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Examining the Relation Between Stocks' Option-Implied Moments and Climate Change Concerns

by

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Abstract

I empirically test if the findings documented by Pástor et al. (2022) and Ardia et al. (2023a)—that green firms outperform brown firms when climate change concerns increase unexpectedly—extends to option-implied returns, and I enhance these findings by examining the relationship between the second, third, and fourth option-implied moments and unexpected increases in climate concerns, using the daily options data of 421 U.S. companies from January 2010 to June 2018. I employ the volatility surface model proposed by François et al. (2022) to convert the daily options data into forward-looking return distributions for each firm and compute the first four moments of these distributions. I then regress daily changes of these moments on the shock component of the Media Climate Change Concerns (UMC) index of Ardia et al. (2023a), a proxy for unexpected increases in climate change concerns. I find that option-implied returns exhibit a weaker relationship with increases in climate change concerns compared to realized returns. Additionally, I show that on days with unexpected increases in climate change concerns, all stocks' option-implied volatility and skewness generally increase, with a more pronounced effect for brown firms. Lastly, I demonstrate that the link between the option-implied moments and the UMC index varies among the index topical clusters.

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1 Introduction

Climate change is recognized as one of the most pressing challenges of our era. However, considerable debate exists over its severity, origins, and the most effective approaches to mitigate its impacts. Such disparities in opinion shape the preferences of consumers, regulators, and investors—some ardently support sustainable practices and investments to mitigate climate change, while others are less concerned. These preferences are not static. They evolve based on new information, subsequently influencing financial asset prices (Fama and French, 2007). Shifts in these preferences have notably accelerated sustainable investing (GSIA, 2018) and sparked significant anti-fossil fuel campaigns (Halcoussis and Lowenberg, 2019). High-profile events, such as the 2012 United Nations Climate Change Conference, the Paris Agreement, and initiatives like the Climate Action Plan, further amplify or intensify these investment trends.

In the context of these shifting preferences, Pástor et al. (2021) propose a theoretical model that links changes in sustainability preferences to asset prices. In particular, they predict that green stocks will outperform brown stocks amid a sudden surge in climate change concerns. Ardia et al. (2023a) construct a daily Media Climate Change Concerns (MCCC) index, using primary U.S. news sources to capture unexpected increases in climate-related concerns and confirm the theoretical predictions of Pástor et al. (2021). Using the MCCC, Pástor et al. (2022) also confirm the theoretical prediction using another sample and an alternative classification for green and brown stocks. Further exploring the economic impact of climate concerns, Bua et al. (2024) introduce two indicators to assess the effect of climate risks on European equity markets, mainly focusing on physical and transition risks. Their findings suggest that sectoral classifications provide a reliable estimate of a company's risk exposure to physical climate impacts. Employing a textual analysis methodology akin to that of Engle et al. (2020), their research detects significant responses to critical events influencing transition and regulatory frameworks. Additionally, using the Latent Dirichlet Allocation method, Faccini et al. (2023) apply textual analysis to news articles to establish market-wide climate-risk factors. This technique aggregates topic shares across various articles, forming a time series reflecting news coverage's intensity and focus on specific themes.

My research extends the existing literature by considering forward-looking option-implied moments into the estimation framework. Given the significant differences between option-implied and realized moments in assessing future dynamics (Han and Park, 2013), my study investigates whether the empirical findings of Ardia et al. (2023a) and Pástor et al. (2021) hold with option-implied returns. Furthermore, I expand upon these findings by analyzing the second, third, and fourth moments of the forward-looking return distribution, enhancing our understanding of the dynamics between stock returns and climate change concerns. Incorporating the second, third, and fourth moments into the analytical framework is particularly pertinent, as these higher order moments significantly shape investor behavior (Lin and Liu, 2018). This relevance is heightened by the increasing recognition of the impact of skewness and kurtosis on investment decisions, especially as markets become more sensitive to the asymmetries and tail risks in return distributions (Madan and McPhail, 2000; Rogach et al., 2019; Lai et al., 2006).

My empirical analysis examines 421 U.S. firms from January 2010 to June 2018. First, I rely on the volatility surface model proposed by François et al. (2022) to convert daily options data into forward-looking return distributions for each firm. Second, I apply the methodology of Breeden and Litzenberger (1978) to calculate the first four option-implied moments. Last, I analyze these option-implied moments by regressing their daily changes against the daily change of the unexpected climate change concerns (UMC) index of Ardia et al. (2023a), utilizing two different methods: a panel regression approach and a green-minus-brown non-parametric approach.

My findings indicate that the relationship between the option-implied underlying first moment and unexpected variations in climate change concerns is weaker than for the realized first moment, a finding that corroborates the results of Poteshman (2001) and Mahani and Poteshman (2008), indicating that options markets tend to underreact to individual daily fluctuations in instantaneous variance, especially for green stocks. I also show that unexpected increases in climate change concerns are linked to higher implied volatility and skewness across all stocks, but more so for brown stocks. This is a reasonably intuitive result for the implied volatility component as investors may perceive green stocks as more resilient and better positioned for the possibility of a future low-carbon economy. This perception could lead to a lower increase in implied volatility for green stocks compared to brown stocks. However, the implied skewness finding is less intuitive and contradicts the hypothesis that an increase in climate change concerns is linked to higher expectations of adverse tail events affecting companies, which leads to a decrease in implied skewness. The results suggest that, on the contrary, the factors contributing to downside risks are perceived to be less likely or less severe than before. Investors might have become more optimistic about the opportunities presented by addressing climate change, such as advancements in green technologies, regulatory incentives, or the transition to a low-carbon economy (Ameli et al., 2020). Finally, I find that the strength of the relation between the implied moments and the UMC varies among topical clusters. This result is supported by the findings of Salisu et al. (2023), which indicate that climate risk impacts the return distributions in the crude oil and natural gas markets, and that transition risks are more predictive of energy market fluctuations, notably the return skewness, than physical risks. This suggests that investors are more responsive to policies, programs, and initiatives to mitigate climate change-related losses and fatalities and adapt to shifts in environmental sustainability rather than to the physical damages caused by climate change. This perspective is also consistent with Faccini et al. (2023), which argue that investors primarily hedge against imminent transition risks due to government interventions rather than the direct risks from climate change itself.

The research is organized as follows: Section 2 reviews the current literature surrounding this subject. Section 3 describes the methodology. Section 4 presents my data. Section 5 shows the empirical results and discusses the main findings. Section 6 examines areas of further research. Finally, Section 7 concludes.

2 Literature Review

This literature review explores several critical domains within the realm of climate finance, underpinning the research with a broad spectrum of theoretical and empirical studies. This review is structured into distinct yet interconnected sections, starting with an overview of climate finance, where the focus is divided between green and brown assets. The review then addresses broader climate change concerns, reflecting on how these apprehensions are measured and quantified. Further, I present the Media Climate Change Concerns (MCCC) index of Ardia et al. (2023a), a tool for quantifying media narratives around climate change concerns.

2.1 Climate Finance

Climate finance is a fundamental component of modern-day finance. It encompasses the financial resources and mechanisms allocated towards mitigating and adapting to climate change, facilitating the transition towards a low-carbon, climate-resilient economy. It is pivotal in addressing the multifaceted challenges posed by climate change, including greenhouse gas emissions reduction, enhancement of renewable energy infrastructures, conservation of biodiversity, and the development of adaptive strategies to withstand climatic impacts. The concept of climate finance is rooted in the principle of "common but differentiated responsibilities," recognizing countries' varying capabilities and contributions to climate change. It is an area of expanding research as it represents a critical component of the global response to climate change, bridging the gap between environmental sustainability and economic development.

Long et al. (2022) provide a comprehensive review of the literature in climate finance, observing that significant scholarly contributions have emerged more recently, mainly motivated by the Paris Climate Agreement. They identified six principal themes dominating the discourse: (i) the broader implications of climate change, (ii) the mechanisms and impact of green financing, (iii) the role of public policy, (iv) the valuation processes for green bonds, (v) the intersection of green financing with banking practices, and (vi) the integration of green bonds within financial markets.

Stroebel and Wurgler (2021) survey 861 participants from finance academia, industry professionals, public sector regulators, and policy economists, focusing on climate finance issues. The survey reveals that regulatory risk is perceived as the most significant climate-related risk to businesses and investors in the next five years. In contrast, physical risk is the primary concern over the next 30 years. The respondents overwhelmingly agreed that current asset prices fail to accurately reflect climate risks, indicating a general underestimation rather than an overestimation due to a widespread misunderstanding of these risks. Furthermore, the findings show that those with a professional stake in climate finance—arguably the respondents with the most informed perspectives—are even more strongly of the opinion that the financial markets do not accurately account for climate risks.

A wealth of research has been devoted to dissecting various facets of climate change, aiming to clarify widespread misconceptions about its nature and impact on corporate financial performance. Below, I underscore the critical role of climate sentiment in the practical deployment of financial theories. Accompanied by a surge in investment activism and unparalleled access to information, there has been an escalating demand for investment strategies that conscientiously consider climate issues.

2.1.1 Green and Brown Assets

It is first necessary to categorize firms into green and brown groups to evaluate the differential impact of climate sentiment shocks on firm's stock price. This categorization allows for a nuanced analysis of how different types of companies—those that are environmentally friendly versus those that are not—react to the same external stimuli such as changes in climate policy or shifts in consumer preferences. By distinguishing between green and brown firms, it is easier to understand investor behavior, as investors may respond differently based on a company's environmental impact. Various classification methodologies have been employed in scholarly research to achieve this delineation. Pástor et al. (2022) attribute greenness levels to individual stocks utilizing the environmental ratings provided by MSCI, which Eccles and Stroehle (2018) describe as a leading global entity in ESG (Environmental, Social, Governance) scoring. The environmental criteria consider how a company performs as a steward of the natural environment. These criteria include carbon emissions, waste management, energy efficiency, resource depletion, and the company's impact on biodiversity. Investors use these criteria to assess potential environmental risks associated with their investments and to identify companies that are leaders in adopting eco-friendly practices. MSCI's ratings, enriched by its research unit comprising over 200 analysts, undergo frequent updates throughout the year. A notable advantage of MSCI's ESG ratings is their provision of non-industry-adjusted scores, enabling Pástor et al. (2022) to discern green and brown stocks irrespective of their industrial sectors. Conversely, Bauer et al. (2022), Garvey et al. (2018), Cheema-Fox et al. (2021), and Ardia et al. (2023a) advocate for the utilization of carbon dioxide emissions data, positing its consistency and reliability over ESG scores as documented by Busch et al. (2022). This approach defines emission intensity ratios, mitigating the influence of a firm's size on its green classification. By dividing greenhouse gas emissions by firm revenue, this metric quantifies the tons of CO2 equivalent emissions required for a firm to generate one million dollars, offering an empirical basis for assessing firm greenness as a determinant of returns and its relevance to consumers and investors. An alternative strategy, eschewing direct stock greenness classification, involves using clean energy ETFs as surrogates for green stocks. Dutta et al. (2023), Li et al. (2023), and Bouri et al. (2022) examine various ETFs within their empirical analyses, explicitly highlighting the Invesco WilderHill Clean Energy ETF (PBW) and the Invesco Global Clean Energy ETF (PBD). These ETFs offer investors access to renewable energy ventures, boasting high liquidity and reduced vulnerability to non-synchronous trading phenomena. For representing brown energy stocks, Bouri et al. (2022) incorporate three ETFs: the Energy Select Sector SPDR Fund (XLE), the iShares Global Energy ETF (IXC), and the iShares U.S. Energy (IYE).

According to Fama and French (2007), shifts in preferences can significantly influence asset prices, a principle underpinning research on how climate change concerns impact the performance of green and brown stocks. Pástor et al. (2021) propose a model to capture the effect of preference variations on asset prices, demonstrating that green assets outperform brown ones amid rising climate change concerns. Supporting this notion, Ardia et al. (2023a) utilize the shock component of their Media Climate Change Concerns (MCCC) index to show that unexpected surges in climate change concerns lead to appreciable increases in green firm stock prices and decreases in brown firm stock prices.

