Duration-driven Carbon Premium*

Yongqi He†

Jiangyuan Li‡

Ruishen Zhang§

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Abstract

This paper reconciles the debates on carbon return estimation by introducing the concept of equity duration. We demonstrate that emission level and emission intensity yield divergent results for green firms, driven by inherent data problems. Our findings reveal that equity duration effectively captures the multifaceted effects of carbon transition risks. Regardless of whether carbon transition risks are measured by emission level or emission intensity, brown firms earn lower returns than green firms when the equity duration is long due to discount rate channel. This relationship reverses for short-duration firms conditional on the near-term cash flow. Our analysis underscores the pivotal role of carbon transitions' multifaceted effects on cash flow structures in understanding the pricing of carbon emissions.

Keywords: carbon premium, climate change, stock return, equity duration

JEL codes: G11, G14

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†**Shanghai Advanced Institute of Finance, Shanghai Jiao Tong University**; Postal Address: 211 West Huaihai Road, 200030, Shanghai, China; E-mail: yqhe.23@saif.sjtu.edu.cn

‡**School of Finance, Shanghai University of Finance and Economics**; Postal Address: 777 Guoding Road, 200433, Shanghai, China; E-mail: lijiangyuan@mail.shufe.edu.cn.

§**University of Hong Kong**; Postal Address: Pok Fu Lam, Hong Kong SAR; E-mail: ruishen@hku.hk.

1. Introduction

Understanding how carbon transition risks are priced in financial markets has become a critical question amid growing climate concerns and regulatory pressures. The existing literature offers mixed evidence. A series of influential papers by Bolton and Kacperczyk (2021, 2023) (hereafter BK), document a positive association between stocks' realized returns and carbon emission levels. Consistent with theoretical predictions, these results suggest that brown firms bear a high cost of capital and that financial markets price in carbon transition risks. Conversely, another stream of studies finds that green firms outperform brown firms, indicating that investors demand more green assets to hedge against increasingly heightened climate concerns and consumers' preferences turn green (Pastor, Stambaugh, and Taylor, 2022; Pedersen, Fitzgibbons, and Pomorski, 2021; Zhang, 2024). Additionally, some research reports an insignificant relationship between stock returns and carbon emissions, depending on the sample and empirical methods used (Aswani, Raghunandan, and Rajgopal, 2024; Zhang, 2024). These conflicting findings primarily stem from debates over empirical methodologies: whether to scale carbon emissions or not, the reliability of disclosed versus estimated carbon data, and the forward-looking information embedded in emissions.

This paper aims to reconcile the debates by revisiting the methodological issues and providing new insights into the pricing of carbon emission risks through the lens of economic fundamentals. Our analyses reveal that the emission level and the emission intensity diverge significantly in green firms, leading to mixed evidence on carbon returns. This divergence stems from inherent data issues in the emission data, suggesting that refining empirical methods without improving emission data quality cannot fully resolve the debates.

We propose a new perspective—equity duration—to reconcile the debates on carbon returns. Equity duration captures the sensitivity of stock prices to the structure of future cash flows (Dechow, Sloan, and Soliman, 2004). Why does equity duration matter for carbon returns? We argue that the existence of a carbon premium depends on how carbon transition risks affect the structure of firms' future cash flows and how these future cash flows are translated into today's stock prices.

First, upcoming policies related to net-zero transitions, such as carbon taxes and fossil fuel restrictions, may dramatically reduce (improve) short-run cash flows of brown (green) firms. Similarly to the argument of Dechow et al. (2021), the stock prices of equally affected firms react more to such events when the duration of the equity is short because a short duration of the equity implies that the price of the stock mainly reflects the near-term cash flows of the firms. Second, green stocks perform better when investors' preferences and consumers' tastes turn green. This transition can be driven by hedging against climate risks and the spread of green values. Hedging requires the cash flows of green assets to cover distant future risks (Pastor, Stambaugh, and Taylor, 2021). Profits from the production of green products increase with the progress of the ongoing green transition (Besley and Persson, 2023). Both explanations emphasize the role of distant-term cash flows in explaining the green premium or negative carbon returns. Therefore, we hypothesize that carbon transition risks are positively associated with stock returns for firms with short equity duration and negatively associated for firms with long equity duration.

To address the methodological debates over carbon returns, we directly compare the portfolio composition when sorting the sample by emission level versus emission intensity. We find that firms in the bottom 10 percent of emission intensity are spread across all deciles of emission level, while both measures identify similar top emitters. Our analysis further shows that a one-standard-deviation decrease in emission level corresponds to an 10.8 percent increase in the absolute value of the difference in the percentile ranking for the same firm using emission level and emission intensity. These divergences in defining green firms contribute to discrepancies in return spread estimates between brown and green firms.

Which measure is preferred for estimating carbon returns: emission level or emission intensity? We argue that both have merits and drawbacks. Several studies recommend emission intensity as a preferred measure because it removes financial fundamentals embedded in emissions, especially those estimated by data vendors, and better captures environmental performance (Aswani, Raghunandan, and Rajgopal, 2024; Nordhaus, 2019; Zhang, 2024). We probe into the difference between vendor-estimated and firm-disclosed emissions and find that vendor-estimated emissions overstate the positive relation between sales and emissions, especially for low-emission firms. Vendor-estimated emissions are 6.7 percent more sensitive to sales than firm-disclosed emissions. In the bottom thirty percent of emitters, this wedge in emissions-sales sensitivity between estimated and disclosed emissions expands to 62.6% (In comparison, this gap at the top thirty percent is only -19.9%.). These findings imply that emission intensity captures estimation biases in addition to teasing out financial fundamentals.

That being said, we do not conclude that emission level is a preferred measure of carbon transition risks to emission intensity, or vice versa. Both measures are plagued by data issues such as estimation biases and noise from financial fundamentals, making them inconclusive for capturing carbon transition risks at least in certain situations. Reducing emissions is the ultimate goal of the net-zero transition, and therefore the emission level is a direct proxy for carbon transition risk exposure (Bolton and Kacperczyk, 2024). However, emission reduction is *de facto* a reallocation of a smaller total emission quota across all firms. For example, Microsoft's emissions increased by 30 percent in 2023 due to AI-related operations, comparable to Alaska Air's carbon emissions[1]. Should we consider Microsoft and Alaska Air similarly exposed to carbon transition risks? We believe not: emissions used to advance AI technology are almost necessary to boost productivity but Alaska Air is unlikely to be. Similarly, start-up firms that have not yet started to generate significant revenues may have a high emission intensity because of the fixed emissions related to basic operations and R&D

[1] In 2020, the carbon emissions of Microsoft and Alaska Air were 4,220,545 metric tons and 4,154,003 metric tons respectively, while their carbon intensities were 29.51 and 1164.89 (tons CO_2e/USD m.) respectively.

activities, even if these firms may be developing green technologies.

We then turn to reconcile the debates on the carbon premium from the perspective of implied equity duration. Our analyses confirm that equity duration effectively captures the multifaceted effects of carbon transition risks on firms. Both emission level and emission intensity are negatively associated with duration, indicating that the distant-term cash flows of carbon-dependent firms are heavily discounted in their current stock prices. Equity duration also reflects different aspects of carbon transition risks. Holding carbon emissions constant, equity duration increases with a firm's exposure to climate change opportunities but decreases with its exposure to climate change regulations. These findings corroborate the idea that upcoming carbon regulations will impact firms' near-term cash flows and impose risks on their future cash flows. Conversely, opportunities related to carbon transition imply growth, which translates to a longer equity duration.

We next estimate the carbon premium conditional on equity duration. We show that brown firms, both in carbon level and intensity, earn significantly lower returns than green firms for long-duration firms (ranks in the top 30th percentile in the cross-section). Compared with a shorter-duration firm, a one-standard-deviation decrease in a long-duration firm's carbon emission level (intensity) corresponds to a 0.50 percent (0.38 percent) more increase in monthly stock returns. We also find that the carbon premium becomes positive or insignificant when equity duration falls in the bottom 30th percentile in the cross-section. These findings remain robust when controlling for sales information, forward-looking bias, and estimation biases.

Moving to portfolio analyses, the value-weighted carbon return spreads per month are -0.37 percent and -0.42 percent for portfolios of long-duration firms sorted by emission levels and emission intensity, respectively. The negative carbon return remains significantly negative but with smaller magnitudes after adjusting for the Fama-French five factors plus momentum.

The asset pricing evidence confirms that implied equity duration can reconcile the mixed findings on carbon returns. Regardless of whether carbon transition risks are measured by emission level or emission intensity, negative carbon returns exist in cross-sections with long equity duration, while carbon returns are zero or positive in cross-sections with short equity duration.

We further explore the mechanism of the duration-driven carbon premium through the discount rate and cash flow channels. Our findings indicate that in long-duration stocks, the pricing of carbon emissions is contingent on the discount rate, with brown firms exhibiting higher implied costs of capital and consequently lower stock returns. In contrast, for short-duration stocks, the pricing of carbon emissions is influenced by near-term cash flows, where brown firms demonstrate higher expected cash flows, leading to higher stock returns.

Previous studies have identified several issues in empirical choices that potentially lead to inaccurate carbon return estimates, including data vendors' estimation biases, fundamental information embedded in emissions (Matsumura, Prakash, and Vera-Munoz, 2014), and forward-looking bias in the emission data. These recommend using emission intensity (Aswani, Raghunandan, and Rajgopal, 2024; Zhang, 2024; Atilgan et al., 2023). Our paper revisits the empirical methods in carbon return estimation and highlights that while scaling emissions by sales removes some fundamental information, it exacerbates vendors' estimation biases. These inherent data problems make it challenging to reconcile the debates on carbon returns by simply refining empirical methods. Our interests diverge significantly: we emphasize the role of equity duration, a measure of the structure of cash flows and discount rate risks, in understanding the pricing of carbon transition risks.

The paper further explores the application of equity duration. Weber (2018) establishes that stocks with high cash flow duration yield significantly lower returns compared to their short-duration counterparts in cross-sectional analysis. Gormsen and Lazarus (2023) utilizes equity duration to elucidate major equity factors—such as value, profitability, and investment—that generate the most immediate cash flows. Gormsen (2021) examines the time-varying structure of equity terms and its countercyclical nature. Dechow et al. (2021) show that equity duration can capture the sensitivity of equity securities to unforeseen macroeconomic developments, including pandemics and impending carbon regulations, which disproportionately affect short-term cash flows. This paper extends these insights by demonstrating that equity duration can also effectively distinguish long-term carbon transition risks.

The rest of the paper proceeds as follows. Section 2 discusses the data and measurement employed in this study. Section 3 describes the divergence between carbon emission level and intensity and the potential estimation bias. Section 4 presents the duration conditional carbon-return relationship. Section 5 concludes.

2. Data and Measurement

In this section, we describe the data and measurements employed in this work, which include corporate carbon emissions from Trucost, firms' financial and market characteristics from CRSP and Compustat, analyst forecast from I/B/E/S, and climate risk exposure from Sautner, van Lent, Vilkov, and Zhang (2023).

2.1. Data on corporate carbon emissions

We obtain firm-level carbon emissions in tons of carbon dioxide equivalent (tCO_2e) from S&P Trucost. We study Scope 1 and Scope 2 emissions. Scope 1 emissions cover emissions from fossil fuels used in production from plants owned or controlled by the firm. Scope 2 includes indirect emissions from the generation of purchased heat, steam, and electricity consumed by the firm. Henceforth, we focus our analysis on the sum of Scope 1 and Scope 2 carbon emissions as greenness measure for the spacious concern based on a series of paper (Griffin, Lont, and Sun, 2017; Pedersen, Fitzgibbons, and Pomorski, 2021). Our main results are robust when investigating them separately.

Trucost collects environmental performance information from annual reports, sustainability reports, websites, and other public sources. Reported data is standardized according to best practice guidelines for comparability, and gaps are filled with modeled values. Trucost does not directly categorize carbon emissions data into "estimated" and "disclosed" categories, but it categorizes the sources of data into 29 different values. Following Aswani, Raghunandan, and Rajgopal (2024) and Atilgan et al. (2023), we first classify these into three types: (i) fully estimated, (ii) partially estimated, and (iii) directly disclosed. Next, we group (i) and (ii) as estimated, and (iii) as disclosed.

