Impact of climate change concerns on the volatility of green and brown stocks

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Abstract

This study investigates the complex relationship between climate change concerns and stock market volatility, focusing on S&P 500 stocks categorized by their environmental impact. Employing the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model with an additional exogenous variable and the Generalized Autoregressive Score (GAS) model, this research explores how environmental news influences market volatility. The study integrates variables such as the Media Climate Change Concerns Index (MCCC) and the Unexpected Media Climate Change Concerns (UMC) to assess the influence of climate-related media coverage. The GARCH-X and GAS models, enhanced with these indices, reveal that market responses to climate news vary significantly across companies, showing no consistent pattern relative to their environmental profiles. These findings suggest the complexities of market mechanisms and investor sensitivities to environmental news. It indicates that investors need to consider multiple factors beyond just the environmental aspects when analyzing financial risks and opportunities associated with climate change. This research contributes to climate finance by providing a detailed understanding of how environmental news affects stock volatility. Finally, it calls for further refinement of financial models to better capture the dynamics of market responses to climate concerns.

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1 Introduction

Financial markets today are increasingly influenced by environmental concerns, with a focus on how climate change impacts investment and market trends. According to Long et al. (2022), the United Nations Framework Convention on Climate Change (UNFCCC) originally describes climate finance as funding from various sources for climate change mitigation and adaptation. They suggest that this definition is quite basic and highlights the need for more complex approaches to encompass the broad challenges of climate change. Viewing climate finance as an investment rather than a cost suggests benefits beyond immediate economic considerations (Wendai and Bin, 2023). The World Bank Group's significant financing efforts in 2022 emphasize the growing priority of climate action worldwide (Long et al., 2022). With global agreements like the Paris Agreement bringing climate issues to the forefront, it's clear that the effects on financial markets warrant close examination. This study looks into the influence of climate risk perceptions on investor decisions and how this shapes stock market volatility.

Our study begins with a comprehensive review of various literature to establish a base, focusing on the heightened interest in climate finance and how it impacts the financial markets from an investor's perspective. Multiple studies categorize climate risks into physical, transition, and liability risks, offering a framework fundamental to various research projects, and highlighting the complex influence of climate uncertainties on financial markets. Our study mainly addresses how investors respond to climate risks, with Ardia et al. (2023) defining these concerns as perceptions of risk and its adverse outcomes. This research methodically integrates climate uncertainty indices like the Media Climate Change Concerns Index (MCCC) and the Unexpected Climate Change Concerns Index (UMC), developed by Ardia et al. (2023). These indices use natural language processing (NLP) to measure the extent of climate concerns in the media and their impact on financial markets. This supports our study's goal to explore the relationship between climate change news and stock market reactions, emphasizing how the financial market responds to environmental news.

Using quantitative methods such as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Generalized Autoregressive Score (GAS) models, this thesis conducts a detailed empirical analysis of S&P 500 companies, which are classified based on their environmental impact. Incorporating Environmental, Social, and Governance (ESG) factors into investment strategies can improve risk management and yield sustainable returns for investors (Dalal and Thaker, 2019). The environmental impact is assessed using ESG scores, environmental (E) scores, and greenhouse gas (GHG) intensity. The statistical models applied in this study play a critical role in analyzing the volatility patterns among green and brown stocks, providing a detailed examination of how both expected and unexpected climate-related issues affect market dynamics. This study thoroughly analyzes how climate-related news impacts stock market volatility. Through an in-depth evaluation of data and statistical models, our study illustrates the complex link between climate risks and market actions. The results demonstrate a complex relationship that isn't consistently supported by the data. We find unevenness in the impact of climate change concerns on market volatility, which emphasizes the complexity of this relationship.

The remainder of the study is organized as follows: The next section reviews the existing literature on climate finance. Section 3 outlines the methodology and data utilized in our study. Section 4 discusses the empirical results and the performance of the models used. The final section concludes the study.

2 Literature Review

2.1 Overview

With the debate about global warming and unprecedented climate changes intensifying, sustainable measures for safeguarding our environment and economic systems have been the highlight of multiple political and environmental discussions. This has led to an increased interest in how changes in weather and climate perceptions influence financial markets, particularly investor behavior, which can affect asset prices and market volatility (Chen et al., 2023). As a result, climate finance has become a key area of study, with researchers focusing on the relationship between climate-related uncertainties and financial market dynamics. Our study reviews the extensive research in this field to identify its implications on asset risk and returns. Specifically, we focus on studies that use NLP techniques where researchers aim to analyze how rising climate concerns are reflected in financial markets.

2.2 Types of climate risks and growing attention on climate finance

The academic literature on green energy investments has witnessed a remarkable expansion over the past decade, mainly due to increasing global concerns over the potential environmental, social, and economic consequences of climate change (Dutta et al., 2023). The volume of academic studies focusing on climate finance significantly increased throughout the 2010s, with a noticeable rise in publications after 2016. This period of increased academic publications coincides with the onset of the sustainable development initiatives in 2015 by the United Nations General Assembly and the Paris Agreement of 2017. Long et al. (2022) point out that studies focusing on sustainability, climate policy, and cleaner production have been the highlight of this recent research trend, highlighting the academic community's growing commitment to understanding and mitigating climate risks.

Climate change risks can be broken down into three main types, as identified by NGFS (2020): physical, transition, and liability risks (Ardia et al., 2023). Physical risks come from climate and weather phenomena like rising sea levels, floods, and heat waves, leading to direct financial losses or increased costs due to these events (Bua et al., 2022). Transition risks are about the shift toward a low-carbon economy (Ardia et al., 2023), involving new regulations to lower greenhouse gas emissions and the push for technological innovation towards a climate-neutral economy (Bua et al., 2022). According to Ardia et al. (2023), liability risks could arise from physical or transition risks, leading to potential legal liabilities linked to climate change.

Bibliometric analysis is becoming a vital tool for studying various aspects of science, offering a quantitative analysis of academic publications (Ellegaard and Wallin, 2015). Using this approach, Long et al. (2022) present a detailed analysis to statistically demonstrate a comprehensive evolution of the academic writings in climate finance. They identify six principal themes: (i) climate change, (ii) green financing, (iii) public policy, (iv) valuation of green bonds, (v) green financing and banking, and (vi) green bonds and financial markets. Within these themes, they explore specific topics such as policy debates around carbon emissions, which has been the main focus area for authors falling under the climate change cluster. In contrast, others examine topics such as green finance, sustainable practices, and corporate social responsibility. The research highlights the importance of green bonds in finance, emphasizing their potential to offer diversification benefits to investors. Ardia et al. (2023) take a similar approach to establish four critical areas in the field of climate finance: (i) business impact, (ii) environmental impact, (iii) societal debate, and (iv) research. They further categorize these themes into sub-topics that align with the types of climate risks — physical, transition, and liability risks. For instance, within the business impact theme, topics like renewable energy and carbon taxation are linked to transition risks, whereas legal challenges are associated with liability risks. This shows the complex nature of climate finance and related challenges.

Thus, the wide-ranging research into climate finance highlights the rising interest in climate change's impact on financial stability. The detailed thematic clusters identified in these studies are critical for developing tools to measure climate-related uncertainties, such as the Climate Policy Uncertainty Index (CPU) introduced by Gavriilidis (2021) and the MCCC index created by Ardia et al. (2023). Such indices are being increasingly employed in various academic studies to examine the influence of climate-related concerns on the financial markets.

2.3 Climate uncertainty indices

The use of NLP techniques has proved to be very effective in developing climate uncertainty proxies, which are essential for exploring the impact of climate concerns on financial markets. By analyzing the text of news articles and other media, NLP allows for creating time series data reflecting climate risks since they cover a wide range of events that can carry potentially relevant information. For instance, newspapers cover in-depth discussions on climate risks from extreme weather conditions (like floods and droughts), significant changes in Earth's physical condition (including the rise in sea level and shifts in ocean temperatures), regulatory developments, and innovations in alternative energy sources (Engle et al., 2020). Thus, the media's role is crucial, not just in covering these topics but also in influencing public opinion about climate change through the volume and informational content communicated in the news articles (Ardia et al., 2023).

Engle et al. (2020) use textual and narrative analysis, utilizing Wall Street Journal (WSJ) articles and construct a monthly WSJ climate change news index. They also developed another index that relies on the Crimson Hexagon (CH) sentiment measure to capture the negative attention about climate change across various news platforms. Both these indices trace the intensity of climate news coverage and display significant peaks during key climate events like the adoption of global climate agreements (e.g., the UNFCCC or the Kyoto Protocol) or important global summits to combat climate change (e.g., the 2009 UN Climate Change Conference in Copenhagen). Gavriilidis (2021) presents the monthly CPU index built on eight major newspapers focusing on uncertainty in climate risk, greenhouse gas emissions, global warming, environmental regulations, and legislation. Like the others, the CPU index highlights several spikes around important events regarding climate policy. Faccini et al. (2023) conduct a similar analysis of Reuters news related to climate change to construct four risk measures of climate uncertainty, focusing on natural disasters, global warming, international summits, and U.S. climate policy.

Ardia et al. (2023) develop a daily index called the MCCC index by analyzing news from ten leading U.S. newspapers like the Los Angeles Times, New York Times, and Wall Street Journal, as well as significant newswires, including Associated Press Newswires and Reuters News. Additionally, they also introduce an index for UMC derived through the prediction errors from a time series regression model adjusted for explanatory variables computed from the MCCC index. This approach helps differentiate between predictable news events (such as scheduled international conferences or minor revisions to existing articles) and unforeseen shifts in climate change concerns. Therefore, the UMC index helps capture the truly unexpected changes in climate concerns, as a 'shock' indicator within the MCCC index. Unlike other indices, such as the WSJ, CH, and CPU, which are compiled monthly, the MCCC and UMC indices are built on daily frequency. This provides a more granular and comprehensive view of how climate change news impacts financial markets, minimizing the issues associated with lower frequency data, such as weekly or monthly, which might overlook the immediate reactions of stock markets to new information.

2.4 Climate change concerns and asset returns

Climate change can significantly affect the quality of life in ways that extend beyond its direct impact on wealth (Pastor et al., 2021). Thus, unanticipated climate changes introduce an additional layer of risk for investors, which has led to increased curiosity in analyzing how such unforeseen events can alter asset prices and investor returns. Researchers have employed various climate uncertainty proxies, such as the CPU, MCCC, and UMC indices, to explore the relationship between climate risk and the performance of stocks. Such studies have provided crucial insights for eco-friendly investors interested in maintaining portfolios with low carbon emissions (Dutta et al., 2023).

Dutta et al. (2023) investigate the effect of increasing climate risk on the returns of green energy investments. They utilize the Markov regime-switching (MRS) model, with the CPU index acting as a climate risk indicator. Analyzing data across both high and low-volatility scenarios, they discover that increased climate risk positively influences investments in alternative energy, driving up both demand and prices for green energy assets. This suggests that investors prioritizing social responsibility and environmental sustainability tend to shift their focus toward cleaner energy options during periods of greater climate risk. Bouri et al. (2022) further examined the relationship between the CPU index and the performance ratio of green to brown energy stocks, and they identified a significantly positive relationship between the two, which is further validated through regression analysis. Through their analysis, they confirm that the CPU index significantly affects the preference for green over brown energy stocks, implying that increased climate policy uncertainty prompts investors to divert their funds from traditional (brown) energy stocks to more sustainable (green) energy options, enhancing the relative performance of green stocks. This observation aligns with other studies, such as that by Pastor et al. (2021), who also identify a link between CPU and the price fluctuations of green and brown stocks.

Engle et al. (2020) construct hedge portfolios to understand how U.S. stock prices are influenced by concerns about climate change, using the WSJ and CH negative climate change news indices as their climate concern proxies. Their analysis of the study reveals that environmentally friendly stocks have a positive and significant relationship with the WSJ index during periods of rising climate concerns and tend to earn higher excess returns. They observed similar results when applying the CH negative climate change news index as an alternative measure of climate risk. Faccini et al. (2023) use a standard portfolio sorting technique to classify stocks based on their sensitivity to climate-related risks. Using their risk measures of climate uncertainty constructed via textual analysis of climate-change-related news, they suggest that the investors demand higher returns from stocks facing higher uncertainties surrounding U.S. climate policy, focusing mainly on short-term transition risks. Interestingly, the study also finds that investors overlook the longer-term risks related to physical climate changes and transition issues highlighted by natural disasters, global warming, and international climate summits.

Ardia et al. (2023) analyze how green and brown stocks react to climate change concerns using the daily MCCC and UMC indices. They assess a company's greenness by their GHG emissions and apply conditional mean and multivariate factor analysis to their data. Their findings indicate that companies with lower GHG emissions (green firms) generally outperform those with higher emissions (brown firms) during times of unexpected increase in climate change concerns. An industry-level analysis of the authors also shows that the response to climate change concerns tends to be uniform within industries. Finally, they suggest that the influence of unexpected climate change concerns on stock performance applies even to firms that haven't disclosed their GHG emissions, indicating a broader sensitivity to climate issues.