Bua et al. (2024) develop two indicators for assessing the pricing of climate risks in European equity markets, focusing on physical and transition risks. Their findings suggest that the sectoral classification effectively approximates firms' exposure to physical risks. The methodology is rooted in textual analysis, akin to the approach used by Engle et al. (2020), and identifies significant spikes corresponding to key events that influenced transition and regulatory actions. Similarly, Santi (2023) conducts a textual analysis on StockTwits posts, finding that heightened climate sentiment is linked to lower returns for long-short portfolios, with the volume of climate-related posts serving as a proxy for climate sentiment. This trend persists when analyzing ETFs as proxies for green versus brown assets, as demonstrated by Brière and Ramelli (2023), who find that increased green sentiment precipitates the outperformance of climate-friendly assets. Bouri et al. (2022) provide empirical evidence that climate policy uncertainty significantly affects the performance of green and brown energy stocks, particularly during crisis periods, with increased uncertainty favoring green assets. Pham et al. (2023) examine the reaction of the green stock market to climate policy events, noting significant responses to positive policy developments, whereas adverse events, such as the Trump election or the announced withdrawal from the Paris Agreement, showed no impact on green asset returns. The discussion extends beyond equity markets to the green and brown fixed-income sectors. Baker et al. (2018) study green municipal bonds, finding they are issued at a premium over similar ordinary bonds, a premium that increases with third-party green certification. Conversely, Huynh and Xia (2021) explores the impact of climate change news risk on corporate bonds, discovering that bonds with higher climate change news beta are associated with lower returns, indicating that higher climate risk concerns elevate prices for bonds issued by environmentally-performant firms.

The relative performance of more versus less climate-friendly assets has garnered attention in recent research, yielding mixed findings. Empirical studies such as Bolton and Kacperczyk (2021) and Bansal et al. (2023) indicate that green stocks typically exhibit lower returns, suggesting the presence of a carbon premium. This concept aligns with basic asset pricing theory, which posits that firms facing higher climate-related risks (i.e., brown firms) command higher expected returns as compensation. Bolton and Kacperczyk (2021) employ panel regressions of equity returns against carbon dioxide emissions, revealing that less climate-friendly firms tend to generate higher returns. Conversely, Bansal et al. (2023) highlights that the stock market already integrates climate risks into pricing, as evidenced by the negative impact of low-frequency variations in global temperature on asset valuations, thus carrying a risk premium. Several studies, including Ardia et al. (2023a), Pástor et al. (2021), Huij et al. (2022), Xiong (2021) report significant outperformance by climate-friendly assets compared to their less climate-friendly counterparts in recent years.

Although these findings may seem contradictory, they underscore the notion that over the long term, brown firms are expected to outperform green firms due to the risk premium associated with brown industries. This trend reverses when there is an unexpected increase in climate change concerns. Pástor et al. (2022) confirm the findings of Ardia et al. (2023a) that the recent superior performance of green assets was mainly driven by unexpected environmental concerns escalations rather than elevated expected returns. Their analysis supports the theoretical framework and corroborates the empirical findings of Chava (2014) and El Ghoul et al. (2011), which also report that green stocks generally have lower expected returns than brown stocks. The expected returns are assessed ex-ante, using implied costs of capital and ex-post, by analyzing realized returns adjusted for climate concern shocks and earnings variations.

Additionally, Bauer et al. (2022) attribute these conflicting results to differences in greenness measurement and the methodologies used to compute stock performance. They suggest that discrepancies in monthly observation counts lead to weighting differences between panel regression and brown-minus-green portfolios. More so, the choice of greenness indicator varies across studies, with some employing emissions levels as the independent variable in regressions, a model Bauer et al. (2022) argue does not align with investor behavior focused on cross-sectional firm comparisons.

2.1.2 Climate Change Concerns

Engle et al. (2020) have significantly contributed to quantifying climate change concerns by proposing two methods for developing climate news indices. Their initial index integrates 19 climate change white papers and 55 glossaries into a dataset of unique terms and their frequencies, further applying these terms to quantify the presence of climate-related discussions in daily editions of The Wall Street Journal. This approach inherently assumes that an increase in discussions on climate change correlates with heightened climate risk, suggesting that the absence of such news indicates positive climate developments—a substantial presupposition. To address potential shortcomings of this assumption, their secondary index concentrates exclusively on negative climate news, leveraging an extensive collection of over one trillion news articles by Crimson Hexagon to categorize articles by sentiment, thus isolating those with predominantly negative connotations.

Building on this work, Gavriilidis (2021) introduces a climate policy uncertainty index that distinguishes itself in two main ways: by analyzing articles from eight significant newspapers for a broader assessment of climate discourse and by focusing specifically on climate policy-related news that could engender uncertainty. This index contrasts with Engle et al. (2020), who considered all climate change-related news. The index is formulated by identifying articles that contain terms associated with uncertainty in conjunction with standard climate change terminology, resulting in a correlation coefficient of 0.41 with the WSJ climate change news index by Engle et al. (2020).

Expanding further upon Engle et al. (2020), Faccini et al. (2023) apply textual analysis to news articles to establish market-wide climate-risk factors via Latent Dirichlet allocation (Blei et al., 2003). This methodology, initially introduced in economics by Hansen et al. (2017) and subsequently in finance, aggregates topic shares from all articles to create a time series reflecting news coverage's intensity on specific topics. Their research includes analyzing over 34,000 articles from the Refinitiv News Archive mentioning “climate change” or “global warming.”

In contrast to conventional media sources, Santi (2023) examines StockTwits posts related to climate change to estimate investor climate sentiment. StockTwits, a social media platform tailored for investors, offers a rich dataset for textual analysis due to its focus on stock-related information. Santi (2023) selects messages based on keywords associated with climate change and global warming and conducts sentiment analysis to quantify investor climate sentiment, employing novel computational packages to calculate text polarity sentiment accurately.

Brière and Ramelli (2023) diverge from news-based indices by estimating demand shocks for green assets through ETF arbitrage activity. They calculate abnormal monthly flows into eco-friendly ETFs to create a Green Sentiment Index, reflecting unpriced shifts in investor demand for green assets. This index, distinct from other climate sentiment measures, aims to capture investor appetite shifts not based on fundamental information, suggesting its predictive power in forecasting green asset performance.

2.2 Media Climate Change Concerns (MCCC) Index

Ardia et al. (2023a) test the prediction by Pástor et al. (2021) that green firms outperform brown firms during spikes in climate change concerns. The research quantifies these shifts by utilizing their novel Media Climate Change Concerns (MCCC) Index, created from extensive textual analysis of climate change coverage in major U.S. media. This index, crafted from news articles across newspapers and newswires, applies natural language processing techniques to assess mentions and sentiment related to climate change, adjusting for media output fluctuations to isolate genuine changes in public concern.

To quantify variations in climate change concerns, they define concerns as "the perception of risk and related negative consequences associated with this risk." Based on this definition, they create a score to measure these concerns from the informational content of news articles. They use two lexicons for this purpose: (i) a risk lexicon to gauge the level of discussion about future risk events and (ii) a sentiment lexicon to assess the increase in risk perception. These tools are used to calculate the "concerns score."

Assuming there are S news sources, where $s = 1, \ldots, S$, and each day $t = 1, \ldots, T$, source s publishes $N_{t,s}$ articles discussing climate change. For each article n published on day t by source s, the concerns score is determined using the number of risk words $RW_{n,t,s}$, the number of positive words $PW_{n,t,s}$, the number of negative words $NW_{n,t,s}$, and the total number of words $TW_{n,t,s}$ in the article:

$$concerns_{n,t,s} = 100 \times \left(\frac{RW_{n,t,s}}{TW_{n,t,s}}\right) \times \left(\frac{NW_{n,t,s} - PW_{n,t,s}}{NW_{n,t,s} + PW_{n,t,s}} + 1\right)/2\,.$$

The first ratio, $\left(\frac{RW_{n,t,s}}{TW_{n,t,s}}\right)$, measures the percentage of risk words in the text, accounting for variability in article lengths. The second ratio, $\left(\frac{NW_{n,t,s}-PW_{n,t,s}}{NW_{n,t,s}+PW_{n,t,s}} + 1\right)/2$, measures the degree of negativity, where zero represents the most positive text, and one means the most negative. This distinction allows for differentiation between negative and positive articles. Consequently, their article-level concerns score can be seen as a weighted textual risk measure, with higher weights assigned to more negative texts and lower weights to more positive ones.

They then construct a daily index to capture changes in climate change concerns by aggregating article-level concern scores. The daily concerns score for day t and source s is defined as the sum of the article-level concern scores across $N_{t,s}$ articles related to climate change:

$$concerns_{t,s} = \sum_{n=1}^{N_{t,s}} concerns_{n,t,s} \,.$$

They adopt the source-aggregation methodology from Baker et al. (2016) to account for source heterogeneity. For each source s, they calculate the standard deviation of the source-specific index over a time range τ_1 to τ_2 ($1 \leq \tau_1 \leq \tau_2 \leq T$):

$$\sigma_s = \sqrt{\frac{\sum_{\tau=\tau_1}^{\tau_2} (concerns_{\tau,s} - \overline{concerns}_s)^2}{\tau_2 - \tau_1}} \,,$$

where $\overline{concerns}_s$ is the sample mean computed over τ_1 to τ_2. They use the standard deviation to normalize the source-specific index over the $t = 1$ to $t = T$ period:

$$nconcerns_{t,s} = \frac{concerns_{t,s}}{\sigma_s} \,.$$

Finally, they compute the MCCC index at day t by applying an increasing concave function $h(\cdot)$ to the average of the normalized source-specific climate change concerns for that day:

$$MCCC_t = h\left(\frac{1}{S}\sum_{s=1}^{S} nconcerns_{t,s}\right) \,.$$

This increasing concave mapping function is designed to reflect the diminishing impact of media attention on climate change concerns: a single concerning article may significantly raise concerns, but more than twenty such articles will not increase concerns twentyfold.

2.2.1 Unexpected Media Climate Change Concerns (UMC) Index

To measure unexpected change (UMC) in climate change concerns, Ardia et al. (2023a) isolate the shock component of the MCCC index, separating it from potential influences of financial markets, energy-related factors, and macroeconomic variables. They use an augmented autoregressive time series model (ARX) with explanatory variables to estimate the expected component of $MCCC_t$ and interpret the prediction error as a proxy for unexpected changes in climate change concerns. By integrating this index with a topic model, they derive topical and thematic UMC variables related to climate change transition and physical risks, specifically: (i) Business Impact, (ii) Environmental Impact, (iii) Societal Debate, and

(iv) Research. This approach transforms news coverage into a dynamic measure of public sentiment, addressing previous data scarcity challenges.

They first examine the contemporary relationship between UMC and the daily return of a green-minus-brown (GMB) portfolio, which is long on green firms and short on brown firms. They find that green stocks tend to outperform brown stocks on days with an unexpected increase in climate change concerns, as evidenced by the significant positive relationship between the GMB portfolio and the index. When analyzing the green and brown portfolios separately, they observe a positive relationship with UMC for green and a negative relationship for brown portfolios. This relationship is stronger for the brown portfolio than for the green portfolio in absolute terms. Consequently, unexpected increases in climate change concerns tend to penalize brown firms more than reward green firms.

Then, by integrating this index into a firm fixed-effect panel regression model, they consider industry differentiation and confirm that green stocks gain value in response to unanticipated increases in climate concerns. In contrast, brown stocks lose, thus supporting the hypothesis of market sensitivity to climate sentiment shifts.

While the study robustly confirms that unexpected increases in climate concerns can sway the immediate performance outlook of green versus brown stocks, the relation of these concern shifts with assets' forward-looking moments remains unexplored.

3 Methodology

The methodology aims to obtain daily forward-looking option-implied moments for assets and examine the comparative effect of climate change concerns on green and brown assets. A parametric model assesses implied volatility surfaces by capturing the moneyness and maturity slopes, smile attenuation, and smirk. This model is particularly beneficial because it allows for interpolation and extrapolation over a wide range of maturity and moneyness. It is twice continuously differentiable and well-behaved asymptotically, which means it can accurately represent the complex dynamics of implied volatility. This, in turn, facilitates the extraction of the risk-neutral moments (François et al., 2022). This extraction of the daily moments allows for two analytical frameworks: a panel regression approach and a green-minus-brown portfolio approach.

Section 3.1 outlines the method for extracting the option-implied moments, Section 3.2 introduces the panel regression framework, and Section 3.3 details the green-minus-brown portfolio regression framework.

3.1 Extracting Option-Implied Moments

The computation of option-implied moments involves several distinct steps. First, I calibrate the implied volatility (IV) surface on option data using the approach of François et al. (2022). I rely on the Bayesian regularization proposed by Gauthier and Simonato (2012) to smooth out erratic fluctuations in the daily calibrations. Second, I use the methodology proposed by Breeden and Litzenberger (1978) to extract the daily forward-looking density function from the IV surface.

3.1.1 Implied Volatility Model

The IV surface model proposed by François et al. (2022) is designed to reflect the dynamics of the surface through mathematically and economically meaningful factors. The model employs factors specifically chosen to represent critical patterns seen in IV surfaces, such as the volatility smile and smirk. The factors are designed for the surface to be twice continuously differentiable, allowing the derivation of a continuous risk-neutral density function. This aligns the model with fundamental financial economics principles, ensuring no-arbitrage conditions and the viability of pricing derivatives through expected payoffs under the risk-neutral measure.