Following the literature (Matsumura, Prakash, and Vera-Munoz, 2014; Ardia et al., 2023; Bolton and Kacperczyk, 2021, 2023; Zhang, 2024; Aswani, Raghunandan, and Rajgopal, 2024), we mainly focus on two important carbon metrics: total level of carbon emission and carbon intensity. Total carbon emission level is defined as the sum of Scope 1 and Scope 2 emissions. Carbon intensity is calculated as the ratio of total carbon emissions to year-end sales[2].

2.2. Measuring carbon divergence

As highlighted in the previous discussion, carbon level and carbon intensity can generate very distinct implications for greenness. Some of the most serious carbon producers could be regarded as green firms from the perspective of carbon intensity. To quantify the difference in measuring greenness with the emission level and the emission intensity, we construct a rank difference metric. Let $p_{i,t}^{level}$ and $p_{i,t}^{intensity}$ represent the percentiles of carbon level and intensity for firm i in year t, respectively. We define the divergence for each firm in each year as:

$$Divergence_{i,t} = |p_{i,t}^{level} - p_{i,t}^{intensity}|, \tag{1}$$

[2] In unreported tables, we also test our main results by Scope 1 and Scope 2 emission separately. Our main results are robust a for both cases.

where the function $|x|$ denotes the absolute value of x, and $Divergence_{i,t}$ represents the absolute difference between the percentiles of carbon level and carbon intensity, illustrating how differently these two measures capture greenness.

2.3. Measuring cash flow duration

Due to the challenges we faced in measuring carbon emissions (Atilgan et al., 2023; Aswani, Raghunandan, and Rajgopal, 2024; Zhang, 2024), we argue that one potential solution is to jointly study carbon emissions and their underlying influence on firms' future cash flows in a transitioning economy. To comprehensively capture a firm's average cash flow structure, we employ the measure of implied equity duration developed by Dechow, Sloan, and Soliman (2004) and subsequently studied by Weber (2018). In a similar spirit, Dechow et al. (2021) apply equity duration to study the pandemic shutdown's influence on short-term cash flows. In this study, we apply equity duration to capture cash flow structure over a longer horizon during the carbon-neutrality transition.

The key challenge in estimating the duration of equities is determining the *unknown* future cash flows of equities. Dechow, Sloan, and Soliman (2004) propose a two-step approach to tackle this problem. First, future cash flows can be divided into a finite period component and a level perpetuity after the finite period. Using past financial data along with an autoregressive model yields predictions of future profitability and growth on the book value of equities, where cash flows can be derived with a clean surplus assumption. Second, the implied equity duration is obtained by plugging the estimated cash flows and an assumed discount rate into the bond duration formula.

In execution, we impute cash flows CF using the clean surplus relation:

$$\begin{aligned} CF_{i,t+s} &= Earnings_{i,t+s} - \Delta BE_t \\ &= BE_{t-1}(ROE_t - g_t), \end{aligned} \tag{2}$$

where ROE_t is return on equity and g_t is growth in book equity. Following Dechow, Sloan, and Soliman (2004) and Weber (2018), we model ROE and g as first-order autoregressive processes and assume they have persistent coefficients of 0.39 and 0.21 and long-run averages of 12 percent and 6 percent, respectively. After calculating the cash flows, implied equity duration is calculated with the following equation:

$$Dur_{i,t} = \frac{\sum_{s=1}^{T} s \times CF_{i,t+s}/(1+r)^s}{P_{i,t}} + (T + \frac{1+r}{r}) \times \frac{P_{i,t} - \sum_{s=1}^{T} CF_{i,t+s}/(1+r)^s}{P_{i,t}}, \tag{3}$$

where T is the number of finite periods. Following Weber (2018) and Dechow et al. (2021), we use a finite forecast horizon T of 15 years and a discount rate r of 12 percent. $P_{i,t}$ is the current market value of equity. The firm-level equity market and accounting data are taken from CRSP and Compustat, respectively.

2.4. Measuring implied cost of capital and cash flow expectation

To investigate whether the duration-driven carbon premium is attributed to the discount rate channel or the cash flow channel, we further estimate the stock-month level discount rate and expected cash flow as follows. Data of analyst forecast is from I/B/E/S.

2.4.1. Implied cost of capital

The implied cost of capital (ICC) is the discount rate that equates the stock's current valuations to the present value of expected future cash flows. We compute each stock's ICC following Mohanram and Gode (2013); Eskildsen et al. (2024); Gormsen and Huber (2024), which consider four accounting measures comprehensively: the residual income models of Gebhardt, Lee, and Swaminathan (2001) and Claus and Thomas (2001) and the dividend discount models of Easton (2004) and Ohlson and Juettner-Nauroth (2005). According to Lee, So, and Wang (2021), ICC is a noisy predictor; thus, we select the median of the four ICC measures above for each stock.

2.4.2. Cash flow expectation

We base our analysis on analyst forecasts as a proxy for future expected cash flows. We define cash flow expectations of firm i at time t as follows:

$$CF\ Forcast_{i,t} = \frac{FY1_{i,t} - FY0_{i,t}}{Price_{i,t-1}} \tag{4}$$

where $FY1$ denotes one-year-ahead annual earnings-per-share (EPS) forecasts. $FY0$ is the actual EPS value from I/B/E/S in fiscal year t. We use the first median value of analyst forecasts made after the earnings announcement of fiscal year t. According to Sloan and Wang (2023), many companies report negative base year EPS, and earnings growth rates cannot be calculated for a subset of firms with negative base year earnings. Therefore, we calculate the change in EPS forecasts divided by the firm's lagged price.

2.5. Sample construction and descriptive statistics

Our primary sample period spans from 2005 to 2020 mainly due to the availability of carbon emission data. We include all U.S. common stocks listed on the NYSE, AMEX, and NASDAQ with available carbon emission information and exclude firms in the financial ($6000 \leq$ SIC < 7000) and utilities ($4900 \leq$ SIC < 5000) industries. Following Zhang (2024), we use the latest carbon emission and accounting data based on their release date to ensure the carbon emission is known before the stock return.

We report summary statistics in Table I. For ease of interpretation, all independent variables have been standardized to zero mean and unit variance in all regressions. To mitigate the influence of outliers, we winsorize all variables at the 1 percent level.

[Insert Table I around here]

Panel A presents the summary statistics of firm-level carbon measures. It shows that during 2005-2020, U.S. firms emit a mean of 11.27 log tCO_2e in the sum of Scope 1 and Scope 2, and a median of 11.40. The mean of carbon intensity is 3.94 log tCO_2e per million U.S. dollars, and the median is 3.72.[3] The mean divergence of 0.20 indicates that the average absolute difference between the percentiles of emissions level and intensity for each company per year is 20 percent. Over 25 percent of firms will have at least 31 percent different environmental performance by carbon level and intensity. It is very likely that a firm regarded as brown in terms of carbon level is actually green in terms of intensity, and vice versa. This divergence could generate significant impacts when financial economists apply portfolio sorting and other professionals to assess firms' actual environmental performance. Carbon emissions level, intensity, and carbon divergence are persistent, with annual autocorrelations of 0.98, 0.97, and 0.92, respectively. The persistent divergence is a mechanical result of the persistence of carbon level and intensity, indicating that the divergence between these two carbon measures is unlikely to disappear.

For equity duration in Panel B, the average payoff horizon implied by stock prices is about 20.26 years. An average standard deviation of four years hints at substantial cross-sectional heterogeneity in this variable. Panel C reports cross-sectional return variables that include monthly stock return, implied cost of capital (ICC), cash flow forecast, size, book-to-market ratio (BM), return on asset (ROA), sales, investment (INV), earnings per share (EPS) growth (ΔEPS), sales growth (ΔSales), market beta, momentum, and volatility. Panel D shows climate risk exposure from Sautner, van Lent, Vilkov, and Zhang (2023). $CCExposure^{Opp}$, $CCExposure^{Reg}$ and $CCExposure^{Phy}$ are relative frequency with which bigrams that capture opportunities, regulatory and physical shocks related to climate change occur in the transcripts of earnings conference calls. Detailed variable definitions are presented in Table A1. Panel E shows that emission level is strongly positively correlated with firm sales and size, as documented in Zhang (2024). In addition, low emission level and low

[3]According to recent progress Chen and Roth (2024), we do not adopt the $log(x + 1)$ form when taking the logarithm of values. Our results are robust when applying $log(x + 1)$.

intensity are associated with high carbon level-intensity divergence and long equity duration. In summary, carbon level and intensity are more divergent for green firms. We will deliver a detailed discussion of the consequences in the next section.

3. Divergence between carbon metrics

In this section, we delve into the details of the relationship between carbon level and intensity. We demonstrate that carbon level and intensity generate significant divergence when evaluating firms' emission performance. The divergence becomes increasingly serious after 2016. The potential reason for this may stem from the data vendors' estimation process.

3.1. Ambiguity of green definition

The existing literature on carbon premiums debates whether it is carbon level or intensity that is priced (Bolton and Kacperczyk, 2021, 2023; Aswani, Raghunandan, and Rajgopal, 2024; Zhang, 2024). Instead of directly proposing another asset pricing test, we first investigate the carbon metrics per se. To understand the relationship between these two measures, we sort carbon intensity against level into 10 even groups. Within each level group, we summarize the minimum, first quartile (25th percentile), median, third quartile (75th percentile), and maximum intensity using a box plot in Figure 1. The two dashed lines represent the whole sample's 10th percentile and 90th percentile of carbon intensity, respectively. For each carbon emission level group, their carbon intensity covers very different ranges. All of the carbon level groups reach the lowest carbon intensity area, while only groups 9 and 10 (the brownest carbon level firms) span to the highest-intensity area. Alternatively, companies within the 10th percentile of carbon intensity are distributed across all ten carbon level groups, and companies above the 90th percentile of carbon intensity are only found in the highest two groups of carbon level. We demonstrate that this relationship remains robust in both disclosed and estimated samples in Appendix Figure A1. Accordingly, this pattern is not introduced by the emission data estimation process of data vendors. This fact implies that these two carbon measures have a relatively consistent definition for brown firms, but there is significant contention regarding their definition for green firms, which echoes the negative correlation coefficients between divergence and carbon measures.

[Insert Figure 1 around here]

Next, we further apply the multivariate analysis by regressing divergence on carbon measures and a bunch of firm's characteristics,

$$Divergence_{i,t} = \alpha_0 + \alpha_1 Carbon_{i,t} + \alpha_2 Controls_{i,t} + \delta_{industry} \times \gamma_t + \epsilon_{i,t} \tag{5}$$

where $Divergence_{i,t}$ denotes the absolute difference between the percentiles of firm i's carbon level and intensity within time t. $Carbon_{i,t}$ is a generic term alternately standing for carbon level and intensity. The vector of controls includes Size, BM, ROA, Leverage, Sales, INV, and ΔEPS. We also include industry-year fixed effects. Standard errors are clustered at the firm level.

We report the results in Panel A of Table II. A one-standard-deviation decrease in carbon level leads to a 10.8% increase in carbon divergence, and a one-standard-deviation decrease in carbon intensity leads to a 5.4% increase in carbon divergence. In unreported coefficients of control variables, firms with higher carbon divergence tend to have higher size, BM ratio, sales, and investment, but lower ROA and leverage. Carbon level (intensity), firm characteristics, and industry-year variation account for 24.2 percent (24.4 percent) of the carbon divergence. The results consolidate the findings in Figure 1 and Table I, indicating that an increase in emissions mitigates the divergence between carbon level and intensity.

Intuitively, for firms with a high emission level and a high emission intensity, there is little doubt in classifying them as brown firms. However, if a company has high carbon emissions but also a large scale of sales or production (resulting in low carbon intensity), should we regard it as a green company? Our results reveal a widespread concern. One viewpoint suggests that total emission levels directly reflect a company's environmental burden and associated risks, which is relevant for complying with strict climate policies where absolute reductions are crucial (BK, 2021, 2023). However, another viewpoint argues that carbon intensity provides a more consistent basis for comparison across firms because it is less influenced by the company's scale of operations and more reflective of its environmental management effectiveness (Aswani, Raghunandan, and Rajgopal, 2024; Zhang, 2024). The high degree of divergence highlights that we should be very careful in drawing conclusions based solely on carbon level or intensity.

