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Media Attention on Climate Change and the Performance of US Firms

by

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Résumé

Cette étude examine les effets de l'attention au changement climatique sur les rendements des actions américaines de 2005 à 2020. Le Google Search Volume Index du terme « Climate Change » est utilisé pour capturer les variations de l'attention au changement climatique. Les effets sont analysés au niveau de la firme ainsi qu'au niveau des portefeuilles. Au niveau de la firme, il n'y a pas d'indication que les changements de l'attention au changement climatique affectent les rendements des actions. En revanche, au niveau des portefeuilles l'analyse montre que les augmentations de l'attention au changement climatique sont reliées positivement aux rendements des actions de compagnie durables ainsi qu'à un portefeuille qui a une position longue sur les firmes qui opèrent dans les industries non-polluantes et une position courte sur les firmes qui opèrent dans les industries polluantes.

Mots-clés: Finance environnementale, Performance environnementale, Performance financière, Attention médiatique, Changement climatique, Régression linéaire, Investissement durable, Pollution

Abstract

This paper empirically examines the effects of attention to climate change on the returns of US stocks from 2005 to 2020. The Google Search Volume Index of the term "Climate Change" is used to capture changes in attention to climate change. The effects are analyzed at the firm-level as well as the portfolio level. At the firm-level, there is no indication that changes in attention to climate change affect the returns of stocks. However, at the portfolio level the analysis reveals that increases in attention to climate change is positively related to the returns of sustainable firms and of a portfolio that is long in firms that operate in non-polluting industries and short in firms that operate in polluting industries.

Keywords: Environmental finance, Environmental performance, Financial performance, Media attention, Climate change, Linear regression, Sustainable investing, Pollution

Table of Contents

List of Tables

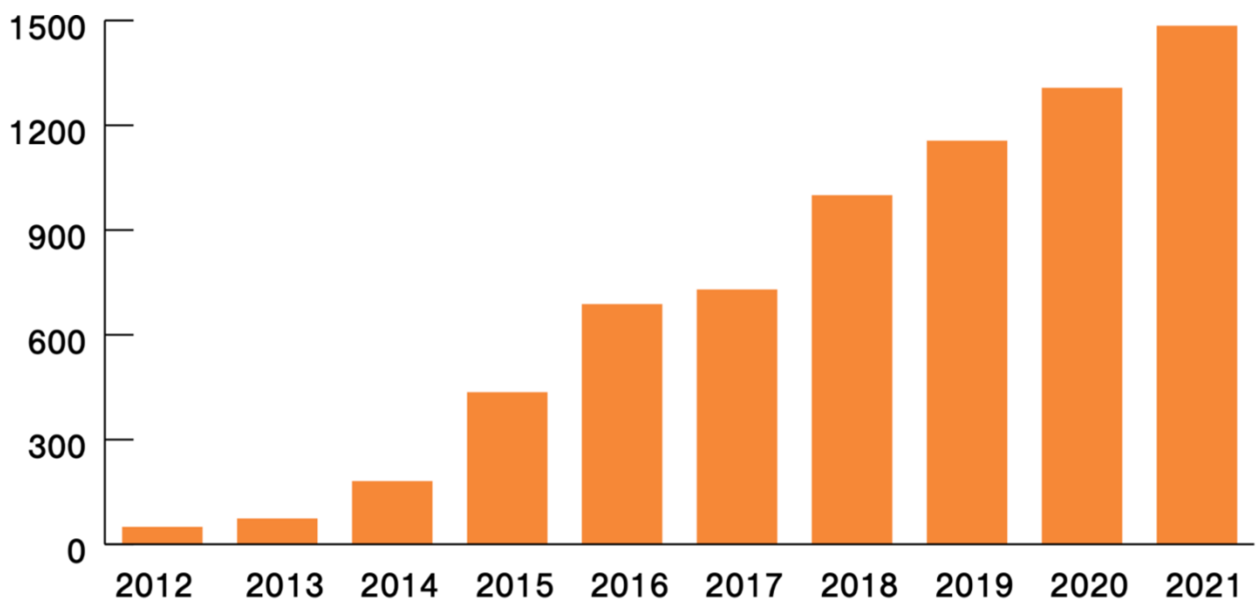
List of Figures

1 Introduction

In January 2021, the United Nations Development Program (UNDP) published the "People's Climate Vote", the largest survey on public opinion about climate change with 1.2 million respondents. Covering 50 countries and about half the world's population, the results of the survey indicate that about 64% of respondents believe climate change is a global emergency (UNDP, 2021). This result shows clearly that climate change is one of the most prominent challenges of our generation. In addition to being concerned about the environment, people are making increasingly eco-friendly decisions. They tend to go for energy-efficient appliances and save energy at home. Some choose to lower their meat consumption, buy a car with lower fuel consumption, and reduce their car usage (Lange et al., 2017).

Climate change has also had a significant impact on the financial industry in recent years. Sustainable investing, which applies environmental, social and governance criteria to investing decisions, has seen rapid growth. In 2019, investors considered ESG factors for $17.1 trillion of assets under management in the United Sates, which was one-third of all professionally managed assets (US SIF Foundation, 2020). Investors can get the motivation to follow sustainable investing strategies for different reasons. The public's concern about climate change has steadily increased over the last decade (Pew Research Center, 2019). As such, customers are shifting their demands for products to greener alternatives, which is likely to lead to increased revenue and higher stock prices for sustainable firms. Increased climate concern can also lead to the government enacting environmental regulations, which would favour environmentally friendly firms and penalize polluting firms. Also, investors' preference for green assets can increase, which would increase capital flow into sustainable funds and thus increase green assets' prices. Another way climate change could impact the financial industry is through divestment from fossil fuel companies. Indeed, fossil fuel divestment has become a global movement in recent years and most of the largest financial institutions have committed some sort of divestment from companies involved in the extraction of fossil fuel. Notable divestment commitments include the Norwegian Sovereign Wealth Fund, the University of Harvard pension fund and the New York City pension fund. According to the Global Fossil Fuel Divestment Commitments Database, in 2021 almost 1500 institutions had publicly committed to some sort of fossil fuel divestment representing around $39 trillion of assets under management. Figure 1 shows the evolution of the number of institutions that have committed to fossil fuel divestment in the last decade.

Figure 1: Total Public Institutional Commitments to Fossil Fuel Divestment



Note. Reprinted from "Invest-Divest 2021: A Decade of Progress Towards a Just Climate Future". (2021). Global Fossil Fuel Divestment Commitments Database.

The actual effect of divestment remains mostly uncertain. However, a study found that the stigmatization of the targeted companies could increase the uncertainty around their future cash flows and decrease their trading multiple (Ansar et al., 2013). The fossil fuel divestment movement could have a significant impact on the targeted firms thus knowing what factors drive this movement could be very useful.

As anyone could expect, outside events related to climate change such as natural disasters, international conferences on climate change (ex. COP26), international agreements (ex. Paris agreement) and investors' coalition (ex. Climate Action 100+) can affect how much sustainability weights in investors' decision. As these events grab the public and investors' attention, it raises the question of whether attention to climate change may influence stock prices. Several factors could explain why attention to climate change may have significant effects on stock returns. First, the growth of the sustainable investing trend could have an accelerating effect on the capital flow into sustainable firms and consequently make investors more responsive to climate change news and events. Second, due to successful divestment campaigns and more common corporate environmental regulations, investors might be more willing to reduce their positions in polluting and non-sustainable firms when climate change is widely covered in the media. Third, pressure from customers as well as the public might increase environmental awareness among the investment industry and thus increase investors' preference toward sustainable products. Fourth, investors without any preference for sustainable firms might expect higher returns from sustainable firms as public awareness of climate change increases. Lower risks could also be expected of sustainable firms compared to non-sustainable firms. Non-sustainable firms are subject to transition risks which are associated with a shift to a more climate-friendly and low-carbon economy. These risks include regulatory, technological, market and reputational risks. Non-sustainable firms are also more at risk from changes in weather and climate (physical risks). For these reasons, investors without any sustainable preference would consequently find it beneficial from an economic perspective to enter sustainable investment strategies. However, a contrary point of view would be that polluting firms would outperform sustainable firms when climate change concerns increase because investors would demand higher returns for holding assets associated with uncertain future cash flows and higher risks, much similar to the sin stock outperformance examined in other studies (Fabozzi et al., 2008; Hong and Kacperczyk, 2009; Statman and Glushkov, 2009).

This paper examines the relationship between investors' attention to climate change and stock returns. More specifically, the analysis is based on the returns of US stocks from January 2005 to December 2020. A challenge in understanding this relationship is that investors' attention is not directly observable, so another more visible variable must be used. Da et al. (2011) propose a measure of investors' attention using search frequency in Google. By using stock tickers, they find that the Google Search Volume Index (GSVI) is correlated with, but different than existing and more conventional proxies of investors' attention such as turnover, extreme returns, news, and advertising expenses. The change in the natural logarithm of GSVI (ΔlogGSVI) is thus used in this paper, with the search topic "Climate Change", to factor in the attention to climate change into the analysis.

Using panel regressions to estimate how much individual stock returns are affected by changes in investors' attention to climate change, no significant evidence is found that investors' attention proxied by the GSVI is associated with stock returns. Using variations in the inputs and methodology used such as the sample timeframe or environmental impact classification method, the same results are found, which validate the robustness of the analysis.

This study also looks at the question of whether green firms, which are firms having a low environmental impact, are affected differently by investors' attention to climate change than brown firms, which are firms having a high environmental impact. A green-minus-brown (GMB) portfolio is constructed replicating an investment strategy that is long in green stocks and short in brown stocks.