2.5 Climate change concerns and asset volatility

In addition to asset pricing and returns, the influence of climate change and policy shifts also extends to the volatility of financial markets. The financial implications of future climate regulation on stock markets have become increasingly challenging, introducing greater tail and variance risks for investors (Chen et al., 2023). Thus, to understand the relationship between climate change concerns and stock market volatility, researchers like Dutta et al. (2023) have applied advanced analytical methods, including MRS regression and asymmetric GARCH models. Their research indicates that while climate risk positively influences the returns on investments in green energy, it conversely impacts their volatility. This suggests that rising climate risk drives a market shift towards alternative energy sectors, leading to increased prices for clean energy investments and a notable reduction in their volatility.

Chen et al. (2023) examine the Chinese stock market's volatility using the Realized GARCH-MIDAS model, focusing on the CPU index and using high-frequency trading data. Their study shows that the CPU index effectively predicts long-term market volatility. Moreover, they discover that combining CPU with high-frequency data enhances the accuracy of volatility forecasts for almost all forecast window sizes. The study also examines how these predictors perform across different economic cycles, finding that the accuracy in forecasting stock volatility improves in the recession period compared to the expansion phase. Bouri et al. (2022) conduct a regression analysis to assess the impact of the CPU index on the realized volatility of stocks, revealing that it significantly reduces the volatility of green energy stocks compared to brown energy stocks, particularly during periods of climate uncertainty. This suggests that the CPU has a stabilizing effect on the volatility of green energy stocks. Ozturk et al. (2022) use various stochastic volatility models for assessing the impact of climate uncertainty on the volatility of carbon markets, utilizing proxies for physical and transition climate risks developed by Faccini et al. (2023). They find that before the Paris Agreement, climate policy and other transition risks like international summits were the key drivers of volatility. However, after the Paris Agreement, the emphasis shifted towards risks from natural disasters and global warming, making them the principal driving factors for price fluctuations in the carbon emissions market. The study concludes that climate risk factors significantly improve the forecasts for market volatility and returns.

Wendai and Bin (2023) investigate how climate change influences stock market volatility across various economic sectors. Applying the Autoregressive (AR) model, they find that the CPU index predicts volatility in energy, materials, industrials, consumer discretionary, healthcare, and utility sectors. Their research also examines the predictive power of the CPU index during different market volatility conditions. They find that in periods of low market volatility, the predictive accuracy of the CPU index holds for almost all sectors except finance and telecommunications. However, in times of high volatility, only the utility sector positively responds to CPU predictions.

Drawing from the increasing focus on the impact of climate uncertainty on the behavior of financial markets, our research further investigates this area by utilizing the daily proxies of climate change concern, namely the MCCC and UMC indices developed by Ardia et al. (2023). The objective of this study is to assess the influence of climate risk on the volatility of the U.S. stock market for which we apply the GARCH and GAS models, incorporating these climate risk proxies as exogenous variables to examine their significance in predicting stock market volatility. The study's methodology and results are discussed in detail in the following sections.

3 Data and Methodology

3.1 S&P 500 stocks and indicators of their greenness

We follow Ardia et al. (2023) and conduct our study on S&P 500 companies over a period starting from January 2014 to August 2022, using data obtained from the Center for Research in Security Prices, LLC (CRSP). For each period under investigation, we account for the addition or removal of stocks from the S&P 500 list of companies. Our research uses a range of factors to identify green and brown firms out of the S&P 500 stock universe. The first measure focuses on the ESG scores of these firms, which have been obtained from Compustat. The concept of ESG can be explained as a combination of environmental, social, and governance elements that illustrate a company's commitment to these areas. According to the Principles of Responsible Investing (PRI), ESG assists investors in employing strategies to manage risks and achieve sustainable returns over the long term (Ahlklo Yrr, 2018). Raisa Almeyda (2019) explain the three elements of ESG. The environmental aspect focuses on a company's efforts towards creating a positive environmental impact by complying with relevant regulations, such as managing pollution, waste, and carbon emissions and tackling climate change. Social actions revolve around the treatment of stakeholders and the company's communities, such as employee relations, workplace safety, community engagement, diversity, and conflict management. The element of governance concentrates on the ethical conduct and integrity of a company's management and board, focusing on policies, tax practices, donations, and efforts to combat corruption and bribery. Investors use ESG scores to assess a company's sustainability and its capability for long-term financial performance (Ahlklo Yrr, 2018). These scores range from 0 to 100, with 100 representing a company's highest level of sustainability. Next, we extend our study beyond ESG scores and focus on a firm's environmental performance, particularly the 'environmental' component of ESG, which are given by E scores (also ranging from 0 to 100, 100 being the greenest). We work with E scores specifically since we aim to assess the direct effects of climate change concerns on stock market fluctuations. These scores typically consider a wide range of metrics such as energy efficiency, renewable energy usage, waste management, environmental impact, and the company's overall carbon footprint. Similar to ESG scores, we source these environmental ratings from Compustat.

Finally, following the methodology of Ardia et al. (2023), we also categorize firms into 'green' or 'brown' based on their GHG emissions obtained from the Asset4/Refinitiv database. The GHG emissions are divided into three categories as per the GHG Protocol Corporate Standard: Scope 1 covers direct emissions from the company's operations, Scope 2 accounts for indirect emissions from purchased energy, and Scope 3 includes all other indirect emissions within the company's value chain, which are not covered in Scope 2. These emissions are measured in carbon dioxide (CO2) equivalents. We primarily focus on the total GHG emissions, which combine Scopes 1, 2, and 3 emissions, and are further scaled by the company's annual revenue, termed as GHG intensity. The GHG intensity helps in evaluating the total carbon footprint of the companies. The lower the GHG intensity, the greener the firm is. Our research applies the GARCH and GAS models with exogenous variables to investigate the effect of climate concerns on stock volatility of the S&P 500 firms, evaluating the findings with the above measures to identify any significant relationships.

3.2 Climate concern proxies

In contrast to the monthly-based CPU index introduced by Gavriilidis (2021), our research incorporates the MCCC and UMC indices from Ardia et al. (2023), which are constructed using daily data. This aligns with our goal to capture the immediate responses of stock markets to news, aligning with the daily returns of the S&P 500 stocks. The MCCC index, derived from a collection of climate change-related news articles from U.S. newspapers and newswires, serves as a score that measures the level of concern generated by these publications. This makes MCCC a reliable measure for determining the impact of media on public perception regarding climate change issues. We source the MCCC index data derived by Ardia et al. (2023) from January 2003 through August 2022 via www.sentometrics-research.com.

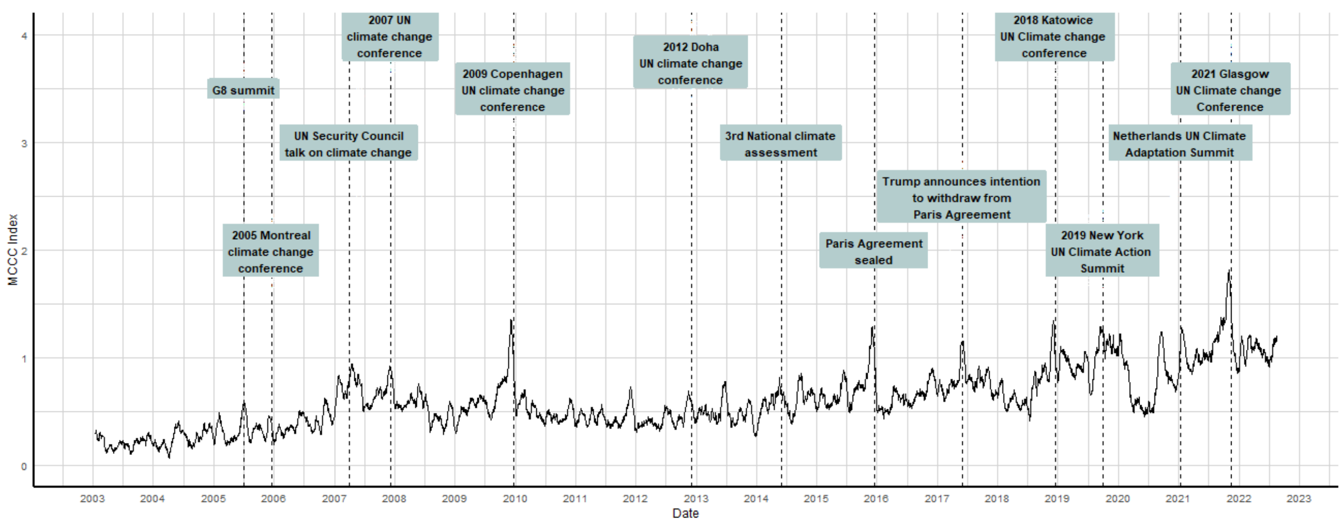


Figure 1: Time series plot for the MCCC Index from January 2003 till August 2022. Major climate-related events have been identified against significant peaks in the graph.

In Figure 1, we show the 30-day moving average of the MCCC index for this period, which aids in recognizing significant news events and patterns. The period from 2003 – 2013 is considered in a forward-looking context and is not directly involved in our analysis. However, it provides valuable insights for the validation of the index. We see significant spikes in the index, which represent major climate change events, such as the 2009 Copenhagen UN Climate Change Conference or the 2019 New York UN Climate Action Summit. The index also saw a significant fall around 2020, which coincides with the COVID-19 pandemic. This drop might likely be because of the excessive news coverage of the pandemic during this period. The index again starts climbing, hitting another high towards the end of 2021, corresponding with the 2021 Glasgow UN climate change conference.

The MCCC index is the foundation for identifying the unexpected or the 'shock' component of climate change concerns. Given that the media often reports unforeseen climate events, the MCCC can be considered an appropriate starting point for identifying sudden changes in climate concerns. However, it is essential to consider that some news stories could be foreseen for several reasons, such as pre-scheduled events (like planned international summits) or the circulation of outdated news with slight alterations. Therefore, to separate the anticipated components from MCCC, we employ an autoregressive time series model given by:

$$MCCC_t = \mu + \rho MCCC_{t-1} + \epsilon_t.$$

We estimate the above AR model using a rolling window of size 1000 and derive the prediction error to measure unexpected shifts in climate change concern, denoted as UMC. We use the MCCC and UMC indices in our analysis to investigate the impact of climate change concerns on stock market volatility.

3.3 GARCH models

3.3.1 Introduction to ARCH and GARCH models

The introduction of the Autoregressive Conditional Heteroskedasticity (ARCH) model by Engle (1982) and its subsequent generalization to the Generalized ARCH (GARCH) model by Bollerslev (1986) marked the beginning of extensive research into the use of time series models for analyzing volatility. Engle (1982) in his model defined the ARCH process as:

$$\begin{aligned} y_t &= \sigma_t \epsilon_t, \\ \sigma_t^2 &= \omega + \sum_{i=1}^{q} \alpha_i y_{t-i}^2, \end{aligned} \tag{1}$$

where y_t is a discrete-time stochastic process, $\{\epsilon_t\}_{t=1}^{T}$ are standard normal innovations with mean zero and unit variance, σ_t is a time-varying function of the past squared values of the ARCH process, $\omega > 0$, and $\alpha_i \geq 0$. This model is known as the univariate ARCH(q) model. It aids in capturing volatility clustering, which refers to the phenomenon where large changes over time in asset prices (up or down) tend to follow more large changes, and small changes tend to follow small changes.

Bollerslev (1986) introduced a generalized version of ARCH, known as the GARCH(p,q) model and follows the below process:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i y_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2,$$

where $\omega > 0$, $\alpha_i \geq 0$, and $\beta_j \geq 0$. The conditional variance σ_t^2 is a function of the previous i iterations, where y_{t-i}^2 is known as the ARCH term and σ_{t-j}^2 is known as the GARCH term. The constraints on the parameters ω, α_i, and β_j ensure that σ_t^2 is strictly positive since y_t^2 is also non-negative. Also, $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$ is required to ensure stationarity.

3.3.2 GARCH(1,1) with exogenous variables (GARCH-X)

The preceding section discusses the GARCH(p,q) model, which offers flexibility in choosing the lagged order for modeling. However, choosing the proper lag orders (p and q) for a GARCH model can be challenging. Higher lag orders can increase computational complexity and may make interpretation more difficult. Thus, to simplify our analysis and avoid these challenges, we restrict our analysis to the GARCH(1,1) model, which is given by:

$$\sigma_t^2 = \omega + \alpha_1 y_{t-1}^2 + \beta_1 \sigma_{t-1}^2,$$

where $\omega > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$. Also, $\alpha_1 + \beta_1 < 1$ is required to ensure stationarity.

Extending the GARCH(1,1) model for the discrete-time stochastic process y_t defined in Equation

(1), we consider the following process:

$$\sigma_t^2 = \omega + \alpha_1 y_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 x_{t-1},$$

where $\omega > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, and $\gamma_1 \geq 0$. In this model, variable x_t represents the exogenous element, and the resulting process is known as the GARCH-X model. Incorporating an extra component x_t often improves the ability to explain fluctuations in the stock market. This approach tends to enhance the model's accuracy for fitting historical data and making future estimations.