[Insert Table II around here]

3.2. Distortion between carbon emissions and sales

After summarizing the divergence between carbon level and intensity, we posit that this divergence is not only derived from the inherent logic used in constructing these indices but is also closely linked to the quality of the carbon data itself. Existing literature has identified that estimated emissions often represent a mechanistic function of financial fundamentals rather than genuine environmental performance (Matsumura, Prakash, and Vera-Munoz, 2014) and firms' disclosed emissions appear bias (Kim and Lyon, 2011, 2015), leading to flawed conclusions in research linking emissions to stock returns or corporate valuation (Zhang, 2024; Aswani, Raghunandan, and Rajgopal, 2024). In this section, we first describe the methodological approaches used by mainstream carbon data providers to estimate emissions data. Subsequently, in the second part, we focus on elucidating how these estimation methods distort the relationship between carbon emissions and sales in the real world.

3.2.1. Estimation methodology

Data vendors frequently use average industry outputs to approximate a firm's emissions in the absence of direct data. This approach assumes that companies within the same industry operate similarly, potentially overlooking the specific emission reduction initiatives or unique operational tactics of individual companies. Estimates from vendors largely depend on measures such as the size and growth of a company[4], which could lead to inaccuracies when comparing the vendor estimated and the company disclosed emissions. In Table A2, we group the firms by their carbon emission level and calculate the number of estimated observations and disclosed observations in Trucost. In the first (greenest) group, there are 1,855 observations in total, with the number of estimated observations being 1,790, accounting for over 96.5 percent. In the tenth group (brownest), there are 1,856 observations in total, with estimated observations numbering 612, accounting for around 33 percent. From the Green to Brown groups, the proportion of estimated observations gradually decreases while the share of disclosed emissions progressively increases. From groups 1 to 8, most of the observations are estimated.

The above empirical facts arise from several important changes made by the data vendor. After 2016, there was a significant increase in the number of observations in Trucost. This increase stemmed primarily from Trucost's estimations of emissions for companies that did not disclose their emissions, rather than from an increase in voluntary emissions disclosures by the companies themselves. Figure 2 visualizes these trends. The solid line represents the average level-intensity divergence on the left axis, illustrating that divergence significantly increased in 2016. The dashed line represents the number of estimated firms on the right axis, showing a significant increase in estimated observations in 2016, which mirrors the pattern of divergence. The dotted line represents the number of disclosed observations on the right

[4] The broad method for compiling emissions data is outlined in the IPCC (2006) "Guidelines for National Greenhouse Gas Inventories", where it is explained that emissions are calculated by multiplying Activity Data by an Emission Factor.

axis, indicating that the number of companies voluntarily disclosing carbon data has only experienced a gradual increase. These group summary statistics and trends indicate several important data issues: 1) the number of estimated observations significantly increased after 2016; 2) most of the low carbon level firms are actually estimated by the data vendor; 3) the estimated observations introduce a significant divergence between carbon level and intensity, challenging our conventional wisdom for evaluating a firm's carbon emission performance.

[Insert Figure 2 around here]

3.2.2. Heterogeneity in carbon emissions-sales relationship

After confirming the carbon level-intensity divergence and the number of estimated carbon emission observations, we explore this issue in-depth. The construction of carbon intensity requires two ingredients: carbon emission level and sales. The underlying logic is that in a carbon-dependent economy, a firm's revenue generation process requires a certain amount of carbon emission. Carbon data vendors also apply this logic to estimate carbon emission levels when disclosed emission observations are missing:

$$Emissions_{i,t} = (Unit\ emissions\ per\ sale)_{i,t} \times Sales_{i,t} \tag{6}$$

To understand the consequence of using a multiplier to estimate carbon emission, we use the following equation to decompose the carbon emission into fixed emissions and variant emissions. In Equation 6, *Unit emissions per sale* represents the intended capture of carbon intensity. The underlying notion is that carbon emissions are all variable, such as processing and use of raw materials, energy consumption, logistics, and transportation. However, due to significant heterogeneity among companies, estimation methods based on industry standards or financial fundamentals overlook individual corporate characteristics. We optimize the model as follows:

$$\text{(7)} \qquad Emissions_{i,t} = (Unit\ \widehat{emissions}\ per\ sale)_{i,t} \times Sales_{i,t} + Fixed\ \widehat{emissions}_i$$

In Equation 7, *Fixed emissions* represents a form of corporate carbon emissions that do not vary with changes in scale or sales, such as maintenance of facilities and buildings, R&D activities, infrastructure operations, and use of fixed equipment. This toy model better captures the heterogeneity in corporate carbon dependency.

For instance, green firms, whose profitability is less dependent on carbon emissions, have a higher proportion of fixed carbon emissions in their total emissions, which leads to an overestimation of their original carbon intensity (carbon emissions divided by sales). Conversely, the carbon intensity of brown firms may be underestimated. Therefore, this leads to a stronger carbon level-intensity divergence. We test this relationship using the following model:

$$\begin{aligned} Emissions_{i,t} = {} & \alpha_0 + \alpha_1 I(Green)_{i,t} \times Sales_{i,t} + \alpha_2 I(Brown)_{i,t} \times Sales_{i,t} \\ & + \alpha_3 Sales_{i,t} + \alpha_4 I(Green)_{i,t} + \alpha_5 I(Brown)_{i,t} + \alpha_6 Controls_{i,t} \\ & + \delta_{industry} \times \gamma_t + \epsilon_{i,t} \end{aligned} \tag{8}$$

$I(Green)$ and $I(Brown)$ are indicator variables set equal to 1 if a firm's total carbon emission level is in the lowest 30 percentile or highest 70 percentile within each cross-section, and 0 otherwise. The regression controls for Size, BM, ROA, Leverage, INV, and ΔEPS. We also include industry-year fixed effects. Our coefficients of interest are α_1 and α_2.

In Panel B of Table II, we report the full sample, disclosed sample, and estimated sample in columns 1, 2, and 3, respectively. As expected, in the full samples, we find a strong positive correlation between carbon emissions and sales. Vendor-estimated emissions are 6.7 percent more sensitive to sales than firm-disclosed emissions (we report the results of the regressions without interaction items of emissions on sales in Table A3). Firm characteristics and industry-year variation explain 93.1% of carbon emission levels in the estimated sample, which is 13.8% higher than the disclosed sample. Interestingly, in the disclosed sample, brown firms exhibit a more significantly positive emission-sales relationship compared to non-brown firms. Even more intriguingly, the pattern in the estimated sample is reversed, with green firms showing a more significantly positive emission-sales relationship, while for brown firms it is significantly negative. In the bottom thirty percent of emitters, the difference of coefficient between vendor-estimated emissions and firm-disclosed emissions expands to 62.6%. But this wedge in sales-emissions sensitivity becomes only -19.9% in the top thirty percent of emitters. These empirical facts align with our hypothesis that due to the misestimation of carbon data, the carbon intensity of green companies is excessively overestimated, leading to a huge carbon level-intensity divergence.

As discussed in this section, divergence and misestimation significantly impact our accuracy in assessing firms' greenness. We argue that the mechanism of carbon intensity as a measure overlooks the fixed carbon emissions of individual firms, distorting the true definitions of green and brown. Therefore, we next adopt an economic perspective to examine the carbon premium based on carbon emission levels. However, for robustness, we will also demonstrate that our main results hold true within the framework of carbon intensity.

4. Characterizing carbon premium in the lens of equity duration

Section 3 examines the contentious carbon footprints and data currently associated with the carbon premium. We discover that inaccurate estimations of carbon emissions by carbon data providers lead to ambiguity in the definition of 'green', exacerbating discrepancies in carbon assessments. Currently, numerous debates surround the carbon premium. BK (2021, 2023) suggest that in the U.S. and globally, brown stocks exhibit a carbon premium, reflecting that carbon transition risk is already priced into equity markets. Other research, such as that by

Pastor, Stambaugh, and Taylor (2021, 2022); Pedersen, Fitzgibbons, and Pomorski (2021); Zhang (2024), indicate that green stocks outperform, suggesting an ongoing transition to a carbon-aware equilibrium. However, reviewing the construction of carbon measures and the underlying data estimation reveals that disputes over the carbon premium are naturally engendered by their inherent differences. Therefore, we propose a novel perspective, utilizing equity duration to reconcile the various controversies regarding the carbon premium.

As discussed in Section 2, we construct implied equity duration following the methodology outlined by Dechow, Sloan, and Soliman (2004) and Weber (2018), who forecast the cash flows of individual stocks and calculate their average maturity based on that forecast. To provide an initial overview of long-duration and short-duration firms, we examine two prominent examples: General Motors (GM) and Tesla. GM specializes in producing internal combustion engine vehicles, while Tesla is a leading electric vehicle manufacturer. We calculate the implied equity duration of these two companies and each year's cash flow as illustrated in Eq. 2. We adopt parameters from Dechow et al. (2021), with a return on equity (ROE) of 6 percent and a terminal growth rate of 0 percent, to closely align with the macroeconomic conditions at the end of 2020. Subsequently, we plot the implied cash flow forecast for these two companies over the next 20 years.

[Insert Figure 3 around here]

The example of GM and Tesla vividly represents the current economic transition over the next two decades. Society is gradually realizing that carbon neutrality is inevitable. Even though the current cash flows of less carbon-dependent companies are negligible, investors still recognize their potential cash flow in the long run.

4.1. Equity duration and climate change exposure

Climate change exposure encompasses various dimensions of risk and opportunity that businesses face due to global climate dynamics. Broadly, climate change exposure can be categorized into physical, regulatory, and opportunity exposures. Physical exposure refers to the direct effects of climate change, such as extreme weather events, which can impact physical assets and operations. Regulatory exposure includes risks from potential governmental actions like carbon pricing or emissions regulations that aim to mitigate climate change. Opportunity exposure relates to the potential benefits companies can capture from the shift towards a greener economy, such as renewable energy and technological innovations in sustainability.

Equity duration, as developed by Dechow, Sloan, and Soliman (2004), measures the sensitivity of a company's equity value to changes in the market's required rate of return. It captures not only the time aspect but also the exposure to various risks and opportunities. In the context of climate change, duration can provide insights into the nature of climate change exposure. Longer duration implies greater sensitivity to future transition and technological changes, which correlates with a higher degree of exposure to opportunity-driven climate change aspects. Conversely, shorter duration indicates a higher sensitivity to immediate regulatory changes, suggesting an increased exposure to regulatory climate change risks.

To better analyze the relationship between equity duration and climate change exposure, we incorporate the relevant indices constructed by Sautner et al. (2023). Sautner et al. (2023) develops a nuanced method to quantify climate change exposure by analyzing earnings call transcripts with machine learning techniques. This method identifies keywords and phrases that reflect the company's exposure to climate change-related opportunities, physical impacts, and regulatory changes. It offers a robust framework for understanding how different companies perceive and respond to the risks and opportunities associated with climate change. It allows us to do a sophisticated analysis of the interplay between a firm's equity duration and its climate change exposure. Specifically, we estimate the following model:

$$Dur_{i,t+1} = \alpha_0 + \alpha_1 CCExposure_{i,t} + \alpha_2 Controls_{i,t} + \delta_{industry} \times \gamma_t + \epsilon_{i,t} \tag{9}$$

where $Dur_{i,t+1}$ measures the equity duration of company i in year $t+1$ and $CCExposure$ is a generic term standing for $CCExposure^{Opp}$, $CCExposure^{Reg}$ and $CCExposure^{Phy}$. Since the dependent variable, equity duration, is a constructed variable, we control for variables related to duration that have been identified in previous literature. Gormsen (2021) emphasizes that BM ratio is closely linked to duration; duration has predictive power for market beta (Dechow, Sloan, and Soliman, 2004); leverage can predict duration (Dechow et al., 2021), and the fundamentals related to size, sales, and ROA are included in the construction of equity duration (Dechow, Sloan, and Soliman, 2004). We also control for total carbon emission levels, which have high correlation with climate change exposure. So the vector of controls includes the variables Emission, Size, BM, ROA, Leverage, Sales, INV and Beta. We additionally include industry-year fixed effects.