When using the impact ratio, which measures to companies' risks toward their environmental impacts (Total Damage Costs in US$ mn divided by total revenue in US$ mn), to classify firms based on their environmental performance, no significant relationship is found between any of the portfolios and the attention to climate change. However, when using an industry classification method, the results suggest that ΔlogGSVI has a significant positive relationship with the returns of a portfolio of green firms as well as the returns of the GMB portfolio. Increases in the attention to climate change translate into higher returns for green stocks. It also means that green firms earn higher returns than brown firms when attention to climate change increases. These results indicate that investors might be influenced by outside events related to climate change and might see green firms as an investment opportunity that would be profitable in the future. However, fossil fuel divestments do not seem to be related to investors' attention to climate change but rather be a continuous movement. Brown firms are thus not necessarily penalized when climate change is reported in the media. This is partly in accordance with the results of Ardia et al. (2021), which reports a positive relationship between a green portfolio and a measure of investors' concerns on climate change as well as a negative relationship between a brown portfolio and investors' concerns. This discrepancy in the results might be explained by the fact that, as Bolton and Kacperczyk (2020) explained, GSVI is more representative of retail investors' attention than institutional investors because the former use platforms such as Bloomberg to acquire information. Institutions hold a lot more weight in the divestment movement than retail investors and thus the impact might not be well represented with the measure of attention used in this paper.

By using the Google Search Volume Index of the topic "Climate Change" to proxy for investors' attention to climate change, this study contributes to the growing number of studies using an alternate measure to capture investor attention (Fang and Peress, 2009; Grullon et al., 2004; Barber and Odean, 2008; Gervais et al., 2001, Hou et al., 2008). However, it is one of the few linking investors' attention to climate change and firms' financial performance. Moreover, it provides a different method of classifying firms between green and brown, using Trucost's Impact ratio to represent the environmental risk of firms. It also complements the existing literature using both a firm-level approach as well as a portfolio approach with a sample covering 15 years of observations in the United States.

This paper is organized as follows. Section 2 provides a literature review of studies associated with the factor of performance of stock returns as well as studies interested in investors' attention. Section 3 describes the sample data used in this paper. Section 4 presents the methodical approach used for the firm-level and the portfolio-level analysis. Then, section 5 presents the results as well as the interpretation and Section 6 concludes and summarizes the findings. This section also lays out the limitations of this paper as well as other future leads of research on investors' attention to climate change.

2 Literature Review

With the recent impressive growth of sustainable investing within the finance industry, researchers have been interested in knowing how much importance investors give to ESG criteria when making investment decisions. Krueger, Sautner and Starks (2020) present results from a survey where institutional investors were questioned about their climate risk perception. They found that institutional investors believe climate risks can influence portfolios primarily from regulatory risks and that risk management and engagement are better approaches than divestment for addressing environmental concerns. Another survey (Amel-Zadeh and Serafeim, 2017) reports that relevance to investment performance, client demand and product strategy are the most frequent motivation for managers to use ESG data in their investment process. Lack of reporting standards, comparability, reliability, quantifiability and timeliness were the most cited barriers to the use of ESG information. This shows how outside factors such as public concern about climate change can influence investors in considering environmental factors in their decisions. It also confirms that as more companies disclose their environmental performance and adhere to disclosure standards such as the Carbon Disclosure Project (CDP), more investors might choose to use ESG data. Dyck et al. (2018) examine the relationship between share ownership and environmental and social performance (E&S). They find that greater institutional ownership is associated with higher E&S performance. Another conclusion of the study is that rather than opting for best-in-class strategy and divestment from environmentally underperforming firms to improve their portfolios E&S performance, institutional investors prefer to engage with firms they already own, which is in accordance with Krueger, Sautner and Starks (2019) survey's results.

A group of studies works on a broader subject called climate finance, which is the "local, national, or transnational financing drawn from public, private, and alternative sources of financing that seeks to support mitigation and adaptation actions that will address climate change", as defined by the United Nations Framework Convention on Climate Change (UNFCCC). Climate finance is the investment that is needed to tackle climate change by transitioning to a low-carbon economy and by reducing greenhouse gases to achieve emissions targets. To have an accurate depiction of the amount of investment needed, researchers need to understand important aspects of climate change economics such as the pricing and hedging of climate change risks, the awareness and risk preferences of investors toward climate change and how climate change risks affect investment decisions. Giglio et al. (2021) review the literature on the interactions between climate change and financial markets and examine different approaches to incorporating climate risk in microfinance models. They then discuss how assets can be used to construct portfolios hedged against climate risk by looking at the literature on climate risks pricing over different asset classes. Similarly, Hong et al. (2020) review the literature on climate finance that originated from the Review of Financial Study's competition. They categorize the articles in subjects that they think should be further researched. The categories are the uncertain social cost of carbon, the hedging of climate risks, the efficiency of capital markets and climate change, beliefs and climate change risks, damage functions, and short-termism and corporate emissions. Additional research in these subjects will unequivocally help have a better understanding of the financing needed to limit the exposure to climate change risks.

Many earlier studies examine the relationship between global warming and financial performance. Using temperature data, Addoum, et al. (2018) find that extreme temperatures significantly influence firms' earnings in more than 40% of industries in the US. Matsumura, Prakash, and Vera-Munoz (2014) find that direct carbon emissions are related to lower firm values, but voluntary disclosure lessens the negative effects of emissions. Carbon emissions are also used by Bolton and Kacperczyk (2020) to study the effect of climate risk on financial performance. They report that firms with higher total CO2 emissions, after controlling for other factors, have higher stock returns. Chava (2014) finds that high environmental concerns, using KLD ESG ratings, are associated with a higher cost of capital. One risk associated with climate change is increased environmental regulations. However, the uncertainty surrounding climate policy makes it hard to price climate risk. In the options market context, Ilhan et al. (2020) look at the carbon intensity of firms and find that the cost of option protection is higher for carbon-intense firms around times of elevated climate policy uncertainty such as the US presidential election in 2016.

Other studies are structured around an event study context. Klassen and McLaughlin (1996) find that firms that are affected by environmental disasters report negative abnormal returns. Capelle-Blancard and Laguna (2010) find that petrochemical firms experience negative stock returns following industrial disasters, just as Carpentier and Suret (2015) find that firms found responsible for environmental incidents experience negative abnormal returns. Another line of event studies looks at the effect on stock returns related to the inclusion or exclusion of companies in sustainability indices (e.g., Curran and Moran, 2007; Capelle-Blancard and Couderc, 2009; Oberndorfer et al., 2013; Hawn et al., 2018). Most of these studies find no significant effects on stock prices following an index event. Some authors used event studies to analyze the relationship between global environmental events and financial performance at the portfolio level. Lei and Shcherbakova (2015) are interested in the effect of the Fukushima nuclear disaster on portfolio returns of renewable, nuclear and coal companies. Mukanjari and Sterner (2018) look at how the Paris Agreement and the election of the US President Donald Trump affected green and brown financial performance. Kollias and Papadamou (2016) analyze the relationship between sustainability stock index financial performance and major natural disasters and find no significant impact.

Multiple studies on the effect of public attention to stock returns have also been published in recent years. Fang and Peress (2009) and Engelberg and Parsons (2011) used media coverage as a proxy for attention to analyze its effect on stock returns. Grullon et al. (2004) introduce advertising expenditure as a proxy for investor attention and find that it has a positive relationship with the number of investors and liquidity. Other measures of attention have been used in previous studies such as abnormal trading volume (e.g., Barber and Odean, 2008; Gervais, Kaniel, and Mingelgrin, 2001; Hou, Peng and Xiong, 2008) and extreme returns (Barber and Odean, 2008). Investor attention measures can be categorized as passive and active (Peillex and Comyns, 2020). These studies assume that if a company's name was in the newspaper or its trading volume was high, then investors would have paid attention to it, which is not always the case. Therefore, some studies have tried to find an active and direct measure of attention. Search engine queries were used as a more direct measure of attention in multiple studies (e.g., El Ouadghiri and Peillex, 2018; Mondria, Wu, and Zhang, 2010; Drake, Roulstone, and Thornock, 2012). Active public attention can be associated with the demand for information. Da, Engelberg, and Gao (2011) argue that search engine users, who are voluntarily taking time to search for a specific topic, are interested in this topic since they actively search for it. In their paper, they find that GSVI measures the attention of retail investors only because institutional investors use other information platforms such as Bloomberg terminals. The authors also find that GSVI contributes to a significantly large first-day return following a stock's IPO. Vlastakis and Markellos (2012) study information demand and supply using GSVI as a proxy for demand. They report that GSVI is significatively associated with market volatility and trading volume. In the same vein, Han et al. (2017) ask the question of whether investors' attention, proxied as GSVI, can predict oil prices in the same way as Afkhami et al. (2017) try to predict energy price volatility using GSVI. Taking a more climate-oriented approach, Choi et al. (2018) use GSVI to capture attention to climate change and find that carbon-intensive firms underperform when there is abnormally warm weather. The geographic context is used by Cziraki et al. (2019) to study the relationship between investors' attention and stock returns. They construct a measure of asymmetric attention using GSVI comparing local investors to nonlocal investors. The results show that firms with high abnormal asymmetric attention earn higher returns. One explanation would be that local investors have access to and act on unobservable private information.

El Ouadghiri et al. (2021) study the effect of public attention to climate change on the returns of US sustainability stock indices, using the GSVI for the search topic "Climate Change" as well as the term "pollution". These two keywords are the ones that have received the highest scientific coverage between 2004 and 2018, according to El Ouadghiri et al. (2021). Using the Carhart factors (Carhart, 1997) as control variables, they find that the return of sustainability stock indices is positively related to the GSVI for climate change and pollution. A distinction between, event studies interested in climate change impact on stock returns and studies using GSVI is that the former considers mostly the short-term effect of unexpected environmental events while the latter studies the continuous effect of public attention to climate change.