We use the garchx package developed by Sucarrat (2021) for estimating the parameters $\theta_0 = \{\omega, \alpha_1, \beta_1, \gamma_1\}$. The normal maximum likelihood (ML) estimator provides asymptotically normal and consistent estimates of GARCH models in which the ϵ_t's are dependent on past observables. Precisely, they follow Francq and Thieu (2019) and show that:

$$\sqrt{T}(\hat{\theta} - \theta_0) \xrightarrow{d} N(0, \Sigma), \quad \Sigma = J^{-1} I J^{-1}, \quad J = E\left(-\frac{\partial^2 l_t(\theta_0)}{\partial\theta\partial\theta'}\right), \quad I = E\left(\frac{\partial l_t(\theta_0)}{\partial\theta}\frac{\partial l_t(\theta_0)}{\partial\theta'}\right) \quad ,$$

where

$$\hat{\theta} = \arg\min_{\theta} \frac{1}{T}\sum_{t=1}^{T} l_t(\theta), \quad l_t(\theta) = \frac{y_t^2}{\sigma_t^2(\theta)} + \ln\sigma_t^2(\theta)$$

is the (normal) Quasi ML (QML) estimate of the true parameter θ_0. The standard errors using the garchx package are computed via the coefficient-covariance given by:

$$\Sigma = \left(\mathbb{E}(\epsilon_t^4) - 1\right) J^{-1},$$

when ϵ_t's are independent of the past. If ϵ_t's are dependent, a more complex formulation for I and subsequently Σ is required. As mentioned by Sucarrat (2021), J is not available in closed form and involves a combination of simulation and numerical differentiation to compute an estimate. The garchx package facilitates the computation of Σ, which is then used to calculate the standard errors. Finally, the standard errors are computed as the square root of the diagonal of the estimate Σ.

We employ the GARCH-X model to analyze the daily log returns of the S&P 500 for two-year intervals. This approach begins from January 2014 to December 2015 and proceeds sequentially, moving one year forward at each step up until August 2022. This methodology is selected to adequately capture the changes in market dynamics and the potential influence of external shocks over time. It aims to mitigate the risk of the model's parameters being biased towards the volatility characteristics of any single period. For each window, only stocks with a complete record of daily returns available throughout the two years are included. This selection condition ensures consistency of results across different periods. Also, it guarantees that the data does not have any gaps that might otherwise lead to inaccuracies in the volatility estimation, ensuring the accuracy of the output from the model.

To incorporate the impact of external factors related to climate change concerns into our model, we separately integrate the two indices as mentioned in Section 3.2 above, i.e., the MCCC and the UMC. The MCCC index is introduced to measure the market's overall concerns regarding climate change, thus reflecting a broader perception of how climate concerns influence market behavior. On the contrary, the UMC index is utilized to assess the influence of unexpected or sudden developments in the context of climate change concerns. It considers climate change's 'shock' component to verify its impact on stock volatility.

Following the application of the GARCH-X model, incorporating the above climate change indices, we calculate and record the estimated model parameters and their associated t-statistics (t-stats) for each two-year interval. With the standard errors calculated using the garchx package, as discussed previously, the t-stat for the exogenous variable is computed by dividing the estimated coefficient by the corresponding standard error. We observe that the t-stats for the exogenous variable are normally distributed under the null hypothesis. We then plot the t-stats related to the climate change indices against various environmental benchmarks of the stocks as mentioned in section 3.1: their ESG scores, E scores, and GHG intensity. This analysis is essential to understand the nature of the relationship between the market's reaction to climate change concerns as measured by the model and the environmental categorization of the stocks, which helps distinguish between 'green' and 'brown' stocks.

To further understand how the market reacts to climate-related concerns about the environmental conduct of companies, we also perform a linear regression analysis on the t-stats derived for the climate change indices through the GARCH-X model. The aim is to understand the general trend of sensitivity of the market to climate change issues and the companies' environmental practices. It specifically examines how 'green' and 'brown' companies (categorized based on their ESG scores, E scores, and GHG intensity) react in terms of the market's sensitivity concerning climate change impact. Recognizing the presence of autocorrelation within our dataset, we additionally verify statistical significance via standard errors of the regression estimates using Newey and West (1987). We use the sandwich package to perform this. This technique is employed to present robust parameter estimates that remain valid even in the presence of autocorrelation, thereby enhancing the reliability and precision of our analysis's conclusions.

3.4 GAS model

Creal et al. (2013) and Harvey (2013) presented the GAS model for time series analysis, which utilizes a score function to capture changes over time in the parameters of non-linear models. It defines a time series y_t having a conditional distribution $p(y_t|\Theta_t)$ where Θ_t contains time-varying parameters which characterize $p(.)$. The evolution of the parameter vector Θ_t is driven by the score of the conditional distribution in addition to an autoregressive component:

$$\Theta_{t+1} = \omega + \alpha s_t + \beta \Theta_t, \tag{2}$$

where ω is a constant, α is the coefficient of the score parameter, β is the autoregressive parameter coefficient, and s_t is proportional to the score of the distribution. Equation (2) can also include exogenous variables, which can then be written as:

$$\Theta_{t+1} = \omega + \alpha s_t + \beta \Theta_t + \gamma x_t,$$

where γ is the coefficient of the exogenous variable. s_t is given by:

$$s_t = S_t(\Theta_t)\nabla_t(y_t, \Theta_t),$$

where S_t is the scaling function of the score known at time t, and the score of the distribution is given by:

$$\nabla_t(y_t, \Theta_t) \equiv \frac{\partial \log p(y_t|\Theta_t)}{\partial \Theta_t}.$$

The GAS model can also be estimated by the ML method, and we obtain the estimated parameter set $\hat{\Theta}_t = \{\omega, \alpha, \beta, \gamma\}$. We choose the conditional distribution to be normal to get consistent estimates. The application of the GAS model to S&P 500 daily log returns is conducted on two-year intervals similar to the GARCH-X model starting from January 2014 and continuing till August 2022. Consistent with the criteria set for the GARCH-X model, the analysis using the GAS model also includes only those stocks within the S&P 500 that have a complete record of daily returns for each window. This condition is essential to avoid any potential misrepresentations in the estimations that might arise due to any discontinuities in the data.

In contrast to the GARCH-X model, the analysis performed via the GAS model integrates only the UMC index as the exogenous variable. Limiting the analysis to just the UMC index stems from the fact that the GAS model involves substantial computational expense. This inclusion aims to examine the implications of the 'shock' component or the unforeseen climate change events on the volatility of individual stocks. We use the gasmodel package to perform this analysis. The GAS model computes and stores the estimated parameters and their corresponding t-stats for each period under consideration. We observe that the t-stats are normally distributed under the null hypothesis. Subsequently, these t-stats associated with the UMC index are plotted against the environmental categorization of the stocks, i.e., their ESG scores, E scores, and GHG intensity. These plots explain how stock market reactions to sudden climate changes, as captured by the model, relate to the environmental profiles of the stocks (i.e., 'green' vs 'brown' stocks).

3.5 Linear regression

We also perform a linear regression analysis to assess how well the t-stats, derived from both the GARCH-X and GAS models can be explained by the firms' environmental classifications. In this analysis, we regress the t-stats against the firms' level of environmental performance, represented by the variables ESG score, E score, and GHG intensity. Specifically, we use the following model:

$$t\text{-}stat_i = \omega + \alpha S_i + \epsilon_i,$$

where $t\text{-}stat_i$ represents the exogenous variable t-stat for each firm computed via the GARCH-X or the GAS model for the period t, $S_i = \{ESG_i, E_i, GHG_i\}$ is the independent variable that represents the environmental status of the firms at time t with α as its coefficient.

The α estimates are obtained using the Ordinary-Least Squares (OLS) method. The coefficient α is calculated separately for each method of environmental categorization (using ESG scores, E scores, and GHG intensity) to explore their relationship with climate risk responses. This approach helps examine the extent to which a firm's environmental performance influences its reaction to climate change issues. Additionally, to address heteroscedasticity and autocorrelation commonly present in time series data, the coefficients are adjusted following the method proposed by Newey and West (1987).

4 Empirical Results

4.1 GARCH-X model analysis

4.1.1 MCCC index as an exogenous variable

Our analysis starts with applying the GARCH-X model, as outlined in Section 3.3.2, incorporating the MCCC index as an exogenous variable. We compute and record the t-stats for these exogenous variables. Table 1 summarizes the average t-stats, segmented into green and brown stocks for each two-year window. These stocks are classified into green and brown based on their ESG scores, as determined at the end of each period. For instance, for the analysis period from January 2014 to December 2015, ESG scores as of 31 December 2015 are used to classify the firms into green or brown. The composition of firms within each category is subject to change throughout the sample period. This variability arises from the addition or removal of companies from the S&P 500 index over the period, and fluctuations in the ESG scores. These fluctuations in the ESG scores reflect the companies' changing dedication toward environmental initiatives. Additionally, the table provides an average of the t-stats for all companies for each two-year interval under consideration.

In our analysis, we employ two distinct methods to classify the firms into green and brown stocks to determine any substantial relationship relative to the t-stats produced by the model: i) a conservative approach where stocks with an ESG or E score below the 10th percentile are categorized as brown and those with a score above the 90th percentile as green (90-10 method). This method identifies only a limited number of stocks as either green or brown; and ii) a more inclusive criteria that considers stocks with an ESG or E score below the 25th percentile as brown and those with a score above the 75th percentile as green, thereby including a broader range of companies in each category (75-25 method). On the contrary, the classification of the stocks into green and brown basis their GHG intensity follows the opposite approach: i) the conservative approach classifies the stocks with a GHG intensity lower than the 10th percentile as green, and those with a GHG intensity above the 90th percentile as brown (90-10 method); and ii) the lenient approach classifies the stocks with a GHG intensity lower than the 25th percentile as green, and those with a GHG intensity above the 75th percentile as brown (75-25 method).

Existing literature (reviewed in section 2.5) suggests an expectation that green firms would exhibit less sensitivity to climate change concerns than brown firms. However, our analysis does not reveal such a consistent pattern in the t-stats across the evaluated periods. While examining the results under the more lenient classification criteria (75-25 method) across all the panels in Table 1, we observe a few optimistic outcomes within our sample where green firms tend to show less sensitivity to climate risk. However, there seems to be no consistency across the entire sample period. For instance, during the 2014-2015, 2015–2016, and 2016–2017 time intervals, green firms exhibit higher t-stats compared to brown firms, as observed from Panel (a) of the table (75-25 method), contrary to the expected trend, while for the rest of the periods, they exhibit lower t-stats. This inconsistency does not suggest a definitive impact of ESG scores on firms' response to climate change concerns. Similarly, we observe higher average t-stats for the intervals 2015-2016 and 2016-2017 when we look at the 90-10 method.

When comparing our findings with the trends observed in the MCCC index, as presented in Figure 1, we find it further challenging to form significant conclusions. For example, our analysis covers considerable climate change events, such as the signing of the Paris Agreement towards the end of 2015. This event falls within both the 2014–2015 and 2015–2016 time intervals of our study. However, as seen in Panel (a) of Table 1, the performance of green stocks during these times was inconsistent, with a subdued reaction observed in the 2014–2015 period but a more pronounced response in the 2015–2016 period as per the 90-10 method. We observe the same result in Panel (c) of the table which categorizes the firms into green and brown based on their GHG intensity (90-10 method). This pattern of contrasting results persists throughout the sample period, with another example observed in 2017, when then-U.S. President Donald Trump announced the country's intention to withdraw from the Paris Agreement. This significant climate policy event falls within the analysis windows of 2016–2017 and 2017–2018, yet the data reveal conflicting outcomes for these periods as per Panel (a) of Table 1.

In a similar analysis, Panel (b) of Table 1 extends our examination by focusing on E scores for classifying firms into green and brown categories. The analysis yields similar observations to those made when evaluating stocks based on overall ESG scores. Across the sample period, no consistent pattern can be seen in the behavior of green versus brown firms in response to climate change concerns. Contradictory findings persist, particularly around significant climate events such as the 2018 Katowice UN Climate Change Conference, as seen in Figure 1. During the 2017–2018 period, green stocks demonstrated less sensitivity to this event as per the 90-10 method, whereas, in the following 2018–2019 window, they displayed increased sensitivity.

Table 1: Summary of t-stats for the coefficient of the MCCC exogenous variable in the GARCH-X model. The table reports the summary of average t-stats computed via the GARCH-X model with the MCCC index as the exogenous variable. The firms have been classified as green or brown using their ESG Scores in Panel (a), E Scores in Panel (b), and GHG intensity in Panel (c) as of the end of the respective periods. ***, **, and * Significant at the 1%, 5%, and 10% levels.