In their framework, the IV denoted by $\sigma(M, \tau)$ is a function of the option's moneyness M and annualized time-to-maturity τ. The moneyness is defined as:

$$M = \frac{1}{\sqrt{\tau}} \log\left(\frac{F_{t,\tau}}{K}\right),$$

where $F_{t,\tau}$ is the underlying forward price at day t for a maturity τ, and K is the strike price. The IV function is specified as follows:

$$\begin{aligned}\sigma(M,\tau) = {} & \beta_1 + \beta_2 e^{-\sqrt{\frac{\tau}{T_{\text{conv}}}}} + \beta_3\left(M 1_{M\geq 0} + \frac{e^{2M}-1}{e^{2M}+1} 1_{M<0}\right) \\ & + \beta_4(1-e^{-M^2})\log\left(\frac{\tau}{T_{\max}}\right) + \beta_5(1-e^{(3M)^3})\log\left(\frac{\tau}{T_{\max}}\right) 1_{M<0}\,,\end{aligned} \tag{1}$$

where 1_M is the indicator function that equals one when the condition is satisfied and zero otherwise, and the constants $T_{\max}$ and T_{conv} are empirically-determined coefficients. The parameter $T_{\max}$ delineates the upper maturity limit that the model aims to represent, set at five years to facilitate extrapolation beyond the maximal maturity of options within the empirical dataset, which is three years. T_{conv}, set at 0.25, indicates the point of rapid convexity alteration in the IV's term structure as a function of time-to-maturity. Considering the more pronounced curvature of the IV over time-to-maturity for short-term options, the model adjusts the convexity correction for maturities shorter than three months. This adjustment involves linking the β_2 factor to a nonlinear function of $\tau/0.25$. Through this mechanism, the term $\tau/0.25$ significantly enhances the convexity for the short-term segment (less than three months) of the IV surface, as presented by François et al. (2022).

The five-factor formula's initial term β_1 is a constant that captures the long-term at-the-money IV. The second coefficient, β_2, quantifies the slope of time-to-maturity for at-the-money IV, notably accentuating the convexity correction for maturities less than three months through a nonlinear adjustment with $\frac{\tau}{0.25}$, thereby enriching the short-term segment of the IV surface with pronounced convexity. The third factor discerns the moneyness gradient distinctly for put and call options, with the hyperbolic tangent function modeling a hockey stick-like curvature, ideal for depicting call IV and furnishing a continuous moneyness gradient. The fourth term modulates the smile's attenuation, ensuring the flattening of the smile as maturity lengthens, with β_4 also regulating the smile's convexity. The final factor, β_5, is designed to model the skewness in the smile for deep-out-of-the-money calls, gradually diminishing as maturity approaches $T_{\max}$.

3.1.2 Bayesian Regularization

The IV model (1) is a linear function of the (explicit) factors. Thus, Ordinary Least Squares (OLS) can be used to estimate it. However, to maintain the economic significance of each factor, I follow Gauthier and Simonato (2012) and François et al. (2022), who combine OLS with a Bayesian approach for regularization. This integration serves to temper the parameter estimates, ensuring their stability and interpretability.

Let me briefly introduce the underlying idea of the Bayesian regularization. A basic linear model can written as $Y = X\beta + \epsilon$, where Y denotes the dependent variable, X the explanatory variables, and ϵ an error term. The model can be expressed in matrix form when prior knowledge on β is added to it, as follows:

$$\begin{bmatrix} Y \\ \beta_{\text{prior}} \end{bmatrix} = \begin{bmatrix} X \\ R \end{bmatrix} \beta + \begin{bmatrix} \epsilon \\ \delta \end{bmatrix} .$$

Here, β_{prior} embodies the anticipated values of the priors, and R is the matrix that associates the parameters with their corresponding priors. The error vector is presumed to adhere to a multivariate normal distribution, characterized by a block diagonal covariance matrix consisting of two diagonal blocks:

$$\Omega = \begin{bmatrix} \Sigma_\epsilon & 0 \\ 0 & \Sigma_\delta \end{bmatrix} .$$

The estimation of β when prior information is accounted for is accomplished through the generalized least squares (GLS) method:

$$\hat{\beta} = \left(\begin{bmatrix} X \\ R \end{bmatrix}^T \Omega^{-1} \begin{bmatrix} X \\ R \end{bmatrix} \right)^{-1} \begin{bmatrix} X \\ R \end{bmatrix}^T \Omega^{-1} \begin{bmatrix} Y \\ \beta_{\text{prior}} \end{bmatrix} .$$

The variance-covariance matrix Ω can be estimated utilizing the Ordinary Least Squares (OLS) methodology absent prior inputs, where Σ functions as a hyperparameter modulating the prior distribution's strictness. Diminishing the diagonal entries of Σ correlates with an augmented alignment of the estimated β towards the prior expectations.

Now, let me apply Bayesian regularization to the IV estimation. I add the time dimension t in the notation as some elements of the prior depend on the IV surface estimated the day before. First, the one-year at-the-money IV ($ATM_{1y,t}$) is posited as the mean for the prior of $\beta_{1,t}$. The prior for the time-to-maturity slope is derived from the one-month at-the-money IV ($ATM_{1m,t}$) via

$$Slope_t = \frac{ATM_{1y,t} - ATM_{1m,t}}{\exp\left(-\sqrt{\frac{4}{12}}\right)} .$$

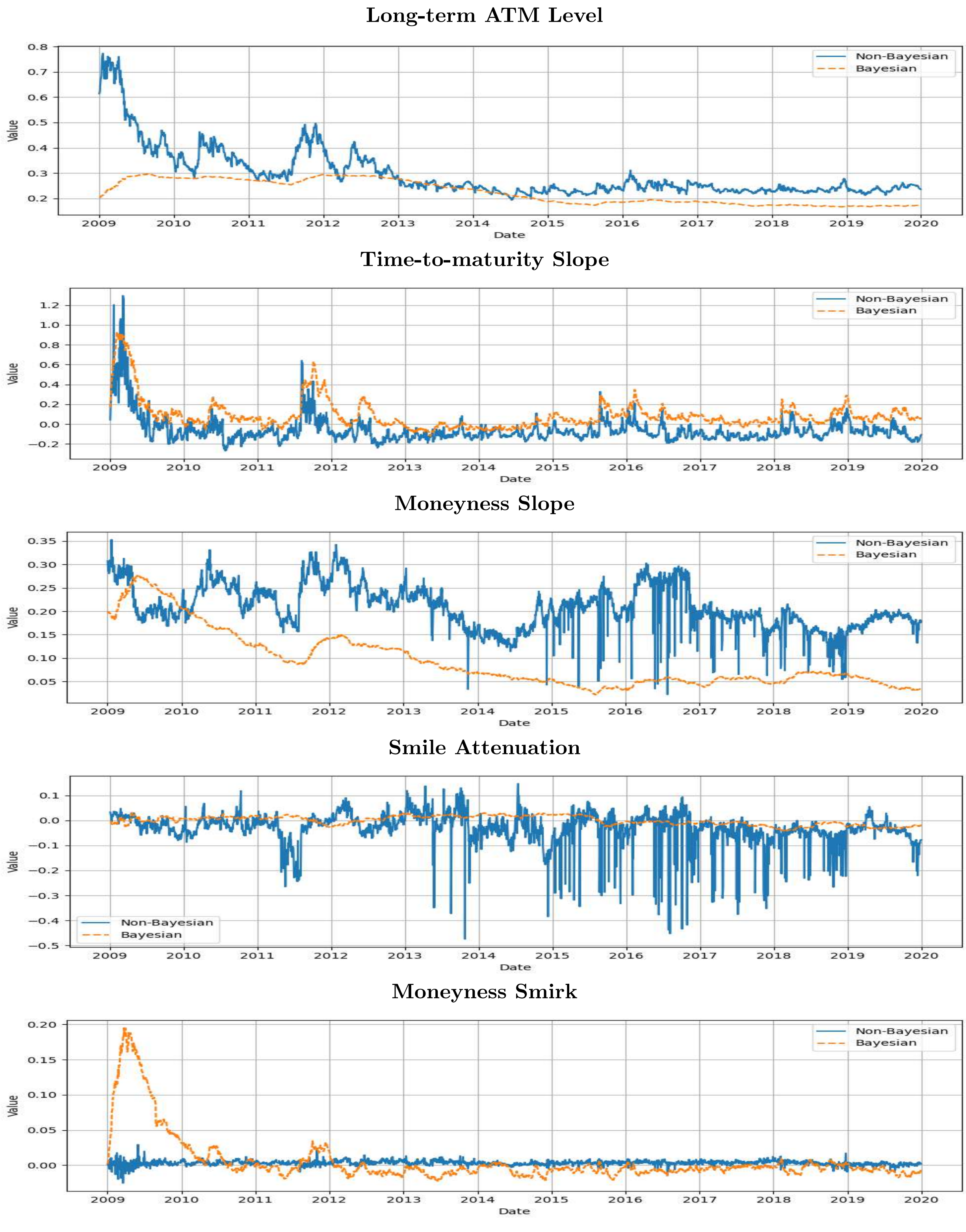
The priors for $\beta_{3,t}$ and $\beta_{5,t}$ are established based on the estimates from the preceding day, $\beta_{3,t-1}$ and $\beta_{5,t-1}$, respectively. Due to its intricate relationship with other parameters, $\beta_{4,t}$ is not assigned a priori. Overall, the regularization for the IV parameters is written as follows:

$$\beta_{\text{prior}} = \begin{bmatrix} ATM_{1y,t} \\ Slope_t \\ \beta_{3,t-1} \\ \beta_{5,t-1} \end{bmatrix}, \quad R = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \quad \Sigma_\delta = \begin{bmatrix} a & 0 & 0 & 0 & 0 \\ 0 & b & 0 & 0 & 0 \\ 0 & 0 & c & 0 & 0 \\ 0 & 0 & 0 & 0 & d \end{bmatrix} \times 10^{-4}.$$

The empirical variance of observables $(ATM_{1y,t}, Slope_t)$ is employed for the initial two priors concerning the long-term and slope levels. The β_3 prior variance is derived from the variance of a proxy for the moneyness slope—specifically, the variance between the one-month ATM IV and the one-month IV for $M = 0.4$. The β_5 prior variance, determined through evaluative judgment, is set at half the magnitude of the parameter's value, resulting in a prior variance of 1×10^{-4}. Given the substantial magnitude of these prior variances, the estimation process is afforded considerable flexibility in fitting the option data while preserving the coefficients' economic significance by mitigating substantial, erratic fluctuations in their time series through regularization.

In Figure 1, I display the daily evolution of the parameters of model (1) before (in blue) and after (in orange) Bayesian regularization for data on J.P. Morgan. The Bayesian regularization stabilizes the outcomes, particularly noticeable in smoothing the smile attenuation and moneyness smirk factors, where the results without Bayesian techniques appear irregular. The results are fairly similar to those presented in Figure 2.3 of François et al. (2022) which examines the daily evolution of the parameters of model (1) after Bayesian regularization for data on the S&P 500 index.

Figure 1: J.P. Morgan – Evolution of IV Model Parameters
The figure shows the daily evolution of estimates of coefficients $\beta = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)$ of (1) for J.P. Morgan Chase & Co. (JPM) from January 1, 2009, to December 31, 2019. The estimates, with corresponding values on the left axis, are obtained by minimizing the sum of squared fitting errors and are shown before and after integrating Bayesian regularization. The model is fitted every day.



3.1.3 Extraction of Density Functions

Breeden and Litzenberger (1978) propose an approach for extracting the implied density function from option prices. Specifically, the implied density function $g(K,\tau)$ for a given strike price K and time-to-maturity τ is obtained as follows:

$$g(K,\tau) = e^{r\tau}\frac{\partial^2 C(K,\tau)}{\partial K^2}, \quad K > 0, \tau > 0\,, \tag{2}$$

where $C(K,\tau)$ denotes the American-style call option price as a function of strike price K and time-to-maturity τ.

