing the conditional distribution of X_1 downwards**. Hence, the **conditional mean** of X_1 is an expectation, $E[X_1|X_2 < c]$, that will typically be **lower than the true mean** of X_1, μ_{X_1}.

To quantify this relationship into a setup, for the following bivariate normal distribution, with truncation at $X_2 < c$:

$$\begin{pmatrix} X_2 \\ X_1 \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_{X_2} \\ \mu_{X_1} \end{pmatrix}, \begin{pmatrix} \sigma_{X_2}^2 & \rho\sigma_{X_2}\sigma_{X_1} \\ \rho\sigma_{X_2}\sigma_{X_1} & \sigma_{X_1}^2 \end{pmatrix} \right) \qquad \textit{Equation 4}$$

Given truncation ($X_2 < c$), positive correlation ($\rho > 0$), and the formulation of the inverse mills ratio ($\lambda(z) = \frac{\phi(z)}{\Phi(z)}$), the conditional mean of X_1 ($E[X_1|X_2 < c]$) is:

$$E[X_1|X_2 < c] = \mu_{X_1} - \rho\sigma_{X_1}\lambda\left(\frac{c-\mu_{X_2}}{\sigma_{X_2}}\right) \qquad \textit{Equation 5}$$

Therefore, the true mean of X_1, μ_{X_1}, is given as:

$$\mu_{X_1} = E[X_1|X_2 < c] + \rho\sigma_{X_1}\lambda\left(\frac{c-\mu_{X_2}}{\sigma_{X_2}}\right) \qquad \textit{Equation 6}$$

As such, the ***conditional mean*** *of the imputed variable is* ***less than the true mean****, because the truncation excludes higher reported values that are associated with higher imputed values. Furthermore, the size of the difference depends on the truncation threshold, correlation, and the variability of the imputations.*

Figure *5* (*use y instead of* X_1) shows the simulated (*10,000 times*) distribution with a positive correlation and a threshold of 20%. The conditional mean comes out to -0.306 whereas the true mean comes out to 0.007. The blue distribution indicates the conditional mean whereas the yellow distribution indicates the true mean.

3–6. Preliminary Statistics

The dependent variable is the ICC to be regressed against a selected carbon emissions variable. The adjacent set of regressions will show that the marginal effect of being brown will cause investors to value a firm at a higher cost. Model methodology is detailed below.

$$Y_{it} = \mu_i carbon_{it} + \beta' X_{it} + \alpha_{ai} + v_i + \epsilon_{it} \qquad \textit{Equation 7}$$

Y_{it} is the dependent variable: firm-year ICC. μ_i is the coefficient of the selected carbon emission variable. $carbon_{it}$ is interchanged between reported and imputed emissions figures, CO2 , HeckCO2. $carbon_{it}$ is also interchanged with the carbon quintiles, $q5_{it}$, which include reported and imputed, co2q5 , heckq5. β' is the vector of coefficients. X_{it} is the vector of explanatory variables: new, mv, exRet, debt/asset. α_{ai} is the vector of specific fixed effects with a being year and SIC2 industry. v_i is the random effect for firm *i*, capturing unobserved characteristics. ϵ_i is the idiosyncratic error term.

Table *4* details the variables selected for regression testing in the next section. Note that the determinants of the cost of capital computation are set on the right side to further dictate that individual forecasts compose of the climate change risk factor and ultimately create the brown carbon risk premium.

Table 5 displays summary statistics for the data. Panel A covers the full sample while Panel B observes the sample from 2016 to 2023. A correlation table is provided below the summary table. **Table 6** tabulates the mean ICC, as a percentage, within emission quintiles and size quintiles. Panels A and B use the reported emissions quintiles; panels C and D use the imputed emissions quintiles. Panels A and C cover the full sample while panels B and D cover the post-2016 sample. Size quintiles are ranked by market capitalization. **Table 6** shows that the mean cost of capital is higher for the brown quintile compared to the green quintile; ICC is also higher within the neutral quintiles as they lean browner in classification.

WeCC is lower for larger firms, based on the trend within the size quintiles. Lastly, the results hold when the imputed quintiles are used instead of the reported quintiles.

Table *6* also provides insights for upcoming testing to support that firms may not be punished for emission activity as strongly as some literature finds. With the notable increase in firms' emissions disclosures in the US market annually since 2016, we posit the case that the new disclosures have actually driven the emissions averages – especially within the greener quintiles – in recent years. Sustainable environmental goals and regulation ultimately require notable emission reduction from the brownest industries.

4. Results

4–1. Cost of Capital and Emission Levels

With the imputations, the forthcoming test is meant to show that the cost of equity capital will still penalize brown firms when compared to green firms. The testing opts for the correlated random effects model since it allows for flexibility in modeling panel data while acknowledging the potential correlation between unobserved individual effects and observed covariates. The mean of the explanatory variables captures the between-individual effects assessing how variations in the average levels of those variables (across firms) relate to variations in the dependent variable.

Table *7* shows that higher emissions point to significantly higher costs of equity capital. With the imputed figures, this marginal effect is greater. And this is consistent throughout the full sample as well as subsamples of reporting and non-reporting firms. The variable, *new*, which is a dummy variable to indicate first time disclosures has a reductive impact on a firm's cost of equity capital. This coincides with the trends in carbon emission disclosure and firms are able to garner ESG scoring with the action of disclosing. The effect is strongest within the reported sample.

Table *8* deals with quintiles and the model is strongest in the reported sample. The coefficients espouse differences in cost of capital from green firms as the base and shows that each quintile has marginally higher costs of capital. This effect is significant and becomes stronger as firms become brown or green. The magnitudes being greater for imputed figures shows that there is an underlying effect of carbon emissions that isn't captured when solely observing reporting firms. The results in **Table *7*** and **Table *8*** present that the brown risk premia (found in **Table *6***) is exists among non-disclosing firms and during the early portions of the data sample.