Panel (a) Categorization according to ESG scores

Period	Mean	Brown ESG<25	Green ESG>75	Brown ESG<10	Green ESG>90
2014 - 2015	0.736	0.681	0.748	0.818	0.719
2015 - 2016	0.490	0.547	0.611	0.580	0.716
2016 - 2017	0.164	0.175	0.208	0.181	0.242
2017 - 2018	0.597	0.625	0.567	0.634	0.423
2018 - 2019	0.475	0.515	0.485	0.529	0.349
2019 - 2020	0.102*	0.135	0.082	0.172	0.049
2020 - 2021	0.079	0.099	0.058	0.119	0.081
2021 - 2022	0.344	0.374	0.298	0.456	0.321
Average	0.373	0.394	0.382	0.436	0.362

Panel (b) Categorization according to E scores

Period	Mean	Brown E<25	Green E>75	Brown E<10	Green E>90
2014 - 2015	0.736	0.757	0.781	0.770	0.656
2015 - 2016	0.490**	0.403	0.570	0.381	0.776
2016 - 2017	0.164	0.135	0.178	0.178	0.235
2017 - 2018	0.597	0.568	0.638	0.554	0.510
2018 - 2019	0.475	0.447	0.490	0.329	0.551
2019 - 2020	0.102	0.144	0.069	0.187	0.072
2020 - 2021	0.079	0.100	0.080	0.119	0.106
2021 - 2022	0.344	0.389	0.318	0.521	0.317
Average	0.373	0.368	0.390	0.380	0.403

Panel (c) Categorization according to GHG intensity

Period	Mean	Green GHG<25	Brown GHG>75	Green GHG<10	Brown GHG>90
2014 - 2015	0.736	0.899	0.734	1.300	0.787
2015 - 2016	0.490***	0.380	0.798	0.526	0.961
2016 - 2017	0.164***	0.112	0.144	0.047	0.017
2017 - 2018	0.597	0.565	0.593	0.626	0.524
2018 - 2019	0.475***	0.402	0.462	0.386	0.198
2019 - 2020	0.102	0.081	0.092	0.062	0.073
2020 - 2021	0.079	0.074	0.035	0.051	0.031
2021 - 2022	0.344***	0.394	0.754	0.000	0.941
Average	0.373	0.363	0.452	0.375	0.442

Further comparison between the results from Panel (a) of Table 1 (based on overall ESG scores for green/brown firm categorization) and Panel (b) of Table 1 (categorization based on E scores) reveals notable differences. For instance, during the 2018–2019 period, firms classified as green based on their E scores exhibited significant sensitivity to climate change events. In contrast, these firms appear less sensitive when categorized based on ESG scores. This discrepancy suggests that the Social (S) and Governance (G) components of the ESG scores might have a mitigating effect on the firms' responsiveness to climate change events. It implies that certain firms, potentially unfavorable from an environmental standpoint, could be classified as green when assessed through the broader lens of ESG scores due to positive attributes in social and governance aspects. This presents the importance of considering the distinct elements of ESG scores in evaluating firm sensitivity to environmental concerns, thus highlighting the potential for social and governance factors to offset the environmental impact of firms in the context of climate change events.

Figures 2 and 3 graphically present the outcomes of each two-year window, spanning from January 2014 to December 2015 and extending through to August 2022. These figures plot t-stats of the coefficients related to the exogenous variable (MCCC index) derived from the GARCH-X model against ESG scores and E scores, respectively. Additionally, Figure 4 presents these t-stats with the GHG intensity of the firms. Figures 2 and 3 show a lack of an apparent pattern in how the t-stats distribute across varying ESG and E scores. The data points representing these t-stats are scattered across the entire range of scores rather than following a relevant pattern. For example, going through previously conducted studies, one might expect these points to be downward sloping (i.e., higher t-stats for brown firms and lower t-stats for green firms) to reveal less sensitivity to climate change concerns for green firms. However, we do not observe such a pattern in these plots. This indicates that the impact of climate change events does not exhibit a significant relationship with firms classified as either green or brown based on their ESG or E scores. Moreover, each figure includes a regression line depicted in red. As observed over the entire sample period, the overall regression analysis does not provide significant insights regarding the impact of climate change events. The lack of a clear trend or direction in the slope of the regression lines across these plots further supports the conclusion that no significant relationship exists between a firm's environmental classification and its response to climate change concerns. The analysis reveals that most regression lines plotted across Figures 2 and 3 are relatively horizontal, suggesting that the impact of climate change concerns might be uniformly distributed across firms, regardless of their classification as green or brown based on their ESG or E scores.

Figure 4 shows a similar pattern but focuses on GHG intensity. This appears somewhat promising, yet it is impossible to draw definitive conclusions. The issue lies in the fact that only a few companies exhibit extreme GHG intensities but significantly influence the direction of the regression line. However, looking at the firms on the left side of these charts, representing the bulk of the S&P 500 companies, we observe both high and low t-stats. This indicates that companies with comparable levels of GHG intensity respond differently to concerns related to climate change.

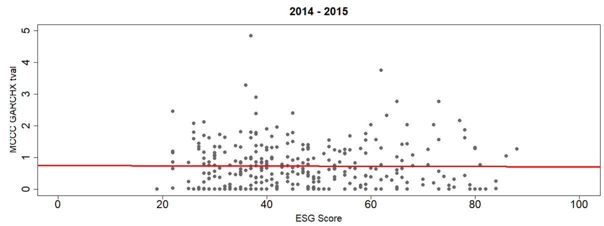
Table 2: Summary of regression results on the t-stats for the coefficients of the MCCC and UMC exogenous variables in the GARCH-X model.
The table reports the summary of regression results with the ESG scores, E scores, and GHG scores (scaled GHG intensity) respectively as independent variables on the t-stats computed via the GARCH-X model with the MCCC and UMC indices as the exogenous variables. Panel (a) reports the regression results for the t-stats of the MCCC exogenous variables and Panel (b) reports the regression results for the t-stats of the UMC exogenous variables. ***, **, and * Significant at the 1%, 5%, and 10% levels.

Panel (a) Regression results for the t-stats of the MCCC exogenous variables.

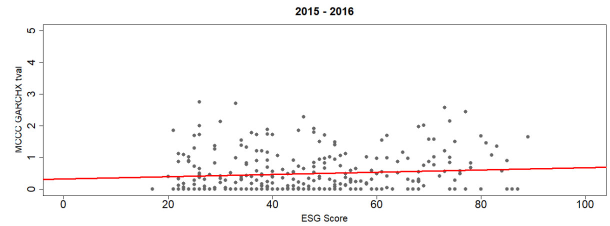
	ESG Scores		E Scores		GHG intensity (scaled)	
Period	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
2014 - 2015	-0.001	-0.186	-0.001	-0.582	0.005	0.656
2015 - 2016	0.003	1.437	0.004**	2.100	0.044***	5.738
2016 - 2017	0.001	0.709	0.001	0.867	-0.008***	-4.639
2017 - 2018	-0.002	-1.228	0.000	0.147	-0.006	-1.333
2018 - 2019	-0.001	-0.573	0.001	0.425	-0.018***	-6.292
2019 - 2020	-0.001*	-1.668	-0.001	-1.645	-0.001	-0.348
2020 - 2021	-0.001	-0.844	-0.001	-0.759	-0.002	-0.620
2021 - 2022	-0.001	-0.808	-0.001	-0.857	-0.013***	-3.278
Average	0.000		0.000		0.000	

Panel (b) Regression results for the t-stats of the UMC exogenous variables

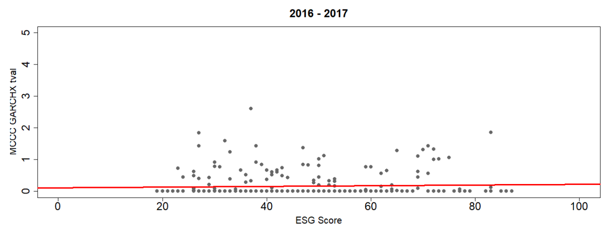
	ESG Scores		E Scores		GHG intensity (scaled)	
Period	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
2014 - 2015	-1.090	-1.018	-0.781	-0.989	5.700	0.928
2015 - 2016	0.002	0.755	0.002	0.975	0.048***	6.968
2016 - 2017	0.001	0.548	-0.000	-0.325	-0.010***	-3.311
2017 - 2018	-0.002	-1.182	-0.000	-0.015	-0.005	-1.204
2018 - 2019	0.252	0.983	-0.204	-0.976	-0.744	-0.488
2019 - 2020	-0.000	-0.420	-0.001	-0.784	-0.005**	-2.068
2020 - 2021	-0.000	-0.131	-0.000	-0.368	-0.002	-0.795
2021 - 2022	-0.001	-0.414	-0.001	-0.346	-0.011**	-2.237
Average	-0.105		-0.123		0.621	