Under IV model specification (1), expression (2) becomes:

$$e^{r\tau}\frac{\partial^2 C}{\partial K^2} = \frac{F_{0,\tau}}{K^2}\varphi(\delta_1)\left(\frac{\partial \delta_1}{\sqrt{\tau}\partial M} - \frac{\delta_1 \partial \delta_1 \partial \sigma}{\sqrt{\tau}\partial M \partial M} + \frac{\partial^2 \sigma}{\sqrt{\tau}\partial M^2}\right), \tag{3}$$

where $\varphi(z)$, defined as:

$$\varphi(z) = \frac{1}{\sqrt{2\pi}}e^{-\frac{z^2}{2}}\,,$$

is the probability density function of a standard normal distribution, and F_τ is the forward price of the underlying. Using the forward price instead of the underlying asset price facilitates leveraging the OptionMetrics dataset, which offers forward prices rather than underlying prices. This approach sidesteps the cumbersome daily extraction of implied dividend rates across different option maturities. Theoretically, pricing formulas based on forward and underlying asset prices are equivalent (Black, 1976; François et al., 2022). Variables $\delta_1(M)$ and $\delta_2(M)$ are given by:

$$\begin{aligned}
\delta_1(M) &= \frac{M}{\sigma(M,\tau)} + \frac{1}{2}\sigma(M,\tau)\sqrt{\tau}\,,\\
\delta_2(M) &= \frac{M}{\sigma(M,\tau)} - \frac{1}{2}\sigma(M,\tau)\sqrt{\tau}\,.
\end{aligned}$$

Furthermore, the derivatives of δ_1 with respect to M, and σ with respect to M, are given by:

$$\frac{\partial \delta_1}{\partial M} = \frac{1}{\sigma} - \left(\frac{M}{\sigma^2} - \frac{1}{2}\sqrt{\tau}\right)\frac{\partial \sigma}{\partial M}\,,$$

$$
\begin{aligned}
\frac{\partial \sigma}{\partial M} &= \beta_3 1_{M\geq 0} + \beta_3 \left(1 - \left(\frac{e^{2M}-1}{e^{2M}+1}\right)^2\right) 1_{M<0} + \beta_4 2Me^{-M^2} \log\left(\frac{\tau}{T_{\max}}\right) \\
&\quad - \beta_5 81M^2 e^{27M^3} \log\left(\frac{\tau}{T_{\max}}\right) 1_{M<0}\,,
\end{aligned}
$$

and the second derivative of σ with respect to M^2 is:

$$
\begin{aligned}
\frac{\partial^2 \sigma}{\partial M^2} &= -\beta_3 8e^{2M} \frac{e^{2M}-1}{(e^{2M}+1)^3} 1_{M<0} + \beta_4 2(1-2M^2)e^{-M^2} \log\left(\frac{\tau}{T_{\max}}\right) \\
&\quad - \beta_5 (162 + 6561M^3) M e^{27M^3} \log\left(\frac{\tau}{T_{\max}}\right) 1_{M<0}\,.
\end{aligned}
$$

By replacing the expressions above in (3), I obtain the risk-neutral density values for all combinations of strike price K and time-to-maturity τ, as formulated by François et al. (2022). I consider a forward-looking horizon of three months in my empirical analyses for simplicity.

From the implied density g, I can compute the first-four implied moments:

$$
\begin{aligned}
Mean &= \int x g(x) dx\,, \\
Std &= \sqrt{\int (x - Mean)^2 g(x) dx}\,, \\
Skew &= \int (x - Mean)^3 g(x) dx / Std^3\,, \\
Kurt &= \int (x - Mean)^4 g(x) dx / Std^4\,.
\end{aligned}
$$

I estimate the integrals by applying a trapezoidal integration method. The formula for the trapezoidal rule for a function $f(x)$ over the interval $[a, b]$ with n sub intervals is given by:

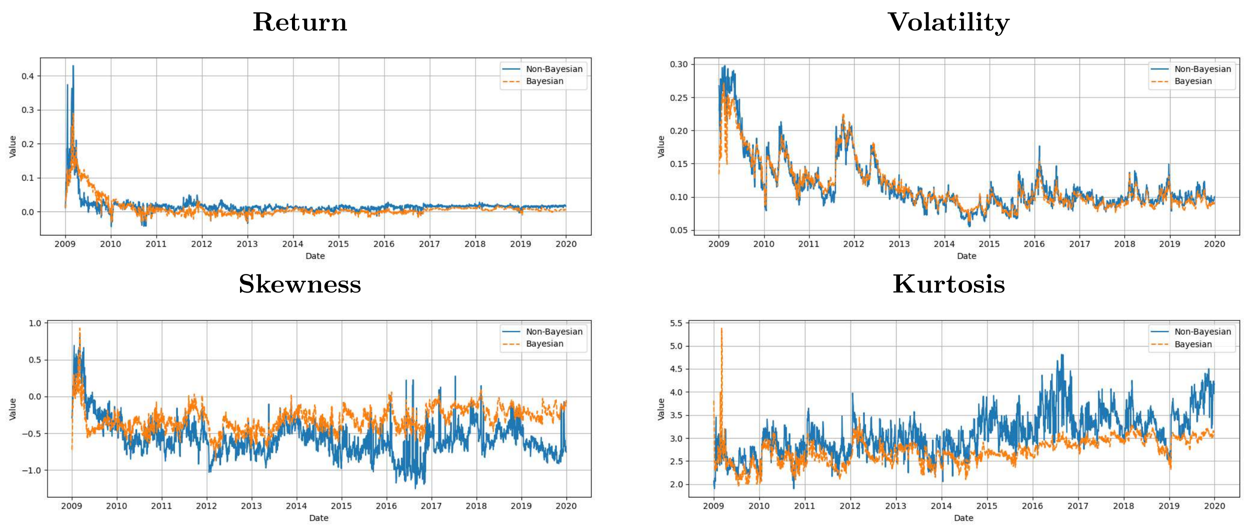
$$
\int_a^b f(x)\, dx \approx \frac{h}{2}\left[f(x_0) + 2\sum_{i=1}^{n-1} f(x_i) + f(x_n)\right],
$$

where a, b are the minimum and maximum strike prices available for a specific stock and time-to-maturity, n is the number of sub-intervals, and $h = \frac{b-a}{n}$. For the purpose of this project, I set n at 10,000.

In Figure 2, I display the daily evolution of the forward-looking implied moments of J.P. Morgan from January 1, 2009, to December 31, 2019, before and after Bayesian adjustments.

Bayesian regularization notably enhances the stability of these moments, making them less erratic and more accessible to interpret. However, the implied moments from 2009 are still noticeably erratic due to the increased stock volatility following the great financial crisis. This volatility is prominent across all four moments during the initial year but gradually decreases as market conditions normalize.

Figure 2: J.P. Morgan – Evolution of Implied Moments
This figure shows the daily evolution of the forward-looking implied moments of JP Morgan Chase & Co. (JPM) from January 1, 2009, to December 31, 2019. The top-left panel presents the expected three-month return of the stock price. The top-right panel presents the three-month expected volatility of the stock price. The bottom-left panel presents the three-month expected skewness of the stock price. The bottom-right panel presents the three-month expected kurtosis of the stock price. The results are shown before and after integrating Bayesian information.



Once I obtain the implied moments, I can compute, for each stock i and date t, the change in implied moments as follows:

$$
\begin{aligned}
IM1_{i,t} &= \frac{Mean_{i,t} - Mean_{i,t-1}}{Mean_{i,t-1}}\,, \\
IM2_{i,t} &= \frac{Std_{i,t} - Std_{t-1}}{Std_{i,t-1}}\,, \\
IM3_{i,t} &= Skewness_{i,t} - Skewness_{i,t-1}\,, \\
IM4_{i,t} &= Kurtosis_{i,t} - Kurtosis_{i,t-1}\,.
\end{aligned}
$$

In my analyses, I use these daily changes in implied moments as dependent variables and measure their relation with daily changes in unexpected changes in climate change concerns (UMC). I rely on a panel regression and a non-parametric portfolio approach.

3.2 Panel Regression Approach

Following the panel regression setup of Ardia et al. (2023a), I first examine if daily changes in implied moments of firms are linked to the interaction between the firms' greenhouse gas (GHG) emissions intensity and the UMC variable. This analysis focuses on variations in GHG emissions intensity within industries instead of across sectors. This perspective aligns with the findings of Ilhan et al. (2021), which suggest that differences in GHG emissions intensity can be primarily attributed to the industry sector.

I first define the variable $lGHG_{i,t}$ is initially delineated as the cross-sectionally normalized logarithm of GHG emission intensity for firm i at time t, with normalization predicated on the cross-sectional disparities among firms. Subsequently, I estimate the following firm fixed-effect panel regression model (Ardia et al., 2023a, Equation 9):

$$IM_{i,t} = c_i + \gamma^{lGHG} lGHG_{i,t} + (\gamma^{UMC} + \gamma^{UMC}_{lGHG} lGHG_{i,t})\, UMC_t + \beta_i^T CTRL_t + \epsilon_{i,t}\,, \tag{4}$$

where $IM_{i,t}$ is the daily change of a particular moment of the implied distribution of the underlying stock price of firm i at time t, $CTRL_t$ is a vector of control variables, and UMC_t is the daily unexpected change in climate change concerns.

Coefficients γ^{lGHG}, γ^{UMC}, and γ^{UMC}_{lGHG} are the same across firms, while c_i and β_i are firm-specific coefficients. The firms' exposure to unforeseen shifts in climate change concerns is captured by $(\gamma^{UMC} + \gamma^{UMC}_{lGHG} lGHG_{i,t})$, which includes a generic component that reflects the exposure of neutral firms (i.e., firms whose log-GHG emissions intensity approximates the cross-sectional mean) and an emissions intensity-dependent component. For instance, an adverse γ^{UMC}_{lGHG} is anticipated in analyses of excess market returns, suggesting that firms with higher (lower) GHG emissions intensity face more negative (positive) exposure to unexpected escalations in climate change concerns (Ardia et al., 2023a; Pástor et al., 2022). This analysis is also performed for each of the four individual thematic components of the UMC, namely: Business Impact, Environmental Impact, Societal Debate, and Research.

3.3 Green-Minus-Brown Portfolio Approach

The second approach I consider also follows Ardia et al. (2023a), where a combination of conditional mean analysis and multivariate factor analysis is employed to investigate the role of an interaction between a firm's greenhouse gas (GHG) emissions intensity and the UMC variable in explaining daily stock returns. This time, the approach involves categorizing stocks into three groups (terciles) based on the firms' GHG emissions data: green, brown, and neutral. Firms in the top tercile of GHG emissions are categorized as brown, those in the bottom tercile are classified as green, and the rest are neutral. For each category, equal-weighted portfolios are constructed daily, and the average performance for the green, brown, and neutral and the differential performance between green and brown portfolios is calculated and related to the UMC.

While this approach is straightforward to apply in the context of realized returns, as in Ardia et al. (2023a), it requires more steps with implied moments as these are not additive. Indeed, a moment (e.g., mean) of a combination of implied densities is not equal to the combination of the same moment of the implied densities. To overcome this difficulty, I adopt a copula-based approach and rely on simulations.

Specifically, I capture the dependence structure by filtering past returns using a GARCH model and a Gaussian copula. Then, I rely on simulations to generate draws from the combination of the implied densities. This estimation is performed once over a fixed window. Thus, I consider a constant dependence structure for simplicity. To calibrate the Gaussian copula, I first transform the standardized returns obtained with the GARCH filtering with the inverse function of the implied density of each margin obtained from the option data. Then, the simulation is performed every day, with the set of implied densities obtained from equation (2). The simulation allows me to generate draws from the implied density of equal-weighted portfolios. I detail the steps below.

3.3.1 Filtering Returns With a GARCH Model

As the dependence structure is obtained from historical returns, I first need to filter the conditional variance of the returns (Malevergne and Sornette, 2003; Hu, 2006; Fernandez, 2008). I use the GARCH model by Bollerslev (1986) for that purpose. For simplicity, I consider the simple but effective GARCH(1,1) specification. In this case, the conditional variance at time t of the stock return, σ_t^2, is expressed as a linear function of the past squared return, y_{t-1}^2, and the past conditional variance σ_{t-1}^2:

$$\sigma_t^2 = \alpha_0 + \alpha_1 y_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 \,.$$

The model is estimated by quasi-maximum likelihood over a fixed window for each stock's returns, and the respective series of returns are standardized with the estimated volatilities.

3.3.2 Capturing the Dependence Structure With a Gaussian Copula

Following the volatility modeling, I determine the dependency structure among the standardized returns using a Gaussian copula, allowing me to model the dependencies separately from the marginals (Malevergne and Sornette, 2003; Hu, 2006; Fernandez, 2008). The parameters of the copula, specifically entries of the correlation matrix, are estimated using Maximum Likelihood Estimation (MLE) (Myung, 2003). This accurately reflects the joint behavior of the assets' returns.

3.3.3 Simulating Draws From the Implied Density

I generate 10,000 simulated draws from the Gaussian copula using the estimated correlation matrix. The draws are passed through the individual option-implied marginal cumulative distributions of the assets daily. The cumulative distributions are obtained through the same process as the implied densities used in the panel regression approach. The process is described in Section 3.1. This results in 10,000 daily prices for each firm, which acts as the new option-implied daily density distribution. I then separate the firms into equally weighted green, brown, and neutral portfolios based on the firms' relative greenhouse gas emissions. This allows me to compute these new portfolios' option-implied daily mean, volatility, skewness, and kurtosis, addressing the issue of non-additive implied moments.