Within the correlated random effects model, higher rho values indicate that a significant portion of the variance in the dependent variable is attributable to the unobserved individual-specific effect. This high value suggests that individual differences play a crucial role in explaining the outcome, and that those differences are likely correlated with the observed explanatory variables. The significance of the individual-level explanatory variables indicates that changes in these variables have a meaningful impact on the dependent variable at the individual level. However, my insignificant means suggest that the average levels of these explanatory variables do not have a significant impact on the dependent variable when considering the random effects.

We constitute this as due to the downward trend of the ICC in my sample and that there must be a change to the climate risk factor over time. Considering that most firms begin disclosing emissions starting in 2016 to the present, and investors are aware of this, we must next delve further into understanding my concepts. Many of the new disclosing firms fall under presumably lower carbon emitting industries such as business services and depository institutions.

4–2. Cost of Capital and Disclosure

Table *9* displays the marginal effect of first-time disclosure and sustained disclosure activity and its impact on the cost of capital. The top panel reports the full sample while the lower panel reports the post 2016 sample. **Table *9*** shows that the disclosing decision is not

actually very significant across the sample and within the quintiles. However, neutral quintile shows some marginal effect in reducing cost of capital; and this may be driven by the fund weighting effect. Green through neutral firms have reasons to disclose (e.g. sustainable investments, ESG ratings), but the notable carbon emitters aren't truly subject to the same voluntary disclosure perspective, and many have mandated disclosure regulation considering their industry. Hence, **Table *9*** shows the significant positive impact of sustain investing for brown firms across the full sample; this dissipates in the latter period. Wef sustainable investing fully explained the cost of capital premium for brown firms, the results in Table 9 would be noticeably different with disclosure being consistently significant and negative with the cost of capital (**to which this is not the case**).

The decision to disclose carbon emissions may not impact on the cost of capital for investors as they efficiently incorporate climate-related risks into asset prices. When sectors with high carbon intensity, investors often apply a generalized risk premium across all firms, treating disclosure as secondary to the overarching risks of regulatory pressures, transition costs, and climate uncertainties. Since disclosure itself does not address the fundamental financial risks posed by carbon intensity, its absence may not meaningfully alter the underlying cost of equity or debt for investors.

5. Conclusion

5–1. Summary and Implications

In conclusion, this research underscores the importance of climate change disclosures and their complex influence on investor valuation and firm cost of capital. By incorporating both reported and imputed emissions data across a comprehensive sample of U.S. firms, the study offers new evidence suggesting a distinctive climate-change risk factor affecting carbon-intensive firms. These findings provide a counter take to prior research suggesting

ESG investing increases the cost of capital for high-emission firms; instead, they indicate that an inherent risk factor is driving this increased cost, independent of disclosure decisions. And the indiscernible impact that disclosure has on cost of capital further supports the climate risk factor.

Investors raise the cost of equity capital for firms they perceive to be higher-risk as a way to compensate for the additional risk. Changing regulations, shifting consumer sentiment, and potential penalties for unsustainable practices can create a level of unpredictability that increases the perceived risk associated with carbon-intensive firms. As such, investors may be concerned about future regulatory penalties, potential legal challenges, or competitive disadvantages that could arise as global regulations surrounding emissions and sustainability continue to evolve.

Another important driver of increased equity capital costs is the rising prominence of ESG (Environmental, Social, and Governance) and sustainability-focused investing. As more funds and individual investors prioritize environmentally responsible companies, firms with high carbon emissions or minimal environmental safeguards can become less attractive in comparison, effectively raising their cost of capital as the pool of interested investors shrinks. That being said, the statistical imputations and research findings show that disclosure activity and sustainable investing can only contribute a portion of the risk. Early portions of the sample show that firms in brown industries have always faced a climate premium due to the environmental deterrents they have always faced.

For regulators, this research signals the potential necessity of standardized climate disclosures to ensure transparent risk assessments, while for firms, it suggests that non-disclosure may not fully insulate them from climate-related financial impacts. Wenvestors and analysts, meanwhile, are given fresh insight into how carbon emissions influence equity valuation, further supporting the integration of climate risk into investment models. Future studies may build on these results by exploring this climate-change risk factor in more granular detail, potentially guiding both corporate disclosure practices and regulatory frameworks in a world increasingly aware of the financial implications of climate risk.

5–2. Future Direction

The paper espoused robustness checks to be done with data and variable selection. Upcoming tests will also examine the role of ESG scores, firms' regulatory incidents, and the analysis with other firm performance indicators and alternate cost of equity measures. The imputation results are bootstrapped within the Heckman 2-stage model used, and we will induce a confidence interval of predictions to allow variability. We posit that once again, the results will hold.

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Figures and Tables

Figure 1

Figure 1 shows that firms have been reducing their emissions since 2003, and this case holds for green and brown firms. After 2015, green firms see a notable decline in the cumulative average carbon reduction that outpaces the decline of brown firms, 44% versus 13%. The trend should be linked with disclosure activity, as in Figure 2.