We report the results in Table III. We find that higher equity duration is significantly associated with higher opportunity exposure, and lower equity duration is significantly associated with higher climate regulatory exposure. For instance, a one-standard-deviation increase in climate opportunity exposure and climate regulatory exposure is associated with a 0.115-year increase (t=3.95) and a -0.044-year decrease (t=-2.02) in equity duration after including industry-year fixed effects. Together, these climate change exposures, firm characteristics, and industry-year variations account for 53.8% of the observed equity duration.

[Insert Table III around here]

4.2. Regression analysis

We argue that the firm's cash flow structure plays a vital role in determining the economic implications of carbon emissions. For short-duration firms, their cash flows are concentrated in the near-term, and high carbon emissions are associated with high regulatory shocks. To compensate for the transition risk, investors require higher returns. Conversely, for long-duration firms, their cash flows are projected into the long-term. Low carbon emissions represent opportunities for generating carbon-neutral cash flows in the future, suggesting a hedging value. For these firms, investors' hedging demand creates high returns for low emissions, resulting in a negative carbon return.

We first investigate the relationship between the carbon emission and stock return by panel regression analysis as BK (2021, 2023). In column (1) of Table IV, we replicate one main result from BK (2021), by regressing monthly stock returns on the carbon metrics and lagged firm-level controls by the following regression model:

$$RET_{i,t} = \alpha_0 + \alpha_1 Emissions_{i,t} + \alpha_2 Controls_{i,t-1} + \delta_{industry} + \gamma_t + \epsilon_{i,t} \tag{10}$$

where $RET_{i,t}$ means the stock return of company i in month t, and $Emissions$ is the natural logarithm of total carbon emission level. The vector of $Controls$ includes a comprehensive set of firm-specific variables known to predict returns, such as $Size$, BM, ROA, $Leverage$, $Sales$, INV, ΔEPS, $Beta$, $Momentum$, and $Volatility$. Year-month and industry fixed effects are controlled for, and standard errors are clustered at the firm and year levels. Our coefficient of interest is α_1. All independent variables are standardized to have a zero mean and unit variance, allowing coefficients to be interpreted as the change in monthly stock returns for a one-standard-deviation increase in the carbon footprint. Our results on carbon level are consistent with those of BK (2021). A one-standard-deviation increase in carbon emissions leads to a 0.35 percent increase in monthly stock returns.

[Insert Table IV around here]

Next, we focus on the carbon premium conditional on equity duration. Our baseline regression model is as follows:

$$\begin{aligned} RET_{i,t} = {} & \alpha_0 + \alpha_1 Emissions_{i,t} \times I(LongDur)_{i,t} + \alpha_2 Emissions_{i,t} \times I(ShortDur)_{i,t} \\ & + \alpha_3 Emissions_{i,t} + \alpha_4 I(LongDur)_{i,t} + \alpha_5 I(ShortDur)_{i,t} \\ & + \alpha_6 Controls_{i,t-1} + \delta_{industry} + \gamma_t + \epsilon_{i,t} \end{aligned} \tag{11}$$

where $I(LongDur)$ and $I(ShortDur)$ are indicator variables that equal to one if Dur is in the top 30 percent or lowest 30 percent respectively within the cross-section, and zero otherwise. In column (2) of Table IV with the specification of including time fixed effect, the statistically significant and negative α_1 shows that the positive association between returns and carbon emission reverses among long-duration stocks. Conditioning on the long-duration group, a one-standard-deviation increase in carbon emission level would decrease returns by 0.48% compared to other firms, with t-statistics of -6.25. For shorter duration firms, the positive level-return relationship mainly driven by baseline effects with α_2 being statistically insignificant and positive. We additionally include industry fixed effect, which is shown in Column (3), the different results between long-duration and short-duration firms still hold.

For robustness, we replace the dependent variable of Equation 11 with a measure of stock returns adjusted for firm characteristics that are known ex-ante predictors of stock returns in the cross-section. Following the methodology outlined by Daniel et al. (1997), we construct 125 benchmark portfolios, which are sequentially triple-sorted based on the previous year's size, book-to-market ratio, and past stock performance. This procedure utilizes NYSE-based breakpoints for sorting and creates value-weighted portfolios to prevent the overweighting of very small stocks. we then subtract the returns of these benchmark portfolios from each firm's stock returns. An adjusted return of zero for a specific stock indicates that its return is fully explained by the firm's size, book-to-market ratio, and past performance. The baseline results of DGTW adjusted returns are shown in Column (4) to (6) of Table IV. Conditioning on the long-duration group, a one-standard-deviation increase in carbon emission level would decrease adjusted returns by 0.49% compared to other firms, with t-statistics of -5.99. The magnitudes of coefficient is comparable with the unadjusted specification.

The conditional results reveal that, the positive carbon-return relationship (BK, 2021; 2023) stems from short-duration firms, while the negative carbon-return (Zhang, 2024) relationship is mostly driven by long-duration firms. We will show our baseline results are robust when controlling for sales, lagging emission data, accounting for disclosure and estimated emissions, and using emission intensity as greenness measure in Section 4.5.

4.3. Asset pricing factor analysis

We then conduct portfolio sorts using proxies of firms' carbon risks. At month t, we adopt the point-in-time carbon emission level data. Then we sort the stocks into tercile portfolios: green, medium, and brown. Concurrently, stocks are also sorted into two groups based on their equity duration: short and long. This sorting results in six portfolios combining the two dimensions (carbon footprints and equity duration): green long, medium long, brown long, green short, medium short, and brown short. After forming the six portfolios, we calculate the value-weighted DGTW adjusted monthly returns on these portfolios at time $t+1$, according to the methodology in Daniel et al. (1997). We report carbon return within different equity duration groups in Panel A of Table V. Column (1) and (2) show short-duration and long-duration portfolio respectively. For long-duration portfolio, from emission portfolio 1 (Green) to 3 (Brown) earns the average returns of 0.31% and -0.06 %, while this relationship weakens in short-duration portfolios. The long-BMG (brown-minus-green) portfolio in Column (2) is then constructed by taking the difference between the returns of the brown-long portfolio and the green-long portfolio, which means taking a long position in the brown portfolio and a short position in the green portfolio. The short-BMG portfolio in Column (1) is then constructed by a brown-short portfolio and a green-short portfolio. Carbon emissions can predict stock returns in cross-section only in long-duration portfolios, while the short-duration portfolios show a smaller magnitude and statistically insignificant excess return. The long-BMG portfolio sorted on carbon emissions earns a significantly negative excess return of -0.37 (t-stat=-2.78) percent per month. This finding is aligned with our panel regression analysis in section 4.2.

[Insert Table V around here]

We next examine whether the negative carbon returns can be explained by existing risk factors. We estimate the following time-series regression model using monthly data:

$$BMG_t = c_0 + \mathbf{c}\mathbf{F_t} + \epsilon_t, \tag{12}$$

where BMG_t is the carbon premium we calculate above within long-duration and short-duration groups. $\boldsymbol{F}$ is the CAPM, FF5 and FF6 factor model (Fama and French, 2018), which include the momentum factor together with the MKT, SIZE, HML, CMA, and RMW. Panel B in Table V reports the results. After adjusting for the factor exposure, the longer-duration BMG portfolio earns significantly lower alphas than the shorter-duration one. The long-BMG portfolio sorted on total carbon emissions earns abnormal returns of -0.29, -0.38, -0.38 percent per month (t-statistics=-2.24, -3.93 and -3.94) after controlling for CAPM, FF5 and FF6 factors, respectively. In sum, the carbon premium is statistically significant and negatively associated with future stock returns and alphas within only long-duration groups.

4.4. Decomposing duration-driven carbon premium through discount rate and cash flow

In the previous section, we demonstrate that long- and short-duration stocks influence the carbon premium differently. Next, we test our hypotheses regarding how carbon emissions are priced in long- and short-duration samples. We investigate this through two channels: discount rates and cash flows. A critical question is whether the duration-driven carbon premium arises from revisions in expected cash flows or discount rates, and to what extent each factor contributes. We design the model conducted separately in long- and short-duration sample, respectively, as follows:

$$\begin{aligned} RET_{i,t} = {} & \alpha_0 + \alpha_1 Emissions_{i,t} \times ICC_{i,t} + \alpha_2 Emissions_{i,t} \times CF\ Forecast_{i,t} \\ & + \alpha_3 Emissions_{i,t} + \alpha_4 ICC_{i,t} + \alpha_5 CF\ Forecast_{i,t} \\ & + \alpha_6 Controls_{i,t-1} + \delta_{industry} + \gamma_t + \epsilon_{i,t} \end{aligned} \tag{13}$$

where ICC is the medium of four accounting measures of the implied cost of capital, according to the methodology in Gebhardt, Lee, and Swaminathan (2001), Claus and Thomas (2001), Easton (2004) and Ohlson and Juettner-Nauroth (2005) and $CF\ Forecast$ is calculated as change in EPS forecast scaled by lagged stock price. The regression results are shown in Table VI. In long-duration sample reported in Column (1) and (2), we see pricing of carbon emission is conditional on the discount rate, with statistically significant and negative coefficient α_1. For long-duration stocks, high emission-level firms have higher discount rates, which causes a lower expected stock return. In short-duration sample reported in Column (3) and (4), pricing of carbon emission is conditional on the near-term cash flow. For short-duration stocks, high emission-level firms have higher cash flows, which causes a higher expected stock return.

[Insert Table VI around here]

A potential concern regarding the above results is that the interaction terms between emissions and discount rates, as well as emissions and expected cash flows, may differ fundamentally between the short- and long-duration samples. We regress ICC and $CF\ Forecast$ separately against emissions, with the results documented in Table VII. The relations between emissions and expected cash flows or discount rates are similar across long- and short-duration groups.

[Insert Table VII around here]

4.5. Robustness analysis

In evaluating the robustness of our baseline model (see Equation 11), it is essential to consider four key concerns: the significant influence of sales information on the carbon premium, potential biases in carbon data estimation due to reliance on firm fundamentals, the presence of forward-looking biases in regression models and divergence caused by alternative greenness measure like carbon intensity. To ensure the accuracy of our findings regarding the conditional duration carbon-return relationship, we address these concerns in this section.

4.5.1. Controlling for sales information

The role of sales information in the carbon premium is pivotal and warrants careful scrutiny. Sales data often play a crucial role in the estimation of carbon emissions, primarily because emissions figures are frequently derived from economic output measures that are closely tied to a company's sales performance. This association can inadvertently lead to a misinterpretation of the carbon premium, where the identified risk premiums might not exclusively reflect the environmental impact or management of carbon emissions but are confounded by the underlying business activities and financial health reflected in sales. Zhang (2024) demonstrates that controlling for sales information shifts the perceived carbon emissions premium from positive to negative, suggesting previous findings may be artifacts of omitted variable bias rather than true market valuations of carbon efficiency.

We first replicate the analysis in Zhang (2024), controlling for sales information during the same period of carbon emission. Column (1) of Panel A in Table VIII presents the results and shows that both total carbon emissions are significantly associated with lower contemporaneous stock returns after controlling for sales information as in Zhang (2024). We further conduct the regression with interaction terms as follows:

$$
\begin{aligned}
RET_{i,t} = {} & \alpha_0 + \alpha_1 Emissions_{i,t} \times I(LongDur)_{i,t} + \alpha_2 Emissions_{i,t} \times I(ShortDur)_{i,t} \\
& + \alpha_3 Emissions_{i,t} + \alpha_3 I(LongDur)_{i,t} + \alpha_3 I(ShortDur)_{i,t} \\
& + \alpha_4 \boldsymbol{Sales}_{i,t} + \alpha_5 Controls_{i,t-1} + \delta_{industry} + \gamma_t + \epsilon_{i,t}
\end{aligned}
\tag{14}
$$

The vector of sales information includes $Sales$ and $\Delta Sales$. Columns (2) and (3) of Panel A in Table VIII present the results of interaction terms. Sales information is strongly associated with higher stock returns. Even after controlling for sales, the duration conditional results still hold. For long-duration firms, a one-standard-deviation increase in level decreases the stock return by 0.55% and 0.58% with t-statistics of -6.14 and -6.65 more than baseline effects after introducing time fixed effect, industry and time fixed effects, respectively. For shorter duration firms, carbon emissions are positively associated with stock returns. It is robust that the sales information is not the driver of the duration conditional carbon-return relationship.