3.3.4 Portfolio Analysis

The copula-based approach above allows me to obtain moments of the implied density of an equal-weighted portfolio of green, brown, and neutral stocks, respectively. I also obtain moments of the implied density of a portfolio of green-minus-brown stocks.

To measure the relation between these implied moments and unexpected changes in climate change concerns, I follow Ardia et al. (2023a) and regress the green-minus-brown ($p = GMB$), green ($p = G$), brown ($p = B$), and neutral ($p = N$) portfolios implied mean ($IM1$), standard deviation ($IM2$), skewness ($IM3$), or kurtosis ($IM4$), $IM_{p,t}$ on UMC_t, and control variables ($CTRL_t$):

$$IM_{p,t} = c_p + \beta_p^{UMC} UMC_t + \beta_p^T CTRL_t + \epsilon_{p,t} \, , \tag{5}$$

where c_p is a constant, β_p^{UMC} and β_p are regression coefficients, and $\epsilon_{p,t}$ is an error term. Given the results in Ardia et al. (2023a) and Pástor et al. (2022), I expect that $\beta_{GMB}^{UMC} > 0$, $\beta_G^{UMC} > 0$, and $\beta_B^{UMC} < 0$ for the first moment of the distribution.

4 Data

This section presents the data used to perform my analyses. I first describe the option data utilized to estimate the IV surfaces in Section 4.1. Section 4.2 details the greenhouse gas emission data used to construct portfolios classified as green, brown, and neutral. In Section 4.3, I introduce the MCCC index by Ardia et al. (2023a), which is my analysis's primary independent variable. Finally, I outline the control variables used in the regression models in Section 4.4.

4.1 Option Data

I use OptionMetrics data, which comprises American-style call and put options traded on the Chicago Board Options Exchange (CBOE) from January 1, 2010, to June 30, 2018. Each option quotation provides essential information, including the date of the quote, expiration date, option type (call or put), strike price, bid and ask prices, IV, and unique identifiers for both the option and the associated company. Furthermore, the dataset includes historical and forward prices of the underlying stocks. The historical prices are required to compute daily returns used in the realized returns validations and for the GARCH calibration.

For interpretability, each strike price is scaled down by 1,000 (François et al., 2022), and the price of an option is calculated as the average of the bid and ask prices:

$$\text{Price} = \frac{\text{Bid} + \text{Ask}}{2}\,,$$

while the difference between the ask and bid prices determines the bid-ask spread:

$$\text{Spread} = \text{Ask} - \text{Bid}\,,$$

and the annualized time-to-maturity is defined as follows:

$$\text{Annualized TTM} = \frac{\text{Date of Expiration} - \text{Current Date}}{365}\,.$$

Data selection adheres to the criteria established by Bakshi et al. (1997) and followed by François et al. (2022). Specifically, I exclude options with:

- Time-to-maturity of less than nine days,
- Price below \$ 0.50 USD,
- A bid price of zero,

- Bid-ask spreads exceeding 175% of the option's price,
- All in-the-money options (puts with $M < 0$ and calls with $M > 0$).

I also exclude firms with fewer than ten distinct strike prices for a specific time-to-maturity, as the volatility surface model's applicability relies on a minimum number of observations.

The dataset comprises over 101 million option quotes from January 1, 2010, to June 30, 2018, for 421 U.S. firms. The number of options traded has been continuously increasing in recent years (Bryzgalova et al., 2023), which is also represented in this dataset as the average number of observations increases fivefold between 2009 and 2019.

The IV of each option is calculated using the Black (1976) formula. Table 1 provides detailed statistics on the IVs derived from all quotes in the dataset. The IV profiles over various days often exhibit asymmetry, typically displaying the well-known smirk pattern. This pattern is characterized by higher implied volatilities for call options with a moneyness $M < -0.2$ compared to those with moneyness $-0.2 < M \leq 0$. Additionally, as indicated in Table 1, options with shorter maturities (90 days or less) are less common than options with longer maturities (more than 90 days). The higher number of put contracts relative to call contracts explains the table asymmetry.

Table 1: Descriptive Statistics of the Options Data
This table reports descriptive statistics of stock options IV daily data from January 1, 2010, to June 30, 2018, across multiple times-to-maturity and moneyness buckets. M is the moneyness and τ is the time-to-maturity.

	Calls		Puts			All
	$M \leq$ -0.2	-0.2 $< M$	$M \leq 0.2$	$0.2 \leq M \leq 0.8$	$0.8 \leq M$	
Mean (%)	34.3	20.5	28.8	37.7	72.5	33.1
Std (%)	15.0	9.3	9.5	11.2	31.6	14.8
#	18,303,807	26,363,186	26,051,363	27,819,988	3,073,589	101,613,933
	Calls		Puts			All
	$\tau \leq 0.125$	$0.125 \leq \tau < 0.25$	$0.25 \leq \tau \leq 0.5$	$0.5 \leq \tau \leq 1$	$\tau > 1$	All
Mean (%)	34.3	33.4	33.0	32.3	31.9	33.1
Std (%)	18.9	15.5	13.5	12.5	10.8	14.8
#	28,881,541	10,764,966	18,564,264	21,150,984	22,250,178	101,613,933

4.2 Greenhouse Gas Emission Data

Greenhouse gas (GHG) emissions data from the Eikon database are used to distinguish between "green" and "brown" firms. Green firms are identified as those that mitigate climate change impacts while generating economic value. The GHG emissions data, adhering to the

GHG Protocol Corporate Standard, is categorized into Scope 1 (direct emissions), Scope 2 (indirect emissions from purchased energy), and Scope 3 (other indirect emissions in the value chain). This analysis concentrates on total GHG emissions expressed in tonnes of CO2 equivalents (aggregate of all scopes), normalized by each firm's annual revenue from Compustat, yielding the intensity of GHG emissions. This intensity, reflecting CO2-equivalent emissions per $1 million in revenue, facilitates the classification of firms as green or brown, contingent on their emissions intensity relative to the overall distribution at a given time. This analysis will encompass all three scopes, but previous research has found that results are similar when excluding Scope 3 (see, e.g., Ardia et al., 2023a).

In Table 2, I report the percentage of firms in the dataset with available GHG emissions. The average yearly coverage of 56.81% is similar to that of Ilhan et al. (2021), who use the Carbon Disclosure Project Database and a different set of firms, and Ardia et al. (2023a), which uses the same GHG emissions source but a different set of firms.

Table 2: Percentage of Firms with Emissions Data
This table reports the percentage of firms in my dataset with available greenhouse gas emissions data for each year (%D). The 2009-2017 data point represents the mean across those years

Year	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2009–2017**
%D	54.14	55.02	46.35	46.71	51.89	55.28	62.79	69.67	82.21	56.81

It is common practice for GHG emissions reporting to lag by one year. I compensate for this delay by adjusting the GHG emissions intensity data by 12 months, a methodology consistent with previous research (Ilhan et al., 2021; Ardia et al., 2023a).

4.3 Media Climate Change Data

The MCCC index of Ardia et al. (2023a) and the related UMC values range from January 1, 2010, to June 30, 2018. Given the necessity of this data in the models, all of my analyses will focus on data within this range.

The MCCC index contains the daily values of the aggregated, topical, and thematic indices relevant to climate change concerns. Figure 3 illustrates that the index peaks align with significant climate change events, such as the 2012 Doha UN Climate Change Conference and the Paris Agreement. The moving average, serving as a proxy for climate change concerns, shows phases of varying intensities. A heightened concern period is observed starting after the 2007 UN Security Council discussions on climate change, extending until early 2010 following the Copenhagen UN Climate Change Conference. A second period of increased concern began towards the end of 2012, coinciding with the UN Climate Change Conference, and continues up to the Paris Agreement. Additionally, a notable spike in concerns occurred around the announcement by U.S. President Donald Trump of the withdrawal from the Paris Agreement. These patterns indicate that the index effectively captures significant events associated with rises in climate change concerns.

Figure 3: Media Climate Change Concerns Index (Ardia et al., 2023a)
This figure displays the daily MCCC index (gray points) and its 30-day moving average (bold line) from January 2003 to June 2017. They also report several major events related to climate change (in boxes). The observations from January 1, 2010 are considered forward-looking, because the data from that period is used to compute the source-specific standard deviation estimate required to normalize the source-specific indices before aggregation into the MCCC index. The observations from January 1, 2010, to the end of the time series are not forward-looking and correspond to the period for my main analysis.

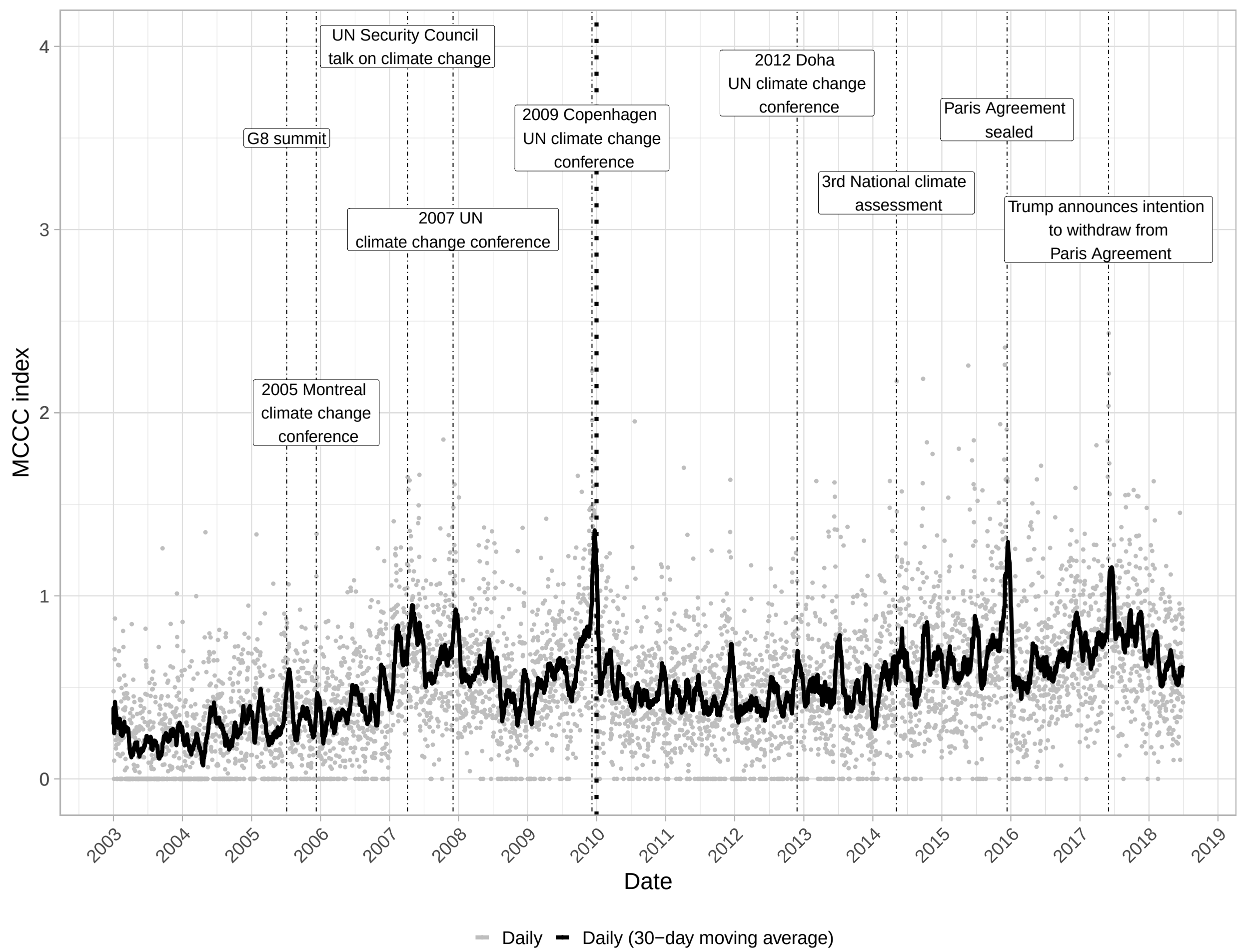
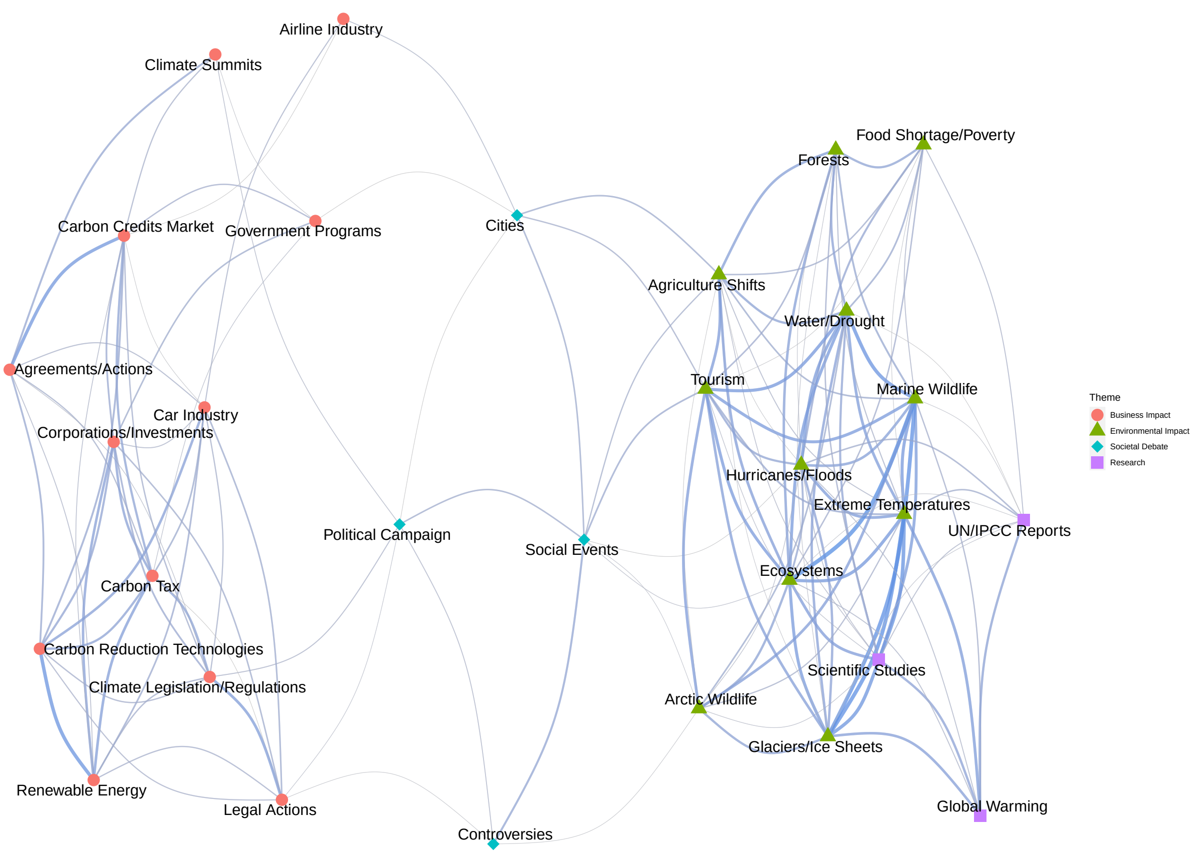