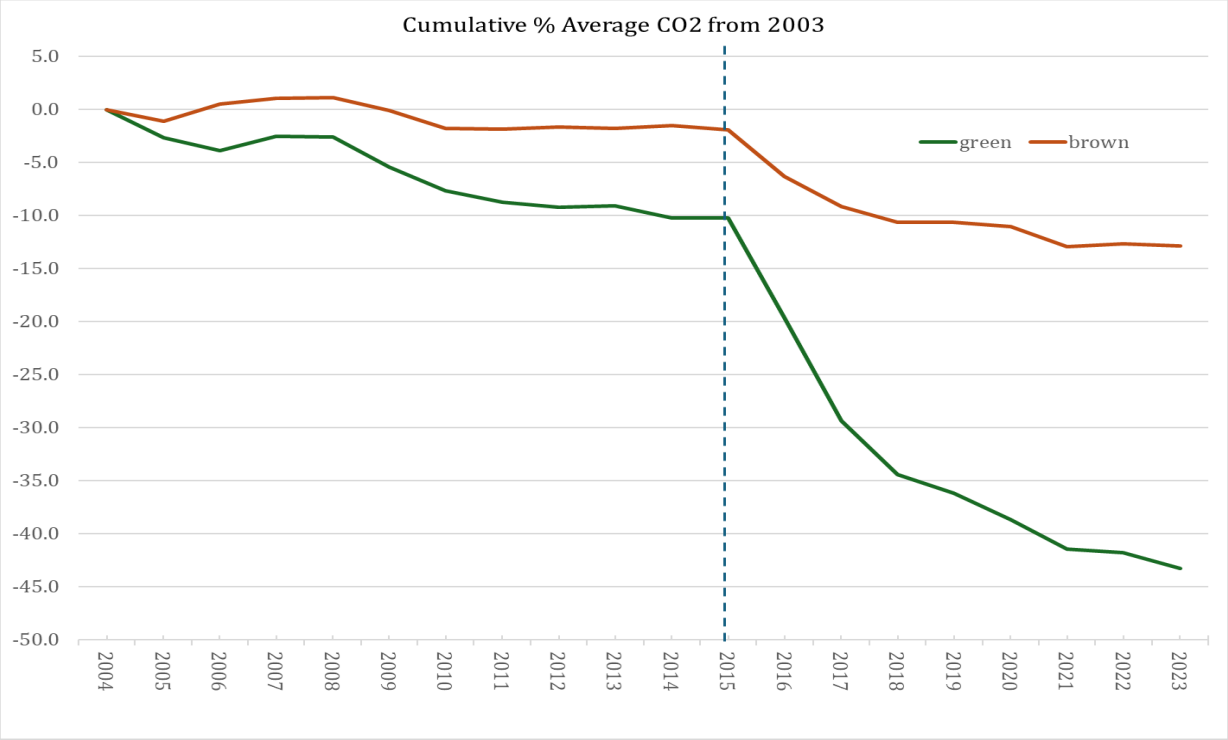


Figure 2

Figure 2 presents disclosure activity, displaying the annual percentage of firms disclosing carbon emissions in their filings. Wet is noteworthy that much of the earlier environmental disclosure policy affected brown industries, and a significant proportion of new firms who began disclosing emissions in 2016 or after were in greener industries (e.g., business services, depository institutions).

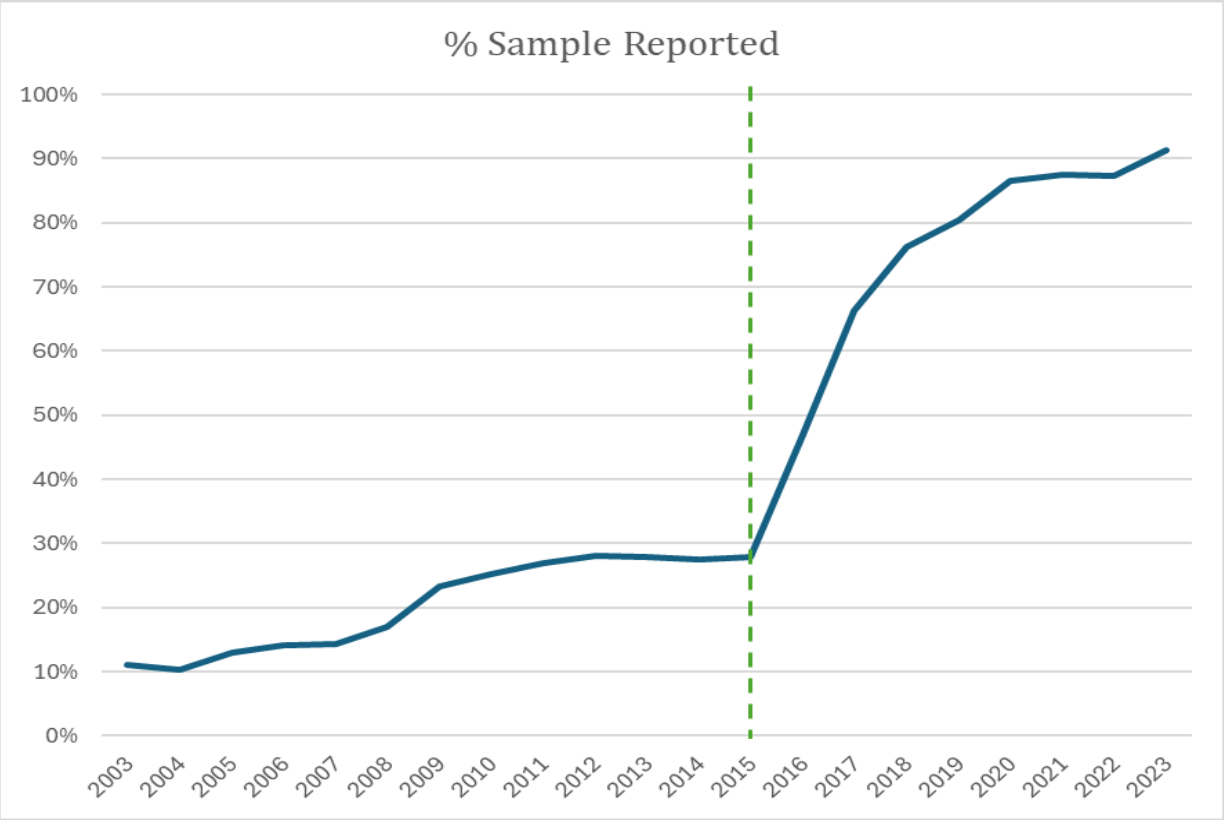


Figure 3

Figure 3 displays the downward trend in the average Inverse Mills Ratio, which points that selection bias is decreasing over time. Given that firms may voluntarily disclose in order to attain ESG scores as a possible incentive, as well as the vast majority of firms disclosing post-2015, the disclosure decision does not hold as much weight.

