Firms' Carbon Emissions and Stock Returns

Cong Wang*

December 23, 2023

Abstract

In recent years, the surge in unanticipated climate change risk has led to green assets outperforming their brown counterparts, a trend that contradicts the theoretical expectation that brown assets, exposed to higher risk associated with climate change, should achieve higher return compensations. This paper presents empirical evidence from the U.S. stock market, utilizing both portfolio and individual stock analyses, to elucidate this discrepancy. Our findings reveal that, from 2002 to 2021, green portfolios, characterized by lower carbon emissions, consistently outperform brown portfolios. Similar patterns are observed at the firm level. We propose that unexpected concerns about climate change have shifted market preferences, leading to a differential demand shock for green and brown assets. This shift in preference is a key factor driving the superior performance of green assets over their brown counterparts.

Keywords: Carbon Emission, Stock Return, Climate Change

JEL Codes: G11, G12, G30

*Department of Economics and Law, Sapienza University of Rome

1 Introduction

In the face of mounting challenges such as geopolitical conflicts, pandemics, and climate change, the call for sustainable investment and environmentally responsible production has never been more urgent. These pressing global concerns have underscored the critical need to prioritize sustainability as a central pillar of our collective future. In addressing these challenges, the United Nations, as outlined in FUND (2015), has published Sustainable Development Goals (SDG) which comprises 17 interlinked objectives that emphasize the intricate connections between environmental, social, and economic aspects of sustainable development. Furthermore, the call for sustainable practices extends into the financial market, where sustainable investing has gained significant traction. Investors are increasingly recognizing the importance of integrating environmental, social, and governance (ESG) criteria into their decision-making processes as discussed in the report by Paribas (2023). In this context, the introduction of the Green minus Brown factor (GMB) in the current asset pricing literature, alongside established aggregate risk factors like small minus big (SMB), high minus low (HML), and robust minus weak (RMW), has emerged as a relevant factor explaining risks associated with climate change. Empirical evidence often shows that Green portfolios, in both stock and bond markets, outperform their Brown counterparts. However, classic asset pricing theories propose a contrasting view. These theories suggest that Brown assets, bearing greater risks associated with climate change, should offer higher returns as compensation for this increased risk. This presents a notable contradiction between empirical findings and theoretical predictions.

Investors frequently turn to ESG (Environmental, Social, and Governance) scores when evaluating companies to gauge their environmental, social and governance practices, especially the E scores for environment. These scores play an important role in categorizing companies into "Green" and "Brown", signifying their commitment to sustainable practices or their lack thereof. However, a notable challenge arises from the fact that multiple ESG rating agencies, such as MSCI ESG Ratings, Sustainalytics, and Bloomberg, among others, operate concurrently. Each of these agencies employs distinct valuation metrics and methodologies, leading to divergent ESG ratings for the same companies. In fact, recent research, as highlighted by Avramov et al. (2022), has revealed that this variation in ESG assessments can introduce uncertainty into the market. Such uncertainty has the potential to increase market premiums and diminish demand for the related stocks that exhibit higher ESG uncertainty, and create a complex landscape for investors to navigate. To circumvent the challenges associated with rating uncertainty, this paper adopts a pragmatic approach by relying on a single, yet robust, indicator to gauge companies' environmental performance: the Green House Gas (GHG) emissions. GHG emissions are recognized as a primary driver of global warming, and they are mandated for disclosure by various stakeholders, including the Securities and Exchange Commission (SEC), investors, and the public media. By focusing on this widely accepted and easily measurable metric, this study seeks to provide a clear and unambiguous assessment of firms' sustainability practice and their stock returns.

Our analysis investigates whether firms characterized as "Brown" due to their higher carbon emissions experience higher stock returns compared to "Green" firms, as posited by classic theoretical studies suggesting that higher risk exposure is associated with higher returns. This analysis focuses exclusively on the U.S. stock market. The dataset utilized in this study encompasses all publicly traded stocks in the U.S. stock market from 2002 to 2021. The initial step of this research involves an exploratory analysis of the relationship between firms' carbon emissions and their stock returns cross-sectionally. For the entire dataset, we categorize all the observations into percentiles based on total CO2 emissions, subsequently computing the average stock return within each percentile. The findings reveal that stocks situated in the lower percentiles consistently exhibit higher average stock returns, with a decline in returns observed as percentiles progress toward the 100th percentile. Remarkably, this pattern persists when we consider different scopes of carbon emissions. It's worth noting that while one might attribute this trend to other firm characteristics such as size, as carbon emissions tend to be positively correlated with firm size, our analysis does not reveal a similar pattern between firm size and stock returns, as well as other factors such as leverage, profitability, and growth. Furthermore, we apply a similar methodology to examine the relationship between firms' stock returns and carbon intensity, defined as a firm's carbon emissions scaled by its revenue. This matric is a crucial proxy for a firm's carbon footprint in the current corporate finance literature. However, in contrast to our findings on carbon emissions, we do not identify a clear and consistent relationship between firms' stock returns and carbon intensity.

Is it, however, conclusive to assert that firms with lower carbon emissions consistently yield higher stock returns? Not necessarily, as there is significant heterogeneity in carbon emissions across different industries. For instance, the Power and Renewable Electricity sector[1] leads with an average emission of 38.15 million tons annually, a stark contrast to the Mortgage Real Estate Investment Trusts (REITs) 0.03 million tons. This disparity makes a direct comparison among firms belonging to different industries akin to contrasting apples with bananas. To address this, we conduct a more nuanced analysis. Stocks within each industry are divided into quintiles based on their carbon emissions. Within each industry, we then create value-weighted portfolios: "Green" for stocks with the lowest emissions, "Brown" for the highest, and "Neutral" for the middle range[2]. Over the entire dataset spanning from 2002 to 2021, the green portfolio realizes impressive cumulative returns, exceeding 600%, while their brown counterparts achieves approximately 270% in cumulative returns, the result coincides with Pástor et al. (2022) who use ESG scores to construct green and brown portfolios. However, when we replicate this approach using firms' carbon intensity, the results diverge. The outperformance of green portfolio is not as clear as before, and it is only observed after 2011.

The green portfolio outperforms the brown by an average of 1.45% each month throughout the sample period. The GMB (green-minus-brown) portfolio, created by taking long positions

[1]The industry classification in this paper follows the Global Industry Classification Standards (GICS).

[2]The second and fourth quintiles are excluded from our analysis for a more distinguish comparison between firms in different range of carbon emissions.

in green stocks and short positions in brown stocks, demonstrates an economically and statistically significant alpha of above 1% on a monthly basis. Notably, this alpha cannot be explained by various factor models currently prevalent in asset pricing literature. This finding presents strong empirical evidence against traditional asset pricing theory, which suggests that green stocks, presumed to have lower climate change risk exposure, actually achieve higher returns than their brown counterparts. It also implies that using carbon emissions as an indicator to quantify a firm's green practices is effective and comparable to ESG scores. However, similar results are not observed when considering firms' carbon intensity.

In the aggregated portfolio analysis, we confirm the efficancy of carbon emissions quantifying firms' sustainable practice, and our findings align with Pástor et al. (2022), who find that green portfolio, which encompasses firms with higher ESG scores (lower carbon emissions in our case), tend to outperform its brown counterpart. These results are also corroborated by Friede et al. (2015), who also indicate that green firms often exhibit better financial performance. However, when we delve into firm-level analyses, as conducted by Bolton and Kacperczyk (2021b), a stark contradiction emerges. Their research suggests that firms with higher carbon emissions tend to yield higher stock returns, directly conflicting with our portfolio performance findings. To address this discrepancy, we shift our focus to firm-level data and employ regression model to explore the relationship between firms' total carbon emissions and stock returns. Recognizing the presence of unobserved time-variant factors and time-invariant industry-specific factors, we incorporate Industry + Time fixed effects in our panel regression model. Our results reveal a positive correlation between firms' stock returns and total carbon emissions indicating that firms with higher carbon emissions tend to have higher stock returns on average, yet this relationship lacks statistical significance.

The choice to incorporate Industry + Time two-way fixed effects is rooted in the assumption that there exist unobserved time-variant factors associated with time periods and time-invariant factors linked to industries. This assumption hinges on the belief that firms within the same industry during the same time period exhibit similar stock return behaviors. A more stringent assumption is that even in the same industry firms' stock returns still behave differently, due to some idiosyncratic characteristics inherited by each specific firm. Under this new assumption, we apply Entity + Time two-way fixed effects. The results of this analysis reveal a significant and negative relationship between firms' carbon emissions and stock returns, both statistically and economically. Specifically, a 1% increase in firms' total carbon emissions corresponds to a 0.66% decrease in stock returns, on average. These findings provide robust support for the notion that higher carbon emissions are associated with lower stock returns alongside our portfolio analysis, emphasizing the importance of accounting for idiosyncratic firm-level characteristics in our analysis. In our robustness analysis, we systematically vary the fixed effects and cluster standard errors at different levels. Notably, whenever we incorporate entity-fixed effects into the model, our findings consistently align with those of our benchmark model. This robustness underscores the reliability and stability of our results across various specifications, and provide empirical evidence algin with our portfolio analysis while against what the classic asset pricing theory suggests.

Finally, we explore the mechanism underlying the discrepancy observed between empirical and theoretical studies. While the theoretical premise that higher risk is compensated with higher returns generally holds, this relationship could be deteriorated by demand shocks for underlying assets. As demonstrated earlier, the mounting challenges posed by climate change can unexpectedly shift financial market preferences, driven by motives to hedge against climate change risks and comply with sustainable investing mandates. This preference shift can result in demand shocks favoring green assets and leading to divestment from brown ones. As Gabaix and Koijen (2021) and Hartzmark and Solomon (2022) discuss, the high elasticity of price to demand causes prices to increase for green assets and decrease for brown ones. Consequently, this leads to higher returns for green assets compared to brown. Utilizing the Unexpected Media Climate Change Concern Index (UMC) developed by Ardia et al. (2022), we find that a unit increase in UMC can lead to a 1.69% increase in returns for green portolio and a 1.26% decrease for brown ones. At the firm level, our analysis shows that an increase in the UMC index further promotes the outperformance of green stocks, as indicated by their lower carbon emissions.

Related Literature

Our study contributes to a vast empirical literature on sustainable investing, encompassing both aggregated portfolio and firm-level analyses. In a broader context, research in this field has gained significant momentum due to growing concerns about climate change and sustainability. For instance, Krueger et al. (2020) conduct a study using survey data to investigate climate perception and find that climate risks, particularly those related to regulations, have started to materialize. Their research indicates that many investors, particularly those with a long-term perspective, larger portfolios, and a focus on ESG (Environmental, Social, and Governance) factors, prioritize risk management and engagement over divestment strategies. This underscores the evolving priorities and strategies of investors in response to climate-related challenges.

Similarly, Faccini et al. (2023) conduct research to assess whether market-wide physical or transition climate risks are priced into U.S. stocks. They find that only the climate-policy factor is priced, especially after 2012. Interestingly, their study reveals that investors seem to be less concerned about natural disasters, global warming, and decisions made at international climate summits. This research highlights the complexity of integrating climate risk into financial markets and the selective focus of investors on specific aspects of climate-related factors.

In the midst of this dynamic landscape, our study adds to the body of knowledge by examining the relationship between firms' carbon emissions, climate change concerns, and stock returns. However, the current literature diverges when it comes to the performance of Green and Brown assets. Garvey et al. (2018) have utilized carbon ratios to select stocks, revealing that lower carbon ratios are associated with higher stock returns and increased profitability. In et al. (2017) construct "Efficient-Minus-Inefficient" portfolios based on carbon intensity, demonstrating their ability to generate positive alpha since 2009. Meanwhile, Andersson et al. (2016) introduce a low carbon index in their paper, and find that when climate change mitigation is pending, the low carbon index performs the same as the benchmark, when carbon emission is priced, the index outperforms the benchmark. Additionally, Hsu et al. (2023) investigate the impact of toxic emissions intensity within industries, showcasing that the portfolio premium could not be explained by traditional factors, sentiment, political connections, or corporate governance, emphasizing the unique role of toxic emissions in stock returns. These studies all suggest that green assets characterized by lower carbon emissions generate climate risk premiums, and outperform brown assets especially when there are emission-related policy shocks.