The literature also covers theoretical frameworks around sustainable investing. Pastor et al. (2020) present an equilibrium model that explains the impact of changes in sustainability on assets prices. They predict that green firms outperform brown firms when customers' preference for green products and investors' preference for green assets increases unexpectedly. However, in equilibrium green firms have lower expected returns because investors derive utility from holding them and because green assets hedge climate risk. According to the authors, agents would be willing to pay more for green firms, which would lower the firms' costs of capital and thus lower the expected returns. Agents would still be satisfied because of the derived utility they earn from green assets. Ardia et al. (2021) test the prediction of Pastor et al. (2020) using a Media Climate Change Concerns index (MCCC) that takes into consideration news about climate change published in newspapers as well as the level of attention. Even if they use information from both the level of attention and media coverage to construct their index, they found that the correlation between an index based on average concerns only and an index based on attention only is 77%, implying that both measures are closely related. They report that when climate change concerns increase unexpectedly, green firms' stock returns outperform brown firms, validating the prediction of Pastor et al. (2020). Moreover, they explain that stock returns are affected by climate change concerns through changes in investors' taste for sustainability and investors updating their expectations about firms' future cash flows. Pastor et al. (2021) construct a measure of concerns about climate change, using as input the MCCC index computed by Ardia et al. (2021), and confirm their theoretical equilibrium model predictions that green firms outperformed brown stocks when climate concerns increased.

The preference for green products is also studied in the bond market. Pastor et al. (2021) touch upon this subject by studying the case of German "twin" bonds, where the German government issued green bonds with almost identical non-green bonds. Under this context, it is easier to understand investors' taste for green products since we can see that green bonds trade at a lower yield than non-green bonds. This difference in yield suggests that investors are willing to accept a lower return in exchange for a product that is more aligned with their values. The authors show that the difference in yield between the two types of bonds, called the “greenium”, tripled since their issuance, thus the green bonds outperformed their counterparts significantly. Using the bond market helps understanding investors’ interest in green products as bonds are more easily compared than stocks.

3 Data

The sample consists of data coming from five different sources. The sample starts in 2005, the year when Trucost first began reporting environmental data, to 2020, the last year of available data provided by Trucost. The analysis covers only US firms. Corporate fundamentals for the first regression come from Compustat. The matching between Compustat data and Trucost data was performed using GVKEY and ISIN with the help of a merging table created from WRDS. The resulting dataset included 2551 unique firms. Monthly returns for the second regression were obtained from CRSP. The matching between CRSP and Trucost was performed using CUSIP and ISIN with the help of the same table and resulted in 2585 unique firms. The next section presents the data we use for the analysis as well as summary statistics. The variables presented in Table 1 will be used in the analysis.

Table 1: Variable Definitions

Variable	Definition
Variable from Google Trends	
ΔlogGSVI	Change in the natural logarithm of the Google Search Volume Index for the topic "Climate Change"
Variables from Compustat	
Ret	Stock return for the holding period
log_size	Natural logarithm of the total assets (in $ million)
B_M	Book to market value of equity ratio, calculated as book value of equity divided by market capitalization.
Leverage	Leverage ratio calculated as debt in current liabilities plus long-term debt over total assets
ROE	Return on equity (%)
Investment	Investment variable calculated as capital expenditure divided by book value of assets
Property_plant_equ	Natural logarithm of plant, property, and equipment (in $ million)
Variables from CRSP	
Ret	Monthly return including dividends
Variables from Fama-French	
RF	Risk free rate
MktRF	Monthly excess return on the market, value-weight return of all CRSP firms in the US.
SMB	Monthly return the portfolio long on small-cap stocks and short on large-cap stocks
HML	Monthly return the portfolio long on value stocks and short on growth stocks
RMW	Monthly return the portfolio long on robust operating profitability stocks and short on weak operating profitability stocks
CMA	Monthly return the portfolio long on conservative investment stocks and short on aggressive investment stocks
Variables from Trucost	
Impact ratio	Total Damage Costs by total revenue (USD mn)
Carbon intensity	Direct and First-tier Indirect emission (tonnes CO2e) by total revenue (USD mn)

3.1 Financial Data

The empirical analysis of stock returns uses monthly and quarterly data. The panel regression uses quarterly data from Compustat while the monthly Fama-French regression uses monthly returns coming from the CRSP database. Table 2 presents summary statistics for Compustat, CRSP and Trucost variables.

Table 2: Summary statistics

Variable	Mean	Median	Std. Dev.	Min	Max
Compustat					
Ret (%)	3.13	2.80	19.50	-88.76	98.47
Log_size	8.08	8.11	1.76	1.12	13.89
B_M (winsorized at 2.5%)	0.50	0.41	0.37	0.07	2.22
Leverage (winsorized at 2.5%)	0.26	0.25	0.17	0.00	0.96
ROE (winsorized at 2.5%)	0.02	0.03	0.08	-0.39	0.18
Investment (winsorized at 2.5%)	0.03	0.02	0.03	0.00	0.14
Log property, plant and equipment	6.36	6.38	2.28	-6.91	12.46
CRSP					
Ret (%)	1.20	1.00	12.52	-44.44	62.33
Trucost					
Carbon intensity	277.21	79.98	554.40	3.08	2,744.43
Impact ratio	1.98	0.14	2.53	0.00	62.87

3.1.1 CRSP Data

The data used from the CRSP database are the *prc*, *shrout* and *ret* variables which represent the monthly share price, shares outstanding and return measures. The return measure retrieved from CRSP is the holding period returns adjusted for dividends and stock splits. The market capitalization, used to separate small firms in secondary regressions is computed from the price and share outstanding values. The variable *ret* is winsorized at the top and bottom 0.5% level to diminish the effect of outliers.

3.1.2 Compustat Data

The data used from the Compustat database are the quarterly share price (prccq), shares outstanding (cshoq), shareholders' equity (teqq), debt in current liabilities (dlcq), long-term debt (dlttq), total assets (atq), net income (niq), capital expenditure (capxy), and property, plant and equipment (ppentq). These values are used to compute the exogenous variables for the panel regression, which are the quarterly return (ret), the natural logarithm of total assets (log_size) and of property, plant and equipment (property_plant_equi), book-to-market value of equity (B_M), firm leverage (Leverage), return on equity (ROE), and investment level (Investment). The variables property, plant and equipment, book-to-market value of equity, leverage, ROE and investment are winsorized, following Bolton and Kacperczyk (2020) at the top and bottom 2.5% level to diminish the effect of outliers. The observations with a return greater than 100% and the ones with a negative book equity value are removed for the same reason. The GICS industry "Financials" is removed because some control variables such as the book to market ratio for this industry are not comparable to the other industries. Table 3 shows the control variables by industry used in the panel regression.

Table 3: Average control variables by industry and by green and brown classification

GICS Sectors	Log_ppe	Log_size	B_M	ROE	Leverage	Investment	VOL	MOM	beta
Communication Services	6.75	8.22	0.63	0.02	0.32	0.03	0.09	0.06	1.02
Health Care	5.04	8.05	0.37	-0.01	0.23	0.02	0.10	0.16	0.92
Information Technology	4.98	7.90	0.43	0.01	0.17	0.02	0.09	0.16	1.27
Consumer Discretionary	6.23	7.75	0.54	0.03	0.27	0.03	0.10	0.11	1.03
Real Estate	6.49	7.96	0.45	0.02	0.25	0.02	0.08	0.13	1.01
Industrials	6.08	7.84	0.46	0.03	0.26	0.03	0.09	0.14	1.01
Consumer Staples	7.12	8.98	0.38	0.05	0.28	0.03	0.07	0.14	0.62
Energy	8.33	8.45	0.80	0.00	0.25	0.07	0.11	0.03	1.09
Materials	7.21	8.18	0.53	0.03	0.29	0.03	0.09	0.13	1.08
Utilities	9.01	8.71	0.62	0.2	0.35	0.04	0.05	0.14	0.48
Green	5.66	8.34	0.41	0.02	0.23	0.02	0.09	0.16	1.10
Brown	8.13	8.49	0.61	0.02	0.30	0.05	0.08	0.11	0.90

3.1.3 Fama-French Factors

The Fama-French monthly factors, SMB, HML, RMW, CMA and the excess market return MktRF are extracted from the Kenneth R. French data library website. The factors are calculated based on stocks incorporated in the US and listed on the NYSE, AMEX, or NASDAQ, available on CRSP. SMB (Small Minus Big) is the monthly return on a portfolio that is long on small stocks and short on large stocks. HML (High Minus Low) is the monthly return of a portfolio that is long on high book-to-market stocks (value stocks) and short on low book-to-market (growth stocks). RMW (Robust Minus Weak) is the monthly return of a portfolio that is long on robust operating profitability stocks and short on weak operating profitability stocks. CMA (Conservative Minus

Aggressive) is the monthly return of a portfolio that is long on conservative investment stocks and short on aggressive investment stocks.

3.1.4 Environmental data

For this study, the Trucost EBoard database by S&P Global was used to retrieve environmental data covering 2005 to 2020. This data was used to categorize firms in green and brown groups. One challenge associated with this study was the selection of a method that would most effectively classify firms based on their environmental impact. The impact ratio provided by Trucost was chosen because it represents the risk companies face toward their environmental impact. The metric is a company's Total Damage Costs (US$ mn) divided by their total revenue (US$ mn). Total Damage Costs are estimated by Trucost and reflect the environmental impact coming from the operations of a company in monetary terms. These estimates are useful as they take into account not only greenhouse gas emissions data but also water use and waste generated. It is a more complete value of environmental impact than measures using only carbon emission data such as direct emissions or carbon intensity. The value is estimated using the company data on the quantity of pollutants emitted multiplied by its environmental valuation coefficients. These coefficients represent the average damage value ensuing a firms' emission of pollutants. Trucost states that the coefficients are a synthesis of existing literature on the subject. However, other environmental measures such as carbon intensity were used to confirm the validity of the impact ratio as a representative environmental variable. Carbon intensity is calculated using Direct and First-tier Indirect emission data. Trucost definitions of Direct and First-tier Indirect differ from the Scope 1 and Scope 2 emissions of the Greenhouse Gas Protocol. Trucost's Direct emissions are defined just as the scope 1 emissions from the GHG protocol, plus other relevant greenhouse gases related to the firm's industry. First-tier indirect emissions are defined as scope 2 from the GHG protocol, plus the firm's first-tier upstream supply chain emissions, which are their direct suppliers.