[Insert Table VIII around here]

4.5.2. Estimation bias

Due to data limitations, current research on carbon emission predominantly relies on estimated data provided by data vendors. The biases inherent in these estimation methods can significantly impact the interpretation of the carbon premium. Existing studies have already identified that such estimations are generally based on firm fundamentals and industry-level factors, which may not accurately reflect actual emissions but rather correlate with other financial metrics like sales or production data (Aswani, Raghunandan, and Rajgopal, 2024). In Section 3, we also observe that the current estimation methods fail to account for the distinctive characteristics of individual firms. This oversight of heterogeneity—whether a firm is "green" or "brown"—roughly bases all firm estimates on an emissions-sales methodology, which distorts reality. Consequently, in this section, we exclude samples where carbon data are estimated and potentially noisier, conducting baseline regression of Equation 11 on samples where firms voluntarily disclose their carbon emissions. We present the results in Panel B of Table VIII.

Compared with Table IV, we find in columns (1) to (3) that the carbon emission premium in the disclosed sample is smaller and much more statistically insignificant than that in the full sample. However, our coefficients of interest, the interaction terms in columns (2) and (3), are still negative and statistically significant. This indicates that our inference remains valid in the sample of disclosed carbon emissions. The duration conditional carbon-return relationship is not introduced by data vendor's estimation.

4.5.3. Forward-looking bias

The issue of looking-ahead bias in regression models used to study carbon premiums involves the premature incorporation of emissions data relative to their actual release to investors. Studies have shown that emissions and related variables, when not sufficiently lagged in analytical models, can lead to an overstatement of the positive relationship between carbon emissions and stock returns. This can occur because emissions data might incorporate future sales information, thus not reflecting the current or past stock performance but rather expectations of future firm performance (Zhang, 2024). BK (2023) studies the relationship between stock returns and emissions lagged by one month and longer lags using Equation 10. Lagging the emission data sufficiently can address the forward-looking bias and avoid incorrect inference. According to Zhang (2024), the median lags are 10 months after the emission fiscal year-end for the U.S. samples, so we use the following specification:

(15)

$$RET_{i,t} = \alpha_0 + \alpha_1 Emissions_{i,t-1} \times I(LongDur)_{i,t} + \alpha_2 Emissions_{i,t-1} \times I(ShortDur)_{i,t}$$
$$+ \alpha_3 Emissions_{i,t-1} + \alpha_4 I(LongDur)_{i,t} + \alpha_5 I(ShortDur)_{i,t}$$
$$+ \alpha_6 Controls_{i,t-1} + \delta_{industry} + \gamma_t + \epsilon_{i,t}$$

where right-hand-side carbon variables are lagged 12 months. The results are reported in Table VIII. Consistent with the empirical findings of Zhang (2024) and Ilhan, Sautner, and Vilkov (2021), the coefficient of carbon emissions turns negative and becomes statistically insignificant when sufficient lags of carbon data are considered. Nevertheless, the key coefficients—the interaction terms of long-duration indicator and carbon emissions in columns (2) and (3)—remain negative and statistically significant. The interactions between short-duration indicator and emissions are positively correlated with stock returns. This suggests that our conclusions remain sound even after accounting for forward-looking bias and incorporating industry-year fixed effects.

4.5.4. Alternative measure of greenness: carbon intensity

A key debate regarding the carbon premium centers on the definition of 'greenness.' Although we previously noted that the carbon intensity measure introduces a measurement bias by ignoring fixed carbon emissions, for the sake of robustness, we replaced the carbon emission level in our baseline model with carbon intensity. The results of the panel regression analysis are presented in Panel A of Table IX, while the portfolio sorting results are shown in Panel B of Table IX. These outcomes align with those of the main table, demonstrating strong robustness.

[Insert Table IX around here]

5. Conclusion

We address the critical complexities involved in estimating the carbon premium by introducing equity duration as a fundamental measure. Our comprehensive analysis underscores that regardless of the measure used, emission level or emission intensity, brown firms consistently exhibit lower returns than green firms among long-duration equities. This inverse relationship highlights the nuanced effects of carbon transition risks on future cash flows and their current market valuation. Through robust empirical analysis, our findings elucidate the significant role of equity duration in reconciling the divergent results across previous studies on carbon pricing in equity markets. This research not only advances our understanding of how carbon transition risks are priced but also contributes to more informed and effective financial decision-making in the context of ongoing climate change challenges.

Looking ahead, future research should focus on refining models that predict and describe carbon emissions with greater precision. Advancements in data quality and methodology can enhance our understanding of the carbon transition risks and their impacts on equity valuation. Specifically, research could explore machine learning techniques to improve the estimation of emissions data, particularly in contexts where disclosures are incomplete or non-standardized. Additionally, incorporating more granular data on sector-specific practices and technological changes could yield insights into the differential impacts across industries. This approach would allow for a more nuanced analysis of how specific strategies, such as technological innovations in carbon capture and sustainable practices, influence firm valuations. Such detailed studies are crucial for developing strategies that can effectively align financial markets with global sustainability goals.

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Figure 1: Emission level-sorted intensity

This figure presents the distribution of carbon emission intensity evenly sorted by emissions level into decile groups. Carbon intensity is the ratio of the total carbon emissions to year-end sales. For each group, we display the distribution of carbon intensity based on the minimum, first quartile (Q1), median, third quartile (Q3), and maximum in a box plot. The gray dashed lines represent the 10th percentile of carbon intensity at the bottom and the 90th percentile of carbon intensity for the whole sample.

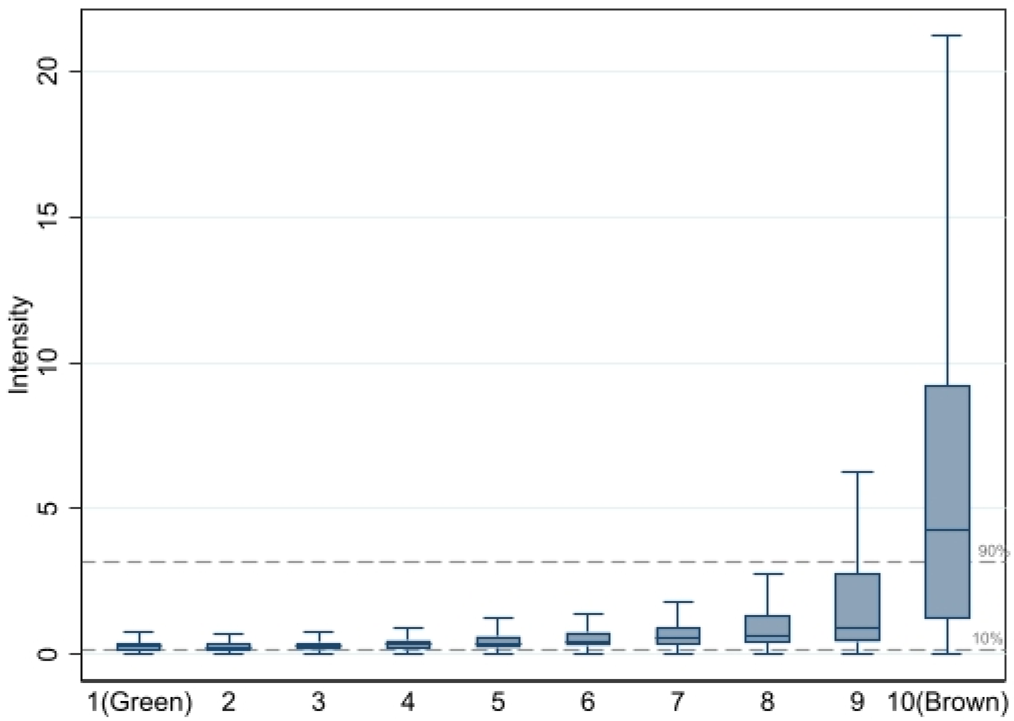


Figure 2: Carbon level-intensity divergence and data estimation

This figure illustrates the average carbon level-intensity divergence (left axis) and the number of firms that disclose their carbon emissions and those estimated by Trucost (right axis) for each year. Carbon level-intensity divergence is calculated as the absolute difference between the percentiles of a firm's total carbon emission level and carbon intensity within each cross-section. The results are based on the 2005-2020 U.S. sample.

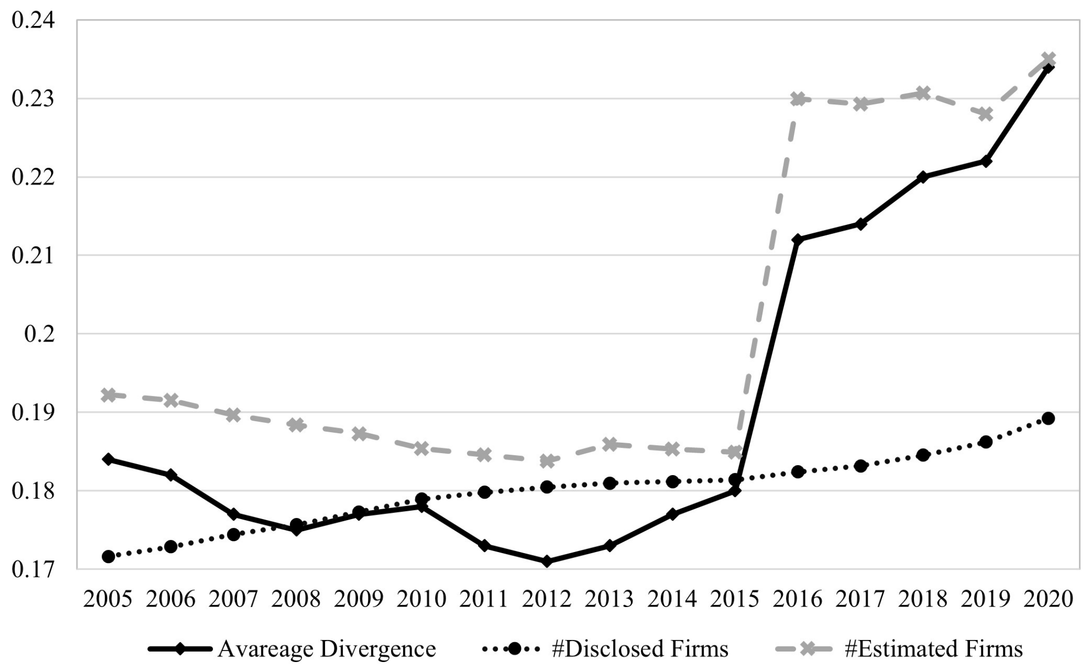


Figure 3: Implied cash flow of General Motors Company and Tesla Inc.

This figure shows the first 20 years' implied cash flow of General Motors Company and Tesla Inc on December 31, 2019. The forecasting algorithm is introduced by Eq.2. Following Dechow et al. (2021), we use a discount rate and terminal ROE of 6% and a terminal period growth rate of 0% in these examples.