Another branch of study declares that investors are already demanding compensation for carbon emission risk, hence brown assets are associated with higher expected returns. Notably, studies like Bolton and Kacperczyk (2021b) and Aswani et al. (2023) have found that firms with high CO2 emissions tend to yield higher stock returns, showcasing the influence of carbon emission on investment choices for institutional investors. Baker et al. (2018) delve into the world of green bonds, which are used for environmentally sensitive purposes, and find that green bonds are issued at a premium compared to otherwise similar ordinary bonds, highlighting investor demand for environmentally responsible investments. Meanwhile, Zerbib (2022) introduce the concept of exclusion premia, encompassing sin stocks, to elucidate the relationship between ESG factors and financial performance. They found that exclusion effects amounted to 2.79% annually, with taste effects varying from -1.12% to 0.14%. Moreover, Chava (2014) analyize the impact of a firm's environmental profile on its cost of equity and debt capital, discovering that investors demand significantly higher expected returns on stocks excluded by environmental screens compared to firms without such concerns. These excluded firms also exhibited lower institutional ownership and fewer banks participating in their loan syndicates. Additionally, Bolton and Kacperczyk (2021a) estimate the market-based premium associated with carbon risk at the firm level across 77 countries, uncovering a widespread carbon premium characterized by higher stock returns for companies with higher levels of carbon emissions. Lastly, Görgen et al. (2020) find that brown firms tend to yield higher average returns, while decreases in the greenness of firms were associated with lower announcement returns. However, when they construct a carbon risk factor-mimicking portfolio, they do not find evidence of a carbon risk premium, emphasizing the complexity of the relationship between carbon risk and investment returns.

In response to the significant divergence between two contradictory branches of existing literature, this study adopts a comprehensive approach encompassing aggregated portfolio analysis and firm-level investigations. By bridging the gap and synthesizing findings from both approaches, we aim to provide a more holistic and nuanced understanding of the relationship between stocks' greenness, measured by their carbon emissions, and their corresponding stock returns.

2 Methodology

The current literature presents seemingly contradictory findings regarding the relationship between a firm's environmental practices and its stock performance. Conventional theoretical studies typically associate higher risk exposure with increased return compensation. Bolton and Kacperczyk (2021b) use firm-level data and find a positive correlation between a firm's carbon emissions and its stock returns, indicating that brown assets outperform green ones. They argue that investors demand higher returns as compensation for climate-related risks aligning with the theoretical perspectives. In contrast, Pástor et al. (2021) develop a new theoretical model suggesting that environmentally friendly assets typically yield higher returns, in the face of unexpected climate change concerns. This model is further supported by empirical evidence from Pástor et al. (2022), who find that in the U.S. stock market, portfolios with higher Environmental, Social, and Governance (ESG) scores (green portfolios) outperform those with lower ESG scores (grown portfolios). A similar trend is observed with German green bonds outperforming their brown counterparts. This paper aims to reconcile these seemingly contradictory findings from existing literature. The methodologies used in this empirical study are introduced in this section.

2.1 Quantify Firms' Environmental Practices

To quantify firms' environmental practices, there are two major indicators in the existing literature. The first one involves utilizing ESG scores provided by third-party rating agencies, such as Bloomberg, Thomson Reuters, and MSCI ESG Ratings etc. However, the diversity of rating agencies and their differing methodologies often lead to variations in the final ESG scores for the same company. This inconsistency can introduce what is known as ESG uncertainty. Avramov et al. (2022) demonstrate that this ESG uncertainty can result in increased CAPM alpha and effective beta, as well as investment outflows from stocks exhibiting high ESG uncertainty. Additionally, ESG scores are susceptible to influences that may not directly relate to a firm's environmental performance. For instance, larger corporations often have greater resources for managing their public image and ESG reporting, potentially resulting in inflated scores (known as "greenwash") that may not accurately reflect their environmental practices, especially in comparison to smaller companies.

The second indicator for quantifying firms' environmental practices involves direct measurements of specific environmental metrics, such as carbon emissions, water usage, and waste production. This method offers a more objective and quantifiable approach, independent of the subjective assessments of third-party ESG ratings. In this paper, we focus on carbon emissions as a key metric for assessing firms' environmental practices. Carbon emissions are a significant contributor to climate change and their reporting has become increasingly mandated by regulatory bodies in recent years, providing a more consistent and standardized data set for analysis. Additionally, this paper considers carbon intensity - a metric that relates a firm's carbon emissions to its revenue. Carbon intensity measures the efficiency with which a firm generates revenue relative to the Greenhouse Gases (GHG) it emits, as highlighted by Ilhan et al. (2021).

2.2 Aggregate Portfolio Analysis

Comparing firms' carbon emissions directly across different industries can be misleading. Becaue different industries have their their unique operational requirements and regulatory environments. For instance, the high emissions in the energy sector, particularly from fossil fuels, cannot be directly compared with the lower emissions of the technology or service sectors. Therefore, in this paper we take a more accurate assessment by comparing emissions within the same industry, allowing for fair benchmarking against industry-specific standards and regulations. This approach highlights companies leading in sustainability and green practices relative to their peers and it could provide a more realistic view of each company's efforts to reduce emissions. It can be expressed in the following equation:

$$Greenness_{i,t} = \mathbb{E}[Ranki, t | CO2\ Emissions_{i,t}, Industry_i] \quad (1)$$

In Equation 1, we measure company i's sustainable practices at time t within industry, based on its carbon emission. Essentially, this method accounts for the heterogeneity between industries, offering a more nuanced understanding of environmental impacts and sustainability efforts. Utilizing this methods, we categorize stocks into quintiles at a monthly basis and create value weighted portfolios for each quintiles. Stocks in the lowest quintile construct "Green" portfolio characterized by low carbon emission. Conversely, portfolios formulated by stocks from the top and middile quintiles are defined as "Brown" and "Netural", respectively. We also build a "Green-Brown" portfolios by long the lowest quintiles and short the top quintiles.

2.3 Individual Stock Analysis

For the analysis of individual stocks, we directly examine the relationship between a firm's carbon emissions and its stock returns. We utilize the two-way fixed effects (TWFE) panel regression in our benchmark regression to investigate this relationship. The specific regression model, expressed in Equation 2, assesses the impact of carbon emissions on stock returns:

$$RET_{i,t} = \alpha + \beta^{co2} * \log(co2\, emission_{i,t}) + \beta^{contr} * Controls_{i,t} + \epsilon_{i,t} \tag{2}$$

Here, the subscript i refers to a specific company, and t indicates a specific month. $RET_{i,t}$ represents the return of stock i in month t. The term α is the cross-sectional intercept, while β^{co2} is the coefficient on firms' carbon emissions. The logarithmic normalized carbon emissions are expressed as $\log(co2\, emission_{i,t})$. The vector β^{contr} comprises coefficients for a series of control variables. Lastly, $\epsilon_{i,t}$ denotes the idiosyncratic error term. The parameter of interest is β^{co2}, which presents the relationship between carbon emissions and firms' stock returns. A significant positive β^{co2} demonstrantes empirical evidence that higher carbon emission associate higher stock return which algin with the classic asset pricing framework that higher risk exposure associate with higher return compensation.

2.4 Preference Shift Quantified by UMC

To understand the discrepancy between recent empirical studies and classic asset pricing theory, we propose the explaination based on the sduties of Koijen and Yogo (2019) and Pástor et al. (2021). Classic asset pricing theory states that higher risk should correspond with higher returns. However, this principle could be overthrown by the preference shift in the financial market. Two primary factors contribute to this change: firstly, the desire to hedge against climate change-related risks, and secondly, the increasing trend of sustainable investing mandates, especially among institutional investors. This shift in preference leads to an increased demand for green assets and divestment from brown ones. Given the high price elasticity in asset demand, as discussed by Gabaix and Koijen (2021) and Hartzmark and Solomon (2022), even a modest rise in demand can significantly elevate asset prices, thereby resulting in higher realized returns. We use unexpected media climate change concern index to quantify this preference shift in the financial market as proposed by Ardia et al. (2022).

To empirically test this hypothesis, we employ a multivariate linear regression model that controls for other factors influencing portfolio returns. We specifically regress the returns of "Green-Brown," "Green," "Brown," and "Neutral" portfolios against the (UMC_t) as stated in Equation 3:

$$RET_{p,t} = \alpha_p + \beta_p^{UMC} * UMC_t + \beta_p^{contr} * Controls_t + \epsilon_{p,t} \tag{3}$$

In this model, $RET_{p,t}$ represent the return of portfolio p, at time t. The intercept is denoted as α_p, while β_p^{UMC} is the coefficient for UMC index, β_p^{contr} presents a vector of coefficients corresponding to a series of control factors, and $\epsilon_{p,tabular}$ is the idiosyncratic error term. The UMC_t index quantifies unexpected media climate change concerns, derived from news about climate change in widely circulated U.S. newspapers. An increase in this index suggests heightened concerns about climate change, which is expected to trigger a shift in investor preferences towards green assets.

Similar to our aggregate portfolio analysis, it is equally interesting to investigate the impact of UMC at the individual stock level, particularly how the interaction between a firm's carbon emissions and UMC influences the firm's stock returns. To assess this, we employ a firm fixed-effect panel regression model as follows:

$$
\begin{aligned}
RET_{i,t} = \alpha + \beta^{co2} * \log(co2\,emission_{i,t}) + \beta^{umc} * UMC \\
+ \beta^{*} * (log(co2\,emission_{i,t}) * UMC_t) \\
+ \beta^{contr} * Controls_{i,t} + \epsilon_{i,t}
\end{aligned}
\tag{4}
$$

Different from Equation 2, we include UMC_t and the interaction between $log(co2emission_{i,t})$ and UMC_t in Equation 4. The key coefficient, β^{*}, is of particular interest as it determines whether UMC amplifies or diminishes the link between a firm's carbon emissions and its stock returns. The relationship is detailed in Equation 5. If β^{co2} and β^{umc} are both positive, high unexpected climate change concerns could lead to even higher returns for brown stocks to compensate for increased risk exposure. Conversely, if β^{co2} and β^{umc} both have negative signs, the green stocks will realize even higher returns. If $\beta^{co2}$and β^{umc} have opposite signs, the impact of unexpected climate change concerns on the relationship between carbon emissions and stock returns could be mitigated.

$$
\frac{\partial RETi,t}{\partial log(co2\,emission_{i,t})} = \beta^{co2} + \beta^{umc} * UMC_t \tag{5}
$$

3 Data

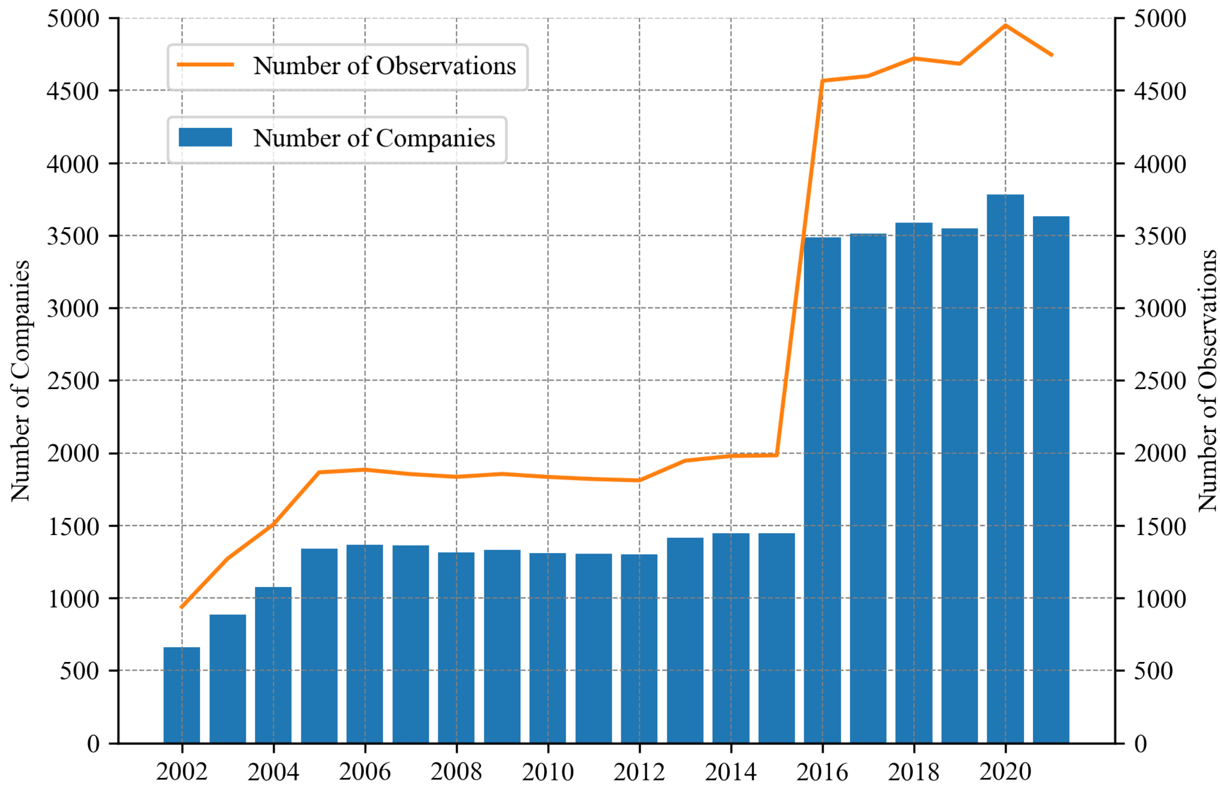
This study exclusively examines publicly traded companies in the U.S. stock market from 2002 to 2021. Our dataset merges carbon emission data from Trucost, financial accounting information from Compustat, and stock return figures from CRSP (The Center for Research in Security Prices), with the CUSIP-PERMNO linkage table serving as the connector. Trucost's dataset offers insights into the environmental impacts of various business activities and evaluates risks associated with a wide array of environmental issues. These include carbon and other pollutants, water dependency, natural resource efficiency, and waste management.