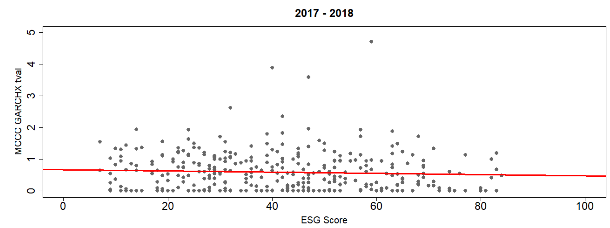
(a) 2014 - 2015



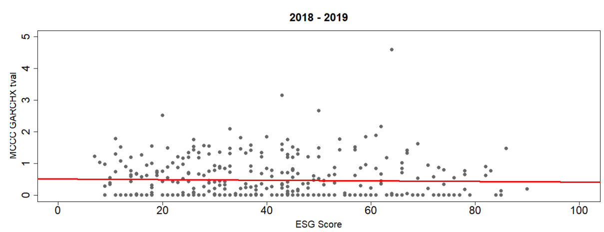
(b) 2015 - 2016



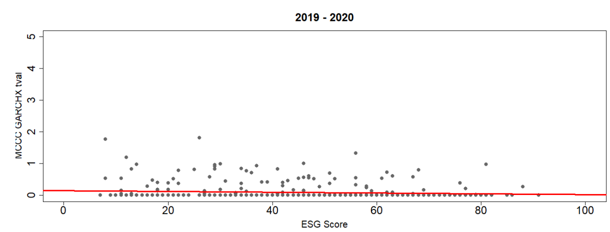
(c) 2016 - 2017



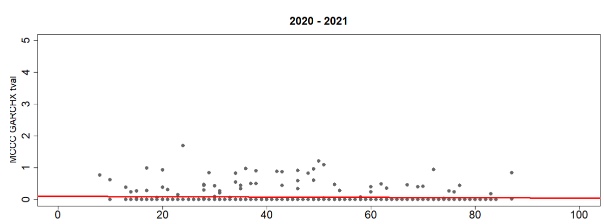
(d) 2017 - 2018



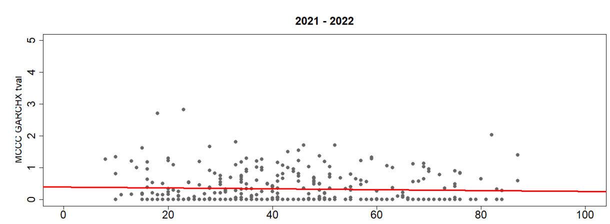
(e) 2018 - 2019



(f) 2019 - 2020

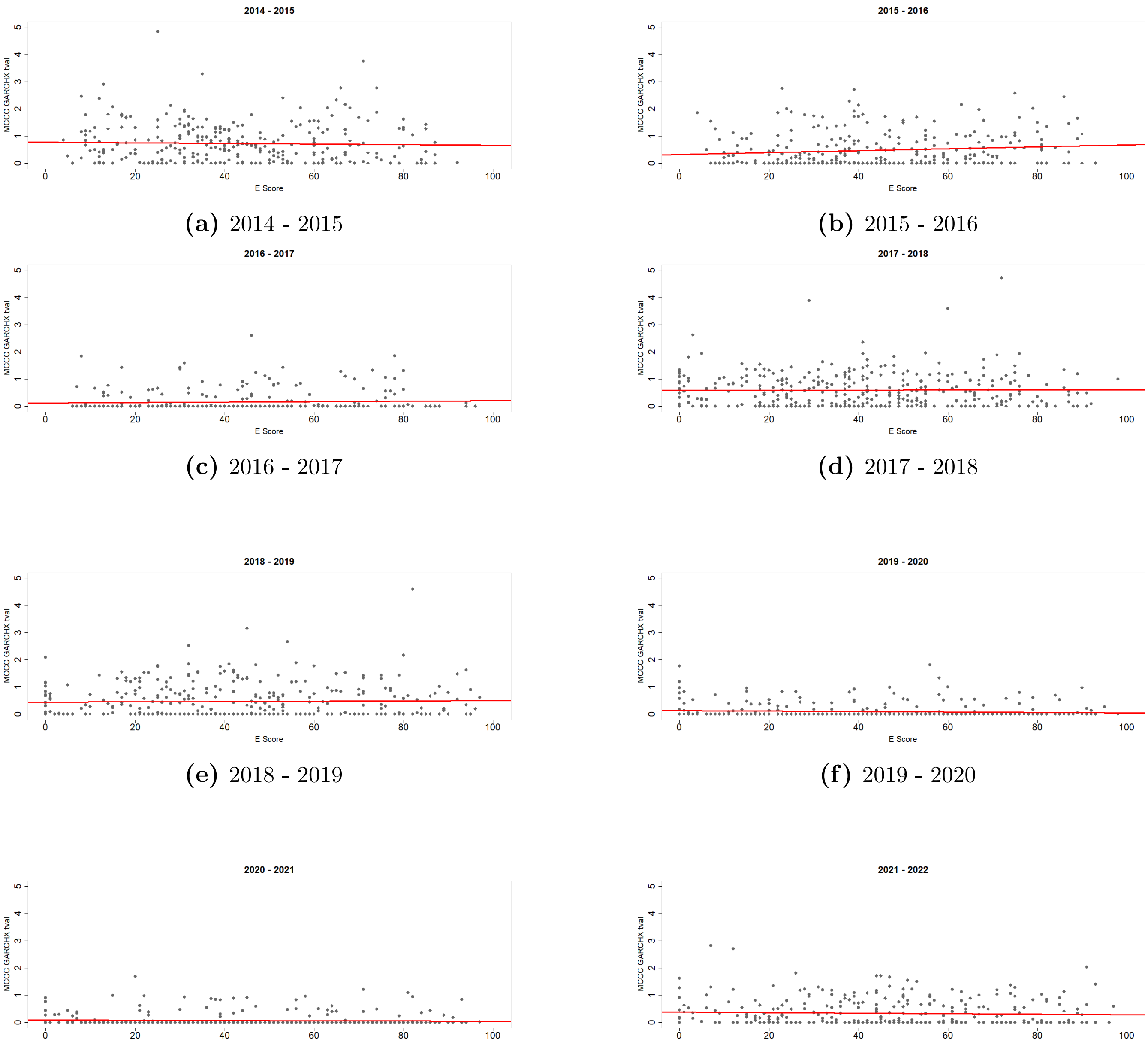


(g) 2020 - 2021



(h) 2021 - 2022

Figure 2: Distribution of t-stats computed using the GARCH-X model with the MCCC index as an exogenous variable mapped against the ESG Scores of the firms, presented for all the periods covered in our sample. The linear regression performed for each period is also included and shown as a straight red line.



(a) 2014 - 2015

(b) 2015 - 2016

(c) 2016 - 2017

(d) 2017 - 2018

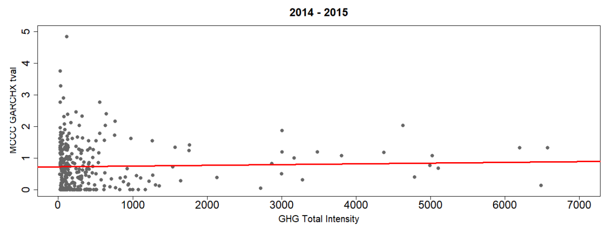
(e) 2018 - 2019

(f) 2019 - 2020

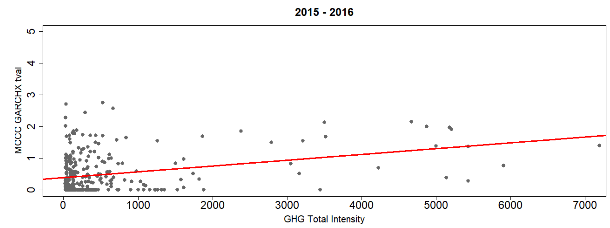
(g) 2020 - 2021

(h) 2021 - 2022

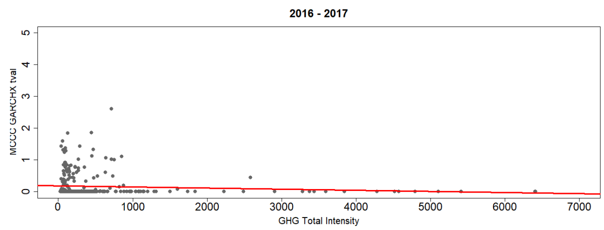
Figure 3: Distribution of t-stats computed using the GARCH-X model with the MCCC index as an exogenous variable mapped against the E Scores of the firms, presented for all the periods covered in our sample. The linear regression performed for each period is also included and shown as a straight red line.



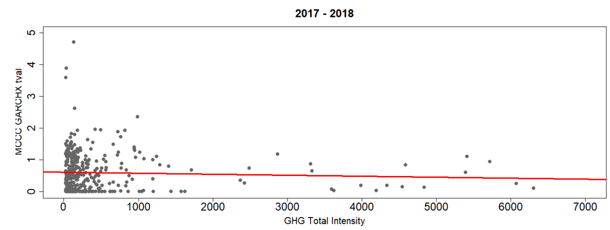
(a) 2014 - 2015



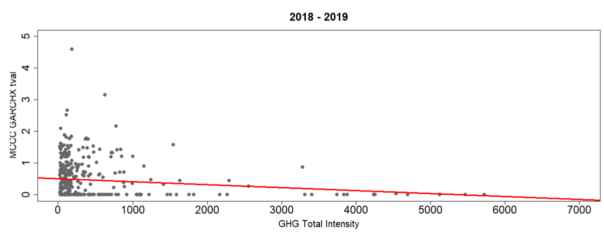
(b) 2015 - 2016



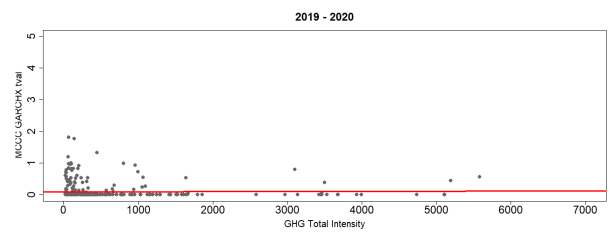
(c) 2016 - 2017



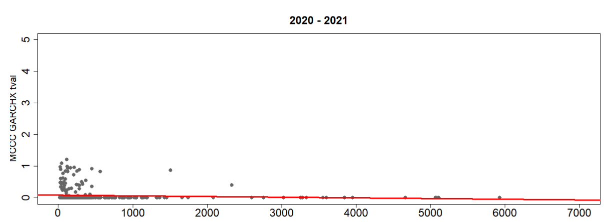
(d) 2017 - 2018



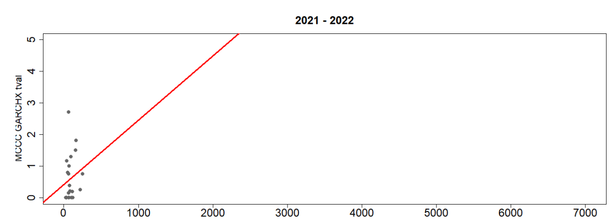
(e) 2018 - 2019



(f) 2019 - 2020



(g) 2020 - 2021



(h) 2021 - 2022

Figure 4: Distribution of t-stats computed using the GARCH-X model with the MCCC index as an exogenous variable mapped against the GHG intensity of the firms, presented for all the periods covered in our sample. The linear regression performed for each period is also included and shown as a straight red line. Note: There are not enough data points for 2021-2022 since the GHG intensity is not available for all the firms in the sample due to a part of the year 2022 (until August 2022) being covered by the analysis. Thus, the regression line slants unusually upward.

Panel (a) Table 2 outlines the results of linear regression analyses conducted across all firms in the S&P 500 without differentiating between green and brown stocks. This analysis, detailed in section 3.5, utilizes ESG scores, E scores, and GHG intensity as separate independent variables for each two-year window under consideration. The findings from this approach reveal a similar picture, i.e., the results lack statistical significance, with only a few periods showing significance for any given parameter. Notably, the periods that display significance for one variable are not necessarily significant for the others. For instance, during the 2015–2016 timeframe, the regression coefficient was significant at the 5% level when E scores were used as the independent variable. However, this significance level is not observed when ESG scores are employed in a similar capacity. GHG intensity, on the other hand, occasionally showcases significant coefficients within the sample period, as can be seen in the table, in contrast to the findings for ESG and E scores, which generally do not exhibit significant coefficients. The regression coefficients for the GHG intensity have been scaled to make them comparable to the ESG and E scores. Even when GHG intensity shows a significant coefficient, the magnitude of the original coefficient (i.e., not scaled) is quite minimal, indicating that it likely has a negligible impact on stock volatility, even when considering significant climate change events.

4.1.2 UMC index as an exogenous variable

In our analysis, similar to the method employed with the MCCC index, we utilize the UMC as an exogenous variable within the GARCH-X model. The UMC measures the unexpected or the 'shock' component related to climate change concerns, capturing the impact of unforeseen climate change events on stock volatility, i.e., this index does not include pre-scheduled events or republished news with minor alterations. The methodology of computing the UMC index has been explained in Section 3.2.

The findings of this approach are presented in Table 3, which outlines the *t*-stats for both green and brown stocks across all two-year intervals. This analysis aims to investigate the effects that sudden climate change incidents might have on the volatility of stock markets. We again employ two methods to distinguish between green and brown stocks based on ESG scores, E scores, and GHG intensity, i.e., the conservative approach (90-10 method) and the broader one (75-25 method). Our analysis utilizing the UMC index as an exogenous variable, specifically focusing on the 75-25 ESG score scenario (Panel (a) of Table 3) yields optimistic results only for a few periods, similar to the outcomes observed in the MCCC index analysis. However, resembling our previous findings, the trends are not uniform across the entire sample period. Similar inconsistencies can be observed for the 90-10 method. Upon comparing our results obtained with the UMC index to the trends indicated by the MCCC index in Figure 1, it becomes even more apparent that we cannot draw significant conclusions to explain these values. Similar to our analysis using the MCCC index, the 2015 Paris Agreement was a significant event covering both the 2014 – 2015 and 2015 – 2016 intervals. However, in the 2014 – 2015 window, green stocks demonstrated a reduced response to climate change events according to the 90-10 method, while in the 2015 – 2016 window, their reaction was higher than brown stocks. This pattern of response aligns with observations made in the analysis utilizing the MCCC index.

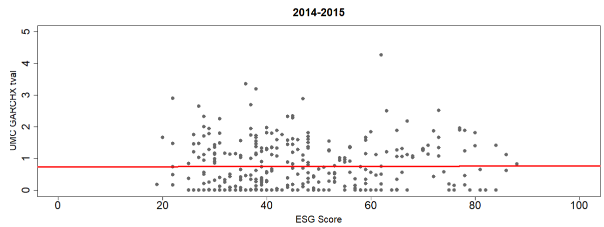
Panel (b) of Table 3, which details the t-stats for green and brown stocks categorized by their E scores, presents findings that differ from those observed in the analysis using the MCCC index across each window period. For instance, during the 2016-2017 period, green stocks demonstrated increased sensitivity when analyzed with the MCCC index as an exogenous variable (refer to Panel (b) of Table 1), indicating an increased response to pre-scheduled climate change events. However, these stocks do not exhibit a significant impact when considering the UMC index as an exogenous variable, suggesting that green firms were perhaps more resilient to unexpected climate change concerns during that year. On the contrary, the 2017-2018 period showcases an opposite trend, where green firms appeared more vulnerable to unforeseen climate change concerns (Panel (b) of Table 3: 90-10 scenario), reflecting a greater sensitivity to the UMC index while showing resistance towards all climate-related events, as analyzed through the MCCC index(Panel (b) of Table 1: 90-10 scenario). Such trends are not observed when ESG scores are taken as the based on for categorizing green and brown stocks. We can also compare the results between the categorization of green and brown stocks based on E scores (Panel (b)) and GHG intensity (Panel (c)) in Table 3. For the period 2015-2016, green firms show less sensitivity to unexpected climate change concerns when categorized based on of GHG intensity (Pancel (c)) but are more sensitive when categorized based on E scores (Pancel (b)). The inconsistency of these trends across the entire sample period does not enable us to generalize the conclusions drawn from our analysis.

Figure 5 presents plots for the two-year intervals beginning from January 2014 to December 2015 and extending to August 2022 representing the t-stats of the exogenous variables computed using the GARCH-X model with UMC as the exogenous variable in relation to ESG scores. Similarly, Figure 6 maps these periods against E scores, and Figure 7 presents them with the GHG intensity. Like with the MCCC index, no clear pattern reveals the relationship between a firm's sensitivity to climate change and its categorization as green or brown. When employing the UMC index as an exogenous variable, the observed t-stats are similarly dispersed across all firms regardless of their environmental categorization. Furthermore, the regression lines depicted in red fail to indicate a significant relationship between a firm's degree of greenness and its response to unforeseen climate change events. This finding remains consistent regardless of the method used to classify stocks into green and brown categories, whether it be through ESG scores, E scores, or GHG intensity.