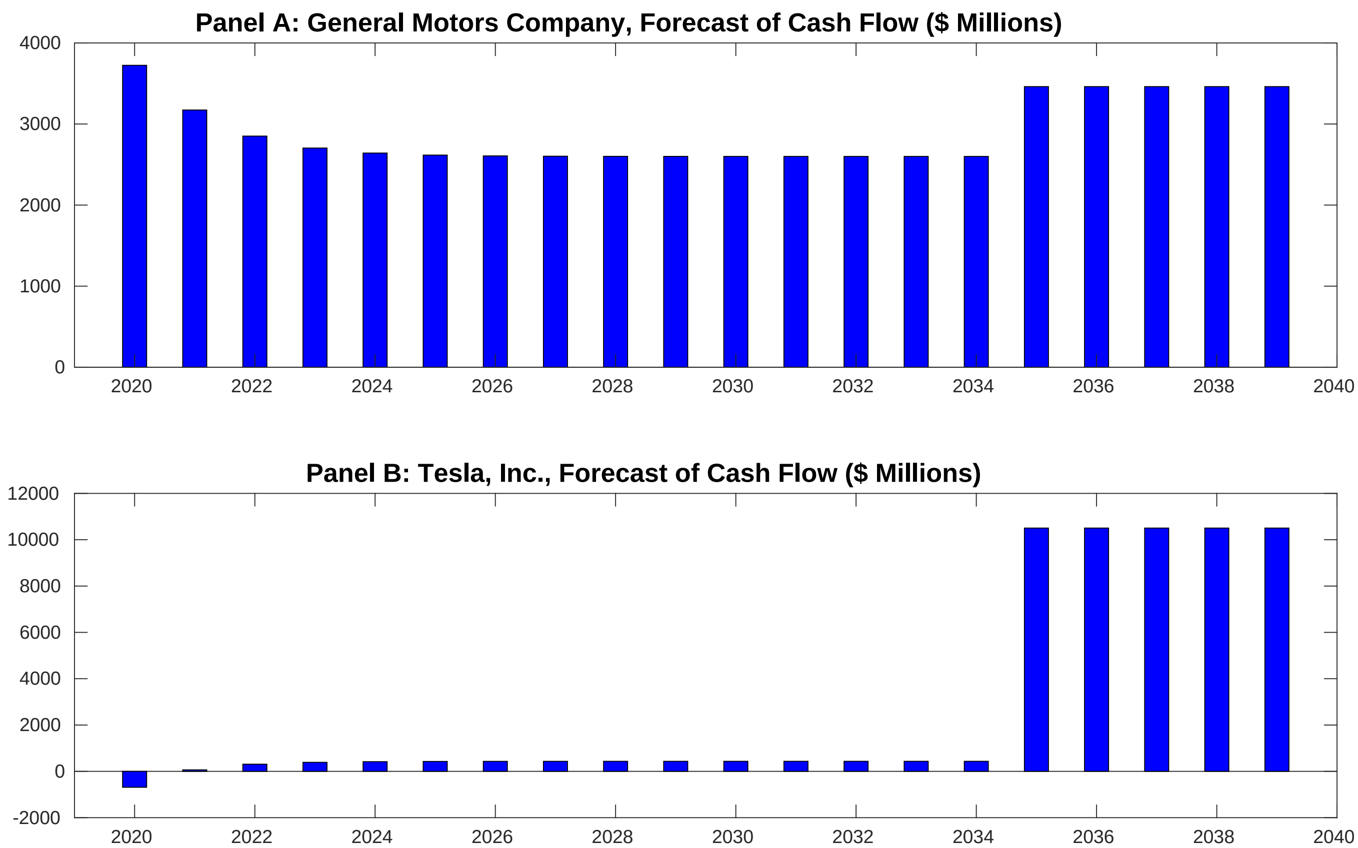


Table I: Summary statistics

The table reports summary statistics (autocorrelations, averages, standard deviations, percentiles, skewness, and kurtosis) of the variables used for regressions. We calculate the autocorrelation (AR) at the annual frequency. The sample period covers 2005-2020 in the U.S. Panel A reports the carbon variables. Emissions is the natural logarithm of the total carbon emission level (the total of scope 1 and 2). Intensity is the natural logarithm of the ratio of total carbon emissions to year-end sales. Divergence is defined as each year's absolute difference between the percentiles of a firm's total carbon emission level and carbon intensity. Panel B reports the equity duration variable. *Dur* is the implied duration of equity. Panel C reports other financial and equity market variables. *RET* is the monthly stock return. *ICC* is stock's implied cost of capital. *CF Forecast* is calculated as change in EPS forecast scaled by lagged stock price. *Size* is the natural logarithm of market capitalization. BM is the book-to-market ratio. *ROA* is the return on assets. *Leverage* is the ratio of debt (long-term debt plus debt in current liabilities) to the book value of total assets. *Sales* is the natural logarithm of year-end sales. *INV* is the CAPEX divided by the book value of assets. *Beta* is the 60-month rolling CAPM beta. *Momentum* is the cumulative stock return over past year skipping the most recent month. *Volatility* is the monthly stock return volatility calculated over the one-year period. ΔEPS and $\Delta Sales$ are the natural logarithms of year-over-year growth in EPS and sales, respectively. Panel C reports climate change exposure variables. Data of climate change exposure is from Sautner et al. (2023). Panel E reports the correlations among emission variables and important cross-sectional return variables. Table A1 provides detailed variable definitions.

	AR	Mean	SD	P25	Median	P75	Skew	Kurt
Panel A: Emission variables								
Emissions	0.98	11.27	2.55	9.80	11.40	12.90	-0.39	3.38
Intensity	0.97	3.94	1.23	3.16	3.72	4.46	0.90	3.81
Divergence	0.92	0.20	0.17	0.06	0.16	0.31	1.05	3.63
Panel B: Implied equity duration								
Dur	0.63	20.26	4.02	18.67	20.90	22.41	-0.81	7.46
Panel C: Cross-sectional return variables								
RET	0.00	1.28	12.54	-5.27	1.03	7.25	0.38	5.05
ICC	0.92	8.67	3.19	6.87	8.36	9.99	1.04	5.66
CF Forecast	0.91	0.76	6.39	-0.39	0.53	1.33	2.06	18.02
Size	0.96	7.89	1.79	6.75	7.95	9.05	-0.11	2.92
BM	0.77	0.51	0.47	0.21	0.38	0.66	2.30	9.74
ROA	0.85	0.08	0.19	0.07	0.12	0.17	-2.51	11.31
Leverage	0.89	0.28	0.23	0.11	0.25	0.40	1.02	4.31
Sales	0.99	7.34	2.11	6.28	7.58	8.68	-0.84	4.37
INV	0.86	0.05	0.05	0.02	0.03	0.06	2.60	11.12
ΔEPS	-0.32	0.05	0.87	-0.28	0.08	0.36	0.04	5.93
Beta	0.83	1.30	0.70	0.84	1.20	1.65	0.93	4.34
Momentum	-0.02	0.09	0.44	-0.17	0.06	0.28	1.21	6.31
Volatility	0.58	0.12	0.08	0.07	0.10	0.15	1.98	7.91
$\Delta Sales$	0.16	0.07	0.29	-0.02	0.06	0.16	0.64	9.49

Table I: Summary statistics (cont')

Panel D: Climate change exposure variables								
	AR	Mean	SD	P25	Median	P75	Skew	Kurt
$CCExposure^{Opp}$	0.89	0.26	1.03	0.00	0.00	0.16	11.10	181.95
$CCExposure^{Reg}$	0.79	0.04	0.22	0.00	0.00	0.00	16.37	398.40
$CCExposure^{Phy}$	0.74	0.01	0.12	0.00	0.00	0.00	32.15	1469.88

Panel E: Correlations						
	Emis.	*Int.*	*Div.*	*Dur*	*Size*	*Sales*
Emissions	1.00					
Intensity	0.57	1.00				
Divergence	-0.21	-0.23	1.00			
Dur	-0.31	-0.25	0.12	1.00		
Size	0.61	-0.03	0.04	0.14	1.00	
Sales	0.87	0.10	-0.11	-0.23	0.75	1.00

Table II: Divergence between carbon metrics

Panel A shows determinants of carbon level-intensity divergence. The dependent variable is *Divergence*. In the regressions for columns (1) to (2), we include year fixed effects. In columns (3) to (4), the regressions include industry-year fixed effects. Panel B studies between-group difference of regressions that relate total carbon emission level to firm sales. $I(Green)$ and $I(Brown)$ are the indicator variables set equal to 1 if a firm's total carbon emissions are in the lowest 30% or highest 70% within each cross-section, and 0 otherwise. In column (1), the results are from the U.S. sample. In column (2), regressions are conducted in the U.S. subsample where firms report their carbon emissions. In column (3), regressions only include the U.S. firms whose carbon emissions are estimated by Trucost. All regressions control for $Size$, BM, ROA, $Leverage$, $Sales$, INV and ΔEPS. All variables are defined in Table A1. The sample period covers from 2005 to 2020. The industry classification standard is the 48 Fama and French industries. The t-statistics are reported in the parenthesis below the coefficients. All standard errors are clustered at the firm level. Statistical significance is denoted by p***<0.01, p**<0.05, p*<0.1.

	$Divergence_{i,t}$			
Panel A.	(1)	(2)	(3)	(4)
$Emission_{i,t}$	-0.082***		-0.108***	
	(-11.23)		(-10.36)	
$Intensity_{i,t}$		-0.041***		-0.054***
		(-11.19)		(-10.34)
Controls	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	No	No
Industry×Year F.E.	No	No	Yes	Yes
Observations	13,787	13,787	13,715	13,715
Adj.R2	0.173	0.174	0.242	0.244

	$Emissions_{i,t}$		
	Full sample	Disclosed sample	Estimated sample
Panel B.	(1)	(2)	(3)
$I(Green)_{i,t} \times Sales_{i,t}$	0.338***	0.203	0.354***
	(7.86)	(1.15)	(7.71)
$I(Brown)_{i,t} \times Sales_{i,t}$	0.086	0.391***	-0.283***
	(1.40)	(3.47)	(-3.48)
$Sales_{i,t}$	1.358***	1.020***	1.495***
	(27.62)	(7.65)	(31.02)
$I(Green)_{i,t}$	-0.761***	-1.235***	-0.596***
	(-18.72)	(-11.22)	(-14.09)
$I(Brown)_{i,t}$	1.197***	1.026***	1.247***
	(17.88)	(9.56)	(14.43)
Controls	Yes	Yes	Yes
Industry×Year F.E.	Yes	Yes	Yes
Observations	13,715	3,501	10,056
Adj.R2	0.941	0.867	0.954

Table III: Equity duration and climate change exposure

This table examines the impact of firm-level climate change exposure on equity duration. The dependent variable is *Dur*. The regression controls for *Size*, *BM*, *ROA*, *Leverage*, *Sales*, *INV*, and *Beta*. All variables are defined in Table A1. Data of climate change exposure is from Sautner et al. (2023). In the regressions for columns (2), we include industry-year fixed effects. The industry classification standard is the 48 Fama and French industries. The t-statistics are reported in the parenthesis below the coefficients. All standard errors are clustered at the firm level. Statistical significance is denoted by p^{***}<0.01, p^{**}<0.05, p^{*}<0.1. The results are from the 2005-2020 U.S. sample.

	$Dur_{i,t+1}$	
Variables	(1)	(2)
$CCExposure^{Opp}_{i,t}$	0.115***	0.115***
	(3.50)	(3.95)
$CCExposure^{Reg}_{i,t}$	-0.066***	-0.044**
	(-3.05)	(-2.02)
$CCExposure^{Phy}_{i,t}$	-0.019	-0.009
	(-0.75)	(-0.46)
$Emissions_{i,t}$	-0.697***	-0.453***
	(-7.51)	(-4.02)
Controls	Yes	Yes
Industry×Year F.E.	Yes	Yes
Observations	12,341	12,304
Adj.R2	0.454	0.538

Table IV: Carbon emissions, stock returns and equity duration

This table explores the role that duration plays in the relationship between carbon measures and stock returns. This table conducts the contemporaneous regression of stock returns in t on the carbon measures in t and lagged control variables. RET is monthly stock return and $Adj.\ RET$ is the return adjusted for size, book-to-market, and momentum, according to the methodology in Daniel et al. (1997). The regression controls for $Size$, BM, ROA, $Leverage$, $Sales$, INV, ΔEPS, $Beta$, $Momentum$ and $Volatility$. All variables are defined in Table A1. $I(LongDur)$ is an indicator that equals one if Dur is in the top 30% within the cross-section, and zero otherwise. $I(ShortDur)$ is an indicator that equals one if Dur is in the lowest 30% within the cross-section, and zero otherwise. All regressions include time fixed effects, and regressions in column (1), (3), (4) and (6) additionally include industry fixed effects. The industry classification standard is the 48 Fama and French industries. The t-statistics are reported in the parenthesis below the coefficients. All standard errors are clustered at the firm and year level. Statistical significance is denoted by p***<0.01, p**<0.05, p*<0.1. The results are from the 2005 to 2020 U.S. sample.