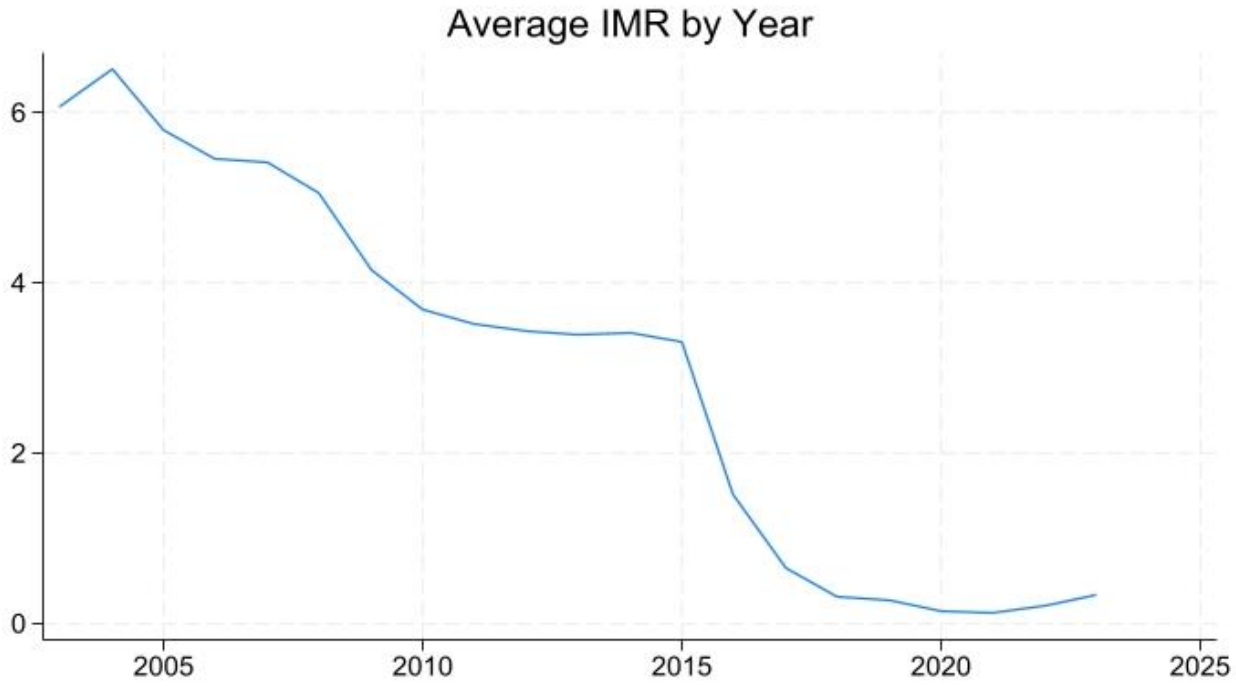


Figure 4

Figure 4 depicts a distribution box plot of the firm-year differences between imputed and reported emissions. Wet is separated by the reported emissions quintile and 2016 as a time break. The lines on the box show the 75th, 50th, and 25th percentiles, top to bottom; the whiskers give the full range.

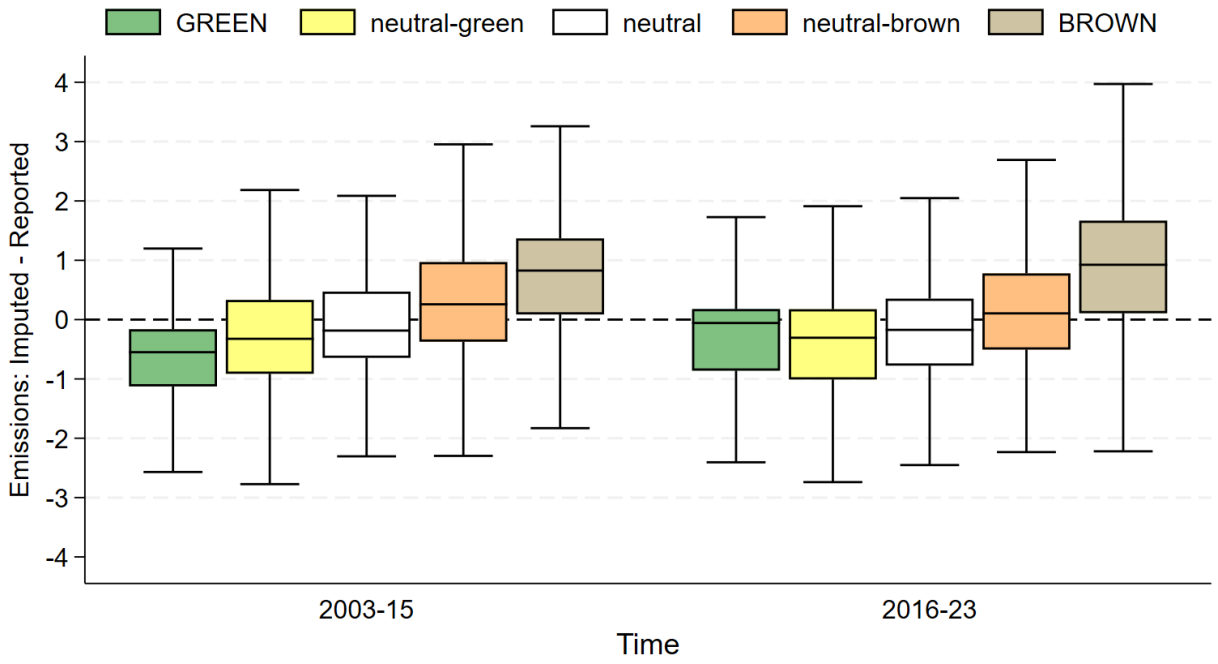


Figure 5

Figure 5 visually depicts that, because the truncation excludes higher reported values that are associated with higher imputed values, the **conditional mean** of the imputed variable is **less than the true mean**. Wen the depiction (*using y instead of* X_1), across 10,000 simulations' distribution with a positive correlation and a threshold of 20%, the conditional mean comes out to -0.306 whereas the true mean comes out to 0.007.

```
# obs → 10 000
rho ρ → 0.5
x truncated at a → 0.2
μx → -0.0142108
μy → 0.00696505
E[x | x<0.2] → -0.668866
E[y | x<0.2] → -0.306051
```