The data covers a period from 2005 to 2020. Table 4 presents summary statistics for the Trucost variable by industry.

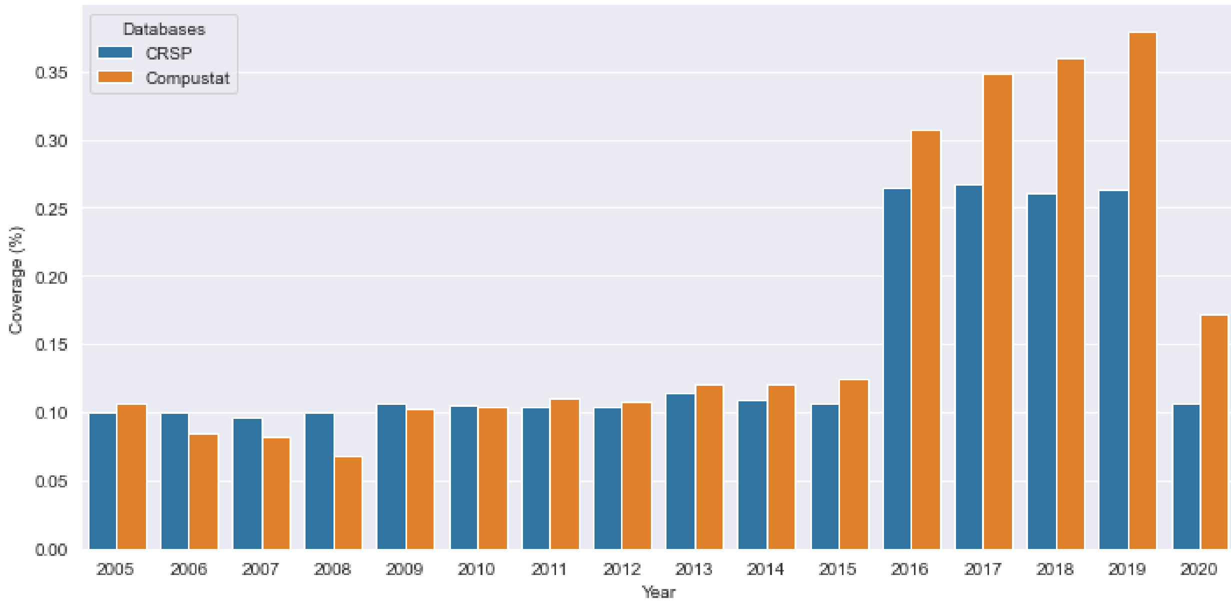
Table 4: Impact ratio summary statistics by industry

	Mean	Median	Std. Dev.	25%	75%
GICS Sectors					
Communication Services	0.03	0.03	0.02	0.02	0.04
Health Care	0.27	0.09	1.20	0.07	0.18
Information Technology	0.11	0.04	0.34	0.03	0.11
Consumer Discretionary	0.15	0.11	0.27	0.05	0.17
Real Estate	0.99	0.07	2.00	0.07	0.85
Industrials	0.77	0.15	2.26	0.08	0.30
Consumer Staples	0.88	0.38	4.84	0.05	0.17
Energy	5.31	1.73	12.63	0.97	2.68
Materials	4.84	2.41	8.00	1.09	5.94
Utilities	20.02	18.23	17.88	2.44	28.69
Total	1.67	0.10	6.73	0.03	0.34

Trucost also differentiates between firms' emissions that are disclosed and emissions that are estimated. Three different types of GHG emissions sources are defined by the Greenhouse Gas Protocol: scope 1 emissions, which come from sources that are controlled or owned by the reporting company, scope 2 emissions, which are indirect GHG emissions tied to the purchase of energy generated upstream, and scope 3 emissions which are from upstream and downstream sources not owned or controlled by the reporting company, but that the company impacts nonetheless (EPA, 2021). Because scope 1 and 2 are more closely tied to a company operation and because they are easier to compute, they have been disclosed by companies more often than scope 3 emissions. Therefore, most environmental data providers except Trucost and ISS ESG do not offer scope 3 emission data. Busch et al. (2018) report that the correlation between reported scope 1 and 2 emissions between the 5 principal data providers are 0.99 and 0.98 but for estimated scope 1 and 2 emissions the correlation is 0.79 and 0.63. This shows that measures derived from estimated emissions values might not be as accurate as disclosed values.

As we can observe from Figure 2, Trucost substantially expanded its coverage in 2016. In 2005, the dataset included approximately 3500 firms, which were mainly large-cap companies in developed markets. As of 2019, it covered around 14000 firms worldwide, or 99% of the global market capitalization. In 2005, the dataset covered 984 firms for the United States and grew to 2885 covered firms in 2019. Even if its coverage almost tripled in 2016, the overall coverage remains relatively low since the Compustat and CRSP databases covered respectively 5945 and 7989 firms in 2019.

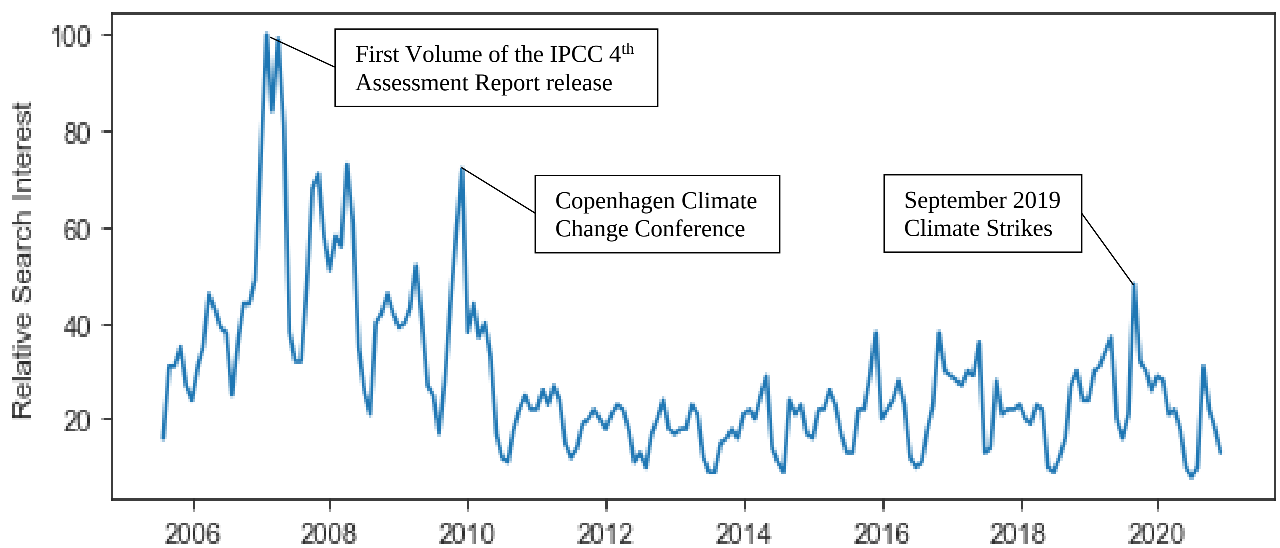
Figure 2: Percentage of firms with emissions data



3.2 Climate Change Attention Data

The attention measure used is the monthly Google Search Volume Index (GSVI) provided by Google Trends for the search topic "Climate Change". The data is confined to searches in the United States only and covers a range from February 2004 to November 2021. An important feature is that by selecting "Climate Change" as a topic, all search queries related to this term are also included. Related search queries in other languages, misspellings and terms like "pollution" and "global warming" will be included which makes it even more representative of the attention to climate change. The value provided by Google represents the query share of the topic for a given geographic specification and time period. It is then normalized relative to the highest query share in the time period. Hence, the data ranges from 0 to 100. An important characteristic of this variable is that a decrease in the GSVI does not necessarily mean that the search queries for a particular term have decreased, but rather that the popularity of this term is decreasing. Figure 3 shows the evolution of the “Climate Change” GSVI since 2004, and we can see the highest point in February 2007 which coincides with the release of the first volume of the IPCC 4th Assessment Report, where it was officially confirmed that human activities were causing global warming. Other notable spikes are the Copenhagen Climate Change Conference in December 2009 and the September 2019 worldwide Climate Strikes.

Figure 3: Google Search Volume for the Topic: Climate Change



Multiple studies have employed this variable to proxy investors’ attention in the past because it is a more direct measure of attention and demand for information. Google’s market share of all search engines is around 90%, while its competitors such as Bing and Yahoo represent less than 10% together (Statista, 2021). Therefore, Google is the logical choice of data provider for this measure since it is representative of the entire internet search behaviour. However, to have a faster query response, the methodology calculates the search volume index from a random subsample of the whole search data. This could potentially cause sampling error if the same query was to provide different data every time it was downloaded. Da et al. (2011) investigated this potential problem by downloading the same SVI multiple times and found that the correlation between the data samples was consistently above 97%, which proves that this sampling method should not impact the analysis significantly. In this study, the change in the natural logarithm of the monthly GSVI measure is used, just as in Da et al. (2011). Table 5 presents summary statistics for the GSVI and the ΔlogGSVI variable used in the analysis.

Table 5: Summary statistic for the GSVI

Variable	Mean	Median	Std. Dev.
GSVI	3.17	3.14	0.50
ΔlogGSVI	0.000686	0.000000	0.316188

4 Methodical Approach

This research aims to understand the relationship between attention to climate change and stock returns. In this paper, the Google Search Volume Index from Google Trends is used as a proxy for investors' attention. Other known investors' attention measures such as trading volume and marketing expenses were found to be associated with stock returns. However, only the attention toward the company itself is represented with these kinds of measures. To get an appropriate representation of investors' attention to climate change, media coverage is used to measure how much investors are exposed to climate change news. Ardia et al. (2021) construct a Media Climate Change Concerns (MCCC) index and Engle et al. (2019) use the Wall Street Journal climate change coverage to build their index. The correlation between the MCCC index, the Wall Street Journal index and the GSVI for "Climate Change" are presented in Table 6.