Figure 4 presents a correlation network that illustrates the relationships between the topics discussed in the news corpus. Ardia et al. (2023a) derive specific topics using the Correlated Topic Model (CTM) of Lafferty and Blei (2005) applied to their news corpus. The CTM model, an unsupervised generative machine-learning algorithm, infers latent, interconnected topics within a body of text.

The network plot emphasizes the correlations in the frequency with which topics co-occur within the same news articles. Notably, the diagram reveals two distinct cluster topics: Business Impact on the left and Environmental Impact on the right. Bridging these clusters, issues associated with Societal Debate appear in the center. Additionally, the bottom right of the figure displays three topics grouped under the Research theme.

Figure 4: Correlation Network of Climate Change Topics (Ardia et al., 2023a)
This figure displays the Spearman correlation network for the 30 climate change topics obtained with the correlated topic model. They keep the network readable; they display only correlations above 0.35. Each topic is assigned to a thematic cluster (Theme 1: Business Impact, Theme 2: Environmental Impact, Theme 3: Societal Debate, and Theme 4: Research).



These clusters are comprised of more detailed topics such as Agreements/Actions, Agriculture Shifts, Airline Industry, Arctic Wildlife, Car Industry, Carbon Credits Market, Carbon Reduction Technologies, Carbon Tax, Cities, Climate Legislation/Regulations, Climate Summits, Controversies, Corporations/Investments, Ecosystems, Extreme Temperatures, Food Shortage/Poverty, Forests, Glaciers/Ice Sheets, Global Warming, Government Programs, Hurricanes/Floods, Legal Actions, Marine Wildlife, Political Campaign, Renewable Energy, Scientific Studies, Social

Events, Tourism, UN/IPCC Reports, and Water/Drought. This data, including the MCCC, UMC, and topical clusters, are obtained from https://sentometrics-research.com.

4.4 Control Variables

The different models employed integrate four distinct arrays of controls, following the approach of Ardia et al. (2023a):

1. **CTRL-1**: *MKT*, representing the excess market return;
2. **CTRL-3**: **CTRL-1** enriched with *HML*, the high-minus-low factor, and *SMB*, the small-minus-big factor, of Fama and French (1992);
3. **CTRL-6**: **CTRL-3** enriched with *RMW*, the robust-minus-weak factor, *CMA*, the conservative-minus-aggressive factor, as in Fama and French (2015), and *MOM*, the momentum factor, as identified by Carhart (1997);
4. **CTRL-15**: **CTRL-6** augmented with *WTI*, crude oil returns, *NG*, natural gas returns, *PROP*, propane returns, *EPU*, the economic policy uncertainty index by Baker et al. (2016), *VIX*, the CBOE volatility index, the *TED* spread, *TERM*, the term spread factor, *DFLT*, the default spread factor as per Fung and Hsieh (2004), and *FTS*, the flight-to-safety index by Baele et al. (2020).

The varibles in CTRL-1, CTRL-3, and CTRL-6 are ubiquitously recognized within finance literature. Data for CTRL-1, CTRL-3, and CTRL-6 is retrieved from Kenneth French's website at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

The CTRL-15 set extends these variables by incorporating energy-related and macroeconomic factors to attenuate the influence of potential confounders. The EPU data comes from http://www.policyuncertainty.com/media/All_Daily_Policy_Data.csv, the TERM and DFLT variables from https://fred.stlouisfed.org/series/DBAA, the WTI data from https://fred.stlouisfed.org/series/DCOILWTICO, the NG data from https://fred.stlouisfed.org/series/DHHNGSP, the PROP data from https://fred.stlouisfed.org/series/DPROPANEMBTX, the TED data from https://fred.stlouisfed.org/series/TEDRATE, and the VIX data from https://fred.stlouisfed.org/series/VIXCLS.

5 Empirical Results

This section presents the empirical results. I start with the panel regression approach in Section 5.1, followed by the green-minus-brown non-parametric approach in Section 5.2. Finally, I suggest several avenues for interpreting the results in Section 5.3. For both methodological approaches, I first validate my implementation with Ardia et al. (2023a) using realized returns for the same period ranging from January 1, 2010, to June 30, 2018.

5.1 Panel Regression Approach

5.1.1 Validation With Realized Returns

In Table 3, I present the findings for the realized returns (daily returns) from my study in Panel A, alongside those reported in Ardia et al. (2023a, Table 9) in Panel B. This comparison aids in validating my implementation. The table reveals negative significant coefficients for the $lGHG \times UMC$ variable across all control specifications, indicating that higher GHG emissions are associated with more negative returns when there is an unexpected rise in climate change concerns. Although the strength of the coefficients varies, their direction and significance align with the results of Ardia et al. (2023a), corroborating the proper application of the methodology. For CTRL-15, I obtain an estimated coefficient of -0.016 for the $lGHG \times UMC$ variable, while Ardia et al. (2023a) obtains an estimated coefficient of -0.022. The observed discrepancies can mainly be attributed to dataset company composition variations, as this study focuses on a subset of high-volume firms. At the same time, Ardia et al. (2023a) uses data from all S&P 500 companies from January 2010 to June 2018.

Table 3: Panel Regression Results – Realized Returns
This table reports the estimation results for the firm fixed-effect panel regression of daily stock returns on daily standardized logarithmic greenhouse gas emissions intensity ($lGHG$), daily unexpected changes in climate change concerns (UMC), and their interaction ($lGHG \times UMC$) with different sets of controls; see model (4). Standard errors of the estimators are reported in parentheses. The model is estimated using data from January 2010 to June 2018. *, **, and *** indicate significant coefficients at the 10%, 5%, and 1% levels, respectively. Panel A shows the results of my research, while Panel B shows the results of Ardia et al. (2023a, Table 9).

	Panel A – My Results			Panel B – Ardia et al. Results		
	$lGHG$	UMC	$lGHG \times UMC$	$lGHG$	UMC	$lGHG \times UMC$
CTRL-1	-0.003 (0.003)	0.000 (0.005)	-0.017*** (0.006)	0.005* (0.003)	-0.006 (0.004)	-0.027*** (0.005)
CTRL-3	-0.002 (0.003)	-0.004 (0.004)	-0.016*** (0.006)	0.004 (0.003)	-0.008** (0.004)	-0.024*** (0.005)
CTRL-6	-0.002 (0.003)	-0.004 (0.004)	-0.016*** (0.006)	0.005 (0.003)	-0.005 (0.004)	-0.023*** (0.005)
CTRL-15	-0.003 (0.003)	-0.004 (0.004)	-0.016*** (0.006)	0.006* (0.003)	-0.001 (0.004)	-0.022*** (0.005)

5.1.2 Implied Moments

Table 4 reports results for the implied moments across the aggregate UMC index and the individual topical indices for CTRL-15. The findings are robust across control sets. The corresponding results for CTRL-1, CTRL-3, and CTRL-6 can be found in the appendix.

The results for the aggregate cluster of the first implied moment are insightful despite being mostly statistically insignificant. While higher GHG emissions are linked to lower implied returns and unexpected increases in climate change concerns are related to higher implied returns across all firms, the interaction term $lGHG \times UMC$ coefficient is negative and equal to -0.006. These results are consistent across clusters, with the Business Impact and Societal Debate clusters having statistically significant interaction term $lGHG \times UMC$ coefficients at the 10% significance level. I obtain estimated coefficients of -0.007 for both clusters. These results indicate that similarly to the conclusions of Ardia et al. (2023a) surrounding realized returns, companies with higher log-GHG emissions intensity face greater sensitivity to unforeseen shifts in climate concerns regarding their option-implied returns. However, it must be noted that the results for the implied returns, as shown in Table 4, are much weaker and are not statistically significant, indicating a clear difference between the reaction of implied and realized returns. I obtain an estimated coefficient of -0.016 for the realized first moment and -0.006 for the implied first moment. The first implied moment is almost three times less sensitive to unexpected variations in climate change concerns. This discrepancy could be explained by the lesser sensitivity of options to daily variations in instantaneous variance compared to the sensitivity of stocks (Poteshman, 2001; Mahani and Poteshman, 2008).

The analysis of the implied volatility component also yields intriguing insights for the aggregate cluster. Higher GHG emissions are linked to marginally higher implied volatility, while unexpected increases in climate change concerns are related to significantly higher expected volatility across all firms. The interaction term $lGHG \times UMC$ coefficient is positive with a value of 0.007, albeit insignificant. These results are consistent across clusters, ranging from 0.004 to 0.007. These results suggest that all companies, regardless of their GHG emissions intensity, will likely experience increased implied volatility following sudden increases in climate change concerns. As climate change is increasingly viewed as a systemic risk that affects entire economies and sectors (Hui-Min et al., 2021), unexpected increases in climate change concerns could lead to more significant uncertainty about future economic conditions, which in turn could result in higher implied volatility across the stock market.

The analysis of the implied asymmetry component yields a similar conclusion for the aggregate cluster. Higher GHG emissions are linked to marginally lower implied asymmetry. In contrast, unexpected increases in climate change concerns are linked to significantly higher expected asymmetry across all firms, with estimated coefficient values ranging from 0.005 to 0.012. The interaction term $lGHG \times UMC$ coefficient is positive, albeit insignificant, with a value of 0.005. These results are consistent across the aggregate, Business Impact, Research, and Societal Debate clusters, which are all significant at the 1% level, except the Research cluster, which is statistically significant at the 5% level. The Environmental Impact cluster stands out as the UMC variable coefficient is statistically insignificant, and the interaction term $lGHG \times UMC$ coefficient shows no clear direction. These results suggest that all companies, regardless of their GHG emissions intensity, will likely experience increased implied asymmetry following sudden increases in climate change concerns. These findings could reflect expectations of severe financial repercussions for companies adversely affected by climate change or substantial gains for those poised to benefit from it, leading to non-normal returns (Boudt et al., 2008).