The data from Trucost includes both raw and calculated values at both the company and sector levels. Following the approach of Aswani et al. (2023), we opt for the calculated carbon emission data, considering its comprehensiveness and relevance to stock returns. The merged dataset comprises 5,250 companies, totaling 526,393 observations. As illustrated in Figure 1, the graph displays the annual count of both companies and observations. Notably, the carbon emission data collection began in 2002 with limited coverage. However, since 2016, there was a substantial surge in the number of companies included in the dataset, for the coverage for samll- amd mid-cap companies starts from 2016. This remarkable expansion algin with the assignement of various international agreements during this period, such as the *Addis Ababa Action Agenda* (AAAA), the *Sendai Framework for Disaster Risk Reduction 2015-2030* (SFDRR), and *The Paris Agreement on Climate Change*. These agreements, as discussed by Engberg-Pedersen (2021), Kelman (2015), and Dimitrov (2016), have played an important role in addressing global climate challenges, emphasizing the importance of sustainable development and initiatives targeting climate change.

3.1 Variable definition and summary statistics

We provide explanations for key variables outlined in Table 1. The stock return data incorporates stocks' capital gains and dividends, observed monthly. The companies' total carbon emission data is the sum of all 3 scopes of emissions collected by Trucost follwo the Greenhouse Gas Protocol: Scope 1 entails direct greenhouse gas emissions, Scope 2 covers indirect emissions from purchased energy consumption, and Scope 3 encompasses a wider range of upstream and downstream indirect emissions. While, carbon intensity is calculated as the ratio of carbon emissions to revenue (tons/million(USD)), indicating how effectively a company utilizes its carbon emissions to generate revenue. Control variables in this analysis encapsulate fundamental financial conditions, which have been substantiated as pertinent factors influencing stock returns through extensive literature such as Perez-Quiros and Timmermann (2000), George and Hwang (2010), and Lamont (2000). The size is a firm's market

Figure 1: **Number of Firms and Observations**



This graphic plots the number of firms and observations across the whole sample period.

capitalization in logarithmic form, serving as a measure of its economic scale; leverage, which quantifies a firm's financial structure risk by assessing the ratio of total liability to market capitalization; B/M (Book-to-Market Ratio) indicating the difference between firms' book value and market valuation; RoE (Return on Equity) capturing firms' profitability through the return generated on shareholders' equity; Invest/AT (Investment to Total Assets) reflecting firms' innovation efforts by scaling investment with total assets; PPE (Property, Plant, and Equipment) measuring their fixed assets; SaleGR (Sales Growth) gauging revenue growth; EPS (Earnings Per Share) as another indicator of profitability; Staff_num, the number of employees presented in logarithmic form; and Firm_age, representing the firm's age since its foundation. These variables collectively provide insights into various financial, operational, and growth aspects that are pertinent to our analysis of the interplay between environmental factors and stock returns.

Table 1: **Variable Definition**

Variables	Definition
RET	Monthly stock return
Co2_tot	Total carbon emissions (log)
Co2_int	Carbon intensity
Size	Total market capitalization (log)
Leverage	Total liability over market capitalization
B/M	Book to market ratio
RoE	Return on equity
Inves/AT	Investment over total assets
PPE	Property, plant, and equipment (log)
SaleGR	Growth in revenue
EPS	Earning per share
Staff_num	Number of employees (log)
Firm_age	Firm age since foundation

This table presents the definition of variables used in our analysis.

Table 2 provides a summary of the statistical characteristics for the majority of variables used in this study. To mitigate the potential impact of outliers, we have applied winsorization to some of the variables at 1% thresholds. This process involves capping extreme values to ensure that the dataset maintains a reasonable balance between standard deviation and mean values. Within the entire dataset, the monthly stock returns in the dataset ranged from -92% to 1625%, with an average of 1% and a standard deviation of 15%. Following winsorization at the 1% level, the mean and median remained unchanged, but the standard deviation decreased to 10%, at the cost of the exclusion of 10,526 observations. Additionally, we scale certain variables using natural logarithms. For instance, firms' total carbon emissions had an average of 5 million tons and a maximum of 400 million tons. After logarithmic transformation, the mean and standard deviation are reduced to 12.75 and 2.66, respectively. Detailed summary statistics for these variables, both before and after manipulation, are available in Table 2.

In Table 3, we report the pairwise Pearson correlations among all the independent variables. Notably, two carbon footprint indicators, namely total carbon emissions and emission intensity, exhibit a positive correlation. However, the correlation coefficient of 0.63 suggests some divergence between these two indicators. Firms' size demonstrates a strong positive correlation with total carbon emissions, with a coefficient of 0.66. This implies that larger firms tend to have higher total carbon emissions. Conversely, the correlation between firm size and carbon intensity is only 0.09, indicating a lack of a strong relationship between firm size and its carbon intensity. This highlights that larger firms may have varying levels of carbon intensity, with some large firms exhibiting low carbon intensity. The highest correlations are observed between PPE (Property, Plant, and Equipment) and carbon emissions, PPE and firm size, Staff_num (number of employees) and total carbon emissions, and Staff_num and firm size. In each of these cases, the correlation coefficient exceeds 0.6 in absolute value, signifying that firms with more PPE and a greater number of employees tend to be larger firms with higher carbon emissions. Nevertheless, these correlations do not indicate a strong association with carbon intensity, emphasizing that the relationship between firm characteristics and carbon intensity is not as pronounced.

Table 2: **Summary Statistics**

	Before Data Manipulation						Methods	After Data Manipulation					
	Count	Mean	STD	Min	50%	Max		Count	Mean	STD	Min	50%	Max
RET	526393	0.01	0.15	-0.92	0.01	16.25	1% winsorize	515865	0.01	0.10	-0.33	0.01	0.42
Co2_tot	526393	5427269.05	21710453.29	0.27	401873.63	414448413.32	Logarithmic	526393	12.75	2.66	0.24	12.90	19.84
Intensity_tot	526393	485.55	1315.78	20.43	148.24	89986.84	Logarithmic	526393	5.18	1.26	3.06	5.01	11.41
Marketcap(Size)	522812	320587.46	13798803.05	0.01	3666.73	998732337.99	Logarithmic	522812	8.21	1.81	0.01	8.21	20.72
Levarage	522175	0.61	0.27	0	0.61	6.92	-	522175	0.61	0.27	0	0.61	6.92
B/M	521618	5.21	937.08	-4127.45	0.44	274698.31	1% winsorize	511184	0.53	0.43	-0.54	0.44	3.01
RoE	521900	-1.38	215.97	-31837	0.10	388.70	1% winsorize	511472	0.06	0.40	-3.20	0.10	2.77
Inves/AT	520278	0.04	0.05	-0.19	0.03	0.87	-	520278	0.04	0.05	-0.19	0.03	0.87
PPE	459439	10593.65	35443.50	0	1416.10	635149.06	Logarithmic	459439	7.07	2.42	0	7.26	13.36
SaleGR	467731	1.75	96.71	-1	0.06	9945	1% winsorize	458396	0.10	0.29	-0.64	0.06	2.60
EPS	522856	5.75	151.89	-998.26	1.44	8548	1% winsorize	512453	1.75	3.02	-9.78	1.44	18.27
Staff_num	515253	26.59	72.31	0	6.10	2300	Logarithmic	515253	2.11	1.49	0	1.96	7.74
Firm_age	513763	70.56	52.56	2	54	657	Logarithmic	513763	3.99	0.79	1.10	4.01	6.49

The table presents summary statistics for the main variables across the entire sample period, with definitions provided in Table 1. In line with conventional regression analysis practices, appropriate data manipulation methods have been applied to scale certain variables and exclude outliers.

Table 3: **Control Variables' Pearson Correlation**

	Co2_tot	Intensity_tot	Size	Levarage	B/M	RoE	Inves/AT	PPE	SaleGR	EPS	Staff_num	Firm_age
Co2_tot	1.0***	0.63***	0.66***	0.09***	0.02***	0.22***	0.24***	0.85***	-0.1***	0.3***	0.72***	0.38***
Intensity_tot		1.0***	0.08***	-0.13***	-0.0**	0.01***	0.37***	0.44***	-0.04***	-0.0	0.13***	0.1***
Size			1.0***	0.02***	-0.21***	0.23***	0.05***	0.68***	0.01***	0.39***	0.69***	0.3***
Levarage				1.0***	-0.06***	0.06***	-0.08***	0.18***	-0.09***	0.03***	0.15***	0.2***
B/M					1.0***	-0.09***	-0.04***	0.11***	-0.12***	-0.06***	-0.05***	0.04***
RoE						1.0***	0.03***	0.18***	0.03***	0.39***	0.19***	0.17***
Inves/AT							1.0***	0.33***	0.07***	0.01***	0.05***	-0.04***
PPE								1.0***	-0.13***	0.27***	0.71***	0.39***
SaleGR									1.0***	0.05***	-0.11***	-0.16***
EPS										1.0***	0.29***	0.25***
Staff_num											1.0***	0.4***
Firm_age												1.0***

* p<.1, ** p<.05, *** p<.01

This table reports the pairwise Pearson correlations among all the control variables and firms' carbon footprint variables. * means significance at 10%, ** at 5%, *** at 1%.

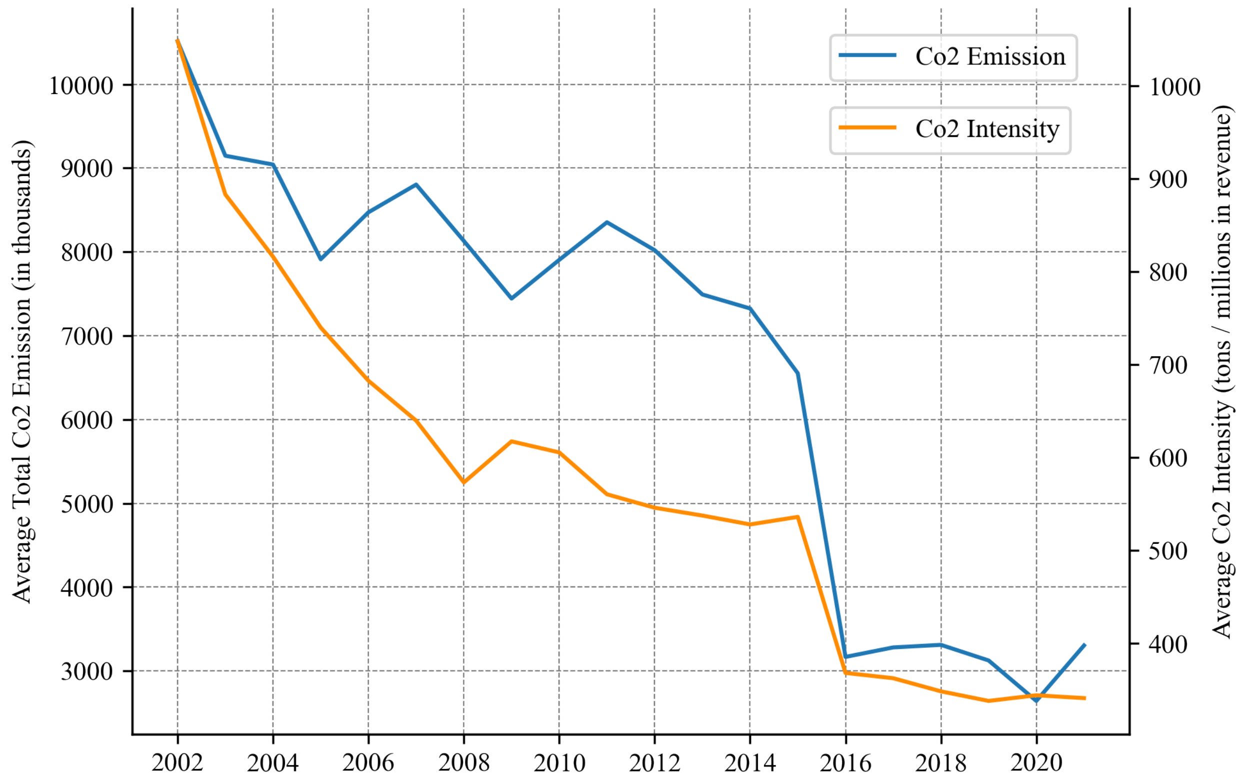
3.2 Carbon Emissions & Intensity

In the current corporate finance literature there are two important indicators quantifying firms' carbon footprints. Alongside firms' total carbon emissions, carbon intensity emerges as a critical metric for evaluating their environmental sustainability. Carbon intensity precisely measures the rate of emissions of a specific pollutant concerning the scale of firms' production activities. In our study, we employ carbon intensity, calculated as firms' total carbon emissions normalized by their revenue, as a means to assess their emission efficiency. Figure 2 illustrates the historical trajectory of firms' carbon footprints, as represented by both of total carbon emissions and carbon intensity. Across the entire sampling period, we observe a consistent downward trend in both metrics for measuring firms' carbon footprint. Notably, a substantial decline is evident in the year 2016 for both total carbon emissions and intensity. This reduction can primarily be attributed to the expanded data coverage of the TRUCOST database in that year, encompassing a broader spectrum of small and medium-sized companies. The overarching decline in both carbon emissions and intensity, except for the significant drop in 2016, underscores the collective endeavor towards greener practices by companies. Furthermore, it reflects the tangible impact of effective green policies on shaping firms' environmental behavior and fostering environmentally conscious practices.