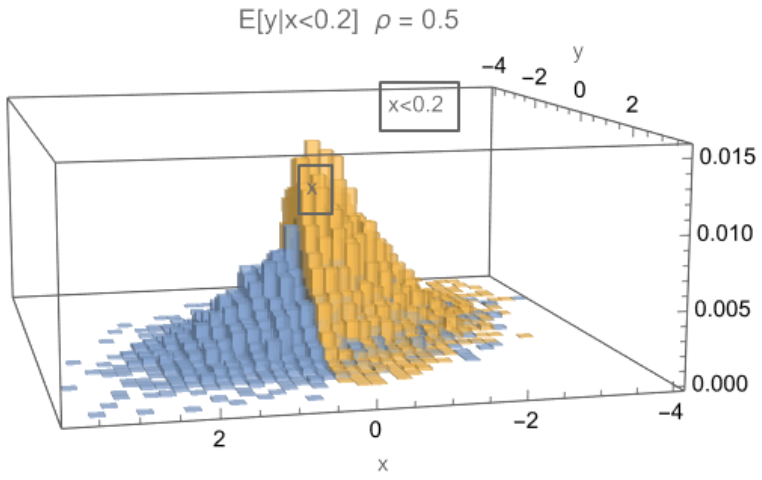


Table 1

Table 1 details the variables used for the imputation; note that the common covariates in both stages are the in the top panel. The 2-Stage imputation model uses $report_{i,t}$ as the binary selection variable which takes a value of 1 if a firm discloses its carbon emissions in a given year; and 0 otherwise. The outcome variable, $CO2_{i,t}$, which is the natural log of carbon emissions in cars for a reporting firm in a given year, is studied in the second stage. The imputed value of carbon emissions, enacted on all observations, is labeled as, $HeckCO2_{i,t}$, which shares the same units as the actual figure. The endogenous selection covariates are $suspect_{i,t}$ and $disclose_{i,t}$.

Label	Definition	Detail
mv	log market value equity	
rev	log revenue	
gmr	gross profit margin (vertical integration)	$gross\ profit/revenue$
emp	log employment	
$dhdiv$	high dividend yield	1 if firm had a dividend yield above the median of dividend payers in the prior year.
$dsicbrn$	highest emitting 2-digit sic	1 if yearly mean sic2 CO2 in top decile
$dsicgrn$	lowest emitting 2-digit sic	1 if yearly mean sic2 CO2 in bottom decile
$epserr$	deviation from forecast eps within 3-month window	$eps_d = actual\ eps - forcast\ eps$ 0 $if\ more\ than\ 3\ month\ from\ forcast\ to\ actual$ 1 $if\ \lvert eps_d \rvert < .1$ 2 $if\ .1 \leq \lvert eps_d \rvert < .3$ 3 $if\ .3 \leq \lvert eps_d \rvert < .5$ 4 $if\ .5 \leq \lvert eps_d \rvert < 1$ 5 $if\ \lvert eps_d \rvert \geq 1$
imr	inverse mills ratio	derived from the selection equation to then be interacted with the panel time variable in the outcome model specification
$disclose$	ratio of industry emissions reporting	sum of firm size (market value ratio every firm year) by all reporters in an SIC2 industry every firm year
$suspect$	notable deviation from forecast eps within 3-month window	$eps_d = actual\ eps - forcast\ eps$ 0 $if\ more\ than\ 3\ month\ from\ forcast\ to\ actual$ 1 $if\ \lvert eps_d \rvert < .05$
$HeckCO2$	imputed CO2 emissions figure	

$report$	discloses emissions in firm-year	$1\ if\ CO2_t > 0$

Table 2

Table 2 shares the results of the second stage of the imputation process. Panel A displays the key prediction results; Panel B displays the yearly selection bias until 2015; and Panel C displays the yearly selection bias 2016 and after. Explanatory means are not shown here but are a part of the CRE model components and integral to the imputation. The interaction between year and IMR is significant and growing through much of the sample. Specifically, I find that the coefficient jumps after 2015 and continues its trajectory up until 2020, showing that selection bias was notably prevalent during this period. Post-2020, the bias falls and becomes insignificant. As such, the effect of selection bias on the outcome becomes stronger until it shows itself to no longer be a key driver of the outcome in later periods.

	Panel A		Panel B		Panel C
mv	-.047***	2004	-.002	2016	.111***
	(.011)		(.010)		(.016)
rev	.243***	2005	.035***	2017	.273***
	(.024)		(.010)		(.025)
gmr	.200**	2006	.047***	2018	.282***
	(.094)		(.010)		(.040)
$epserr$	-.002	2007	.043***	2019	.241***
	(.007)		(.010)		(.042)
emp	.481***	2008	.041***	2020	.224***
	(.022)		(.010)		(.059)
$dhdiv$	-.068***	2009	.064***	2021	.099
	(.020)		(.010)		(.067)
$dsicgrn$	.113***	2010	.069***	2022	.060
	(.033)		(.011)		(.053)
$dsicbrn$	.364***	2011	.065***	2023	-.024
	(.038)		(.011)		(.037)
$control$	-4.303***	2012	.065***		
	(.037)		(.011)		
$\boldsymbol{N}$	18,072	2013	.061***		
$\boldsymbol{\rho_{rho}}$	.815		(.011)		
$\boldsymbol{\chi^2_{Mundlak}}$	2.2e+03***	2014	.053***		
$\boldsymbol{R^2_{Within}}$	.130		(.011)		
$\boldsymbol{R^2_{Between}}$	.796	2015	.044***		
$\boldsymbol{R^2_{Overall}}$	.787		(.011)		