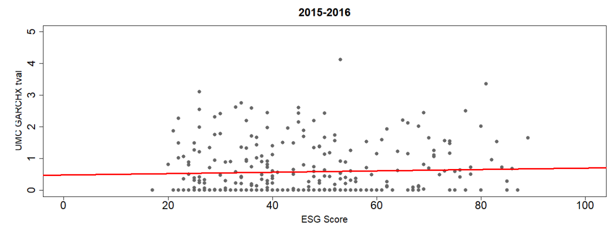
Table 3: Summary of t-stats for the coefficient of the UMC exogenous variable in the GARCH-X model. The table reports the summary of average t-stats computed via the GARCH-X model with the UMC index as the exogenous variable. The firms have been classified as green or brown using their ESG Scores in Panel (a), E Scores in Panel (b), and GHG intensity in Panel (c) as of the end of the respective periods. ***, and ** Significant at the 1%, and 5% levels.

Panel (a) Categorization according to ESG scores					
		Brown	Green	Brown	Green
Period	Mean	ESG<25	ESG>75	ESG<10	ESG>90
2014 - 2015	0.754	0.712	0.816	0.855	0.845
2015 - 2016	0.580	0.626	0.637	0.643	0.719
2016 - 2017	0.221	0.230	0.257	0.173	0.289
2017 - 2018	0.647	0.687	0.599	0.775	0.534
2018 - 2019	0.629	0.700	0.702	0.648	0.715
2019 - 2020	0.135	0.157	0.127	0.163	0.084
2020 - 2021	0.116	0.129	0.132	0.165	0.118
2021 - 2022	0.371	0.367	0.347	0.359	0.331
Average	0.432	0.451	0.452	0.473	0.454
Panel (b) Categorization according to E scores					
		Brown	Green	Brown	Green
Period	Mean	E<25	E>75	E<10	E>90
2014 - 2015	0.754	0.757	0.815	0.845	0.770
2015 - 2016	0.580	0.499	0.549	0.567	0.741
2016 - 2017	0.221	0.250	0.221	0.373	0.279
2017 - 2018	0.647	0.655	0.683	0.585	0.604
2018 - 2019	0.629	0.586	0.764	0.521	0.886
2019 - 2020	0.135	0.183	0.115	0.186	0.146
2020 - 2021	0.116	0.160	0.130	0.203	0.233
2021 - 2022	0.371	0.407	0.353	0.526	0.395
Average	0.432	0.437	0.454	0.476	0.507
Panel (c) Categorization according to GHG intensity					
		Green	Brown	Green	Brown
Period	Mean	GHG<25	GHG>75	GHG<10	GHG>90
2014 - 2015	0.754	0.753	0.929	1.109	0.998
2015 - 2016	0.580***	0.407	0.924	0.513	1.071
2016 - 2017	0.221***	0.126	0.217	0.053	0.032
2017 - 2018	0.647	0.542	0.692	0.623	0.601
2018 - 2019	0.629	0.591	0.604	0.670	0.324
2019 - 2020	0.135**	0.102	0.098	0.112	0.052
2020 - 2021	0.116	0.101	0.077	0.069	0.062
2021 - 2022	0.371**	0.163	0.553	0.327	0.822
Average	0.432	0.348	0.512	0.435	0.495

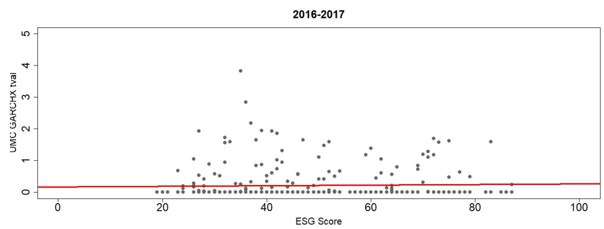
Consistent with the methodology applied in the MCCC index analysis, Panel (b) of Table 2 showcases the results of robust linear regression analyses (according to Newey and West (1987)) conducted for the entire S&P 500 without distinguishing between green and brown stocks. This



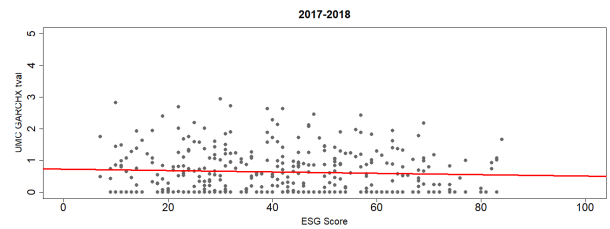
(a) 2014 - 2015



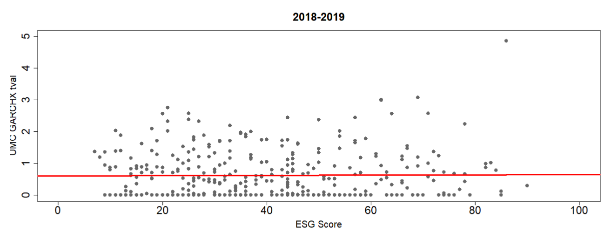
(b) 2015 - 2016



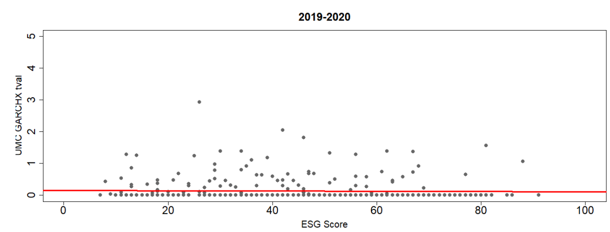
(c) 2016 - 2017



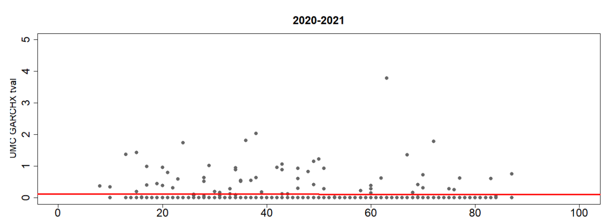
(d) 2017 - 2018



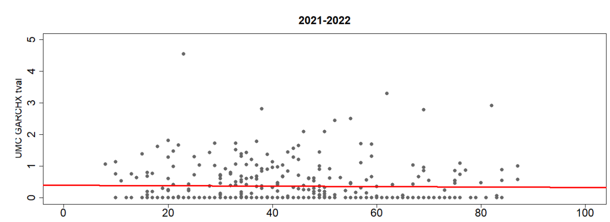
(e) 2018 - 2019



(f) 2019 - 2020

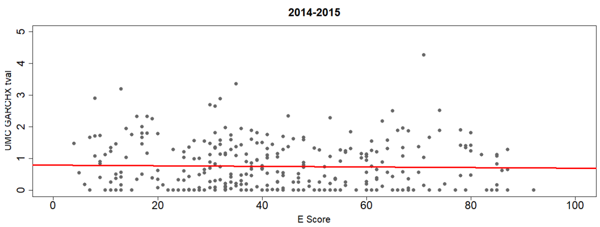


(g) 2020 - 2021

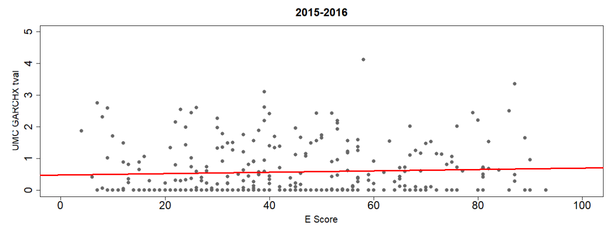


(h) 2021 - 2022

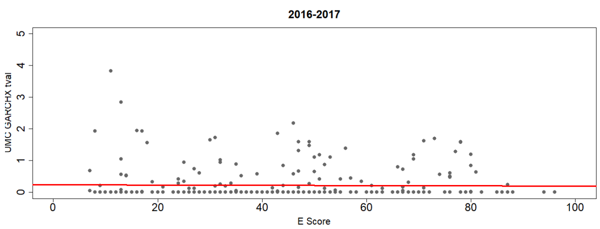
Figure 5: Distribution of t-stats computed using the GARCH-X model computed with UMC as an exogenous variable mapped against the ESG Scores of the firms, presented for all the periods covered in our sample. The linear regression performed for each period is also included and shown as a straight red line.



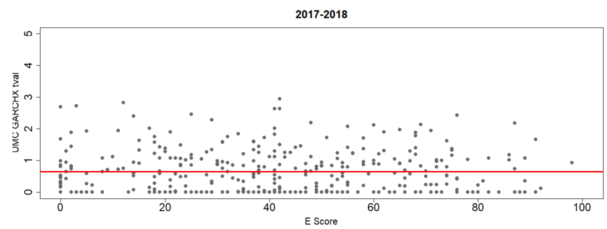
(a) 2014 - 2015



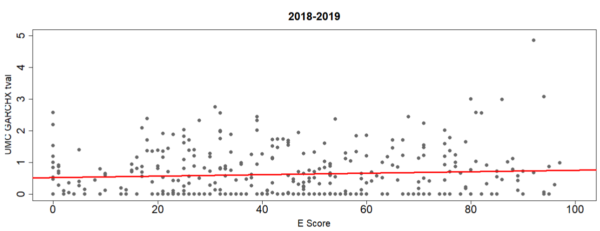
(b) 2015 - 2016



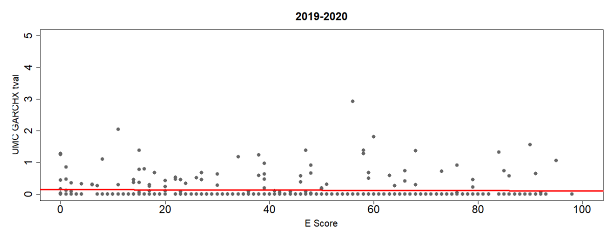
(c) 2016 - 2017



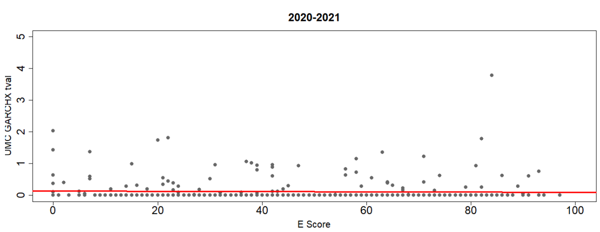
(d) 2017 - 2018



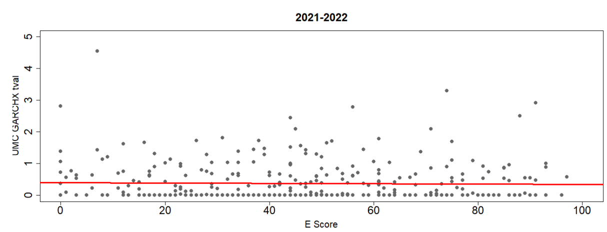
(e) 2018 - 2019



(f) 2019 - 2020

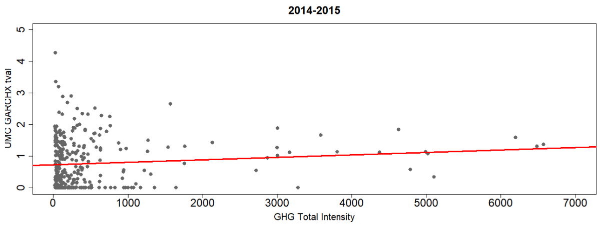


(g) 2020 - 2021

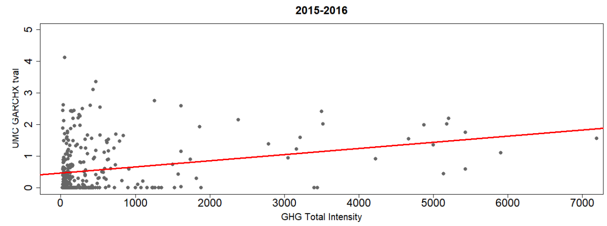


(h) 2021 - 2022

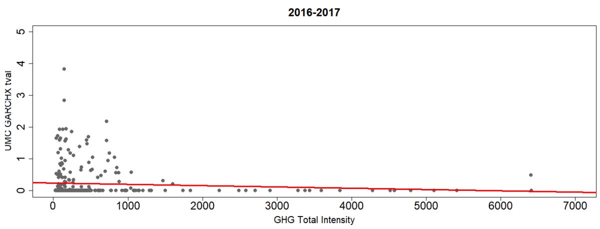
Figure 6: Distribution of t-stats computed using the GARCH-X model computed with UMC as an exogenous variable mapped against the E Scores of the firms, presented for all the periods covered in our sample. The linear regression performed for each period is also included and shown as a straight red line.