3.3 Total Carbon Emissions in Different Industries

Table 4 provides a ranking of industries according to their average total carbon emissions over the period from 2002 to 2021. Notably, the industries with the most substantial average carbon emissions are Power and Renewable Electricity Productions, which exhibit an annual average of approximately 38.15 million tons. Electric Utilities and Oil, Gas, and Automobiles sectors secure the second and third positions, emitting around 37.46 million and 30.04 million tons of CO_2 on average during the entire sampling period, respectively. These sectors are renowned for their notable environmental impacts due to the higher levels of carbon emissions they generate. On the contrary, industries with the least average carbon

Figure 2: **Carbon Emissions & Intensity**



This graphic illustrates the historical trajectory of firms' total carbon emissions and intensity on average. Firms' total carbon emissions are measured in thousand tons, while intensity is quantified by tons of CO2 emitted per million US dollars of revenue. Both trajectories represent the mean value in each specific year.

emissions encompass Industrial REITs, Health Care Technology, and Mortgage Real Estate Investment Trusts (REITs) sectors, showcasing relatively smaller environmental footprints based on their total carbon emissions. Taking into account the entire sampling period and a comprehensive range of industries, the average greenhouse gas emissions stand at 5.43 million tons. Strikingly, the most environmentally impactful sector, exemplified by Independent Power and Renewable Electricity Productions, demonstrates total carbon emissions that are nearly 8 times higher than the average. In contrast, the most environmentally friendly industry, like Health Care Technology and Mortgage Real Estate Investment Trusts (REITs) sectors, emit only approximately 1/100th of the average emissions. This highlights a substantial diversity across industries concerning their total carbon emissions, underlining the significant heterogeneity in their environmental impacts.

Table 4: Industries Ranked by Average Total CO2 Emission

Rank	GICS Industry Name	Total CO2 Emission	Rank	GICS Industry Name	Total CO2 Emission
1	Power and Renewable Electricity Producers	38.15	38	Electronic Equipment, Instruments and Components	1.23
2	Electric Utilities	37.46	39	Semiconductors and Semiconductor Equipment	1.11
3	Automobiles	30.04	40	Specialty Retail	1.09
4	Oil, Gas and Consumable Fuels	28.28	41	Textiles, Apparel and Luxury Goods	1.08
5	Multi-Utilities	21.05	42	Construction and Engineering	1.07
6	Passenger Airlines	16.34	43	Marine Transportation	1.05
7	Construction Materials	16.25	44	Communications Equipment	1.01
8	Industrial Conglomerates	14.31	45	Health Care Equipment and Supplies	0.93
9	Metals and Mining	13.48	46	Trading Companies and Distributors	0.86
10	Food Products	12.75	47	Leisure Products	0.86
11	Financial Services	10.05	48	Specialized REITs	0.82
12	Chemicals	9.66	49	IT Services	0.78
13	Personal Care Products	9.11	50	Interactive Media and Services	0.71
14	Consumer Staples Distribution and Retail	7.62	51	Distributors	0.70
15	Household Products	7.48	52	Life Sciences Tools and Services	0.63
16	Tobacco	7.22	53	Entertainment	0.61
17	Aerospace and Defense	6.28	54	Media	0.56
18	Air Freight and Logistics	6.26	55	Capital Markets	0.45
19	Containers and Packaging	6.25	56	Insurance	0.40
20	Beverages	5.90	57	Transportation Infrastructure	0.36
21	Paper and Forest Products	3.88	58	Water Utilities	0.31
22	Technology Hardware, Storage and Peripherals	3.80	59	Diversified Consumer Services	0.29
23	Automobile Components	3.72	60	Banks	0.26
24	Building Products	2.90	61	Professional Services	0.23
25	Ground Transportation	2.64	62	Software	0.21
26	Household Durables	2.59	63	Consumer Finance	0.21
27	Machinery	2.37	64	Hotel and Resort REITs	0.20
28	Diversified Telecommunication Services	2.15	65	Real Estate Management and Development	0.18
29	Energy Equipment and Services	2.07	66	Health Care REITs	0.17
30	Broadline Retail	2.07	67	Office REITs	0.13
31	Wireless Telecommunication Services	2.05	68	Biotechnology	0.11
32	Health Care Providers and Services	2.00	69	Retail REITs	0.11
33	Pharmaceuticals	1.91	70	Diversified REITs	0.11
34	Gas Utilities	1.87	71	Residential REITs	0.09
35	Electrical Equipment	1.40	72	Industrial REITs	0.06
36	Commercial Services and Supplies	1.38	73	Health Care Technology	0.06
37	Hotels, Restaurants and Leisure	1.31	74	Mortgage Real Estate Investment Trusts (REITs)	0.03

This table presents the ranking of different industries based on their average total CO2 emissions. The measurements for total CO2 emissions are provided in million tons. And the industry is categorized according to the GICS (Global Industry Classification Standard) industry classification.

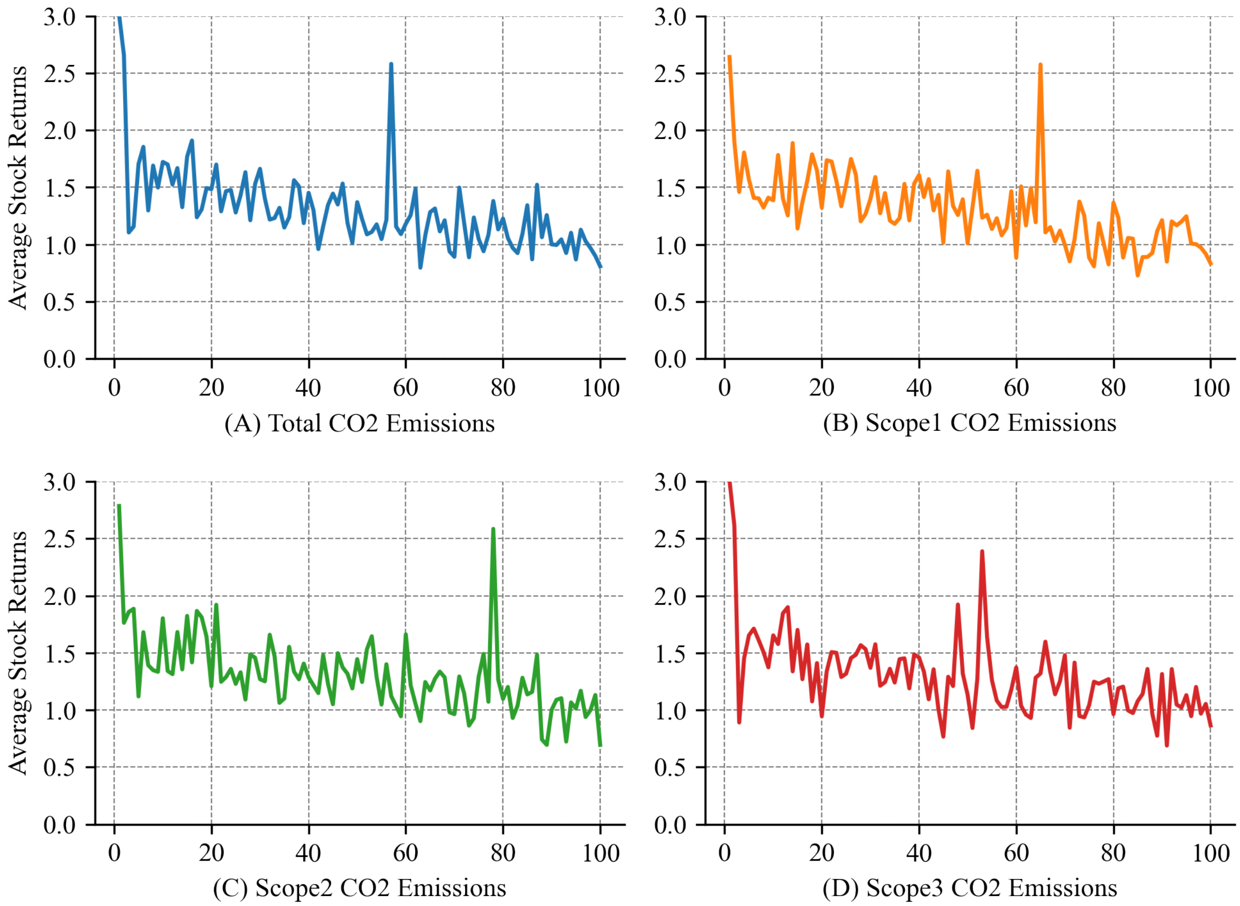
4 Result

The primary goal of this paper is to explore the relationship between firms' carbon emissions and their stock returns. Our approach is structured in several steps. Firstly, in Section 4.1, we conduct a preliminary analysis to examine the unconditional relationship between firms' carbon emissions and stock returns. Next, in Section 4.2, we delve into portfolio analysis. The third step, detailed in Section 4.3, involves presenting firm-level evidence. Finally, in Section 4.4, we attempt to resolve the contradictions observed in the empirical analysis vis-à-vis traditional asset pricing theory.

4.1 Average Monthly Return on Firms' Carbon Footprint

Our first practice delves into the unconditional relationship between firms' carbon footprint and their stock returns. Over the entire sample period, we adopt a cross-sectional approach, sorting carbon emissions into 100 percentiles. Within each percentile, we compute the average monthly stock returns to gain an overarching understanding of the link between firms' carbon emissions and their stock performance. Figure 3 visually presents these findings. Panel A focuses on the average stock returns concerning firms' total carbon emissions, while panels B, C, and D examine emissions within different emission scopes. Across all four panels, a distinguished downward trend emerges, indicating that firms with higher carbon emissions tend to exhibit lower stock returns on average. Additionally, we observe peaks in average stock returns occurring when firms' carbon emissions fall around the 1st percentile for all scopes. Another set of peaks in average returns is notable for different emissions categories, such as total carbon emissions around the 58th percentile, scope 1 emissions near the 65th percentile, scope 2 emissions at approximately the 79th percentile, and scope 3 emissions around the 55st percentile. These clusters of companies may share common characteristics, possibly belonging to the same industry, with similarities in terms of size, profitability, and growth. It's important to note that in this analysis, we specifically sort firms based on their carbon emissions only, without considering other stock return-related factors. Nevertheless, these initial findings provide valuable insights into the preliminary relationship between firms' carbon emissions and their realized stock returns.