	$RET_{i,t}$			$Adj.\ RET_{i,t}$		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
$Emissions_{i,t}$	0.353***	0.258*	0.748***	0.312***	0.245	0.642***
	(3.47)	(1.83)	(5.35)	(3.30)	(1.72)	(5.25)
$I(LongDur)_{i,t} \times Emissions_{i,t}$		-0.476***	-0.499***		-0.477***	-0.488***
		(-6.25)	(-6.65)		(-6.28)	(-5.99)
$I(ShortDur)_{i,t} \times Emissions_{i,t}$		0.059	0.046		0.083	0.072
		(0.66)	(0.60)		(0.87)	(0.73)
$I(LongDur)_{i,t}$		1.446***	1.479***		1.171***	1.202***
		(12.15)	(13.55)		(14.77)	(16.25)
$I(ShortDur)_{i,t}$		-1.901***	-1.879***		-1.676***	-1.661***
		(-16.34)	(-17.28)		(-18.22)	(-19.35)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	No	Yes	Yes	No	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	160,850	161,426	160,850	155,845	156,346	155,845
Adj.R2	0.244	0.250	0.251	0.004	0.011	0.012

Table V: Carbon sorted portfolios and equity duration

This table presents monthly value-weighted raw returns of the carbon-duration portfolios of unconditional sorts. DGTW-adjusted return is the return adjusted for size, book-to-market, and momentum, according to the methodology in Daniel et al. (1997). From column (1) to (2), the sorting variable is equity duration. In Panel A, we calculate the *Brown-minus-green (BMG)* portfolio between the portfolios with the highest and lowest carbon emissions. We show *BMG* within the shortest duration portfolios in column (1) and the longest duration portfolios in column (2). Panel B shows the alphas of BMG. We use FF6 factor models (Fama and French, 2018), which adds a momentum factor to the controls in FF5. We report the results of the time-series regression with standard errors adjusted for autocorrelation with 12 lags using the Newey-West test (Newey and West, 1987). The t-statistics are reported in the parenthesis below the coefficients. Statistical significance is denoted by p^{***}<0.01, p^{**}<0.05, p^{*}<0.1. The results are from the 2005 to 2020 U.S. sample.

	Portfolios sorted on duration	
	Short	Long
Panel A. DGTW-adjusted excess return	(1)	(2)
Portfolios sorted on carbon emissions		
1 (Green)	0.073	0.312**
	(0.55)	(2.38)
2	-0.012	0.186**
	(-0.12)	(2.35)
3 (Brown)	-0.177*	-0.055
	(-1.91)	(-0.84)
BMG	-0.250	-0.367***
	(-1.27)	(-2.78)
	Brown-Minus-Green portfolios Monthly return	
	Short	Long
Panel B. Alphas	(1)	(2)
α-CAPM	-0.265	-0.287**
	(-1.09)	(-2.24)
R^2	-0.004	0.025
Obs.	180	180
α-FF5	-0.289	-0.380***
	(-1.53)	(-3.93)
R^2	0.280	0.477
Obs.	180	180
α-FF5+MOM	-0.289	-0.380***
	(-1.52)	(-3.94)
R^2	0.278	0.474
Obs.	180	180

Table VI: Carbon premium and equity duration: the channel of implied cost of capital and cash flow expectation

This table conducts the contemporaneous regression of stock returns in t on the interaction terms of carbon emissions and implied cost of capital, cash flow expectation in t, respectively. RET is monthly stock return. ICC is the medium of four accounting measures of the implied cost of capital, according to the methodology in Gebhardt, Lee, and Swaminathan (2001), Claus and Thomas (2001), Easton (2004) and Ohlson and Juettner-Nauroth (2005). $CF\ Forecast$ is calculated as change in EPS forecast scaled by lagged stock price. The regression includes lagged controls of $Size$, BM, ROA, $Leverage$, $Sales$, INV, ΔEPS, $Beta$, $Momentum$ and $Volatility$. All variables are defined in Table A1. Column (1) and (2) show the results from the sample of long duration (the top 30% within the cross-section). Column (3) and (4) show the results from the sample of short duration (the lowest 30% within the cross-section). All regressions include time fixed effects, and regressions in column (2) and (4) additionally include industry fixed effects. The industry classification standard is the 48 Fama and French industries. The t-statistics are reported in the parenthesis below the coefficients. All standard errors are clustered at the firm and year level. Statistical significance is denoted by p***<0.01, p**<0.05, p*<0.1. The results are from the 2005 to 2020 U.S. sample.

	$RET_{i,t}$			
	Long sample		Short sample	
Variables	(1)	(2)	(3)	(4)
$Emissions_{i,t} \times ICC_{i,t}$	-0.273**	-0.339***	-0.115	-0.089
	(-2.93)	(-3.66)	(-1.27)	(-0.99)
$Emissions_{i,t} \times CF\ Forecast_{i,t}$	-0.033	-0.060	0.206**	0.212**
	(-0.38)	(-0.63)	(2.17)	(2.17)
$Emissions_{i,t}$	0.013	0.237	0.282	0.532***
	(0.07)	(1.35)	(1.68)	(3.09)
$ICC_{i,t}$	-0.826***	-0.933***	-1.043***	-1.160***
	(-6.15)	(-6.94)	(-8.50)	(-8.64)
$CF\ Forecast_{i,t}$	0.168	0.159	0.205	0.200
	(0.98)	(0.95)	(0.94)	(0.93)
Controls	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes
Year/month F.E.	Yes	Yes	Yes	Yes
Observations	37,677	37,677	40,794	40,770
Adj.R2	0.240	0.241	0.324	0.325

Table VII: Subsample analysis: carbon emission, implied cost of capital and cash flow forecast

This table presents the relationship between emissions and implied cost of capital, emissions and cash flow expectation respectively. The dependent variable in Panel A is ICC, the medium of four accounting measures of the implied cost of capital, according to the methodology in Gebhardt, Lee, and Swaminathan (2001), Claus and Thomas (2001), Easton (2004) and Ohlson and Juettner-Nauroth (2005). The dependent variable in Panel B is $CF\ Forecast$, which is calculated as change in EPS forecast scaled by lagged stock price. Column (1) shows the results from the sample of long duration (the top 30% within the cross-section) and Column (2) shows the results from the sample of short duration (the lowest 30% within the cross-section). All regressions include time fixed effects and industry fixed effects. The regression includes lagged controls of $Size$, BM, ROA, $Leverage$, $Sales$, INV, ΔEPS, $Beta$, $Momentum$ and $Volatility$. All variables are defined in Table A1. The industry classification standard is the 48 Fama and French industries. The t-statistics are reported in the parenthesis below the coefficients. All standard errors are clustered at the firm and year level. Statistical significance is denoted by p***<0.01, p**<0.05, p*<0.1. The results are from the 2005 to 2020 U.S. sample.

	$ICC_{i,t}$	
	Long sample	Short sample
Panel A.	(1)	(2)
$Emissions_{i,t}$	0.443**	0.498**
	(2.70)	(2.84)
Controls	Yes	Yes
Industry F.E.	Yes	Yes
Year/month F.E.	Yes	Yes
Observations	37,903	41,188
Adj.R2	0.366	0.257
	$CF\ Forecast_{i,t}$	
	Long sample	Short sample
Panel B.	(1)	(2)
$Emissions_{i,t}$	1.259***	0.713**
	(3.21)	(2.94)
Controls	Yes	Yes
Industry F.E.	Yes	Yes
Year/month F.E.	Yes	Yes
Observations	45,708	41,398
Adj.R2	0.120	0.142

Table VIII: Robustness analysis: carbon premium and equity duration

This table explores robustness of the role that duration plays in the relationship between carbon measures and stock returns. Panel A conducts the contemporaneous regression of stock returns in t on the carbon emissions in t while controlling for contemporaneous sales information. The regression includes lagged control variables of $Size$, BM, ROA, $Leverage$, INV, ΔEPS, $Beta$, $Momentum$ and $Volatility$. Panel B conducts the same regression as Table IV with the sample including only firm-reported emission data. Panel C conducts the regression of stock returns in t on the lagged carbon emissions. The regression includes the same lagged control variables as Panel A, as well as lagged sales information. All variables are defined in Table A1. $I(LongDur)$ is an indicator that equals one if Dur is in the top 30% within the cross-section, and zero otherwise. $I(ShortDur)$ is an indicator that equals one if Dur is in the lowest 30% within the cross-section, and zero otherwise. All regressions include time fixed fixed effects. Column (1) and (3) additionally include industry fixed effects. The industry classification standard is the 48 Fama and French industries. The t-statistics are reported in the parenthesis below the coefficients. All standard errors are clustered at the firm and year level. Statistical significance is denoted by p***<0.01, p**<0.05, p*<0.1. The results are from the 2005 to 2020 U.S. sample.

	$RET_{i,t}$		
Panel A. Controlling for sales information	(1)	(2)	(3)
$Emissions_{i,t}$	-0.155**	0.002	0.191*
	(-2.31)	(0.02)	(1.96)
$I(LongDur)_{i,t} \times Emissions_{i,t}$		-0.548***	-0.578***
		(-6.14)	(-6.65)
$I(ShortDur)_{i,t} \times Emissions_{i,t}$		0.111	0.094
		(1.15)	(1.05)
$I(LongDur)_{i,t}$		1.396***	1.425***
		(11.48)	(12.98)
$I(ShortDur)_{i,t}$		-1.959***	-1.930***
		(-17.65)	(-18.25)
$Sales_{i,t}$	0.563***	0.970***	0.995***
	(4.50)	(5.97)	(8.10)
$\Delta Sales_{i,t}$	0.526***	0.485***	0.477***
	(7.17)	(6.46)	(6.19)
Controls	Yes	Yes	Yes
Industry F.E.	Yes	No	Yes
Year/month F.E.	Yes	Yes	Yes
Observations	160,850	161,426	160,850
Adj.R2	0.246	0.252	0.253

Table VIII: Robustness analysis: carbon premium and equity duration (cont')

	$RET_{i,t}$		
Panel B. Firm-reported emissions only	(1)	(2)	(3)
$Emissions_{i,t}$	-0.080	0.072	0.195
	(-0.58)	(0.57)	(1.42)
$I(LongDur)_{i,t} \times Emissions_{i,t}$		-0.436***	-0.505***
		(-5.32)	(-5.09)
$I(ShortDur)_{i,t} \times Emissions_{i,t}$		0.042	0.105
		(0.47)	(1.01)
$I(LongDur)_{i,t}$		1.217***	1.294***
		(8.34)	(9.39)
$I(ShortDur)_{i,t}$		0.042	0.105
		(0.47)	(1.01)
Controls	Yes	Yes	Yes
Industry F.E.	Yes	No	Yes
Year/month F.E.	Yes	Yes	Yes
Observations	43,874	44,030	43,874
Adj.R2	0.334	0.338	0.339

	$RET_{i,t}$		
Panel C. Forward-looking bias	(1)	(2)	(3)
$Emissions_{i,t-1}$	-0.111	-0.040	0.172
	(-1.29)	(-0.27)	(1.56)
$I(LongDur)_{i,t} \times Emissions_{i,t-1}$		-0.556***	-0.566***
		(-6.87)	(-7.23)
$I(ShortDur)_{i,t} \times Emissions_{i,t-1}$		0.171*	0.174**
		(1.94)	(2.60)
$I(LongDur)_{i,t}$		1.353***	1.380***
		(11.07)	(12.19)
$I(ShortDur)_{i,t}$		-1.885***	-1.871***
		(-13.29)	(-13.56)
Controls	Yes	Yes	Yes
Industry F.E.	Yes	No	Yes
Year/month F.E.	Yes	Yes	Yes
Observations	145,862	146,390	145,862
Adj.R2	0.255	0.261	0.261

Table IX: Carbon intensity, stock returns and equity duration

This table explores robustness of the role that duration plays in the relationship between carbon measures and stock returns. Panel A conducts the contemporaneous regression of stock returns in t on the carbon emissions in t while controlling for contemporaneous sales information. The regression includes lagged control variables of $Size$, BM, ROA, $Leverage$, INV, ΔEPS, $Beta$, $Momentum$ and $Volatility$. Panel B conducts the same regression as Table IV with the sample including only firm-reported emission data. Panel C conducts the regression of stock returns in t on the lagged carbon emissions. The regression includes the same lagged control variables as Panel A, as well as lagged sales information. All variables are defined in Table A1. $I(LongDur)$ is an indicator that equals one if Dur is in the top 30% within the cross-section, and zero otherwise. $I(ShortDur)$ is an indicator that equals one if Dur is in the lowest 30% within the cross-section, and zero otherwise. All regressions include time fixed fixed effects. Column (1) and (3) additionally include industry fixed effects. The industry classification standard is the 48 Fama and French industries. Panel B presents monthly value-weighted raw returns of the intensity-duration portfolios of unconditional sorts. DGTW-adjusted return is the return adjusted for size, book-to-market, and momentum, according to the methodology in Daniel et al. (1997). From column (1) to (2), the sorting variable is equity duration. In Panel B, we calculate the *Brown-minus-green (BMG)* portfolio between the portfolios with the highest and lowest carbon intensity. We show BMG within the shortest duration portfolios in column (1) and the longest duration portfolios in column (2). Panel B shows the alphas of BMG. We use FF6 factor models (Fama and French, 2018), which adds a momentum factor to the controls in FF5. We report the results of the time-series regression with standard errors adjusted for autocorrelation with 12 lags using the Newey-West test (Newey and West, 1987). The t-statistics are reported in the parenthesis below the coefficients. All standard errors are clustered at the firm and year level. Statistical significance is denoted by p***<0.01, p**<0.05, p*<0.1. The results are from the 2005 to 2020 U.S. sample.