Table 6: Correlation between Climate Change attention indexes

	ΔlogMCCC	ΔlogWSJ	ΔlogGSVI
ΔlogMCCC	1.00	0.492	0.275
ΔlogWSJ	0.492	1.00	0.170
ΔlogGSVI	0.275	0.170	1.00

The correlation between the ΔlogGSVI with the Δlog of the other two indexes is positive and between 17% to 28%, while the correlation between the Δlog of the two indexes is positive at 49%. The ΔlogGSVI is thus used since it resembles these two indexes. However, using news articles is a passive attention measure since it assumes investors read the articles about climate change while the GSVI is an active attention measure since it directly represents a demand for information (Peillex and Comyns, 2020).

The first part of the analysis focuses on the cross-sectional returns while the second part investigates how the attention to climate change relates to traditional risk factors under the portfolio approach.

4.1 Portfolio Construction

The first step is to construct mutually exclusive equal-weighted portfolios based on the environmental impact of firms in the sample. The composition of the portfolio is reviewed every period and only the firms that meet the criteria are kept. Two portfolios are constructed for each period of the sample, a green portfolio which includes the least environmentally impactful firms, and a brown one which includes the most environmentally impactful firms. Selecting the right criteria to have portfolios that represent the appropriate environmental risk is crucial. Looking at papers that used the green and brown classification, multiple methods are employed to define what green and brown firms are. Ardia et al. (2021) use data from the ASSET4/Refinitive database. They use carbon-dioxide-equivalent (CO2-equivalent) greenhouse gas (GHG) emissions scaled by firms' revenue. This measure translates to the number of tones of CO2-equivalent GHG emissions it takes for a firm to generate \$1 million in revenue. Green firms are below the 25th percentile and brown firms are above the 75th percentile across all firms. This method does not distinguish between industries and thus entire industries might be left out of the portfolios. Pastor et al. (2021) use a different method. They compute their environmental scores based on MSCI ESG ratings data. Their measure is calculated using the firm-level "Environmental Pillar Score" as well as

“Environmental Pillar Weight” and includes industry effect. Using this method allows for the least carbon-intense companies in very polluting industries to be classified as green and the most carbon-intense companies in the least polluting industries to be classified as brown because their score is standardized across industries. In their paper, they define green firms in the top third of the greenness score, and brown firms as firms in the bottom third. In Choi et al. (2018), yet another classification method is used. They rely on the Inter-governmental Panel on Climate Change (IPCC) industry definitions which classify specific industries as major emissions sources. The authors match the subcategories provided by DataStream, which they use for financial data, with these five IPCC industries and classify all included firms as high emission firms, or brown firms.

All these methods are reasonable as investors might react differently to variations in attention to climate change. Some investors might give particular attention to stocks within the most polluting industries, while others might invest in green and brown industries.

For this paper, the impact ratio provided by Trucost is used, where green firms are defined as being below the 25^{th} percentile and brown firms as being above the 75^{th} percentile across all firms. The ratio represents the economic risk a firm could face if it was linked to an environmental disaster. A third portfolio, Green Minus Brown (GMB), is calculated as the difference in equal-weighted returns in each period between the green and brown portfolios. This third portfolio represents the relationship between environmentally friendly firms and polluting firms and can give some indications on how investors value environmental risks.

However, to check the validity of this categorization method, the method used in Choi et al. (2018) is considered over Pastor et al. (2021) because of data availability. This method uses the five industries (Energy, Transport, Buildings, Industry and Agriculture, Forestry, and Other Land

Use (AFOLU)) classified by the Inter-governmental Panel on Climate Change (IPCC) as major emission sources. The IPCC then defines subcategories within these industries. The GICS industries that match the definitions of the IPCC subcategories are defined as polluting industries (see Appendix A for a list of these industries).

4.2 Cross-sectional Returns

The first part of this research is to understand how attention to climate change is related to stock returns at the firm-level in the US. A pooled ordinary least square (OLS) regression model is estimated as follows:

$$ret_{i,t} = a_0 + a_1 \Delta logGSVI_t + a_2 Controls_{i,t-1} + \mu_i + \varepsilon_{i,t} \qquad (1)$$

where $ret_{i,t}$ is the quarterly stock returns of company *i* in month *t* and ΔlogGSVI is the change in the natural logarithm of the monthly GSVI for the search topic "Climate Change". The ΔlogGSVI coefficient a_1 is the coefficient of interest in this regression. The change in value of the natural logarithm of $GSVI_t$ is used as it is common in previous papers (ex. Da et al., 2011; Choi et al., 2018). $Controls_{i,t-1}$ is the vector of control variables that includes firm-specific variables that have been used in studies interested in firm-level returns such as in Bolton and Kacperczyk (2020). These variables are *log_size*, *B/M*, *ROE*, *Leverage*, *MOM*, *VOL*, *Investments*, *log_ppe* and *beta*. *Log_size*, *B/M* and *beta* are included since they are widely used as firm-level stock return determinants (Fama and French, 1993; Berkowitz et al., 2001). A momentum factor is also added as well as a volatility factor to make sure the recent performance of the stock does not influence the results. These two variables are also known to impact stock returns (Jegadeesh and Titman, 1993; Ang et al., 2006). Since the purpose of this analysis is to understand how investors might react to changes in attention to climate change, a lag of one period is introduced to the control variables since the impact on stock returns is not instant. Time-fixed effects are not included since adding a fixed effect would completely absorb the effect of ΔlogGSVI. However, industry-fixed effects are included in the model to capture systematic differences between industries. Industries such as the financial industry have undoubtedly very different risk factors and performance regarding the environment than the mining industry, which is what the industry-fixed effects aim to capture. These effects are based using the 11 GICS sector classification. As we can see in Table 7, there is a lot of variation in environmental performance between sectors, which confirms the decision to add industry-fixed effects.

Table 7: Average Carbon Intensity by GICS Sector

GICS Sectors	Carbon Intensity (tonnes of CO2e/USD mn)
Financials	22.815
Communication Services	31.222
Health Care	56.482
Information Technology	69.514
Consumer Discretionary	102.159
Real Estate	191.213
Industrials	259.911
Consumer Staples	297.433
Energy	647.579
Materials	836.068
Utilities	3,239.481

Standard errors are clustered at the firm and quarter levels. Indeed, observations from the same firm from one period to another are not independent, which could introduce autocorrelation problems.

4.3 Time-series Returns

The second part of the analysis uses a portfolio approach to study the impact that the attention to climate change has on stock returns. Following previous studies on portfolio analysis (ex. Ardia et al., 2021; El Ouadghiri et al., 2021; Pastor et al., 2021), the five-factor model as in Fama and French (2015) is used. The portfolio approach enables us to look at the effect of the attention to climate change using market characteristics instead of firm-specific characteristics.

The next step is to estimate the model on the constructed portfolios. The model is estimated as follows:

$$ret_t = a_0 + a_1 \Delta logGSVI_t + a_2 RF_t + a_3 MktRF_t + a_4 SMB_t + a_5 HML_t + a_6 RMW_t + a_7 CMA_t + \varepsilon_t \qquad (2)$$

where ret_t is the monthly return on stock portfolios constructed from available US firms on CRSP. ΔlogGSVI is the same variable as in the previous model, the log of monthly GSVI for the term "Climate Change". $MktRF_t$, SMB_t, HML_t, RMW_t and CMA_t are the five risk factors from Fama and French (2015). $MktRF_t$ is the excess return on the US market. Based on the three-factor model that took into consideration the market risk (MktRF), the size risk (SMB) and the value risk (HMB), the five-factor model additionally takes into consideration risks related to profitability (RMW) and investment (CMA). Other asset pricing models are used in the literature. The CAPM

(Capital Asset Pricing Model) is the most widely known due to its simplicity. It is a single factor model using the excess market return as the sole factor explaining variations in the stock returns. However, due to a lot of criticism related to the oversimplification of the model, Fama and French (1993) introduced the three-factor model. This model adds two factors to the CAPM equation, a size factor (SMB) and a value factor (HML). The authors argue that the addition of these two factors helps explain better the variation in stock returns than the CAPM. The four-factor model (Carhart, 1997) is also used which is the same as the previous one with an added factor known as the momentum factor (UMD). Then there is the Fama and French (2015) five-factor model which introduces two new factors that were not accounted for in the three-factor model, the profitability factor (RMW) and the investment factor (CMA). For the context of our analysis, the five-factor model seems the most appropriate since the level of investment as well as the quality of the firms might be differentiating factors between green and brown firms (Ardia et al., 2021). The regression estimation is adjusted for heteroskedasticity-autocorrelation (HAC) standard errors with a lag of five months, to account for the serial correlation and heteroskedasticity problems associated with time series.

5 Results

In this section, the results of the different analyses performed are presented. First, the results of the cross-sectional analysis are described, followed by the results of the time-series analysis. Then, a series of robustness checks are presented to confirm the validity of the principal results.

5.1 Cross-sectional results

The cross-sectional analysis is done using US firms' quarterly data available on Compustat from 2005 to 2020 after merging with Trucost's database.

Table 8 presents the correlations between the variables used in the cross-sectional regression. P-values are included in the table to show the significance of the correlation value. Looking at the correlation between variables can highlight potential problems of multicollinearity in the model, which happens when one or more variables have a high degree of correlation with other variables. This could lead to incorrect inferences about individual variables.