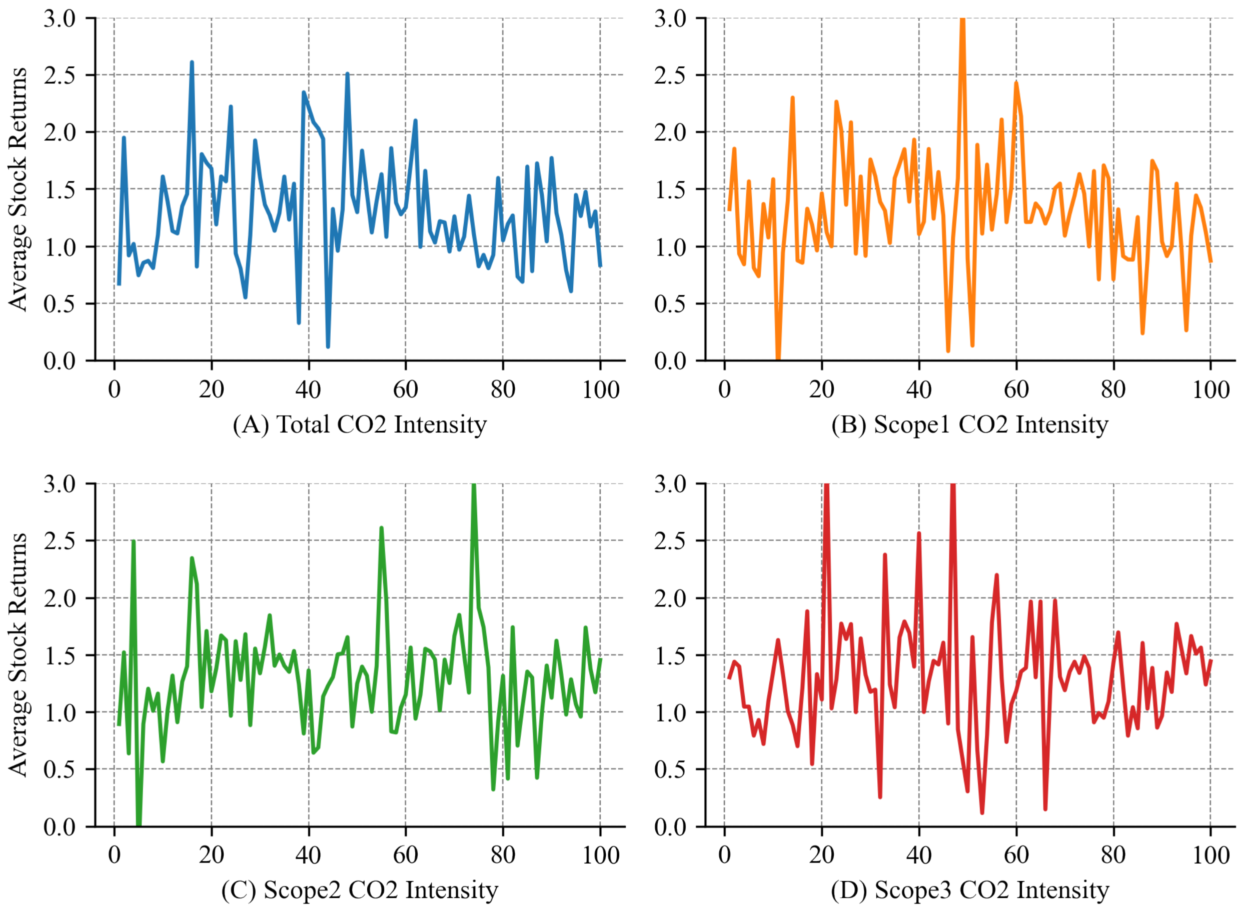
Figure 3: **Average Stock Returns Based on Carbon Emissions**



This presents the average monthly stock returns in relation to different percentiles of carbon emissions. Panel A depicts the average stock return in relation to firms' total carbon emissions, while Panel B illustrates the average stock return concerning firms' scope 1 carbon emissions. Panel C showcases the average stock return with respect to firms' scope 2 carbon emissions, and Panel D presents the average stock return in connection with firms' scope 3 carbon emissions.

Following the same analytical approach, we explore whether a similar pattern emerges with another crucial indicator in corporate finance literature pertaining to firms' carbon footprint. Figure 4 illustrates the average monthly stock returns across different percentiles of firms' carbon intensity. In contrast to the previous analysis of carbon emissions, we do not discern a clear and consistent trend in firms' average monthly stock returns across all four panels, where each representing different scopes of firms' carbon intensity. The absence of a discernible trend suggests that the relationship between firms' carbon intensity and their stock returns may not exhibit the same patterns as strongly as observed with carbon emissions.

Figure 4: **Average Stock Returns Based on Carbon Intensity**



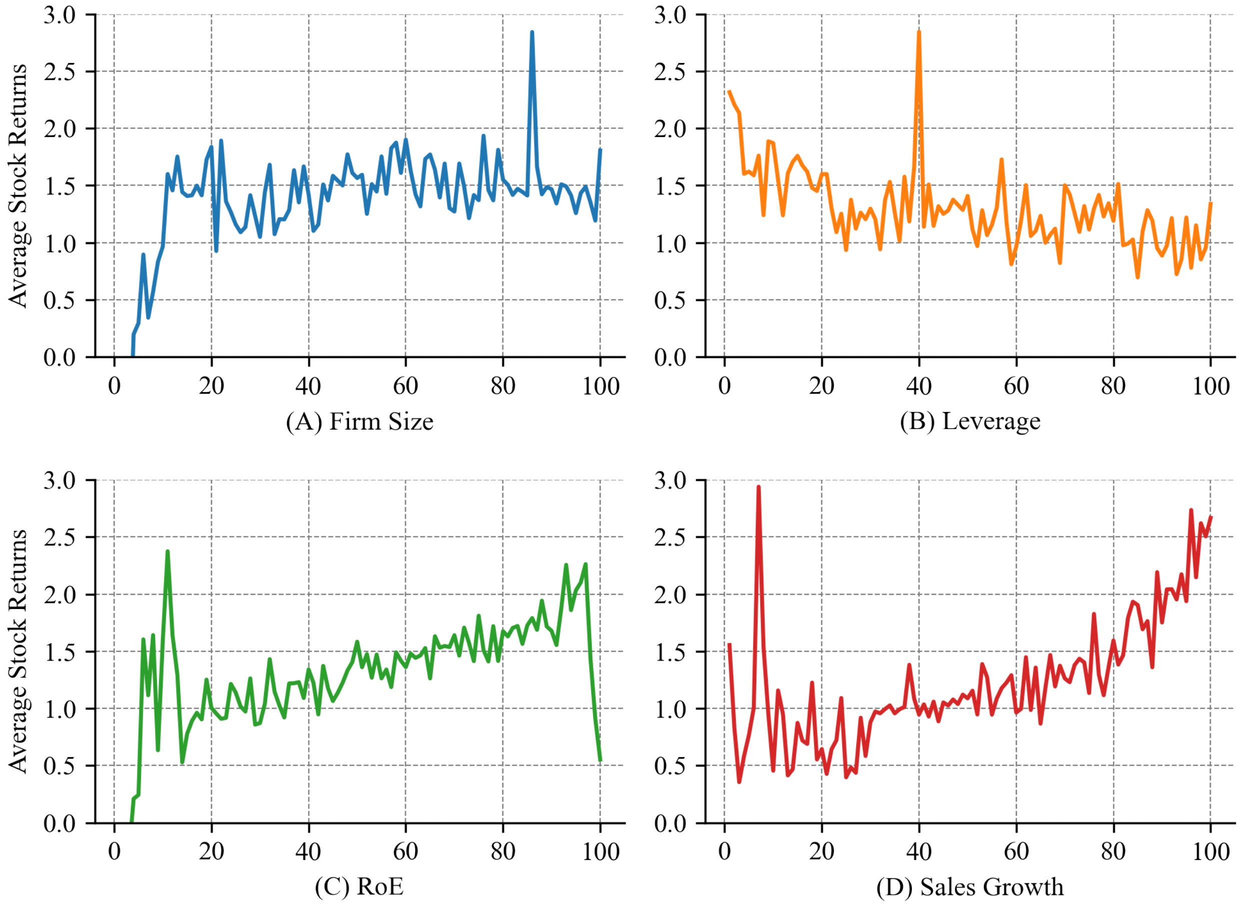
This presents the average monthly stock returns in relation to different percentiles of carbon intensity. Panel A depicts the average stock return in relation to firms' total carbon intensity, while Panel B illustrates the average stock return concerning firms' scope 1 carbon intensity. Panel C showcases the average stock return with respect to firms' scope 2 carbon intensity, and Panel D presents the average stock return in connection with firms' scope 3 carbon intensity.

Similar patterns are not observed when plotting other key firm characteristics alongside stock returns. Some may raise concerns that the cross-sectional relationship between firms' stock returns and carbon emissions could be influenced by confounding factors such as firm size, leverage, profitability, and growth, as illustrated in Table 3 the strong correlation between firms' carbon emissions and some characteristic variables. Notably, the high and statistically significant positive correlation between firms' carbon emissions and size. To address these concerns, we present the average monthly stock returns in relation to various firms' characteristics in Figure 5. In panel (A), we observe a positive association between firm size and stock returns within the first 20 percentiles; however, beyond this range, the relationship becomes less apparent. It is important to remember that firm size has a high correlation with carbon emissions. The most similar pattern emerges from the plot between leverage and stock return, however the correlation between leverage and carbon emission only is 0.09. While other patterns emerge in stock returns concerning variables like RoE and revenue growth, it's essential to note that these variables exhibit weak correlations with firms' carbon emissions.

4.2 Realized Cumulative Return for Green and Brown Portfolios

The green portfolio outperforms its brown counterpart over the entire sample period, with firm total carbon emissions determining their categorization. Following the methodology presented in Equation 1, we sort stocks into quintiles monthly based on their industry-specific carbon emissions. Generally, firms with higher emissions, categorized as brown, are those exceeding the 80th percentile in carbon emissions due to their significant environmental impact. Conversely, firms below the 20th percentile are assigned to the green portfolio. Those between the 40th and 60th percentiles are placed in the neutral portfolio. Firms falling between the 20th and 40th percentiles, as well as those between the 60th and 80th, are excluded for a clearer comparison. The green portfolio demonstrates superior cumulative realized returns, as depicted in Figures 6 for the period from 2002 to 2021. Each portfolio is value-weighted based on the market capitalization of the included firms to ensure fairness

Figure 5: **Average Stock Returns Based on Other Indicators**

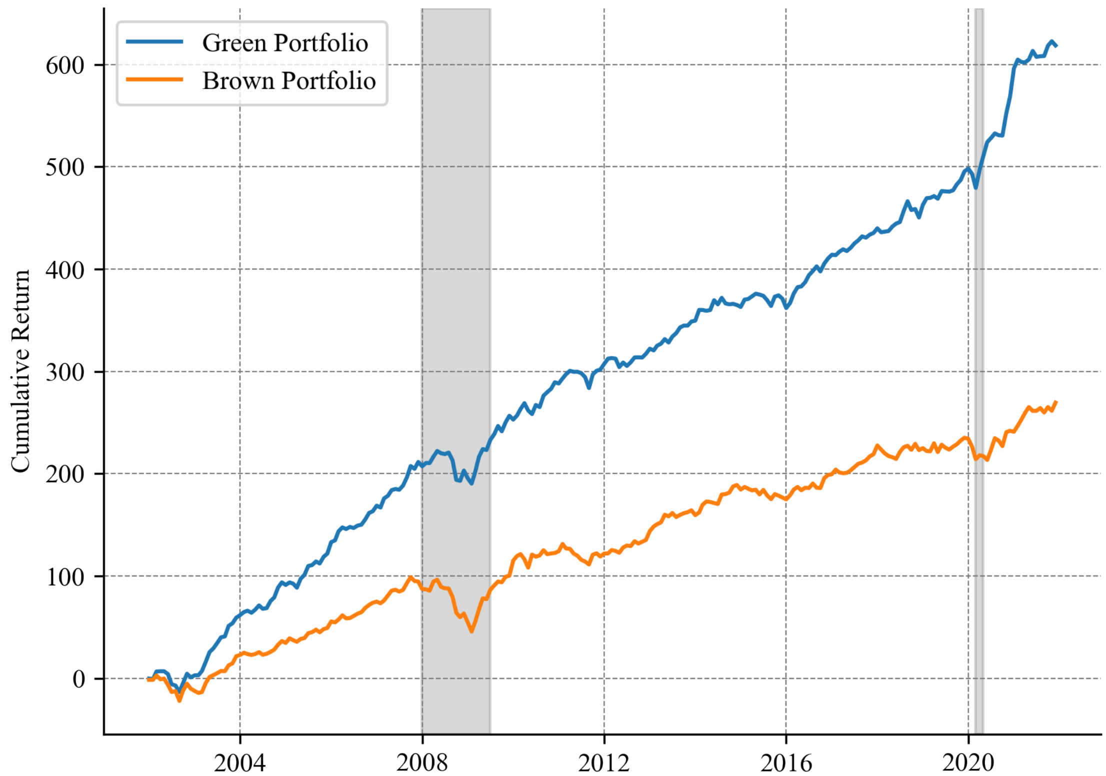


This presents the average monthly stock returns in relation to different percentiles of various firms' characteristic indicators. Panel A depicts the average stock return in relation to firms' market capitalization, while Panel B illustrates the average stock return concerning firms' leverage. Panel C showcases the average stock return with respect to firms' profitability ROE, and Panel D presents the average stock return in connection with firms' growth in revenue.

and accuracy[3]. Notably, portfolio reallocation is an annual process due to the yearly update of firms' carbon emission data, allowing us to disregard transaction fees in this analysis. At the end of the sample period the brown portfolio realized less than 300% cumulative returns, while the green portfolio realized cumulative returns more than 600% twice higher its brown counterpart.

[3]In the portfolio analysis we use the data without manipulation. Since the outliers are often observed in samll-cap stocks and portfolio is value weighted, so the influence of these outliers will be minimized. And the the un-manipulated data help us aviod the critisim of data manipulation.