Finally, the implied kurtosis component results yield insignificant and mostly aimless results for the aggregate index. Both GHG emissions and unexpected increases in climate change concerns are not linked to variations in the implied kurtosis of stocks. However, the interaction term $lGHG \times UMC$ coefficient is positive, albeit insignificant. These results are primarily inconsistent across the topical clusters, as the interaction term $lGHG \times UMC$ coefficient is positive and statistically significant for the Environmental Impact cluster with a value of 0.008, and the UMC variable coefficient is positive and significant at the 1% level for the Research cluster with a value of 0.011. The Business Impact cluster's interaction term $lGHG \times UMC$ coefficient is, on the contrary, negative, albeit insignificant. These results would mostly appear to be statistical artifacts rather than relevant findings, in which case GHG emissions and unexpected increases in climate change concerns have no apparent link with the implied kurtosis of stocks.

Table 4: Panel Regression Results – Implied Moments
This table reports the estimation results for the firm fixed-effect panel regression of the stocks' implied first four moments on daily standardized logarithmic greenhouse gas emissions intensity ($lGHG$), daily unexpected changes in climate change concerns (UMC), and their interaction ($lGHG \times UMC$) with CTRL-15; see model (4). Standard errors of the estimators are reported in parentheses. The model is estimated using data from January 2010 to June 2018. *, **, and *** indicate significant coefficients at the 10%, 5%, and 1% levels, respectively. BI, Business Impact; EI, Environmental Impact; SD, Societal Debate; R, Research.

Implied Moment	Cluster	$lGHG$	UMC	$lGHG \times UMC$
IM1	Aggregate	-0.002 (0.002)	0.004 (0.003)	-0.006 (0.004)
	BI	-0.002 (0.002)	0.004 (0.003)	-0.007* (0.004)
	EI	-0.002 (0.002)	0.003 (0.003)	-0.002 (0.004)
	R	-0.002 (0.002)	0.001 (0.003)	-0.003 (0.004)
	SD	-0.002 (0.002)	0.003 (0.003)	-0.007* (0.003)
IM2	Aggregate	0.002 (0.003)	0.023*** (0.004)	0.007 (0.005)
	BI	0.002 (0.003)	0.023*** (0.004)	0.004 (0.005)
	EI	0.002 (0.003)	0.014*** (0.003)	0.006 (0.004)
	R	0.002 (0.003)	0.027*** (0.003)	0.006 (0.005)
	SD	0.002 (0.003)	0.014*** (0.003)	0.006 (0.004)
IM3	Aggregate	-0.001 (0.003)	0.012*** (0.004)	0.005 (0.005)
	BI	-0.001 (0.003)	0.012*** (0.004)	0.005 (0.005)
	EI	-0.001 (0.003)	0.005 (0.003)	0.000 (0.004)
	R	-0.001 (0.003)	0.008** (0.004)	0.003 (0.005)
	SD	-0.001 (0.003)	0.011*** (0.003)	0.006 (0.004)
IM4	Aggregate	0.000 (0.003)	0.000 (0.003)	0.003 (0.005)
	BI	0.000 (0.003)	0.005 (0.004)	-0.001 (0.005)
	EI	0.000 (0.003)	-0.003 (0.003)	0.008* (0.004)
	R	0.000 (0.003)	0.011*** (0.003)	0.006 (0.004)
	SD	0.000 (0.003)	0.001 (0.003)	0.000 (0.004)

5.2 Green-Minus-Brown (GMB) Approach

5.2.1 Validation With Realized Returns

In Table 5, I present the findings for the realized returns (daily returns) from my study in Panel A, alongside those reported in Ardia et al. (2023a, Table 7) in Panel B. This comparison aids in validating my implementation.

The table reveals remarkably similar results between the two panels for the variable of interest and the control variables, confirming the proper application of the methodology. First, I consider the green portfolio. The estimated coefficient for UMC is positive in both panels, although only statistically significant in Panel B. Looking at the brown portfolio, both panels have negative estimated coefficients for the UMC variable, but only statistically significant in Panel B. Finally, the estimated coefficient for UMC is positive for the GMB portfolio of both panels, but only statistically significant for Panel B. The estimated coefficients for the control variables also indicate the GMB portfolio of both panels is positively related to MKT, HML, SMB, MOM, and $TERM$, negatively associated with CMA, RMW, WTI, and $PROP$. The observed discrepancies between both panels can again be attributed to variations in dataset company composition.

Table 5: GMB, Green, Brown, and Neutral Portfolios – Realized Returns
This table compares the results of regressing the daily returns of GMB (GMB), green, brown, and neutral portfolios on the contemporaneous daily unexpected changes in climate change concerns (UMC) and the daily values of the control variables in the set CTRL-15; see model (5). The composition of the four portfolios is based on greenhouse gas intensities. Newey and West (1987) standard errors are displayed below the coefficients. The model is estimated using data from January 2010 to June 2018. *, **, and *** indicate significant coefficients at the 10%, 5%, and 1% levels, respectively. Panel A shows my results, and Panel B shows the results of Ardia et al. (2023a, Table 7).

	Panel A – My Results				Panel B – Ardia et al. Results			
	GMB	Green	Brown	Neutral	GMB	Green	Brown	Neutral
Intercept	0.025	-0.005	-0.03	0.003	0.068*	0.017	-0.051*	0.018
	(0.034)	(0.021)	(0.027)	(0.016)	(0.038)	(0.019)	(0.028)	(0.014)
UMC	0.042	0.017	-0.025	-0.007	0.072**	0.029**	-0.042*	0.006
	(0.028)	(0.016)	(0.020)	(0.012)	(0.031)	(0.014)	(0.023)	(0.010)
MKT	0.058***	1.066***	1.008***	1.049***	0.127***	1.100***	0.973***	1.036***
	(0.014)	(0.009)	(0.012)	(0.007)	(0.016)	(0.008)	(0.013)	(0.005)
HML	0.108***	0.167***	0.059***	-0.052***	0.112***	0.178***	0.066***	-0.095***
	(0.030)	(0.017)	(0.022)	(0.014)	(0.036)	(0.018)	(0.024)	(0.011)
SMB	0.027	-0.019	-0.046**	0.019**	0.071***	0.017	-0.055***	0.017**
	(0.023)	(0.013)	(0.019)	(0.009)	(0.026)	(0.011)	(0.020)	(0.008)
CMA	-0.408***	-0.055**	0.353***	0.146***	-0.462***	-0.088**	0.382***	0.231***
	(0.042)	(0.027)	(0.031)	(0.020)	(0.048)	(0.028)	(0.035)	(0.016)
RMW	-0.302***	-0.155***	0.147***	0.093***	-0.296***	-0.122**	0.174***	0.137***
	(0.036)	(0.021)	(0.027)	(0.017)	(0.040)	(0.019)	(0.031)	(0.013)
MOM	0.048***	-0.029**	-0.077***	-0.059***	0.078***	-0.088***	-0.165***	-0.075***
	(0.018)	(0.012)	(0.014)	(0.008)	(0.023)	(0.011)	(0.017)	(0.007)
WTI	-5.275***	-3.283***	1.992***	0.158	-8.457***	-2.956***	5.501***	0.125
	(0.629)	(0.324)	(0.455)	(0.259)	(0.695)	(0.336)	(0.510)	(0.221)
NG	-0.306	-0.203*	0.104	-0.106	-0.362	-0.066	0.296	-0.100
	(0.225)	(0.120)	(0.173)	(0.073)	(0.269)	(0.113)	(0.208)	(0.074)
$PROP$	-1.323***	-0.755***	0.568*	0.063	-1.254***	-0.405	0.849**	-0.150
	(0.416)	(0.223)	(0.341)	(0.179)	(0.482)	(0.251)	(0.351)	(0.135)
EPU	0.000	0.000	0.000	0.000*	0.013	-0.005	-0.018	-0.016***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)	(0.009)	(0.013)	(0.006)
VIX	-0.001	0.002	0.003*	0.001	-0.003	0.001	0.004**	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)
FTS	0.022	-0.151***	-0.172*	-0.007	0.079	-0.043	-0.122	-0.002
	(0.108)	(0.052)	(0.099)	(0.062)	(0.125)	(0.057)	(0.097)	(0.053)
$TERM$	2.472***	0.746***	-1.725***	-0.348***	3.322***	1.122***	-2.202***	0.215*
	(0.257)	(0.133)	(0.205)	(0.100)	(0.366)	(0.164)	(0.273)	(0.111)
$DFLT$	-0.143	0.141	0.285	0.303*	0.291	0.146	-0.145	0.144*
	(0.462)	(0.260)	(0.340)	(0.179)	(0.211)	(0.103)	(0.159)	(0.082)
TED	0.003	-0.020	-0.023	-0.001	-0.062	-0.059	0.003	-0.060*
	(0.073)	(0.039)	(0.057)	(0.031)	(0.080)	(0.041)	(0.061)	(0.027)

5.2.2 Implied Moments

Table 6 reports results for the implied moments across the aggregate UMC variable and the individual topical indices. The corresponding individual tables for all implied moments and clusters are in the appendix.

The results for the aggregate index of the implied return component are particularly insightful. The UMC variable is associated with a slightly higher implied return for the green portfolio, indicated by a coefficient of 0.017. Conversely, the brown portfolio shows a slight decrease in implied return, with a coefficient of -0.014. The neutral portfolio demonstrates no apparent directional influence, with a coefficient of 0.009. The GMB portfolio shows a positive link with a coefficient of 0.031, but this result, like all other results for IM1, lacks statistical significance. These observations are consistent across the aggregate, Environmental, Research, and Societal Debate clusters. However, the Business Impact cluster is distinctive as the implied return of green, brown, and neutral portfolios positively correlates with increases in the UMC variable. The connection with the GMB portfolio is considerably weaker than other topical clusters. These results suggest that similar to findings by Ardia et al. (2023a) on realized returns, companies with higher log-GHG emissions intensity are more sensitive to unforeseen shifts in climate concerns regarding their option-implied returns. Notably, the results for the realized returns, although showing a more substantial effect, remain statistically insignificant, indicating a possible discrepancy between the immediate reactions of implied and realized returns.

Regarding the aggregate index of the implied volatility component, the UMC variable is linked to a notable increase in implied volatility for the green portfolio by 0.059. The brown portfolio sees a more substantial increase in implied volatility, marked by a coefficient of 0.197, underlining a significant sensitivity. The neutral portfolio is similarly linked with a rise of 0.084 implied volatility. Contrarily, the GMB portfolio displays a decrease in implied volatility by 0.138, yet this result, like the others, is not statistically significant. These findings underscore the consistency of increased volatility across all stocks as determined by the panel regression approach, reinforcing the notion that companies, regardless of their GHG emissions intensity, are likely to face increased implied volatility following sudden rises in climate change concerns. The observed increments in volatility align with the GHG emissions intensity of the portfolios, offering an intriguing insight into market reactions specific to climate change concerns. This reinforces that climate change, increasingly viewed as a systemic risk, could propel more significant uncertainty about future economic conditions, leading to heightened implied volatility across the stock market.

The results for the aggregate index of the implied asymmetry component are compelling. The UMC variable shows a solid link to higher implied asymmetry for the brown portfolio, significantly highlighted by a coefficient of 0.448 at a 5% significance level, compared to that of the green portfolio and the neutral portfolio with coefficients of 0.059 and 0.084, respectively. In contrast, the GMB portfolio presents a lower implied asymmetry of -0.312, emphasizing a different market reaction to climate concerns. These findings remain consistent across various clusters except for the Environmental Impact cluster, where the link between the UMC variable and the implied asymmetry of green, brown, neutral, and GMB portfolios is considerably weaker. The observed significant relationship between GHG emissions and the linkage of the UMC variable to implied asymmetry suggests that market expectations might include severe financial repercussions for companies adversely affected by climate change and substantial gains for those positioned to benefit, potentially leading to non-normal returns.

Finally, the examination of the aggregate index of the implied kurtosis component yields mostly indeterminate and statistically insignificant results. The UMC variable is associated with lower implied kurtosis for both green and brown portfolios, with coefficients of -0.065 and -0.157, respectively, and a slight increase for the neutral portfolio by 0.051. The GMB portfolio exhibits a minor rise in implied kurtosis by 0.091, yet this finding is inconclusive. The inconsistency of these results across topical clusters suggests that GHG emissions and sudden increases in climate change concerns do not have a clear connection with the implied kurtosis of green, brown, neutral, or GMB portfolios.

Table 6: GMB, Green, Brown, and Neutral Portfolios – Implied Moments
This table reports the results of regressing the first four moments of GMB (GMB), green, brown, and neutral portfolios on the contemporaneous daily unexpected changes in climate change concerns (UMC) and the daily values of the control variables CTRL-15; see model (5). The composition of the four portfolios is based on greenhouse gas intensities. Newey and West (1987) standard errors of the estimators are reported in parentheses. The model is estimated using data from January 2010 to June 2018. *, **, and *** indicate significant coefficients at the 10%, 5%, and 1% levels, respectively. The complete tables for each cluster and the corresponding control variables are in the Appendix. BI, Business Impact; EI, Environmental Impact; SD, Societal Debate; R, Research.