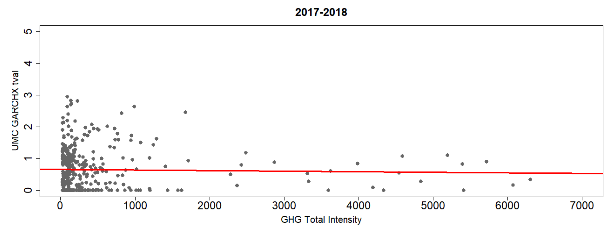
(a) 2014 - 2015



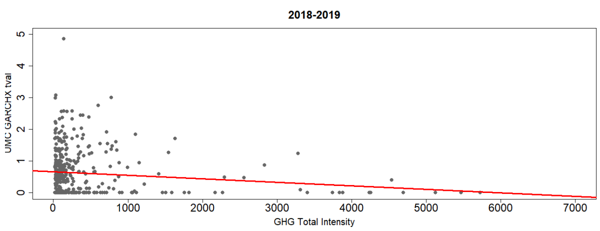
(b) 2015 - 2016



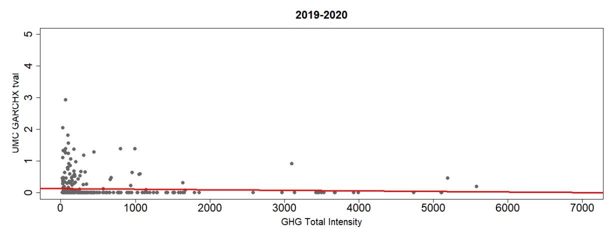
(c) 2016 - 2017



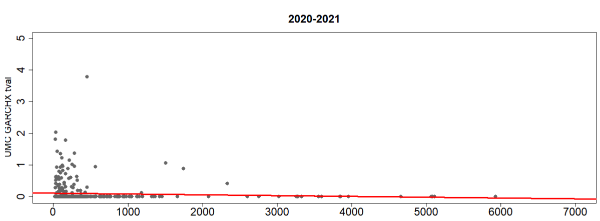
(d) 2017 - 2018



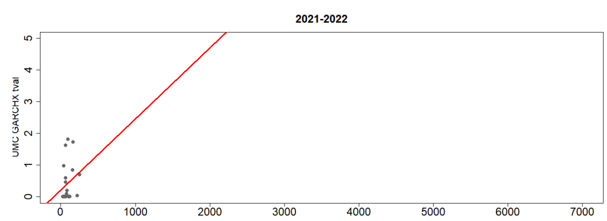
(e) 2018 - 2019



(f) 2019 - 2020



(g) 2020 - 2021



(h) 2021 - 2022

Figure 7: Distribution of t-stats computed using the GARCH-X model computed with UMC as an exogenous variable mapped against the GHG intensity of the firms, presented for all the periods covered in our sample. The linear regression performed for each period is also included and shown as a straight red line. Note: There are not enough data points for 2021-2022 since the GHG intensity is not available for all the firms in the sample due to a part of the year 2022 (until August 2022) being covered by the analysis. Thus, the regression line slants unusually upward.

analysis is performed separately for each variable, i.e., ESG scores, E scores, and GHG intensity for every two-year window. The analysis utilizing ESG scores and E scores as independent variables did not yield statistically significant results for any period. This outcome contrasts only slightly with the analysis conducted using the MCCC index, where a few years demonstrated some significance. For instance, our examination through linear regression reveals that in contrast to a specific instance during the 2019-2020 period with ESG scores (Panel (a)), none of the regression coefficients, as seen in Panel (b) in the current analysis, are statistically significant. This outcome suggests a lack of conclusive evidence when using the UMC index as the set of exogenous variables in the GARCH-X model. Similar to the MCCC index analysis, the regression coefficients for the GHG intensity have been scaled to make them comparable to the ESG and E scores. Even when GHG intensity shows a significant coefficient, the magnitude of the original coefficient (i.e., not scaled) is relatively minimal, indicating that it likely has a negligible impact on stock volatility, even when considering significant climate change events.

Our analysis using the GARCH-X model, therefore highlights, the complex and often inconsistent relationship between the environmental profile of firms and their responses to climate change concerns. Establishing a clear relationship still proves challenging despite applying various classification standards and methodologies. We now aim to extend our investigation through the use of the GAS model to explore these connections further.

4.2 GAS model analysis

We now analyze using the GAS model to assess the impact of unexpected climate change concerns on stock volatility. For this purpose, we perform this analysis for each two-year window, similar to the GARCH-X model, from January 2014 until August 2022, focusing exclusively on the UMC index since the implementation of this model is computationally expensive. Following the methodology in section 3.4, we estimate the relevant parameters and store their corresponding t-stats. We categorize the stocks into green and brown like the one we did while analyzing the GARCH-X model. Thus, Table 4 shows the average t-stats for companies sorted into green and brown groups based on the

90-10 and 75-25 categorizations using their ESG scores, E sores, and GHG intensity. According to the average t-stats computed through the GAS model, most years show green firms less susceptible to volatility fluctuations during heightened climate change concerns. However, in 2018-2019 and 2020-2021, green firms had a more significant impact than brown ones when we look at Panel (a), where the firms are characterized as green and brown according to the ESG scores. Similarly, Panel (b) of the table uses E scores to categorize firms into green and brown using the same method as seen above (i.e., 75-25 and 90-10 methods). Focusing on the 75-25 categorization, we still see mixed outcomes: green firms show more sensitivity to climate concerns in 2016-2017, 2018-2019, 2019-2020, and 2020-2021 but are less sensitive in other years. Green firms display a greater impact in the 90-10 breakdown, with higher average t-stats than brown firms for 2015-2016, 2019-2020, and 2020-2021. Among these, only the intervals 2019-2020 and 2020-2021 align across both categorization methods. Panel (c) of the table, which categorizes the stocks according to their GHG intensity, shows that green firms have higher average t-stats for the periods 2015-2016, 2016-2017, and 2021-2022 with both the categorization methods. Period 2014-2015 shows higher average t-stats for green firms only with the 75-25 method. Thus, we can see substantial conflicting outcomes, leading to inadequate results due to these inconsistencies.

Table 4: Summary of t-stats for the coefficient of the UMC exogenous variable in the GAS model. The table reports the summary of average t-stats computed via the GAS model with the UMC index as the exogenous variable. The firms have been classified as green or brown using their ESG Scores in Panel (a), E Scores in Panel (b), and GHG intensity in Panel (c) as of the end of the respective periods. ***, **, and * Significant at the 1%, 5%, and 10% levels.

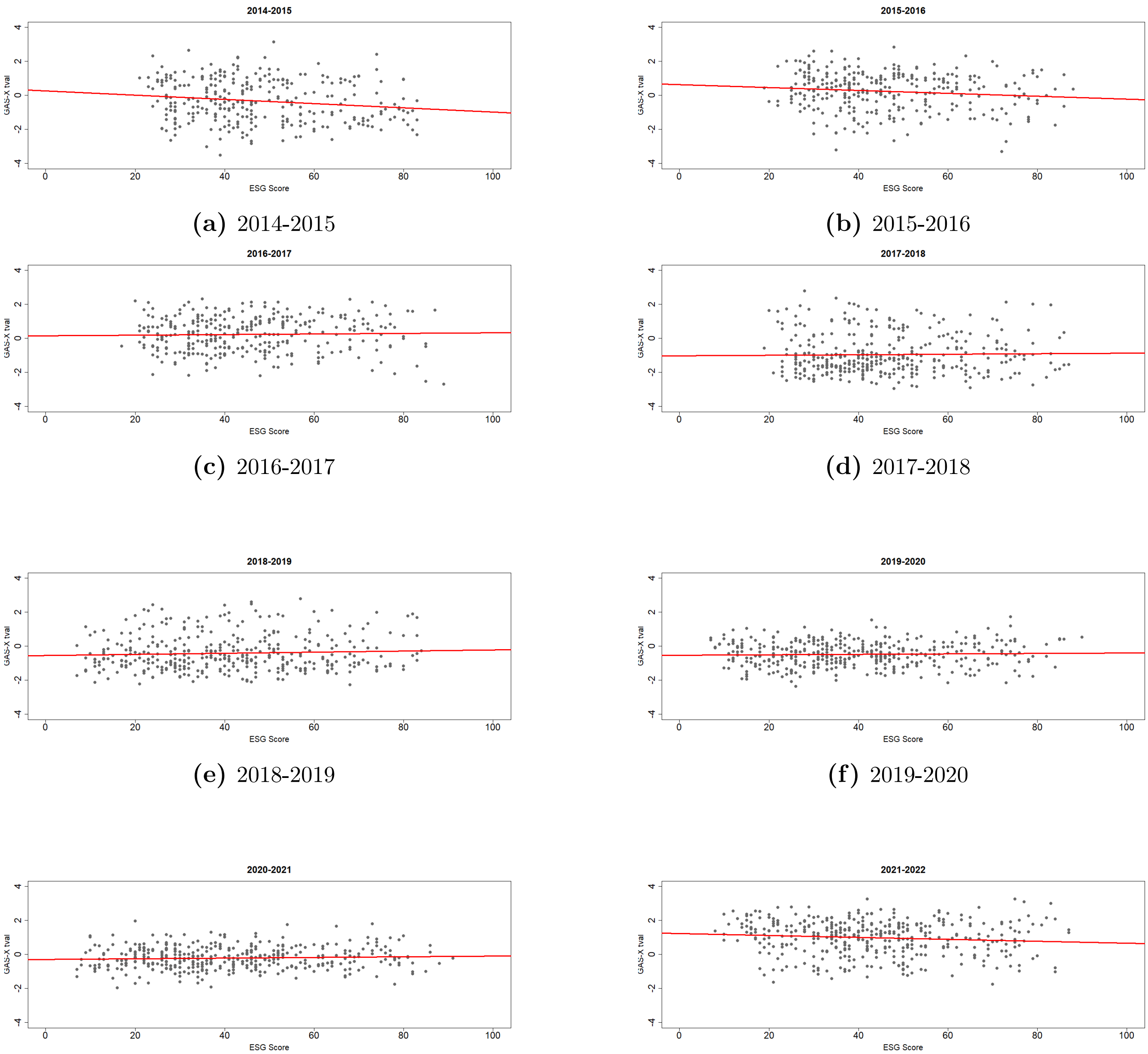
Panel (a) Categorization according to ESG scores					
Period	Mean	Brown ESG<25	Green ESG>75	Brown ESG<10	Green ESG>90
2014 - 2015	-0.326***	-0.120	-0.625	0.181	-0.766
2015 - 2016	0.235**	0.517	0.115	0.479	-0.214
2016 - 2017	0.237	0.148	0.311	0.218	0.190
2017 - 2018	-0.953	-0.859	-0.859	-0.706	-0.782
2018 - 2019	-0.410	-0.488	-0.427	-0.684	-0.319
2019 - 2020	-0.470	-0.430	-0.468	-0.157	-0.303
2020 - 2021	-0.207	-0.248	-0.147	-0.270	-0.140
2021 - 2022	0.977**	1.188	0.883	1.540	0.858
Average	-0.115	-0.037	-0.152	0.075	-0.184
Panel (b) Categorization according to E scores					
Period	Mean	Brown E<25	Green E>75	Brown E<10	Green E>90
2014 - 2015	-0.326**	-0.192	-0.609	0.132	-0.524
2015 - 2016	0.235	0.336	0.116	0.035	0.192
2016 - 2017	0.237	0.145	0.406	0.267	0.212
2017 - 2018	-0.953	-0.873	-0.891	-0.698	-1.019
2018 - 2019	-0.410	-0.483	-0.291	-0.353	-0.353
2019 - 2020	-0.470	-0.450	-0.436	-0.381	-0.338
2020 - 2021	-0.207	-0.255	-0.180	-0.163	-0.031
2021 - 2022	0.977*	1.235	0.876	1.468	1.062
Average	-0.115	-0.067	-0.126	0.038	-0.100
Panel (c) Categorization according to GHG intensity					
Period	Mean	Green GHG<25	Brown GHG>75	Green GHG<10	Brown GHG>90
2014 - 2015	-0.326**	-0.464	-0.527	-0.812	-0.605
2015 - 2016	0.235***	0.662	-0.133	0.579	-0.351
2016 - 2017	0.237***	0.724	0.050	0.937	0.053
2017 - 2018	-0.953	-1.177	-1.085	-1.185	-0.884
2018 - 2019	-0.410	-0.634	-0.572	-0.642	-0.559
2019 - 2020	-0.470	-0.570	-0.421	-0.749	-0.537
2020 - 2021	-0.207	-0.289	-0.083	-0.419	-0.158
2021 - 2022	0.977**	1.039	0.730	0.871	0.773
Average	-0.115	-0.089	-0.255	-0.177	-0.283

Table 5 outlines the linear regression outcomes for the three parameters (ESG Scores, E Scores, and GHG intensity (scaled)), individually assessed, to establish a link between a firm's greenness and its climate change response. It reveals that, with few exceptions, both ESG and E scores generally lack statistical significance in explaining this relationship. Examining GHG intensity reveals that its coefficients are often statistically significant across multiple years. Yet, no clear pattern can be seen to explain this relationship fully. Moreover, despite being statistically significant, the original coefficients (i.e., not scaled) are small enough that their impact on volatility is minimal. Consequently, this prevents establishing a conclusive relationship between a firm's environmental status and its response to climate change issues.

Table 5: Summary of regression results on the t-stats for the coefficients of the UMC exogenous variables in the GAS model.
The table reports the summary of regression results with the ESG scores, E scores, and GHG scores (scaled GHG intensity) respectively as independent variables on the t-stats computed via the GAS model with the UMC indices as the exogenous variables. ***, **, and * Significant at the 1%, 5%, and 10% levels.