*Sig: *0.10 ; **0.05 ; ***0.01*

Table 3

Table 3 compares yearly ρ and R^2 between predicted and disclosed emissions, with and without sample bias. The comparison distinguishes the fitting nature of the imputed values (Heckman) and predicted values from a fixed effects regression adapted from the outcome equation (FE). Panel A shares the yearly correlations. Panel B runs a fixed effects regression with reported emission values as the dependent; the regression includes time fixed effects. The second and third columns observe firm-years in brown and green quintiles. Heckman-imputed values show better fitting except when it comes to the within R^2. Specifically, the imputed values show better fitting across the full sample, except for green quintiles after 2019.

Panel A	Overall			Brown			Green		
Year	*Heckman*	*FE*	*Obs.*	*Heckman*	*FE*	*Obs.*	*Heckman*	*FE*	*Obs.*
2003	.891	.570	239	.625	.092	47	.704	.569	48
2004	.894	.557	239	.629	-.066	47	.751	.573	48
2005	.895	.570	312	.686	.332	62	.717	.634	63
2006	.879	.560	351	.556	.145	70	.601	.587	71
2007	.879	.517	351	.552	.158	70	.665	.620	71
2008	.875	.493	376	.545	-.038	75	.608	.526	76
2009	.887	.560	459	.581	.101	91	.673	.509	92
2010	.883	.575	527	.622	.152	105	.581	.442	106
2011	.888	.599	561	.609	.054	112	.608	.418	113
2012	.872	.586	581	.566	.169	116	.538	.526	117
2013	.883	.587	577	.561	.079	115	.546	.452	116
2014	.876	.608	586	.517	.010	117	.622	.626	118
2015	.885	.618	593	.543	.024	118	.588	.562	119
2016	.896	.677	943	.643	.154	188	.713	.635	189
2017	.905	.726	1304	.629	.211	260	.639	.625	261
2018	.909	.752	1507	.655	.267	301	.657	.607	302
2019	.907	.743	1563	.643	.248	312	.666	.673	313
2020	.905	.771	1617	.629	.214	322	.566	.631	324
2021	.893	.756	1773	.613	.258	354	.535	.683	355
2022	.892	.741	1815	.626	.237	363	.478	.574	363
2023	.886	.740	1798	.590	.251	359	.338	.556	360

Panel B	Overall			Brown			Green		
Metric	*Heckman*	*FE*	*Heckman×Post16*	*Heckman*	*FE*	*Heckman×Post16*	*Heckman*	*FE*	*Heckman×Post16*

R^2_{Within}	.148	.155	.103	.166	.178	.161	.307	.338	.242
$R^2_{Between}$	.829	.610	.820	.403	.122	.401	.749	.787	.718
$R^2_{Overall}$	.830	.571	.812	.503	.131	.502	.795	.816	.774

Table 4

Table 4 details the variables selected for regression testing. Y_{it} is the dependent variable: firm-year ICC. μ_i is the coefficient of the selected carbon emission variable. $carbon_{it}$ is interchanged between reported and imputed emissions figures, $CO2$, $HeckCO2$. $carbon_{it}$ is also interchanged with the carbon quintiles, $q5_{it}$, which include reported and imputed, $co2q5$, $heckq5$. β' is the vector of coefficients. X_{it} is the vector of explanatory variables: $new, mv, exRet, debt/asset$. α_{ai} is the vector of specific fixed effects with a being year and SIC2 industry. v_i is the random effect for firm i, capturing unobserved characteristics. ϵ_i is the idiosyncratic error term. *Note that the determinants of the cost of capital computation are set on the right side*.

Label	Definition	Detail
$exRet$	firm return in excess of value-weighted market {annualized}	$firm\ ret - valueW\ CSRP\ ret$
mv	log market value equity	
$debt/asset$	book leverage	$total\ debt/total\ assets$
$epserr$	deviation from forecast eps within 3-month window	$eps_d = actual\ eps - forcast\ eps$ 0 if $more\ than$ 3 $month$ $from$ $forcast$ to $actual$ 1 if $\lvert eps_d \rvert < .1$ 2 if $.1 \leq \lvert eps_d \rvert < .3$ 3 if $.3 \leq \lvert eps_d \rvert < .5$ 4 if $.5 \leq \lvert eps_d \rvert < 1$ 5 if $\lvert eps_d \rvert \geq 1$
new	first time disclosing	0 if $never$ $reports$ 1 $ONLY$ in the $first$ $firm$ $year$ of $reporting$
$CO2$	log of emissions in unit of cars	ln($CO2$/4.6)
$HeckCO2$	imputed emissions figure	
$co2q5$	quintiles by emissions reported	0 is non-reported, 1 is green, and 5 is brown
$heckq5$	quintiles by emissions imputed	1 is green and 5 is brown
$mcq5$	quintiles by market capitalization	1 is smallest and 5 is largest
ICC	implied cost of equity capital	computed following Gebhardt methodology (2001)

$FROE_t$	forecasted ROE	computed following Gebhardt methodology (2001) and helps strengthen model; $t = 1,2,3,12$
$dpay$	dividend payout ratio	computed following Gebhardt methodology (2001) and helps strengthen model

Table 5

Table 5 displays summary statistics for the data. Panel A covers the full sample, 2003-2023 (*44,392 obs.*) while Panel B observes the partial sample, 2016-2023 (*15,832 obs.*). A correlation table is provided with each.