Table 8: Cross-sectional variables correlations

	logPPE	logSize	B\M	Lev	ROE	Invest	MOM	VOL	beta	Impact	Intensity	ΔlogGSVI	ret
logPPE	1												
logSize	0.72***	1											
	(0.00)												
B/M	0.05***	-0.38***	1										
	(0.00)	(0.00)											
Lev	0.37***	0.12***	0.01**	1									
	(0.00)	(0.00)	(0.02)										
ROE	0.22***	0.35***	-0.23***	-0.02***	1								
	(0.00)	(0.00)	(0.00)	(0.00)									
Invest	0.37***	0.06***	0.04***	0.08***	0.02***	1							
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)								
MOM	-0.03***	0.13***	-0.27***	-0.08***	0.15***	-0.05***	1						
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)							
VOL	-0.32***	-0.48***	0.3***	0.03***	-0.37***	-0.02***	-0.04***	1					
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)						
beta	-0.13***	-0.08***	0.06***	0.00	-0.12***	-0.04***	0.01	0.31***	1				
	(0.00)	(0.00)	(0.00)	(0.52)	(0.00)	(0.00)	(0.16)	(0.00)					
Impact	0.31***	0.06***	0.14***	0.15***	-0.03***	0.15***	-0.02***	-0.11***	-0.19***	1			
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)				
Intensity	0.42***	0.12***	0.15***	0.19***	-0.02***	0.22***	-0.02***	-0.12***	-0.18***	0.76***	1		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
ΔlogGSVI	-0.01	0.00***	0.00***	0.01***	0.01***	0.05***	0.01*	0.01***	0.00	0.00**	0.00	1	
	(0.25)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)	(0.00)	(0.29)	(0.03)	(0.60)		
ret	-0.02	-0.01*	0.04***	-0.02***	0.05***	-0.03***	0.29***	0.04***	0.02***	-0.02***	-0.02***	0.03***	1
	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

* 10% significance, ** 5% significance, *** 1% significance

As shown in Table 8, the highest correlation between two independent variables is 0.72 between the log of property, plant and equipment (logPPE), and the log of assets (logSize). Also, none of the variables shows a high level of correlation with the variable of interest, ΔlogGSVI.

Moving on to the main analysis, Table 9 presents the results of the cross-sectional regression estimation based on equation 1.

Table 9: Cross-sectional regression results of Green, Brown, and Neutral firms

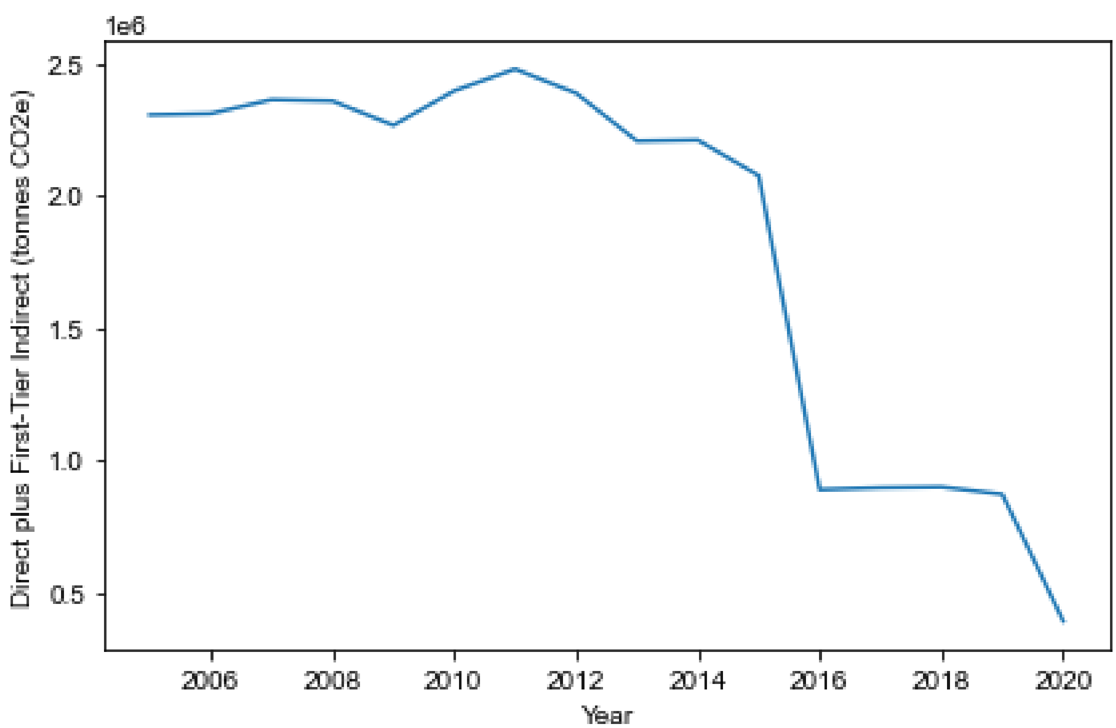
Variables	(1) Green	(2) Brown	(3) Neutral
Intercept	-0.031	-0.006	-0.080**
	(-1.00)	(-0.16)	(-2.51)
log_size	-0.004	-0.010	0.001
	(-0.86)	(-1.31)	(0.31)
log_ppe	0.004	0.009	0.003
	(0.76)	(1.29)	(0.64)
B/M	0.078***	0.035*	0.094***
	(6.50)	(1.88)	(9.05)
ROE	0.121**	0.041	0.123***
	(2.14)	(0.61)	(3.26)
Leverage	0.000	0.001	0.003
	(0.00)	(0.02)	(0.14)
Investment	-0.078	-0.074	0.010
	(-0.37)	(-0.31)	(0.07)
VOL	0.163	0.232	0.214
	(0.71)	(1.15)	(1.13)
MOM	0.154***	0.140***	0.172***
	(10.28)	(6.65)	(10.69)
beta	0.010*	-0.020*	-0.005
	(1.75)	(-1.80)	(-0.89)
ΔlogGSVI	0.014	0.035*	0.015
	(0.60)	(1.79)	(0.63)
Time F.E.	No	No	No
Industry F.E.	Yes	Yes	Yes
Observations	8178	7663	15931
R-squared	0.100	0.088	0.125

* 10% significance, ** 5% significance, *** 1% significance

The first column indicates how the ΔlogGSVI for Climate Change impacts the return of green firms, defined as the bottom 25th percentile based on the impact ratio. The second and third columns indicate the same impact on brown and neutral firms. The coefficient of the change in log GSVI is not significant at the 10% level for green and neutral, thus the null hypothesis that it is different than zero cannot be rejected. It is however significant at the 10% threshold for brown firms. As for the control variables, ROE is found to be significant for the green and neutral firms but not for brown firms. The beta variable is significant at the 10% level for green and brown firms. The book to market ratio as well as the momentum factor are significant for all types of firms. The other variables do not seem to be significant.

As seen in Figure 1, Trucost coverage changed significantly in 2016. Moreover, because of the Covid-19 pandemic, firms' operations worldwide were disrupted heavily in 2020. Some industries were more affected than others, such as airlines for example, which saw a decline of

Figure 4: Average Direct plus First-Tier Indirect US Carbon Emissions



64.6% of global passenger traffic (ACI, 2021). This means that emission data reported for 2020 might not be representative of the normal business activity. Figure 4 confirms this statement by showing the decrease in average direct plus first-tier indirect carbon emissions in 2020. The impact of the change in coverage can also be seen in 2016. The added firms, which Trucost calls the "Core Plus" universe, comprise mostly of mid-, small and micro-cap companies and are a major reason for the large decline in average emissions in 2016.

Because of the low coverage before 2016 and of the effect of the pandemic on emissions in 2020, the regression was estimated again using data from 2016 to 2019 only. Table 10 reports the results.

Table 10: Results of the cross-sectional regression for the sub-sample 2016-2019

Variables	(1) Green	(2) Brown	(3) Neutral
Intercept	0.002	-0.007	-0.058
	(0.04)	(-0.14)	(-1.74)
log_size	-0.008	-0.007	-0.003
	(-1.17)	(-0.71)	(-0.47)
log_ppe	0.007	0.007	0.006
	(1.48)	(1.01)	(1.31)
B/M	0.074***	0.037	0.083***
	(5.12)	(1.58)	(6.55)
ROE	0.135*	0.014	0.113***
	(1.93)	(0.16)	(2.68)
Leverage	-0.013	0.005	0.010
	(-0.59)	(0.16)	(0.48)
Investment	-0.114	-0.040	-0.042
	(-0.52)	(-0.12)	(-0.20)
VOL	-0.128	0.062	0.083
	(-0.57)	(0.34)	(0.52)
MOM	0.180***	0.139***	0.199***
	(10.38)	(5.93)	(11.33)
beta	0.020***	-0.014	0.002
	(5.86)	(-1.22)	(0.37)
ΔlogGSVI	-0.024	0.017	-0.017
	(-1.02)	(0.78)	(-0.65)
Time F.E.	No	No	No
Industry F.E.	Yes	Yes	Yes
Observations	4398	4258	8661
R-squared	0.136	0.084	0.157

* 10% significance, ** 5% significance, *** 1% significance

The coefficient of the change in log GSVI is again not significant when using a shorter but more complete sub-sample for all types of firms. These results indicate that using ΔlogGSVI as a proxy for investors' attention to climate change might not be a correct methodical choice to help predict firm-level returns. On one hand, it was found in previous studies that investors were actively responding to climate change news and events. Addoum et al. (2018) explain that earnings are affected significantly by extreme temperatures. Ardia et al. (2021) find significant evidence that green firms outperform brown firms when climate change concerns increase unexpectedly, just as Pastor et al. (2021) found that green firms' outperformance is due to an increase in climate concerns. On the other hand, some studies argued that the Google Search Volume Index is a valid proxy for investors' attention. In particular, Da et al. (2011) find that SVI is correlated with other more traditional measures of attention to a particular stock. This would mean that GSVI is not effectively representing investors' attention as well as the MCCC measure that Ardia et al. (2021) uses or the WSJ Climate Change News Index that Engle et al. (2019) construct. It would rather represent the retail investors' attention as well as the public's attention to climate change, which does not impact stock returns as much as institutional investors. The cross-sectional regression is performed again with both alternative investors' attention measures, the MCCC (see Appendix B) and the WSJ Climate Change News Index (see Appendix C). The results are in accordance with the regression results done with the GSVI where the coefficient for the attention measure variable is still not significant

The same regression is done using the industry classification method (see Appendix D). Under this classification, the ΔlogGSVI coefficient for green and brown firms is still not significant.