	$RET_{i,t}$		
Panel A. Panel regressions	(1)	(2)	(3)
$Intensity_{i,t}$	-0.096***	0.069	0.168***
	(-2.98)	(0.98)	(3.43)
$I(LongDur)_{i,t} \times Intensity_{i,t}$		-0.404***	-0.378***
		(-4.64)	(-4.16)
$I(ShortDur)_{i,t} \times Intensity_{i,t}$		-0.108	-0.109
		(-1.22)	(-1.50)
$I(LongDur)_{i,t}$		1.367***	1.404***
		(11.30)	(12.59)
$I(ShortDur)_{i,t}$		-1.838***	-1.822***
		(-15.51)	(-16.13)
Controls	Yes	Yes	Yes
Industry F.E.	Yes	No	Yes
Year/month F.E.	Yes	Yes	Yes
Observations	160,850	161,426	160,850
Adj.R2	0.244	0.250	0.251

Table IX: Carbon intensity, stock returns and equity duration (cont')

	Portfolios sorted on duration	
	Short	Long
Panel B. DGTW-adjusted excess return	(1)	(2)
Portfolios sorted on carbon intensity		
1 (Green)	-0.033	0.190***
	(-0.28)	(2.92)
2	-0.107	-0.009
	(-1.22)	(-0.10)
3 (Brown)	-0.234	-0.230**
	(-1.32)	(-2.23)
BMG	-0.201	-0.420***
	(-0.84)	(-3.09)

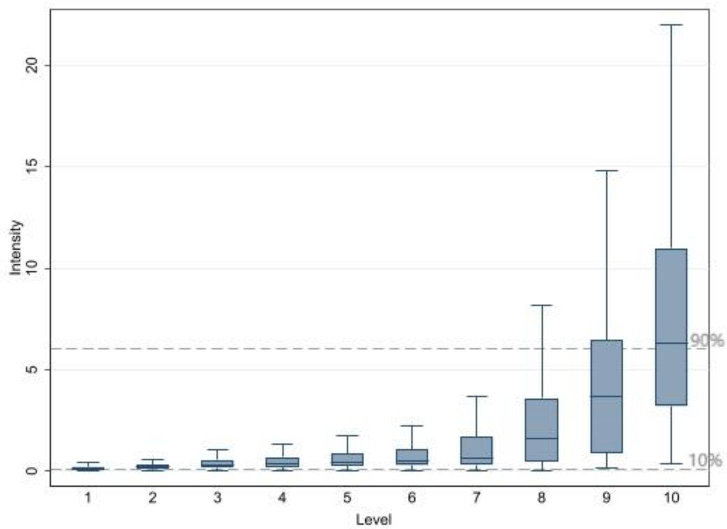
	Brown-Minus-Green portfolios Monthly return	
	Short	Long
Panel C. Alphas	(1)	(2)
α-CAPM	-0.208	-0.394***
	(-0.76)	(-2.70)
R^2	-0.005	0.000
Obs.	180	180
α-FF5	-0.121	-0.369**
	(-0.51)	(-2.59)
R^2	0.075	0.079
Obs.	180	180
α-FF5+MOM	-0.121	-0.370***
	(-0.51)	(-2.62)
R^2	0.075	0.089
Obs.	180	180

Appendix

Figure A1: Emission-level sorted carbon intensity

This figure presents the distribution of carbon emission intensity evenly sorted by emissions level. Carbon intensity is the ratio of the total carbon emissions to the year-end sales. We display the distribution of carbon intensity based on minimum, first quartile (Q1), median, third quartile (Q3), and maximum. The gray dashed lines represent the 10th percentile of carbon intensity at the bottom and the 90th percentile of carbon intensity at the top. We exclude outside values. Panel A reports the disclosed U.S. sample. Panel B reports the estimated U.S. sample. The sample period is from 2005 to 2020.

Panel A. Disclosed sample



Panel B. Estimated sample

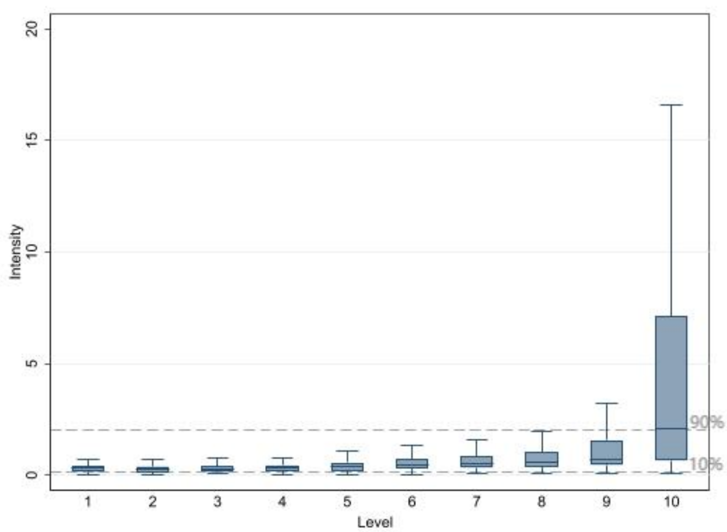


Table A1: Variable definitions

Variable	Years	Definition
Emissions	2005 to 2020	The natural logarithm of total emissions from the sum of Scope 1 and Scope 2. Source: Trucost.
Intensity	2005 to 2020	The natural logarithm of the ratio of the total emissions from the sum of Scope 1 and Scope 2 to the year-end sales. Source: Trucost.
Divergence	2005 to 2020	The absolute difference between the percentiles of a firm's total carbon emission level and carbon intensity within each cross-section. Source: Self-constructed.
Dur	2005 to 2020	Equity duration. Sources: Dechow, Sloan, and Soliman (2004) and Weber (2018).
RET	2005 to 2020	The monthly stock return. Source: CRSP.
ICC	2005 to 2020	The medium of four accounting measures of the implied cost of capital, according to the methodology in Gebhardt, Lee, and Swaminathan (2001), Claus and Thomas (2001), Easton (2004) and Ohlson and Juettner-Nauroth (2005). Source: CRSP, I/B/E/S
CF Forecast	2005 to 2020	calculated as change in EPS forecast scaled by lagged stock price. Source: I/B/E/S
Size	2005 to 2020	The natural logarithm of market capitalization. Source: CRSP.
BM	2005 to 2020	The book value of equity divided by market value of equity. Source: CRSP and Compustat.

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Table A1 – continued from previous page

Variable	Years	Definition
ROA	2005 to 2020	The ratio of operating income before depreciation to the book value of total assets. Source: Compustat.
$Leverage$	2005 to 2020	The ratio of debt (long-term debt plus debt in current liabilities) to the book value of total assets. Source: Compustat.
$Sales$	2005 to 2020	The natural logarithm of year-end sales. Source: Compustat.
INV	2005 to 2020	The CAPEX divided by book value of asset. Source: Compustat.
ΔEPS	2005 to 2020	The natural logarithm of year-by-year growth of EPS. Source: Compustat.
$Beta$	2005 to 2020	The CAPM beta calculated over a 60-month rolling window. Source: CRSP.
$Momentum$	2005 to 2020	The cumulative stock return over the one-year period. Source: CRSP.
$Volatility$	2005 to 2020	The monthly stock return volatility calculated over the one-year period. Source: CRSP.
$\Delta Sales$	2005 to 2020	The natural logarithm of year-by-year growth of sales. Source: Compustat.
$I(Green)$	2005 to 2020	The indicator variable set equal to 1 if a firm's total carbon emissions are in the lowest 30% within each cross-section, and 0 otherwise. Source: Self-constructed.
$I(Brown)$	2005 to 2020	The indicator variable set equal to 1 if a firm's total carbon emissions are in the highest 30% within each cross-section, and 0 otherwise. Source: Self-constructed.

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Table A1 – continued from previous page

Variable	Years	Definition
$I(LongDur)$	2005 to 2020	The indicator that equals one if equity duration is in the top 30% within the cross-section, and zero otherwise. Source: Self-constructed.
$Carbon$	2005 to 2020	The generic term alternately standing for the natural logarithm of total carbon emission level and carbon intensity. Source: Trucost.
MKT	2005 to 2020	Monthly return on the value-weighted stock market net of the risk free rate. Source: Fama and French (1993).
SMB	2005 to 2020	The average monthly return on the three small portfolios minus the average return on the three big portfolios. Source: Fama and French (1993).
HML	2005 to 2020	The average monthly return on the two value portfolios minus the average return on the two growth portfolios. Source: Fama and French (1993).
RMW	2005 to 2020	The difference between the monthly returns on diversified portfolios of stocks with robust and weak profitability. Source: Fama and French (2015).
CMA	2005 to 2020	The difference between the returns on diversified portfolios of the stocks of low and high investment firms. Source: Fama and French (2015).
MOM	2005 to 2020	Monthly return on the porfolio long 12-month stock winners and short 12-month past losers. Source: Carhart (1997).
RET	2005 to 2020	Monthly stock return. Source: CRSP

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Table A1 – continued from previous page

Variable	Years	Definition
$CCExposure^{Opp}$	2005 to 2020	Relative frequency with which biagrams that capture opportunities related to climate change occur in the transcripts of earnings conference calls. We count the number of such bigrams and divide by the total number of bigrams in the transcripts. Source: Sautner et al. (2023)
$CCExposure^{Reg}$	2005 to 2020	Relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of earnings conference calls. We count the number of such bigrams and divide by the total number o f bigrams in the transcripts. Source: Sautner et al. (2023)
$CCExposure^{Phy}$	2005 to 2020	Relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of earnings conference calls. We count the number of such bigrams and divide by the total number o f bigrams in the transcripts. Source: Sautner et al. (2023)

Table A2: Disclosure distribution within each emission sorted portfolios

This table reports the number distribution of rebalanced decile portfolios sorted on total carbon emissions in carbon-estimated sample and carbon-disclosed sample. The sample period covers from 2005 to 2020.

Emission sorted portfolios	#Estimated obs.	#Disclosed obs.	#Total obs.
1 (Green)	1,790	65	1,855
2	1,736	129	1,865
3	1,684	182	1,866
4	1,596	269	1,865
5	1,551	311	1,862
6	1,508	359	1,867
7	1,413	452	1,865
8	1,182	684	1,866
9	984	881	1,865
10 (Brown)	612	1,244	1,856
#Total obs.	14,056	4,576	18,632

Table A3: Emissions and sales in the disclosed and estimated sample

This table studies the regressions that relate total carbon emission level to firm sales. The firm-year carbon emission data is from S&P Trucost. The regression controls for $Size$, BM, ROA, $Leverage$, INV and ΔEPS. All variables are defined in Table A1. In column (1), the results are from the U.S. sample. In column (2), regressions are conducted in the U.S. subsample where firms report their carbon emissions. In column (3), regressions only include the U.S. firms with estimated carbon emissions. The sample period covers from 2005 to 2020. The industry classification standard is the 48 Fama and French industries. All regressions include industry-year fixed effects. The t-statistics are reported in the parenthesis below the coefficients. All standard errors are clusterd at the firm level. Statistical significance is denoted by p***<0.01, p**<0.05, p*<0.1.

	$Emissions_{i,t}$		
	Full sample	Disclosed sample	Estimated sample
Variables	(1)	(2)	(3)
$Sales_{i,t}$	2.065***	2.005***	2.072***
	(53.80)	(15.43)	(65.17)
Controls	Yes	Yes	Yes
Industry×Year F.E.	Yes	Yes	Yes
Observations	13,715	3,501	10,056
Adj.R2	0.913	0.793	0.931