Panel A	Mean	SD	p10	p50	p90
ICC	8.87	5.14	4.52	8.43	12.66
CO2	9.69	2.79	5.98	9.59	13.47
HeckCO2	8.93	2.42	5.84	8.82	12.19
exRet	.04	.52	-.42	-.02	.49
Debt/Asset	.57	.24	.22	.58	.90
epserr	.23	.72	.00	.00	1.00
mv	21.17	1.65	19.15	2.99	23.47
rev	2.73	1.77	18.49	2.63	23.09
gmr	.35	.16	.14	.34	.59
emp	7.93	1.76	5.71	7.89	1.26

	ICC	*CO2*	*HeckCO2*	*exRet*	*debt/asset*	*epserr*	*mv*	*rev*	*gmr*	*emp*
ICC	1.00									
CO2	.09	1.00								
HeckCO2	.07	.91	1.00							
exRet	-.05	-.01	.00	1.00						
debt/asset	.16	.05	.09	.00	1.00					
epserr	-.03	.05	.08	.02	-.08	1.00				
mv	-.16	.57	.61	.01	.13	.08	1.00			
rev	.07	.75	.80	-.01	.25	.10	.82	1.00		
gmr	-.16	-.39	-.45	-.03	.02	-.06	-.05	-.40	1.00	
emp	.04	.65	.70	-.02	.20	.11	.68	.86	-.36	1.00

Panel B	Mean	SD	p10	p50	p90
ICC	8.56	5.00	3.76	8.15	12.93
CO2	9.00	2.74	5.58	8.83	12.77
HeckCO2	8.76	2.48	5.57	8.72	12.03
exRet	.02	.55	-.45	-.04	.46
Debt/Asset	.60	.23	.27	.62	.90
epserr	.24	.83	.00	.00	.50
mv	21.59	1.71	19.41	21.45	23.93
rev	21.04	1.76	18.76	21.00	23.34
gmr	.36	.17	.14	.34	.61
emp	8.05	1.79	5.75	8.04	1.37

	ICC	*CO2*	*HeckCO2*	*exRet*	*debt/asset*	*epserr*	*mv*	*rev*	*gmr*	*emp*
ICC	1.00									
CO2	.09	1.00								
HeckCO2	.08	.90	1.00							

exRet	-.08	-.02	-.01	1.00						
debt/asset	.15	.04	.05	.01	1.00					
epserr	-.03	.07	.09	.02	-.07	1.00				
mv	-.21	.56	.62	.05	.07	.10	1.00			
rev	.08	.75	.82	.00	.18	.11	.81	1.00		
gmr	-.14	-.42	-.47	-.04	.14	-.07	-.07	-.40	1.00	
emp	.05	.65	.72	-.03	.18	.12	.68	.86	-.34	1.00

Table 6

Table 6 tabulates the mean ICC, as a percentage, within emission quintiles and size quintiles. Panels A and B use the reported emissions quintiles; panels C and D use the imputed emissions quintiles. Panels A and C cover the full sample while panels B and D cover the post-2016 sample. Size quintiles are ranked by market capitalization. Table 6 shows that the mean cost of capital is higher for the brown quintile compared to the green quintile; ICC is also higher within the neutral quintiles as they lean browner in classification. WeCC is lower for larger firms, based on the trend within the size quintiles.

Panel A: 2003-23 (44,392)						*Reported Quintile; Market Cap Quintile*
	small	2	3	4	large	average
NR(58%)	10.00	9.16	8.73	8.45	7.86	9.06
green	9.52	7.53	6.60	7.41	8.34	8.01
2	10.63	8.56	8.28	7.60	7.63	8.20
3	11.63	10.17	8.65	8.35	7.48	8.57
4	14.94	11.24	9.77	8.54	7.71	8.87
brown	17.67	12.26	10.57	9.88	8.36	9.27
average	10.17	9.17	8.69	8.38	7.91	8.87
Panel B: 2016-23 (15,832)						*Reported Quintile; Market Cap Quintile*
	small	2	3	4	large	average
NR(22%)	9.66	8.69	8.60	7.55	6.91	8.80
green	9.40	7.33	6.17	5.66	5.16	7.70
2	10.63	8.58	8.17	7.09	6.04	8.11
3	11.58	10.11	8.52	7.84	6.54	8.56
4	14.09	11.06	9.43	8.41	7.29	8.94
brown	17.17	12.09	10.52	9.70	7.74	9.18
average	10.24	8.97	8.48	7.94	7.18	8.56
Panel C: 2003-23 (44,392)						*Imputed Quintile; Market Cap Quintile*
	small	2	3	4	large	average
green	9.15	7.86	6.81	5.30	4.72	8.28
2	10.08	8.63	7.89	7.31	6.09	8.38
3	11.98	9.98	8.90	8.20	7.35	9.24
4	12.39	10.93	9.58	8.55	7.83	9.22
brown	12.73	11.05	10.53	9.67	8.26	9.21
average	10.17	9.17	8.69	8.38	7.91	8.87
Panel D: 2016-23 (15,832)						*Imputed Quintile; Market Cap Quintile*
	small	2	3	4	large	average

green	8.77	7.06	5.65	3.08	4.77	7.63
2	11.14	8.53	7.67	6.93	4.59	8.28
3	12.06	10.04	9.32	7.75	6.42	9.03
4	12.58	10.70	9.33	8.21	7.24	9.02
brown	13.57	11.54	10.14	9.35	7.68	8.85
average	10.24	8.97	8.48	7.94	7.18	8.56

Table 7

Table 7 shows results of ICC against raw emissions output in a correlated random effects regression. The model includes controls, the determinants of the ICC derivation, time and industry fixed effects, and time-averaged values. Column 1 uses reported emissions while columns 2, 3, and 4 use imputed emissions. Columns 1 and 2 only use reported observations; column 3 uses non-reported observations; and column 4 uses the full sample. Higher emissions, reported versus imputed and disclosed versus undisclosed, point to significantly higher costs of equity capital.