5.2 Time-series returns results

Table 11 presents the correlations between the variables used in the time-series regression.

Table 11: Cross-correlation of independent variables in the time-series regression

	MktRF	SMB	HML	RMW	CMA	RF	ΔlogGSVI	ret_green	ret_brown	ret_GMB
MktRF	1									
SMB	0.44***	1								
	(0.00)									
HML	0.28***	0.35***	1							
	(0.00)	(0.00)								
RMW	-0.27***	-0.32***	-0.13**	1						
	(0.00)	(0.00)	(0.08)							
CMA	-0.09	0.05	0.48***	0.04	1					
	(0.21)	(0.49)	(0.00)	(0.62)						
RF	-0.11	-0.10	-0.01	0.03	0.00	1				
	(0.14)	(0.19)	(0.94)	(0.70)	(0.99)					
ΔlogGSVI	0.02	-0.07	-0.09	0.05	0.04	0.05	1			
	(0.10)	(0.94)	(0.51)	(0.09)	(0.76)	(0.00)				
ret_green	0.92***	0.61***	0.47***	-0.36***	-0.04**	-0.10	-0.03	1		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.59)	(0.19)	(0.69)			
ret_brown	0.91***	0.60***	0.35***	-0.22***	-0.02	-0.06	-0.02	0.89***	1	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.79)	(0.39)	(0.82)	(0.00)		
ret_GMB	-0.11	-0.05	0.19***	-0.25***	-0.04***	-0.06	-0.02	0.10	-0.36***	1
	(0.13)	(0.52)	(0.01)	(0.00)	(0.61)	(0.41)	(0.76)	(0.17)	(0.00)	

* 10% significance, ** 5% significance, *** 1% significance

The highest correlation between independent variables is 0.48 between the RMW and the HML variable. However, the strength of the correlation is not high enough to justify any adjustment to the model.

Table 12 presents the results of the time-series regression.

Table 12: Regression results of the Green, Brown and GMB portfolios

Variables	(1) Green	(2) Brown	(3) GMB
Intercept	0.247*	-0.266	0.513**
	(0.13)	(0.20)	(0.21)
RF	0.908	3.004***	-2.095*
	(0.66)	(1.05)	(1.24)
MktRF	1.036***	1.076***	-0.040
	(0.03)	(0.04)	(0.04)
SMB	0.506***	0.593***	-0.087
	(0.06)	(0.08)	(0.07)
HML	-0.111	0.031	-0.142*
	(0.08)	(0.11)	(0.08)
RMW	-0.165**	0.272**	-0.437***
	(0.07)	(0.11)	(0.11)
CMA	-0.205**	0.191	-0.396***
	(0.10)	(0.14)	(0.15)
ΔlogGSVI	0.002	0.002	0.000
	(0.00)	(0.00)	(0.00)
Observations	185	185	185
R-squared	0.937	0.871	0.198

* 10% significance, ** 5% significance, *** 1% significance

The first and second columns represent the results of the Fama-French five-factor regression on the returns of a green portfolio and a brown portfolio. The third column is the results of the regression on a Green Minus Brown portfolio. Looking at our variable of interest, the ΔlogGSVI, it seems that none of the coefficient are positively significant. The null hypothesis that the coefficient is different from zero cannot be rejected for any of the portfolios. For the green portfolio, all the five Fama-French factors are significant except for the HML variable while the brown portfolio shows no association with the value factor (HML) and the investment factor

(CMA). The GMB portfolio shows significant relationships with the HML, RMW and the CMA factors. However, the RMW and the CMA factors change sign between green and brown firms just as in Ardia et al. (2021). This could mean that investors favour low operating profits and aggressive investment policies for green firms and the inverse for brown firms. The regression is estimated again with the Fama-French three-factor model (see Appendix E) as well as with the market model (see Appendix F). The results are still in line with the results from the Fama-French five-factor model. None of the coefficients of the ΔlogGSVI variable are significant for both the Fama-French three-factor model and the market model. The market, SMB and HML factor are significant for the green portfolio of the three-factor model while only the market and SMB factor are significant for the brown portfolio. The GMB portfolio shows significant relationship with the HML factor only. For the market model, the market factor is significant for both the green and brown portfolios but not for the GMB portfolio.

Because of the low coverage of the Trucost database before 2016 and the impact of Covid-19 had on carbon emissions in 2020, the regression is estimated again without 2020 data and without small and mid-size firms[1]. Table 13 presents the results.

[1] Defined as below the 66th percentile in Market Capitalization.

Table 13: Time-series regression results without 2020 and small and mid-size firms

Variables	(1) Green	(2) Brown	(3) GMB
Intercept	0.603***	0.209	0.394**
	(0.08)	(0.18)	(0.23)
RF	0.557	2.587***	-2.030**
	(0.45)	(0.89)	(1.14)
MktRF	1.055***	0.954***	0.101
	(0.02)	(0.05)	(0.06)
SMB	0.099***	0.156***	-0.057
	(0.05)	(0.09)	(0.12)
HML	-0.199***	-0.145***	-0.054*
	(0.04)	(0.13)	(0.14)
RMW	-0.123	0.292	-0.415***
	(0.076	(0.13)	(0.17)
CMA	-0.171***	0.192***	-0.363
	(0.05)	(0.17)	(0.19)
ΔlogGSVI	0.190	-0.027	0.217
	(0.24)	(0.43)	(0.51)
Observations	173	173	173
R-squared	0.950	0.784	0.160

* 10% significance, ** 5% significance, *** 1% significance

Over the 2005-2019 period and without small and mid-size firms, the coefficient of the ΔlogGSVI measure is not significant for any of the portfolios, which confirms the previous results. However, this only help with the validity of the results by having a more stable coverage throughout the sample. The impacts due to changes in the composition of the sample made by Trucost in 2016 when smaller firms were added to the database to form the *Core Plus Universe* could have had an impact on how the environmental risk is represented in the sample. Investors might see smaller firms as being less able to adapt to climate change as they have fewer resources to invest in new clean technologies and fewer resources to comply with new environmental regulatory requirements. As others have suggested before (Hong and Kacperczyk, 2009), investors might see climate change coverage as an additional risk for holding smaller firms and thus demand to be compensated for it. The regression is re-estimated using the 2016-2019 period with only large firms, which are defined as above the 75^{th} percentile by market capitalization (see Appendix G) and then again using only small firms, which are below the 25^{th} percentile by market capitalization (see Appendix H). The results confirm the previous explanation since the ΔlogGSVI coefficient is not significant when considering only large firms but becomes highly significant for green firms (1% level) when considering only small firms. Investors would reward small sustainable firms because they see them as less risky than small polluting firms. Small brown firms are more at risk to get financially affected by a new environmental regulation or by an environmental lawsuit than small green firms.

The time-series regression is re-estimated using the industry classification method over the entire sample (See results in Appendix I). The results obtained using this method are very similar to other studies (Ardia et al., 2021; Pastor et al., 2021), but differs from the results of the regression using the impact ratio as the classification method. The HML factor, which is significant for both green and brown firms, changes sign. This indicate that investors favour lower growth for green firms but higher growth for brown firms. The CMA factor is the largest of the Fama-French factors for the GMB portfolio, which is consistent with green firms investing more and brown firms investing less (Pastor et al., 2021). The coefficient for the ΔlogGSVI is positively and significantly associated with the returns of the green portfolio as well as the GMB portfolio below the 1% threshold. This means that when investors react to climate change events, they might not differentiate firms based on their environmental impact but rather based on the industry they operate in. When climate change news coverage increases, investors increase their holdings in firms that are in non-polluting industries and decrease their holdings in firms that are in polluting industries. The difference in the results between the impact ratio and the industry classification method reveals that the impact ratio is not an appropriate measure to classify firms on their environmental performance because investors might only look at broad industry classification to do so.

6 Conclusion

Climate change is global issue that most people think should be addressed. However, it is an issue that is surrounded by uncertainty. Some governments are pro-active in the fight against climate change by enacting regulations while others act more moderately because they see climate change as a future problem. This uncertainty can be recognized in the financial industry as climate risk has only been recently taken into consideration by investors. Nonetheless, climate change will only have larger repercussions in the future. Many researchers have been interested in linking climate change to the financial market with studies relating to the relationship between financial performance and environmental performance. However, only a handful have studied the relationship between the level of investors' concern about climate change and firms' financial performance. As sustainable investing continues to grow, climate change will become even more integrated in investors' decisions. Some studies have explored the effect of demand for information of a particular topic on the stock returns. For example, El Ouadghiri and Peillex (2018) have linked public attention of Islamic terrorism to the returns of US Islamic stock indices. This raises the question of whether public attention to climate change might affect different kind of firms in terms of environmental performances differently.

In this paper, data from Google Trends is used as a proxy for attention to climate change. It is found that under a firm-specific approach, the attention to climate change is not a good asset-pricing factor. No difference is found between green, brown and neutral firms when looking at the impact of the level of attention to climate change and stock prices. However, when looking at this relation under a portfolio approach, attention to climate change portrayed by the Google Search Volume Index can be seen as a reliable pricing factor. More precisely, investors react to changes in attention to climate change by rewarding green firms when it increases. Also, a portfolio consisting of a long position in green firms and a short position in brown firms will have higher returns when attention to climate change increases. However, the method which is used to classify firms based on their environmental performance may impact the results greatly. The impact ratio provided by Trucost is found to be unreliable as a measure to differentiate green and brown firms. The measure is calculated using estimates and as such investors might not be fully confident on its trustworthiness. Investors might choose the industry classification method over a measure such as the impact ratio because of its simplicity.