Regression results for the t-stats of the UMC exogenous variables						
	ESG Scores		E Scores		GHG intensity (scaled)	
Period	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
2014 - 2015	-0.012***	-2.778	-0.008**	-2.500	-0.030**	-2.402
2015 - 2016	-0.009**	-2.150	-0.002	-0.572	-0.064***	-4.992
2016 - 2017	0.002	0.463	0.002	0.934	-0.026***	-2.997
2017 - 2018	0.002	0.388	0.000	0.017	0.005	0.877
2018 - 2019	0.003	1.168	0.002	0.705	-0.002	-0.602
2019 - 2020	0.001	0.696	0.001	0.725	-0.002	-0.880
2020 - 2021	0.002	1.170	0.002	1.248	0.001	0.539
2021 - 2022	-0.006**	-2.013	-0.004*	-1.682	-0.007**	-1.972
Average	-0.002		-0.001		-0.016	

Figures 8 and 9 illustrate the t-stats from the GAS model plotted against ESG and E scores for each two-year interval. Similar to the patterns seen in the GARCH-X model analysis, the t-stats are dispersed among all stocks without demonstrating a noticeable pattern. This distribution of t-stats suggests that the impact of climate change events does not show a significant relationship with how firms are classified as green or brown, according to their ESG or E scores. Additionally, each figure also displays a regression line in red. Similar to our observations while analyzing the GARCH-X model, the GAS model supports the inference that there seems to be no significant relationship between a firm's environmental classification and its reaction to climate change. Figure 10 presents the relationship between firms' responses to unexpected climate change events and their GHG intensity. Again, clear conclusions are difficult to make since only a few firms have significantly high GHG intensities, which significantly impact the slope of the regression line. Yet, when focusing on



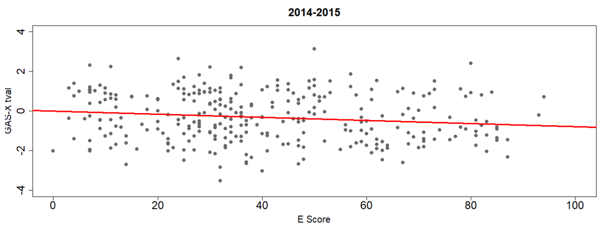
(a) 2014-2015 **(b)** 2015-2016

(c) 2016-2017 **(d)** 2017-2018

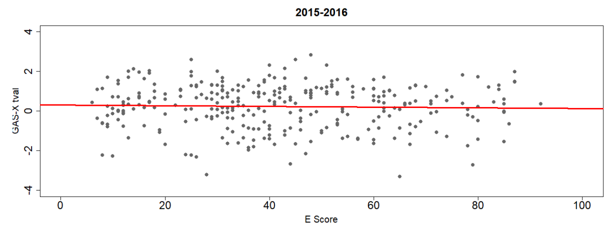
(e) 2018-2019 **(f)** 2019-2020

(g) 2020-2021 **(h)** 20212022

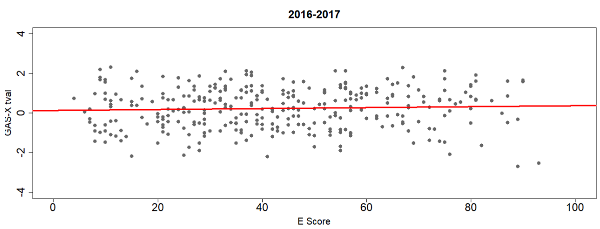
Figure 8: Distribution of *t*-stats computed using the GAS model with UMC as an exogenous variable mapped against the ESG Scores of the firms, presented for all the periods covered in our sample. The linear regression performed for each period is also included and shown as a straight red line.



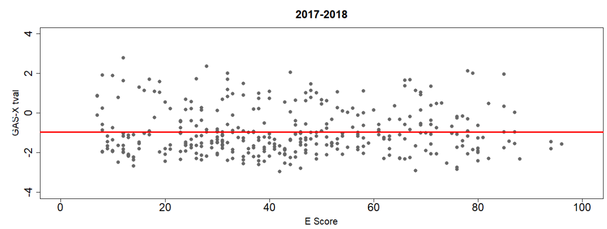
(a) 2014-2015



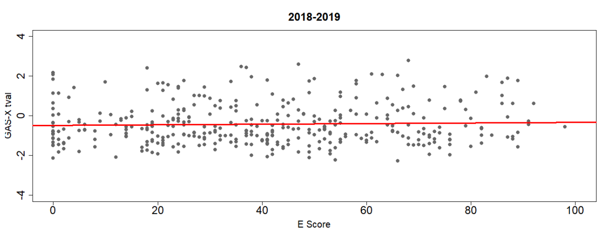
(b) 2015-2016



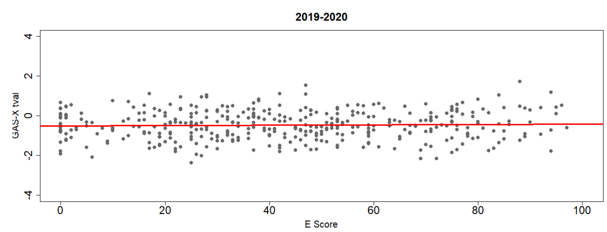
(c) 2016-2017



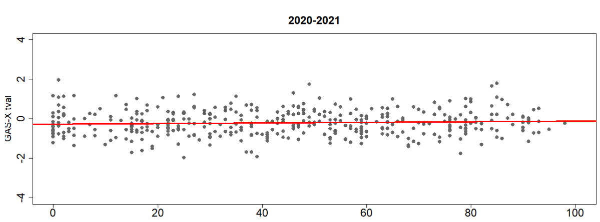
(d) 2017-2018



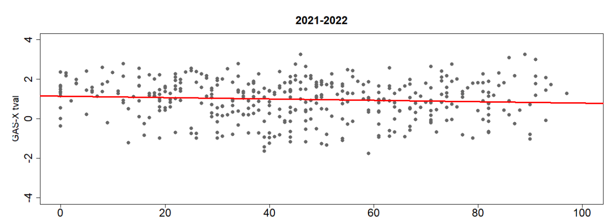
(e) 2018-2019



(f) 2019-2020

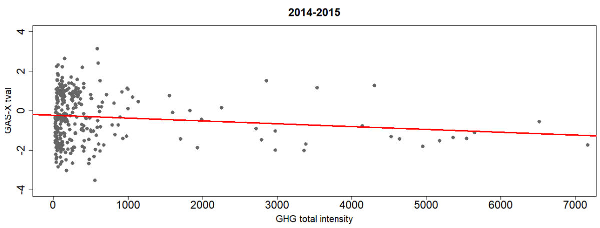


(g) 2020-2021

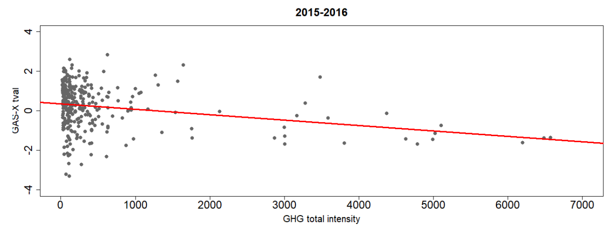


(h) 2021-2022

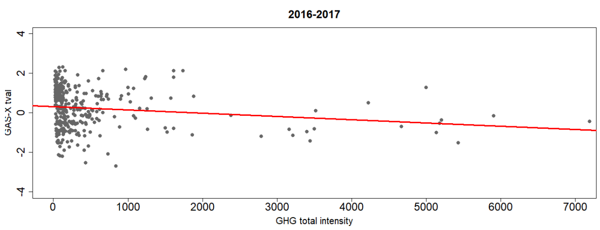
Figure 9: Distribution of t-stats computed using the GAS model with UMC as an exogenous variable mapped against the E Scores of the firms, presented for all the periods covered in our sample. The linear regression performed for each period is also included and shown as a straight red line.



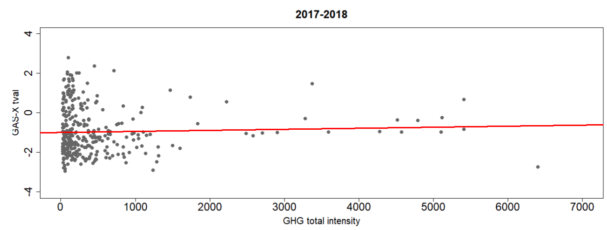
(a) 2014-2015



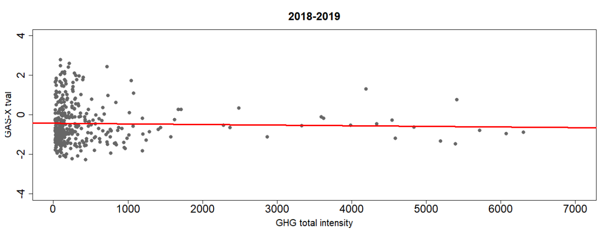
(b) 2015-2016



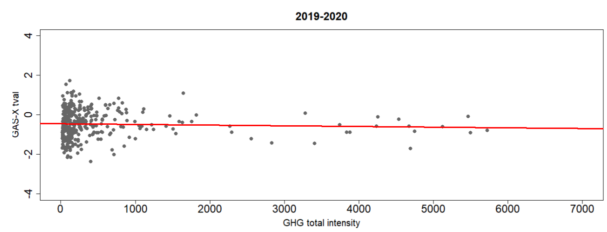
(c) 2016-2017



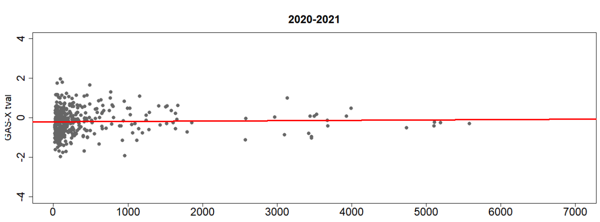
(d) 2017-2018



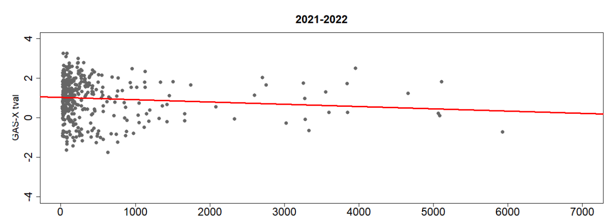
(e) 2018-2019



(f) 2019-2020



(g) 2020-2021



(h) 2021-2022

Figure 10: Distribution of t-stats computed using the GAS model with UMC as an exogenous variable mapped against the GHG intensity of the firms, presented for all the periods covered in our sample. The linear regression performed for each period is also included and shown as a straight red line.

most S&P 500 firms, concentrated towards the left side of these graphs, we can observe a noticeable variance in t-stats, which is consistent with what we observed in the GARCH-X findings. This again suggests that even among firms with similar GHG intensities, reactions to climate change can differ for different firms.

Thus, the analyses conducted using the GAS model to examine the volatility response of firms to climate change events highlight a complex relationship without a definitive pattern across the years. Despite the mixed impact observed across different years and the slight significance of GHG intensities, the principal findings indicate a lack of a clear, consistent relationship between a firm's environmental classification and its response in the face of climate events.

5 Conclusion

This study employs advanced statistical models to analyze the relationship between climate concerns and stock market volatility. It uses both the GARCH model and the GAS model to closely examine S&P 500 stocks and how their volatility is affected by environmental news. We employ the GARCH-X model (an extension of the GARCH model), which includes exogenous variables to include the effects of climate-related events reported in the media. The GARCH-X model in this analysis uses the MCCC Index and the UMC to capture the general perceptions and sudden shifts in climate concerns, respectively. Meanwhile, the GAS model provides a flexible approach to assess this relationship. It also utilizes the UMC to measure how the market reacts to unexpected climate news. The inputs for these models include ESG scores, E scores, and GHG intensity, which help categorize firms according to their 'greenness' and provide a basis for analyzing the differences in market responses between green and brown stocks.

The findings from each model illustrate a complicated relationship between market volatility and climate change concerns. The GARCH-X model shows that the market's reactions to climate change vary among firms and do not align consistently with their environmental profiles. Similarly, the GAS model findings highlight that unexpected climate news does not consistently impact stock volatility and cannot be aligned with a firm's greenness. While some firms show expected volatility patterns in response to climate news, others did not, suggesting a complex and not-so-straightforward market reaction to climate-related news and events. In summarizing the findings from both models, it is clear that while climate concerns and media coverage of climate change affect market behavior, the responses across different stocks are highly varied. This variability suggests that other factors, possibly related to individual firm characteristics or broader economic conditions, might also play significant roles in shaping how stock markets react to climate-related news. The results highlight the complexity of financial markets and the diverse aspects of climate risk that affect stock market volatility.

This research adds to the expanding field of climate finance by emphasizing the importance for investors to consider a broad array of factors when evaluating climate risks in their portfolios. It also suggests that there is a need for further development and refinement of financial models that can more accurately capture the impacts of climate change concerns on market volatility, thereby aiding in the development of more robust and informed financial strategies.

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