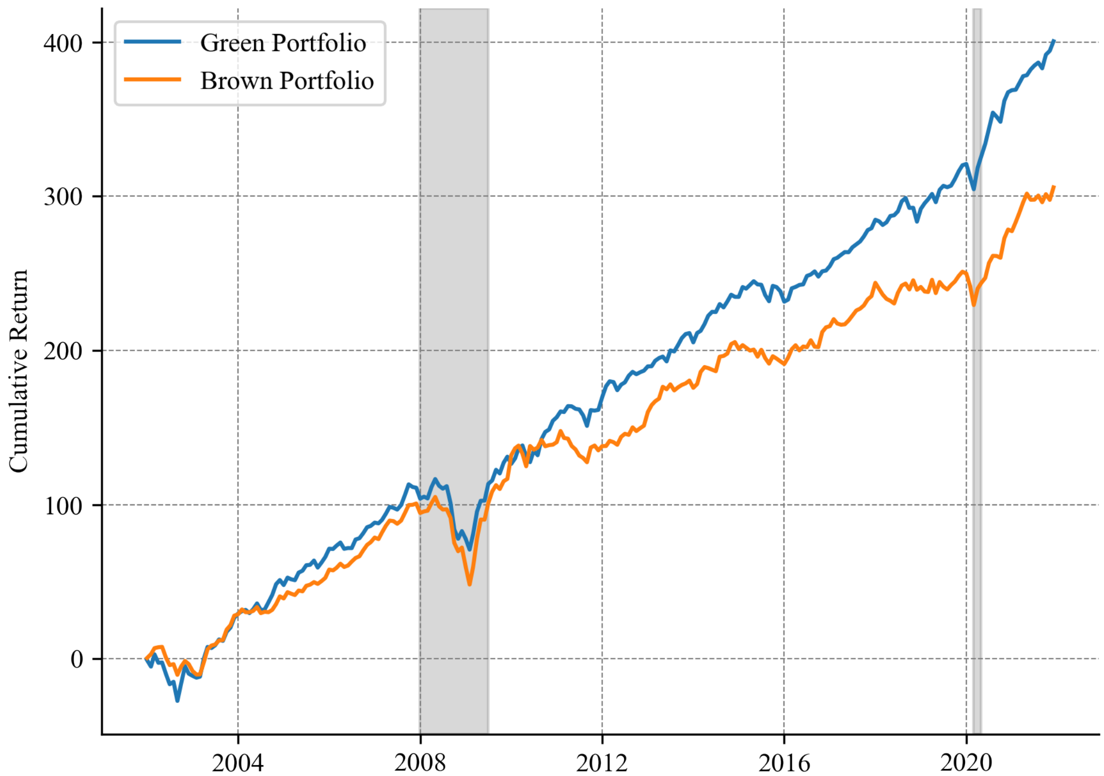
Figure 6: **Cumulative Portfolio Return by Carbon Emissions**



This graphic dispicts the cumulative return of green and brown portfolios, categorized based on firms' carbon emission. The shaded regions represent recession periods as suggested by the National Bureau of Economic Research (NBER).

The green portfolio, categorized based on firms' carbon intensity, shows only slight outperformance compared to its brown counterpart, and this outperform is observed only after 2011. Following the same methodology, we group stocks into green and brown groups based on their carbon intensity. The cumulative returns of these portfolios are presented in Figure 7. Throughout the entire sample period, the green portfolio achieves a cumulative return of approximately 400%, and its brown counterpart realizes a cumulative return around 300%. Notably, the green portfolio's outperformance is only evident post-2011; prior to this, both portfolios exhibited similar cumulative return trajectories.

Figure 7: **Cumulative Portfolio Returns by Intensity**



This graphic dispicts the cumulative return of green and brown portfolios, categorized based on firms' carbon intensity. The shaded regions represent recession periods as suggested by the NBER.

Considering carbon emissions, the green-minus-brown (GMB) portfolio, which constructed by a long position in the green portfolio and a short position in the brown, yielded a monthly return of 1.45%, statistically significant at the 1% level. Compared with Pástor et al. (2022), who used the E score from MSCI ESG scores to construct a GMB portfolio averaging a 0.65% monthly return, this result indicates that the carbon emission indicator is as good as ESG scores in quantifying a company's green practices[4]. The results are detailed in Table 5,

[4]While the GMB portfolio in this study shows a higher monthly average return, it does not necessarily imply that firms' carbon emission is a superior indicator compared to ESG scores for quantifying firms' sustainable practices. This is because the methodologies for grouping stocks into green and brown portfolios differ between the two studies.

where the first column highlights the GMB premium based on firms' overall carbon emissions. Conversely, the 4th column of Table 5 presents the GMB premium based on firms' carbon intensity. Here, the green portfolio shows a smaller outperformance of only 0.39% against the brown with a standard error of 23.4 bp. This performance is less pronounced than that observed with carbon emissions.

In columns 2, 3, and 4 of Table 5, the GMB portfolio's return is regressed on the Fama-French 3 and 5 factors models, as well as FF5 + MOM (momentum factor) + LIQ (liquidity factor), following the discussions in Fama and French (2015), Fama and French (1993), Jegadeesh and Titman (1993), and Pástor and Stambaugh (2003). The results provide consistent evidence that the strong performance of the GMB portfolio cannot be fully attributed to the return factors commonly recognized in asset pricing literature, as indicated by the economically and statistically significant intercepts. This significant alpha implies, on one hand, the effectiveness of carbon emissions in quantifying firms' sustainable practices, and on the other hand, challenges the traditional asset pricing theory that less risky green assets outperform brown ones. When constructing the GMB portfolio based on firms' carbon intensity, as shown in columns 6-8 of Table 5, we observe mixed evidence. The difference between using total carbon emissions versus carbon intensity to shape the portfolio is significant. The empirical data highlights total carbon emissions as a more robust indicator for assessing firms' greenness, contrary to the intuitive appeal of carbon intensity. This finding underscores that, as per the current data, carbon intensity does not hold a superior position as an indicator of greenness.

4.3 Firm Level Evidence

In the previous section, we constructe green and brown portfolios based on firms' total carbon emissions. Interestingly, our findings showcase the green portfolio's consistent outperformance over the brown counterpart. This observation deviates from traditional asset pricing theory. In this section, we present firm-level evidence to further illustrate the relationship

Table 5: Green - Brown Portfolios Regress on Factors

	CO2 Emission				Intensity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	1.454***	1.169***	1.181***	1.073***	0.395*	0.124	0.080	1.073***
	(0.319)	(0.268)	(0.280)	(0.298)	(0.234)	(0.209)	(0.218)	(0.298)
Mkt_RF		0.072	0.070	0.120		0.251***	0.266***	0.120
		(0.065)	(0.069)	(0.073)		(0.051)	(0.054)	(0.073)
SMB		1.092***	1.078***	1.039***		0.199**	0.200**	1.039***
		(0.113)	(0.119)	(0.119)		(0.088)	(0.092)	(0.119)
HML		-0.543***	-0.554***	-0.470***		-0.575***	-0.625***	-0.470***
		(0.100)	(0.114)	(0.119)		(0.078)	(0.089)	(0.119)
RMW			-0.045	-0.112			0.030	-0.112
			(0.138)	(0.140)			(0.107)	(0.140)
CMA			0.062	0.071			0.173	0.071
			(0.182)	(0.181)			(0.142)	(0.181)
MOM				0.178**				0.178**
				(0.076)				(0.076)
LIQ				-2.381				-2.381
				(4.143)				(4.143)
Obs	240	240	240	240	240	240	240	240
R-squared	0.000	0.327	0.327	0.343	-0.000	0.243	0.248	0.343

* p<.1, ** p<.05, *** p<.01

This table presents the regression results of the Green minus Brown portfolio on different factor models. In the left panel, the portfolio is formulated based on firms' total carbon emissions, and in the right panel, the portfolio is based on firms' carbon intensity. Columns 1 and 5 only show regression results with intercept, the rest columns show regression results with various factors model.

between firms' carbon emissions and their stock returns.

4.3.1 Benchmark Result

Based on Equation 2, the findings are presented in Table 6, showcasing the results of firm-level analysis across two different fixed effects specifications for both the restricted and unrestricted models. In our approach, we use time-fixed effects at the month level. This choice serves to mitigate the impact of temporal variations across time, including the overall economic conditions, shifts in investors' sentiments in the stock market, the evolving concern for climate change, and other unobserved time-dependent factors. Columns 1 and 2 present the outcomes of the regression analysis for the unrestricted and restricted models, respectively, both with month + industry two-way fixed effects. Notably, these techniques align with the methodologies employed by Bolton and Kacperczyk (2021b). By integrating industry-fixed effect, we effectively control for variations across distinct industries. This approach permits us to find the average correlation between firms' total carbon emissions and stock return cross-sectionally without the influence to which industry a firm belongs.

In column 1's unrestricted model, we observe a positive correlation between firms' total carbon emissions and stock returns. However, the near-zero R-squared value suggests limited explanatory power, possibly due to omitted variables. In column 2, we present the outcomes of the restricted model with a serices of control variables including, Size, leverage, B/M, Inves/AT, PP&E, SaleGR, EPS, Stuff_num, Firm_age. And we notice the positive relationship between firms' total carbon emissions and stock returns continues, albeit without statistical significance. This contrasts with Bolton and Kacperczyk (2021b), who find significant positive relationship between stock returns and various scopes of carbon emissions by excluding firms from specific industries (GIC 19, 20, 23). In our analysis, we include all firms, regardless of their industry[5]. This result algins with the classic asset pricing theory that higher risk exposure associates higher return compensation, however, this raises the question: Why does the firm-level analysis again yield results that contradict our portfolio analysis?

Fortunately, we are not the first to address this issue. Aswani et al. (2023) have warned the carbon premium should be treated cautiously and noted the high collinearity between firms' carbon emissions and factors such as firm size, production volume, and industry classification. They suggest that this collinearity could significantly bias the estimated relationship between firms' carbon emissions and stock returns. It is widely recognized that larger firms typically have higher carbon emissions, and firms with greater production or those in certain industries are likely to emit more carbon dioxide. However, industry-level fixed effects alone may not sufficiently account for this collinearity. Our solution is to adopt nonth + entity (firm) two-way fixed effects to address this issue. Different from month + industry two-way

[5]To align with their research desgin, we have applied winsorization to certain variables in our data set to mitigate the influence of outliers, a common practice in regression analysis. Detailed information about the data can be found in Table 2.

fixed effects, with month + entity fixed effects the analysis considers both time-specific variations and variations unique to individual entities (firms). By including Entity-fixed effects, we are accounting for firm-specific factors that may be constant over time but vary across different firms. This is a more stringent restriction by the assumption that investors not only distinguish industry-specific characteristics but also place a heightened emphasis on each firm's specific inherent attributes. Columns 3 and 4 in Table 6 showcase the results for un/-restricted models with this new specification.

First, it is important to note that the results remain consistent between the un-/restricted models presented in columns 3 and 4. Then, the most intriguing revelation arises from the incorporation of month + entity two-way fixed effects, leading to an astonishing sign reversal of the coefficient on carbon emissions. This change takes place under the assumption that investors place greater emphasis on each firm's intrinsic attributes rather than industry-specific characteristics. Specifically, firms with higher carbon emissions, implying increased exposure to climate risks, tend to exhibit lower stock returns on average. Importantly, this observation maintains both economic and statistical significance. And it's important to underscore that this finding aligns with the persistent outperformance of the green portfolio over the brown counterpart. Finally, given that the positive relationship between firm size and stock returns persists, concerns of collinearity between CO2 emissions and firm size in predicting stock returns, as brought up by Aswani et al. (2023) are no longer applicable. This is corroborated by Table 3, which indicates a positive correlation between firms' carbon emissions and size, however each factor have opposite correlation with stock returns.

Table 6: Firm Level Analysis

	Returns			
	(1)	(2)	(3)	(4)
CO2_tot	0.075*	0.034	-0.176**	-0.659***
	(0.040)	(0.053)	(0.090)	(0.127)
Size		0.250**		1.535***
		(0.101)		(0.197)
Levarage		-0.226		0.173
		(0.203)		(0.422)
B/M		-1.879***		-2.729***
		(0.181)		(0.276)
RoE		0.526***		0.292***
		(0.086)		(0.101)
Inves/AT		-4.447***		-12.650***
		(1.132)		(1.874)
PPE		-0.008		-0.426***
		(0.048)		(0.162)
SaleGR		0.916***		0.799***
		(0.224)		(0.237)
EPS		0.057***		0.018
		(0.022)		(0.027)
Staff_num		-0.278***		-0.835***
		(0.066)		(0.213)
Firm_age		-0.047		1.789***
		(0.065)		(0.517)
Constant	0.162	0.526	3.353***	-3.421
	(0.505)	(0.643)	(1.137)	(2.940)
Firm F.E.	No	No	Yes	Yes
Industry F.E.	Yes	Yes	No	No
Year-Month F.E.	Yes	Yes	Yes	Yes
Obs	466999	295704	466999	295704
R-squared	0.000	0.013	0.000	0.019

* $p<.1$, ** $p<.05$, *** $p<.01$

This table presents the regression results depicting the influence of firms' CO2 emissions on stock returns. To account for potential dependencies within the data, the standard errors are clustered at the specified level along with the fixed effects integrated into the model.