This paper contributes to the scarce literature using internet search volume as demand for information. It evaluates a different method of classifying green and brown firms by using Trucost's Impact ratio and verifies the results with the industry classification method used by multiple studies. The paper also contributes to the existing literature linking climate change and financial performance by using a firm-level approach and a portfolio approach.

However, many limitations could potentially constrain the interpretation of the results. First, defining GSVI as an investors' attention metric might not be the most appropriate method. It was found in an earlier study (Da et al., 2011) that GSVI measures mostly retail investors' attention. This means that the impact portrayed in the results represent the reaction of retail investors only. If the assumption that institutional investors and retail investors react in the same manner to environmental risk, then the results hold. Otherwise, another measure more closely related to institutional investors' demand for information such as Bloomberg, Refinitiv or Capital IQ platforms search queries should be used to account for the reaction of institutions. Second, the low coverage of the Trucost's database over the CRSP and Compustat databases could potentially alter the results. Even if the sample is representative of the whole datasets, only about 10% is covered until 2015 and then the coverage goes up to only about 30% until today. Better coverage could lead to results more representative of the market reaction and thus more significative results. The IPCC industry method is used in the analysis to validate the results obtained by the Trucost method. However, this method classifies every company in selected industries. Some of the least polluting companies in these polluting industries could be seen by investors as sustainable so the results of the analysis could deviate from the real market reaction.

It would be interesting to research if investors' attention has the same relationship in another geographical context, more particularly in Europe. Environmental disclosure is much more prevalent in European countries so the coverage of environmental data over the total companies could substantially improve.

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Appendix A

List of polluting industries according to the IPCC classification

GICS Sector	GICS Industry
Utilities	• Electric Utilities • Independent Power and Renewable Electricity Producers • Multi-Utilities • Gas Utilities
Materials	• Paper & Forest Products • Metals & Mining • Containers & Packaging • Chemicals • Construction Materials
Energy	• Oil, Gas & Consumable Fuels
Consumer Staples	• Food Products • Tobacco • Household Products • Food & Staples Retailing • Beverages
Industrials	• Airlines • Air Freight & Logistics • Industrial Conglomerates • Road & Rail
Consumer Discretionary	• Automobiles

Appendix B

Panel regression results with the MCCC attention measure

Variables	(1) Green	(2) Brown
Intercept	-0.052*	0.038
	(-1.65)	(0.87)
log_size	0.002	-0.014
	(0.60)	(-1.28)
log_ppe	-0.004	0.009
	(-1.45)	(0.97)
B/M	0.087***	0.019
	(4.72)	(0.75)
ROE	0.124	0.030
	(1.42)	(0.29)
Leverage	0.012	-0.039
	(0.65)	(-1.08)
Investment	0.420**	0.265
	(2.25)	(0.94)
VOL	0.303	0.346
	(1.53)	(1.46)
MOM	0.142***	0.099***
	(8.45)	(3.72)
beta	-0.003	-0.019
	(-0.36)	(-1.07)
MCCC	0.024	-0.004
	(0.68)	(-0.10)
Time F.E.	No	No
Industry F.E.	Yes	Yes
Observations	4817	4464
R-squared	0.098	0.061

* 10% significance, ** 5% significance, *** 1% significance

Appendix C

Panel regression results with the WSJ Climate Change News Index

Variables	(1) Green	(2) Brown
Intercept	-0.048	0.037
	(-1.59)	(0.83)
log_size	0.002	-0.014
	(0.53)	(-1.26)
log_ppe	-0.004	0.009
	(-1.40)	(0.96)
B/M	0.084***	0.019
	(4.55)	(0.78)
ROE	0.125***	0.031
	(1.43)	(0.30)
Leverage	0.013	-0.039
	(0.70)	(-1.07)
Investment	0.397**	0.278
	(2.23)	(1.14)
VOL	0.310	0.344
	(1.55)	(1.46)
MOM	0.141***	0.099***
	(8.31)	(3.68)
beta	-0.003	-0.019
	(-0.41)	(-1.06)
WSJ	0.018	-0.007
	(0.67)	(-0.19)
Time F.E.	No	No
Industry F.E.	Yes	Yes
Observations	4817	4464
R-squared	0.098	0.061

* 10% significance, ** 5% significance, *** 1% significance

Appendix D

Panel regression results for green and brown firms under the industry classification method

Variables	(1) Green	(2) Brown
Intercept	-0.065**	-0.038
	(-2.36)	(-1.08)
log_size	0.000	-0.003
	(0.03)	(-0.47)
log_ppe	0.002	0.004
	(0.50)	(0.79)
B/M	0.084***	0.059***
	(9.05)	(3.69)
ROE	0.111***	0.093*
	(3.16)	(1.65)
Leverage	0.007	0.008
	(0.31)	(0.35)
Investment	-0.048	-0.006
	(-0.25)	(-0.03)
VOL	0.234	0.163
	(1.15)	(0.79)
MOM	0.174***	0.135***
	(11.36)	(6.95)
beta	-0.002	-0.017
	(-0.29)	(-1.61)
ΔlogGSVI	0.019	0.025
	(0.76)	(1.40)
Time F.E.	No	No
Industry F.E.	Yes	Yes
Observations	21420	8998
R-squared	0.120	0.082

* 10% significance, ** 5% significance, *** 1% significance

Appendix E

Three-factor Fama-French regression results

Variables	(1) Green	(2) Brown	(3) GMB
Intercept	0.167	-0.157	0.324
	(0.13)	(0.19)	(0.21)
RF	0.999	2.899***	-1.900
	(0.69)	(1.04)	(1.26)
MktRF	1.061***	1.047***	0.014
	(0.03)	(0.04)	(0.04)
SMB	0.538***	0.545***	-0.007
	(0.06)	(0.07)	(0.06)
HML	-0.171***	0.087	-0.258***
	(0.06)	(0.09)	(0.08)
ΔlogGSVI	0.002	0.002	-0.000
	(0.00)	(0.00)	(0.00)
Observations	185	185	185
R-squared	0.848	0.913	0.067

* 10% significance, ** 5% significance, *** 1% significance

Appendix F

Market model regression results

Variables	(1) Green	(2) Brown	(3) GMB
Intercept	0.007	-0.146	0.152
	(0.26)	(0.22)	(0.26)
RF	0.298	1.927*	-1.629
	(0.96)	(1.12)	(1.20)
MktRF	1.136***	1.195***	-0.059
	(0.04)	(0.05)	(0.06)
ΔlogGSVI	0.002	0.000	0.003
	(0.01)	(0.01)	(0.01)
Observations	185	185	185
R-squared	0.848	0.837	0.016

* 10% significance, ** 5% significance, *** 1% significance

Appendix G

Five-factor Fama-French regression results over the 2016-2019 period using small firms

Variables	(1) Green	(2) Brown	(3) GMB
Intercept	-2.104**	-0.996	-1.108
	(0.95)	(1.20)	(1.59)
RF	-0.510	-5.239	4.729
	(2.35)	(3.80)	(5.27)
MktRF	0.652***	1.376***	-0.725***
	(0.04)	(0.10)	(0.12)
SMB	0.995***	1.248***	-0.253
	(0.08)	(0.13)	(0.16)
HML	0.401***	0.181	0.220
	(0.11)	(0.14)	(0.21)
RMW	-0.119	-0.333*	0.214
	(0.11)	(0.19)	(0.18)
CMA	-0.310**	0.640***	-0.950***
	(0.14)	(0.16)	(0.25)
ΔlogGSVI	0.843***	0.142	0.700
	(0.31)	(0.44)	(0.59)
Observations	48	48	48
R-squared	0.941	0.913	0.581

* 10% significance, ** 5% significance, *** 1% significance

Appendix H

Five-factor Fama-French regression results over the 2016-2019 period using large firms

Variables	(1) Green	(2) Brown	(3) GMB
Intercept	-0.673	0.230	-0.903
	(0.86)	(1.24)	(1.82)
RF	0.544	-2.361	2.905
	(2.00)	(2.57)	(3.50)
MktRF	1.010***	1.011***	-0.002
	(0.05)	(0.09)	(0.13)
SMB	0.021	0.144	-0.123
	(0.08)	(0.13)	(0.19)
HML	0.405***	-0.148**	0.554***
	(0.07)	(0.06)	(0.11)
RMW	-0.182*	0.083	-0.264*
	(0.11)	(0.10)	(0.15)
CMA	-0.343**	0.606***	-0.949***
	(0.14)	(0.13)	(0.25)
ΔlogGSVI	0.378	0.095	0.283
	(0.26)	(0.44)	(0.62)
Observations	48	48	48
R-squared	0.924	0.905	0.356

* 10% significance, ** 5% significance, *** 1% significance

Note:

Appendix I

Five-factor Fama-French regression results using the industry classification method

Variables	(1) Green	(2) Brown	(3) GMB
Intercept	-0.035	0.191	-0.255
	(0.12)	(0.41)	(0.41)
RF	1.200	-3.893	5.093*
	(1.00)	(3.30)	(3.06)
MktRF	1.073***	1.125***	-0.053
	(0.02)	(0.09)	(0.08)
SMB	0.850***	0.530***	0.320**
	(0.04)	(0.13)	(0.13)
HML	-0.175***	0.137***	-0.312***
	(0.04)	(0.05)	(0.05)
RMW	-0.017	0.101	-0.118
	(0.07)	(0.19)	(0.22)
CMA	-0.006	0.681***	-0.687***
	(0.04)	(0.14)	(0.14)
ΔlogGSVI	1.068***	-0.505	1.573***
	(0.19)	(0.49)	(0.44)
Observations	88	88	88
R-squared	0.988	0.921	0.663

* 10% significance, ** 5% significance, *** 1% significance