	(1)	(2)	(3)	(4)
$carbon$	.254***	2.445***	2.124***	1.886***
	(.052)	(.159)	(.196)	(.107)
new	-.362***	-0.191***	—	-.120*
	(.066)	(.063)	—	(.068)
mv	-1.965***	-2.404***	-2.313***	-2.212***
	(.089)	(.097)	(.120)	(.072)
$exRet$	-.473***	-.319***	-.202***	-.243***
	(.068)	(.069)	(.060)	(.051)
$debt/asset$	-1.203***	-2.246***	-1.894***	-1.871***
	(.457)	(.490)	(.626)	(.384)
$epserr$	-.012	-.001	.046	-.012
	(.031)	(.030)	(.050)	(.032)
μ_{carbon}	.623***	-1.098***	-1.218***	-.894***
	(.138)	(.240)	(.208)	(.135)
$constant$	34.559***	37.485***	21.740***	23.933***
	(3.200)	(2.987)	(1.732)	(1.395)
N	18,072	18,072	26,320	44,392
ρ_{rho}	.780	.793	.479	.571
$\chi^2_{Mundlak}$	371.599***	146.577***	146.080***	174.958***
R^2_{Within}	.427	.461	.286	.321

$R^2_{Between}$	.387	.379	.513	.476
$R^2_{Overall}$	.448	.474	.392	.408

*Sig: *0.10 ; **0.05 ; ***0.01*

Table 8

Table 8 shows results of ICC against emissions quintile (*base is neutral*) in a correlated random effects regression. The model includes controls, the determinants of the ICC derivation, time and industry fixed effects, and the time-averaged values. Column 1 uses reported emissions while columns 2, 3, and 4 use imputed emissions. Columns 1 and 2 only use reported observations; column 3 uses non-reported observations; and column 4 uses the full sample. Browner (higher-emitting) quintiles, reported versus imputed and disclosed versus undisclosed, face significantly higher costs of equity.

	(1)	(2)	(3)	(4)
$q5 = 2$	.677***	.958***	.864***	1.228***
	(.104)	(.156)	(.213)	(.157)
$q5 = 3$	.872***	1.889***	1.831***	2.191***
	(.139)	(.270)	(.307)	(.234)
$q5 = 4$	1.130***	2.864***	2.627***	3.197***
	(.178)	(.330)	(.402)	(.291)
$q5 = 5$	1.449***	4.019***	3.788***	4.510***
	(.230)	(.378)	(.499)	(.326)
$\mu_{q5=2}$	1.637***	1.570***	.493	.188
	(.601)	(.528)	(.304)	(.278)
$\mu_{q5=3}$	2.033***	1.679***	.808**	.658*
	(.629)	(.646)	(.404)	(.363)
$\mu_{q5=4}$	3.468***	1.534*	.196	-.090
	(.739)	(.793)	(.529)	(.450)
$\mu_{q5=5}$	5.477***	2.810***	.640	.620
	(1.137)	(1.010)	(.693)	(.587)
$constant$	41.748***	38.975***	23.057***	25.100***
	(3.275)	(3.043)	(1.914)	(1.530)
N	18,072	18,072	26,320	44,392
ρ_{rho}	.779	.786	.476	.567

$\chi^2_{Mundlak}$	555.768***	357.099***	187.999***	290.775***
R^2_{Within}	.427	.431	.273	.306
$R^2_{Between}$	.389	.370	.509	.471
$R^2_{Overall}$	.446	.438	.382	.390

*Sig: *0.10 ; **0.05 ; ***0.01*

Table 9

Table 9 displays the marginal effect of first-time disclosure and sustained disclosure activity and its impact on the cost of capital in a correlated random effects regression. The model is measured within each quintile. The top panel reports the full sample while the lower panel reports the post 2016 sample. Disclosing decision, initial and continued, primarily shows insignificance with cost of equity.

Full Sample	*GREEN*	*n.green*	*neutral*	*n.brown*	*BROWN*
$1^{st} disc$	.110	.043	-.483**	-.446**	.051
$cont. disc$	.235	-.059	-.256	-.121	.634***
$exRet$	-.260*	-.362***	-.383***	-.357	-.373***
$\mu_{1^{st}}$	.224	2.015	1.400**	1.799*	2.842***
μ_{cont}	1.342	.839**	.402	.368	.238
$constant$	20.111***	30.285	37.731***	30.799***	22.718***
N	8,888	8,876	8,882	8,876	8,870
ρ_{rho}	.685	.615	.414	.411	.608
$\chi^2_{Mundlak}$	132.620***	170.812***	94.531***	153.344***	191.914***
R^2_{Within}	.427	.453	.453	.360	.520
$R^2_{Between}$	.464	.642	.542	.553	.695
$R^2_{Overall}$	.465	.529	.514	.454	.559
2016 —	*GREEN*	*n.green*	*neutral*	*n.brown*	*BROWN*
$1^{st} disc$	.177	.304	-.904**	-.007	.145
$cont. disc$	.268	.124	-.706*	.158	.270
$exRet$	-.121	-.389***	-.325***	-.602***	-.545***
$\mu_{1^{st}}$	.427	1.102	1.580*	1.326	1.604
μ_{cont}	1.149*	.597	1.215**	.458	.964**
$constant$	23.994***	34.583	42.390***	41.799***	27.486***
N	3,169	3,166	3,168	3,166	3,163
ρ_{rho}	.750	.716	.753	.616	.664
$\chi^2_{Mundlak}$	76.068***	126.661***	68.401***	116.469***	166.738***
R^2_{Within}	.382	.494	.666	.470	.445
$R^2_{Between}$	.369	.660	.491	.526	.544
$R^2_{Overall}$	.459	.549	.571	.539	.514

*Sig: *0.10 ; **0.05 ; ***0.01*