4.3.2 Robustness Check

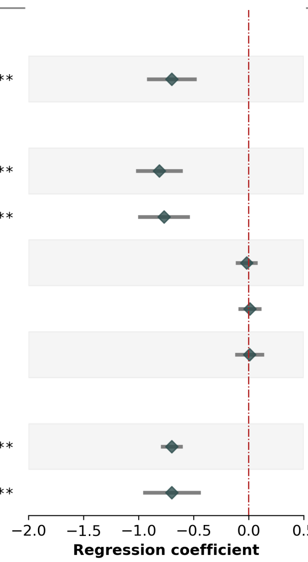
In the context of the regression model 2, the choice of fixed effects can vary depending on the underlying assumptions. In conventional cross-sectional stock return analyses, it is a common practice to assume significant heterogeneity between industries, with the belief that firms within a particular industry exhibit similar characteristics in terms of their stock returns. This assumption has garnered substantial empirical support in the existing literature. However, it's crucial to recognize that investors base their investment allocation decisions on more than just industry categorizations. While they may initially screen industries, their ultimate investment choices often depend on the specific attributes of individual companies. In such scenarios, even firms within the same industry can exhibit significant variations in their stock performance. Therefore, considering heterogeneity at the firm level may be a more suitable approach than relying solely on industry-level assumptions. In the following analysis, we perform a robustness check with various fixed effects and cluster standard errors at different levels.

The first six models depicted in Figure 8 include the benchmark model along with variations involving different fixed effects. In the case of considering only the Entity fixed effect, we observe a coefficient of -0.81 for total carbon emissions, which is statistically significant at the 1% level. Similarly, when we incorporate both Entity and Year two-way fixed effects, the coefficient on carbon emissions remains statistically significant at the 1% level, with a slightly reduced value of -0.77. These specifications maintain consistency with the benchmark model, showing only minor coefficient adjustments. Moving on to models 4, 5, and 6, where we introduce industry fixed effects, industry + month, and industry + year two-way fixed effects, we observe a different pattern. In these models, the coefficients on carbon emissions all become statistically insignificant and approach zero.

White (1980) in his seminar paper first introduced Robust standard errors in econometrics to account for heteroscedasticity. In Model 2, where we retain the same fixed effects as the benchmark model, the application of robust standard errors significantly increases statistical significance and narrows down the confidence intervals as depicted by the 7th model in Figure 8. Furthermore, as highlighted by Petersen (2008), when dealing with panel data the residuals may be correlated across firms or across time. In such cases, standard errors can be biased. To mitigate this, Petersen recommends clustering standard errors at the same level, as is done in our benchmark model. Additionally, Angrist and Pischke (2009) advocates for clustering standard errors at a level one step above the sample data. In line with this recommendation, we cluster the standard errors at the industry and year level for the benchmark model to test its robustness. After applying clustering to standard errors at the industry + year level, we observe a slight increase in standard errors compared to the benchmark model. Nonetheless, the results remain statistically significant at the 1% level, as shown by the last model in Figure 8.

Figure 8: **Change of Fixed Effects and Cluster Levels**

Variable	No. Obs	R-squared	P-value	Est. (95% Conf. Int.)
Benchmark				
1. Benchmark model	359749.0	0.019	0.0***	-0.70(-0.93 to -0.47)
Fixed effects				
2. Entity F.E.	359749.0	0.018	0.0***	-0.81(-1.02 to -0.60)
3. Entity + Year F.E.	359749.0	0.023	0.0***	-0.77(-1.01 to -0.54)
4. Industry F.E.	359749.0	0.011	0.7	-0.02(-0.12 to 0.08)
5. Industry + Month F.E.	359749.0	0.013	0.85	0.01(-0.09 to 0.11)
6. Industry + Year F.E.	359749.0	0.013	0.92	0.01(-0.12 to 0.14)
Clustered standard errors				
7. Robust Standard Errors	359749.0	0.019	0.0***	-0.70(-0.80 to -0.60)
8. Industry + Year	359749.0	0.019	0.0***	-0.70(-0.96 to -0.44)



This graphic presents coefficients and associated confidence intervals for various fixed effects and clustered standard error configurations. The benchmark model includes entity + month fixed effects, with standard errors clustered at the same level. In the "Fixed Effects" group, we explore different fixed effects for each model, while maintaining standard errors clustered at the same level. In the "Clustered Standard Errors" group, we examine how standard errors are clustered at various levels while keeping the fixed effects consistent with the benchmark model.

4.4 Expalin the Contradiction Between Empirical and Theoretical Studies

Building upon the equilibrium model by Pástor et al. (2021) and Pedersen et al. (2021), along with the demand system asset pricing model by Koijen and Yogo (2019), we aim to present empirical evidence supporting the notion that a shift in financial market preferences due to climate change has led to the observed contradiction between empirical findings and classic asset pricing theory, regarding the risk-return puzzle.

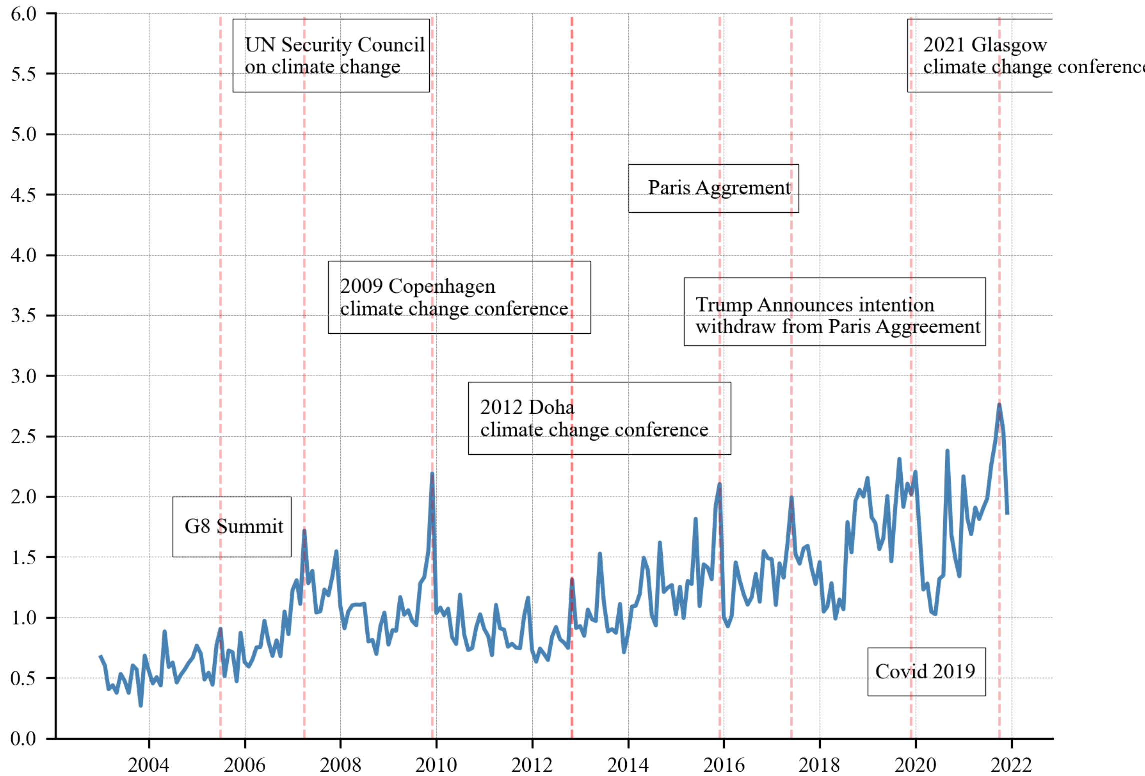
4.4.1 Quantify the Preference Shift in the Financial Market

The shift in financial market preferences due to unanticipated climate change risks can be measured using the Unexpected Media Climate Change Concern Index (UMC), developed by Ardia et al. (2022). To construct this index, they gather news from eight major U.S. newspapers and two prevalent newswires, known for their extensive circulation. For each article, a unique "concern score" is assigned, reflecting the degree of negativity and risk addressed in the content. Considering the diversity in coverage, thematic focus, and levels of concern, they normalize the scores of individual articles adjusting for heterogeneity across newspapers. These normalized scores are then aggregated to form a comprehensive daily Media Climate Change Concern Index (MCCC)[6], encapsulating the overall media sentiment on climate change. The historical trajectory of the monthly MCCC index is plotted in Figure 9.

Ardia et al. construct the UMC by calculating the difference between actual $MCCC_t$ and its expected $\widehat{MCCC}_t$ index by an ARX model as specified in Equation 6. Their model incorporates a variety of control variables, including the FF5 factors, momentum factor, WTI return, gas return, propane return, U.S. economic policy uncertainty index, VIX, TED spread, term factor, default factor, etc. In our study, we use a different set of control variables in the model, which includes the FF5 factors, CFNAI index, investor sentiment index, WTI index, VIX index, and a lagged one-period MCCC index to compute UMC, but the difference between the resultant two UMC indcies is found to be negligible. The construction of the UMC index makes it an appropriate proxy for measuring shifts in market preferences. An increase in UMC, indicating heightened concerns about climate change risks, is likely to bolster investor demand for green assets and lead to divestment from brown ones, and vice versa. And as we discussed in Section 2.4, this demond shock could result in the surplus of green assets' return and damage the return of brown assets, supported by the theoretical

[6]It is noteworthy that several other studies have explored text-based methodologies for constructing similar indices, including Engle et al. (2020), Kapfhammer et al. (2020), and Faccini et al. (2021).

Figure 9: **Media Climate Change Concerns Index**



This figure presents the monthly MCCC (Media Climate Change Concerns) index from 2003 to 2022 together with the major climate-related events.

studies by Koijen and Yogo (2019) and Pástor et al. (2021).

$$MCCC_t = \alpha + \beta MCCC_{t-1} + \gamma Controls_t + \epsilon_t \tag{6}$$

4.4.2 Portfolio analysis with UMC

Next, we are going to test our hypothesis empirically by using regression analysis as outlined by the Equation 3, wherein we regress GMB, Green, Brown, and Neutral[7] portfolios on UMC.

[7]Here the carbon neutral portfolios do not mean that the underlying companies have zero carbon emission, but these companies are ranked in the middle quintile in the industry with respect to carbon emission.

As presented in Table 7, the regression findings illuminate the outcomes of diverse portfolios structured based on firms' carbon emissions in relation to the UMC index, accompanied by a set of control variables.

For the green portfolio, as shown in the second column of Table 7, the coefficient on UMC is 1.786. This suggests that a one-unit increase in the UMC index could lead to a average 1.786% increase in returns for the green portfolio. Conversely, for the brown portfolio (third column), the coefficient on UMC is -1.263%, indicating that a one-unit increase in the UMC index could result in a 1.263% decrease in returns on average. These results strongly support the idea that shifts in financial market preferences due to climate change significantly impact the returns of green and brown assets. An increase in climate change concerns favors green assets and, conversely, reduces the returns of brown assets. For the GMB portfolios, the coefficient on UMC is 3.049, implying that a one-unit increase in UMC could lead to an average return increase of 3.049% for GMB portfolios. All the results mentioned demonstrate both economic and statistical significance at the 1% level. In contrast, for the carbon neutral portfolio, the coefficient on UMC is relatively minor and does not reach statistical significance.

The underlying mechanism explaining the observed contradiction between empirical analyses and theoretical studies becomes clear based on our previous reasoning. When unexpected climate change concerns arise, a shift in financial market preferences occurs. Driven by the motives of hedging and adherence to green investing mandates, investors increase their demand for green assets while divesting from brown ones. This preference shift triggers a demand shock for both types of assets. As supported by Gabaix and Koijen (2021) and Hartzmark and Solomon (2022), the price to demand elasticity is extremly high. This demand shock elevats the prices of green assets and adversely affecting those of brown assets. Consequently, this leads to green assets realizing higher expected returns.

Table 7: Green - Brown on UMC

	Dependent Variable			
	Green-Brown	Green	Brown	Neutral
Intercept	1.310	1.665**	0.355	1.040**
	(1.179)	(0.844)	(0.857)	(0.430)
UMC	3.049***	1.786**	-1.263*	-0.029
	(1.029)	(0.736)	(0.748)	(0.375)
Mkt_RF	0.083	0.920***	0.837***	0.965***
	(0.080)	(0.057)	(0.058)	(0.029)
SMB	1.079***	0.724***	-0.355***	0.318***
	(0.133)	(0.095)	(0.096)	(0.048)
HML	-0.557***	-0.216**	0.341***	-0.008
	(0.122)	(0.088)	(0.089)	(0.045)
RMW	-0.164	-0.198*	-0.033	-0.024
	(0.167)	(0.119)	(0.121)	(0.061)
CMA	0.112	0.041	-0.070	-0.145*
	(0.208)	(0.149)	(0.151)	(0.076)
SENT	1.277**	0.971**	-0.306	0.072
	(0.611)	(0.437)	(0.444)	(0.223)
WTI	-0.010	-0.014*	-0.005	-0.006
	(0.012)	(0.009)	(0.009)	(0.004)
CFNAI	-0.046	0.121	0.167	-0.016
	(0.200)	(0.143)	(0.145)	(0.073)
VIX	0.037	0.062**	0.025	0.016
	(0.040)	(0.028)	(0.029)	(0.014)
Obs	227	227	227	227
R-squared	0.368	0.742	0.590	0.903

* $p<.1$, ** $p<.05$, *** $p<.01$

This table represents the regression results of Green-Brown, Green, Brown, and Neutral portfolios on the UMC index and a group of control variables. Ardia et al. (2022) constructed the MCCC index since January 2003, hence the number of observations is less than 240. The Green Portfolio contains firms with total CO2 emissions up to the 20rd percentile, Neutral Portfolio contains firms with total CO2 emissions ranging from the 40th to 60th percentile, and firms with CO2 emissions higher than the 80th percentile are included in the Brown Portfolio. Green-Brown Portfolio is the monthly difference between Green and Brown portfolios.

4.4.3 Firm level analysis with UMC

In the firm-level analysis of the previous section, we observe a negative relationship between firms' carbon emissions and stock returns, particularly when employing month + entity two-way fixed effects. We propose that this negative relationship may stem from a shift in financial market preferences, motivated by a desire to hedge against climate change risks and a growing commitment to sustainable investing. A likely hypothesis is that during periods of heightened climate concern, firms with higher CO2 emissions (i.e., more environmentally impactful) tend to see lower stock returns. This outcome occurs as investors increasingly avoid brown stocks in favor of green ones, leading to a surge in demand and consequently higher returns for green assets. Following Equation 4, we further explore how the interaction between firms' carbon emissions and the UMC index impacts stock returns.

Table 8: Cross-section Stock Return with UMC

	Dependent variable: Return			
	(1)	(2)	(3)	(4)
CO2_tot	-0.569***	-0.580***	-0.580***	-0.578***
	(0.112)	(0.109)	(0.109)	(0.111)
UMC	1.648***	1.688***	1.460***	1.749***
	(0.402)	(0.401)	(0.403)	(0.405)
interaction	-0.135***	-0.145***	-0.133***	-0.150***
	(0.029)	(0.028)	(0.029)	(0.029)
Mkt_RF	0.999***	0.909***	0.915***	0.949***
	(0.010)	(0.009)	(0.008)	(0.009)
SMB		0.383***	0.360***	0.321***
		(0.013)	(0.013)	(0.013)
HML		0.012	0.002	0.046***
		(0.010)	(0.010)	(0.010)
RMW			-0.065***	-0.042***
			(0.014)	(0.015)
CMA			0.063***	0.048***
			(0.016)	(0.016)
SENT				-0.497***
				(0.042)
WTI				-0.009***
				(0.001)
CFNAI				0.012
				(0.013)
VIX				0.047***
				(0.003)
Constant	1.828	1.100	0.992	-0.911
	(1.915)	(1.940)	(1.946)	(1.936)
Controls	Yes	Yes	Yes	Yes
Entity F.E.	Yes	Yes	Yes	Yes
Obs	295215	295215	295215	295215
R-squared	0.203	0.212	0.213	0.215

* p<.1, ** p<.05, *** p<.01

Table 8 presents the regression results for Model 4. Alongside a list of control variables reflecting firms' fundamental characteristics such as size, leverage, B/M, RoE, Investment, PP&E, SaleGR, EPS, staff number, and firm age (included in $Controls_{i,t}$), we also incorporate variables to capture the time-varying global macroeconomic conditions, including the

FF5 factors, investor sentiment, WTI index, CFNAI index, and VIX. Across all specifications, the coefficient on $CO2\_tot_{i,t}$ consistently displays a statistically significant negative relationship with stock returns, in line with the results in Table 6. Additionally, the coefficient on UMC_t is consistently positive, suggesting when there are high unexpected climate concerns investors ask more returns from the stock market compensating climate change related risks. Moreover, the coefficient on $interaction_{i,t}$ remains negative across various controls. As Equation 5 indicated, it implies that during periods of heightened unexpected climate concern, the stock returns of brown firms, identified by higher total CO2 emissions, tend to decrease further due to the preference shift. Green stocks on the contrary are benefited from the unexpected climate change concerns. All results with the statistical significance maintained at the 1% level.

5 Conclusion

Firms' carbon emissions are frequently used as a metric to gauge their sustainability practices. Utilizing this indicator, we construct green and brown portfolios and observe a notable outperformance of the green portfolio over the brown. Our findings suggest that in assessing the relationship between firms' sustainability practices and stock returns firms' carbon emissions are as effective as ESG scores, an indicator employed by Pástor et al. (2022) for the similar analysis, yet firms' carbon emissions are more straightforward and robust. At the firm level, our analysis reveals a consistent trend: green stocks, characterized by lower carbon emissions, tend to yield higher realized stock returns. However, this pattern is not replicated when using carbon intensity, another seemingly logical proxy for quantifying firms' sustainable practices.

In exploring the relationship between firms' carbon emissions and stock returns, another strand of empirical analysis suggests that higher carbon emissions are associated with higher stock returns. This aligns with the classic asset pricing theory, which asserts that greater risk exposure is compensated with higher returns, thereby presenting a direct contradiction to our findings. To explain this contradiction, we draw on the theoretical frameworks developed by Koijen and Yogo (2019) and Pástor et al. (2021), demonstrating how the conventional belief about risk and return could be violated in the respone of unexpected climate change concern. Our conclusions are in line with similar findings from Ardia et al. (2022), Choi et al. (2020), and Engle et al. (2020).

Although our paper is the first to directly address the contradiction between two lines of research on the relationship between firms' carbon emissions and stock returns in current asset pricing literature, similar cautionary notes have been previously raised by studies like Aswani et al. (2023). While the datasets and methodologies we employ are well-established in the field, the novelty of our paper may not lie in these aspects. However, we contribute significantly by offering plausible explanations for the existing discrepancies, delving into the underlying mechanisms that drive these divergent findings.

References

Mats Andersson, Patrick Bolton, and Frédéric Samama. Hedging climate risk. Financial Analysts Journal, 72(3):13–32, 2016.

Joshua D Angrist and Jörn-Steffen Pischke. Mostly harmless econometrics: An empiricist's companion. Princeton University Press, 2009.

David Ardia, Keven Bluteau, Kris Boudt, and Koen Inghelbrecht. Climate change concerns and the performance of green vs. brown stocks. Management Science, 2022.

Jitendra Aswani, Aneesh Raghunandan, and Shivaram Rajgopal. Are carbon emissions associated with stock returns? Review of Finance, forthcoming, 2023.

Doron Avramov, Si Cheng, Abraham Lioui, and Andrea Tarelli. Sustainable investing with esg rating uncertainty. Journal of Financial Economics, 145(2):642–664, 2022.

Malcolm Baker, Daniel Bergstresser, George Serafeim, and Jeffrey Wurgler. Financing the response to climate change: The pricing and ownership of us green bonds. Technical report, National Bureau of Economic Research, 2018.

Patrick Bolton and Marcin Kacperczyk. Global pricing of carbon-transition risk. Technical report, National Bureau of Economic Research, 2021a.

Patrick Bolton and Marcin Kacperczyk. Do investors care about carbon risk? Journal of Financial Economics, 142(2):517–549, 2021b.

Sudheer Chava. Environmental externalities and cost of capital. Management Science, 60 (9):2223–2247, 2014.

Darwin Choi, Zhenyu Gao, and Wenxi Jiang. Attention to global warming. The Review of Financial Studies, 33(3):1112–1145, 2020.

Radoslav S Dimitrov. The paris agreement on climate change: Behind closed doors. Global Environmental Politics, 16(3):1–11, 2016. doi: 10.1162/GLEP_a_00361.

Lars Engberg-Pedersen. Is the influence of neoliberalism on development norms waning? evidence from the addis ababa action agenda and the 2030 agenda for sustainable development. Development Policy Review, 39(4):682–700, 2021. doi: 10.1111/dpr.12521.

Robert F Engle, Stefano Giglio, Bryan Kelly, Heebum Lee, and Johannes Stroebel. Hedging climate change news. The Review of Financial Studies, 33(3):1184–1216, 2020.

Renato Faccini, Rastin Matin, and George Skiadopoulos. Are climate change risks priced in the us stock market? Technical report, Danmarks Nationalbank Working Papers, 2021.

Renato Faccini, Rastin Matin, and George Skiadopoulos. Dissecting climate risks: Are they reflected in stock prices? Journal of Banking & Finance, 155:106948, 2023.

Eugene F Fama and Kenneth R French. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1):3–56, 1993.

Eugene F Fama and Kenneth R French. A five-factor asset pricing model. Journal of Financial Economics, 116(1):1–22, 2015.

Gunnar Friede, Timo Busch, and Alexander Bassen. Esg and financial performance: aggregated evidence from more than 2000 empirical studies. Journal of Sustainable Finance & Investment, 5(4):210–233, 2015.

SDG FUND. Sustainable development goals. Available at this link: https://www. un. org/sustainabledevelopment/inequality, 2015.

Xavier Gabaix and Ralph SJ Koijen. In search of the origins of financial fluctuations: The inelastic markets hypothesis. Technical report, National Bureau of Economic Research, 2021.

Gerald T Garvey, Mohanaraman Iyer, and Joanna Nash. Carbon footprint and productivity: does the "e" in esg capture efficiency as well as environment. Journal of Investment Management, 16(1):59–69, 2018.

Thomas J George and Chuan-Yang Hwang. A resolution of the distress risk and leverage puzzles in the cross section of stock returns. Journal of financial economics, 96(1):56–79, 2010.

Maximilian Görgen, Andrea Jacob, Martin Nerlinger, Ryan Riordan, Martin Rohleder, and Marco Wilkens. Carbon risk. Available at SSRN 2930897, 2020.

Samuel M Hartzmark and David H Solomon. Predictable price pressure. Technical report, National Bureau of Economic Research, 2022.

Po-hsuan Hsu, Kai Li, and Chi-yang Tsou. The pollution premium. The Journal of Finance, 78(3):1343–1392, 2023.

Emirhan Ilhan, Zacharias Sautner, and Grigory Vilkov. Carbon tail risk. The Review of Financial Studies, 34(3):1540–1571, 2021.

Soh Young In, Ki Young Park, and Ashby Monk. Is "being green" rewarded in the market? an empirical investigation of decarbonization risk and stock returns. International Association for Energy Economics (Singapore Issue), 46(48), 2017.

Narasimhan Jegadeesh and Sheridan Titman. Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of finance, 48(1):65–91, 1993.

Felix Kapfhammer, Vegard H Larsen, and Leif Anders Thorsrud. Climate risk and commodity currencies. 2020.

Ilan Kelman. Climate change and the sendai framework for disaster risk reduction. International Journal of Disaster Risk Science, 6:117–127, 2015. doi: 10.1007/s13753-015-0046-5.

Ralph SJ Koijen and Motohiro Yogo. A demand system approach to asset pricing. Journal of Political Economy, 127(4):1475–1515, 2019.

Philipp Krueger, Zacharias Sautner, and Laura T Starks. The importance of climate risks for institutional investors. The Review of Financial Studies, 33(3):1067–1111, 2020.

Owen A Lamont. Investment plans and stock returns. The Journal of Finance, 55(6): 2719–2745, 2000.

BNP Paribas. The esg global survey 2023 (4th edition). Technical report, BNP Paribas Securities Services, 2023.

L'uboš Pástor and Robert F Stambaugh. Liquidity risk and expected stock returns. Journal of Political economy, 111(3):642–685, 2003.

L'uboš Pástor, Robert F Stambaugh, and Lucian A Taylor. Sustainable investing in equilibrium. Journal of Financial Economics, 142(2):550–571, 2021.

L'uboš Pástor, Robert F Stambaugh, and Lucian A Taylor. Dissecting green returns. Journal of Financial Economics, 146(2):403–424, 2022.

Lasse Heje Pedersen, Shaun Fitzgibbons, and Lukasz Pomorski. Responsible investing: The esg-efficient frontier. Journal of Financial Economics, 142(2):572–597, 2021.

Gabriel Perez-Quiros and Allan Timmermann. Firm size and cyclical variations in stock returns. The Journal of Finance, 55(3):1229–1262, 2000.

Mitchell A Petersen. Estimating standard errors in finance panel data sets: Comparing approaches. The Review of Financial Studies, 22(1):435–480, 2008.

Halbert White. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica, pages 817–838, 1980.

Olivier David Zerbib. A sustainable capital asset pricing model (s-capm): Evidence from environmental integration and sin stock exclusion. Review of Finance, 26(6):1345–1388, 2022.