Implied Moment	Cluster	GMB	Green	Brown	Neutral
IM1	Aggregate	0.031 (0.033)	0.017 (0.020)	-0.014 (0.027)	0.009 (0.016)
	BI	0.007 (0.033)	0.014 (0.021)	0.007 (0.027)	0.016 (0.016)
	EI	0.036 (0.030)	0.020 (0.018)	-0.016 (0.025)	0.001 (0.015)
	R	0.022 (0.034)	0.003 (0.019)	-0.019 (0.030)	0.001 (0.016)
	SD	0.031 (0.029)	0.024 (0.018)	-0.007 (0.024)	0.012 (0.013)
IM2	Aggregate	-0.138 (0.180)	0.059 (0.162)	0.197 (0.210)	0.084 (0.155)
	BI	-0.079 (0.192)	0.113 (0.176)	0.192 (0.214)	0.141 (0.165)
	EI	-0.144 (0.173)	0.030 (0.140)	0.175 (0.198)	0.047 (0.136)
	R	-0.202 (0.193)	0.089 (0.147)	0.291 (0.213)	0.151 (0.155)
	SD	-0.041 (0.156)	0.055 (0.148)	0.096 (0.187)	0.027 (0.128)
IM3	Aggregate	-0.312 (0.227)	0.136 (0.191)	0.448** (0.193)	0.107 (0.141)
	BI	-0.386* (0.230)	0.111 (0.201)	0.497***(0.212)	0.187 (0.143)
	EI	-0.050 (0.187)	0.083 (0.162)	0.134 (0.175)	0.006 (0.134)
	R	-0.148 (0.216)	0.121 (0.184)	0.269 (0.198)	0.116 (0.142)
	SD	-0.388* (0.212)	0.143 (0.189)	0.530*** (0.197)	0.116 (0.117)
IM4	Aggregate	0.091 (0.241)	-0.065 (0.234)	-0.157 (0.264)	0.051 (0.216)
	BI	0.281 (0.249)	0.084 (0.238)	-0.197 (0.291)	0.191 (0.204)
	EI	-0.008 (0.222)	-0.151 (0.204)	-0.143 (0.250)	-0.052 (0.195)
	R	-0.238 (0.241)	0.109 (0.203)	0.347 (0.267)	0.185 (0.217)
	SD	0.005 (0.247)	-0.042 (0.216)	-0.047 (0.256)	0.022 (0.185)

5.3 Main Findings and Discussion

The empirical results of the panel regression and the GMB approaches offer three novel findings on the relationship between stocks' option-implied moments and climate change concerns.

Finding #1. The relationship between the option-implied underlying first moment and unexpected variations in climate change concerns is weaker than it is for the historically realized first moment.

Based on the insights from Ardia et al. (2023a) and Pástor et al. (2022), I anticipated that the GMB approach would show that unexpected increases in climate change concerns are linked to higher implied returns for the green and GMB portfolios but are also linked to lower implied-returns for the brown portfolio. Additionally, I expected that the link between the interaction term of the GHG emissions intensity and unexpected increases in climate change concerns would prove to be negative in the panel regression analysis. These expectations reflected the hypothesis that companies with higher (lower) intensities of GHG emissions are likely to experience more adverse (favorable) effects due to sudden increases in concerns about climate change.

Although the estimated coefficients' signs are consistent with the hypotheses, their magnitudes are statistically insignificant and weaker compared to the coefficients from the realized return validations. Suppose the strength of these coefficients matched those of the validation results. In that case, the differences between the realized returns and the implied moments might have been attributed to methodological variations, as presented in Section 3.3. Still, given the current findings alongside the validation results, the association between the option-implied first moment and sudden shifts in climate change concerns is weaker than that observed with the historically realized first moment.

Research by Poteshman (2001) demonstrates that investors in the options market tend to underreact to individual daily fluctuations in instantaneous variance. Conversely, these investors often overreact when facing a sequence of mainly increasing or decreasing daily fluctuations in instantaneous variance. Specifically, investors tend to underreact to daily changes in instantaneous variance that follow predominantly opposite-sign changes, while overreacting to those that follow changes of the same sign. Considering that the UMC focuses on daily variations that are unexpected, it is logical to expect a relative underreaction from options market investors to these fluctuations. This would explain the weaker link between unexpected variations in climate change concerns and the option-implied first moment.

Additionally, Mahani and Poteshman (2008) show that growth stocks are much more (less) prone to option overreaction (underreaction) than value stocks. Given the preponderance of growth stocks in green portfolios and of value stocks in brown portfolios (Bauer et al., 2022; Pástor et al., 2022), we can infer that green portfolios are more (less) prone to option overreaction (underreaction) than brown portfolios. Therefore, a general underreaction of brown portfolios relative to historical returns would explain the difference in implied moment results relative to realized returns, which have a stronger relationship with the UMC variable (Poteshman, 2001; Mahani and Poteshman, 2008).

Finding #2. Unexpected increases in climate change concerns are linked to higher implied volatility and skewness across all stocks, but more so for brown stocks.

The aggregate UMC variable is positively linked to the implied volatility of all stocks. This result is statistically significant across all topical clusters and for each control set of the panel regression approach. This is a reasonably intuitive result, as Duan and Wei (2009) show that systematic risk significantly impacts individual equity options' prices. They specifically argue that a higher amount of systematic risk leads to a higher level of implied volatility. More so, Bansal et al. (2019) highlight climate change is a source of systematic risk. They use the findings of Jagannathan et al. (2018) to show that incorporating Environmental concerns in investment portfolio decisions helps reduce exposure to systematic risks. Consequently, a rise in the UMC variable suggests an increase in systematic risk that is not encapsulated by my control variables, such as the VIX or FTS variables. This unrecognized systematic risk could, therefore, drive higher levels of implied volatility across the market, which corroborates my findings.

These results are consistent across the green, brown, and neutral portfolios of the GMB approach, albeit insignificantly. However, the aggregate UMC variable is negatively linked to the implied volatility of the GMB portfolio, as the positive link is greater for the brown than the green portfolio. This is also a reasonably intuitive result as investors may perceive green stocks as more resilient and better positioned for the possibility of a future low-carbon economy. This perception could lead to a lower increase in implied volatility for green stocks compared to brown stocks. More so, higher perceived climate risk poses risks to brown stocks as they may face challenges adapting their business models. How these companies react to these new challenges could result in highly profitable transformations or lead to their downfall, reflected in the higher implied volatility.

The same aggregate UMC variable is also positively linked with the implied skewness of all stocks. This result is statistically significant across all topical clusters except the Environmental Impact cluster and each control set of the panel regression approach. This finding is less intuitive and contradicts the hypothesis that an increase in climate change concerns is linked to higher expectations of adverse tail events affecting companies, which leads to a decrease in implied skewness. The results suggest that, on the contrary, the factors contributing to downside risks are perceived to be less likely or less severe than before. Investors might have become more optimistic about the opportunities presented by addressing climate change, such as advancements in green technologies, regulatory incentives, or the transition to a low-carbon economy (Stephens and Markusson, 2018; Ameli et al., 2020). This increase in the implied skewness could also reflect a higher degree of speculation or uncertainty, where investors are betting on significant positive developments but acknowledge that the future is less predictable. The findings are intuitive by highlighting how climate risks and the development of green technologies influence investor behavior (Infante and Estevez-Mendoza, 2024).

Similarly to the implied volatility analysis, the aggregate UMC variable is negatively linked to the implied skewness of the GMB portfolio. This link is statistically significant for the Societal Debate and Business Impact clusters. It is driven mainly by strong positive links between the UMC variable and the implied skewness of the brown portfolios. These results seem counter-intuitive as they suggest that the factors contributing to downside risks are perceived to be less likely or less severe than before. This is more significant for the brown portfolio than the green portfolio following unexpected increases in climate change concerns. However, as mentioned before, this could reflect a belief that the less environmentally friendly firms would be forced to innovate and adapt, which could lead to unexpectedly high performance through new technologies or efficiency improvements (Stephens and Markusson, 2018; Ameli et al., 2020; Infante and Estevez-Mendoza, 2024).

Finding #3. The strength of the relation between the implied moments and the UMC varies among topical clusters.

Given the nature of the topics within each theme, notably Business Impact, Environmental Impact, Research, and Societal Debate, I anticipated that the various clusters would have different relationships with the stocks' implied moments. Specifically, specific themes and topics may be more relevant and have a stronger connection than others in relation to the implied moments. That is mainly due to the difference between physical and transition risks (Gambhir et al., 2022). Climate-induced physical risks are primarily associated with acute or chronic events such as rising temperatures, sea levels, intensified storms, floods, and wildfires, leading to significant damages and losses. In contrast, transition risks emerge from the gradual shift towards a low-carbon economy, which includes changes in climate policies, shifts in consumer preferences, and the emergence of competitive green technologies (Stan et al., 2021). The nature of the specific topics within each theme can explain the correlation between the various themes. For instance, the Business Impact theme, featuring topics like Renewable Energy and Carbon Tax, aligns with transition risk. In contrast, the Societal Debate theme, highlighted by such issues as Political Campaign, is similarly linked to transition risk. Conversely, the Environmental Impact theme, which includes topics like Extreme Temperatures and Glaciers/Ice Sheets, pertains to physical risks. The Research theme uniquely comprises transition-related issues and physical risks (Ardia et al., 2023a).

In Table 7, I present the correlations among the aggregate and four thematic UMC indices of Ardia et al. (2023a). The unconditional correlations range between 0.47 and 0.73. Among the themes, Business Impact and Environmental Impact exhibit the lowest correlation, while Environmental Impact and Research are the most highly correlated. These findings are consistent with the network analysis depicted in Figure 4.

Table 7: Correlation Matrix Between Daily Aggregate and Thematic UMC Indices of (Ardia et al., 2023a)
This table reports the pairwise correlations between the daily aggregate and thematic UMC indices. BI, Business Impact; EI, Environmental Impact; SD, Societal Debate; R, Research.

	BI	EI	SD	R
Aggregate	0.85	0.79	0.82	0.81
BI		0.47	0.66	0.57
EI			0.51	0.73
SD				0.58

My findings show different relationships between the topics and the stocks' implied moments. Themes linked with transition risks demonstrate a stronger negative correlation with the implied returns of brown stocks compared to other themes. In the panel regression framework, only the Business Impact and Societal Debate clusters show statistically significant associations with stock implied returns, particularly when considering the interaction with the GHG emission variable, corroborating the finding of Faccini et al. (2023) that stock prices of U.S. firms primarily reflect the news-based policy factor, rather than physical risk factors. Zhang (2022) further observes that investors are attentive to global transition and physical risks. However, the market's response to perceived physical risks is relatively muted compared to transition risks, indicating equity investors' potential underemphasis on physical risks. This is echoed in an earlier study by the IMF (Monetary and Department, 2004), which suggested that global aggregate equity indices have only modestly responded to significant climatic disasters over several decades. Nonetheless, the negative impact on brown stocks' implied returns from transition risk themes appears less pronounced than from other themes. This finding aligns with Bua et al. (2024), which notes that transition risks typically result in higher returns for green stocks and lower returns for brown stocks.

Furthermore, the themes of transition risks, specifically Business Impact and Societal Debate, exhibit a stronger positive correlation with the implied skewness of stock returns. In the panel regression and GMB methodologies, these themes are the only ones that show statistically significant associations with stocks' implied skewness. This result is supported by the findings of Salisu et al. (2023), which indicate that climate risk impacts the return distributions in the crude oil and natural gas markets, and that transition risks are more predictive of energy market fluctuations, notably the return skewness, than physical risks. This suggests that investors are more responsive to policies, programs, and initiatives to mitigate climate change-related losses and fatalities and adapt to shifts in environmental sustainability rather than to the physical damages caused by climate change. This perspective is also consistent with Faccini et al. (2023), which argue that investors primarily hedge against imminent transition risks due to government interventions rather than the direct risks from climate change itself.

6 Areas of Further Research

This section highlights the significance of my research constraints, emphasizing how they frame the findings and point toward opportunities for future studies.

First, the three-month forward horizon was chosen to balance the analysis between short-term and long-term market behaviors, shedding light on their impacts. This time frame has underscored the potential for variations in market reactions, as daily fluctuations often go unnoticed by investors in the options market. Exploring longer timelines, such as six or twelve months, could provide deeper insights into the alignment—or divergence—between implied and realized market behaviors.

Second, my research unveiled a weaker correlation between the option-implied underlying first moment and shifts in climate change concerns compared to the historically realized first moment. This finding invites further investigation into whether similar patterns exist in higher-order moments or are unique to the first moment of the return distribution. Although higher-order moments were not validated due to the unavailability of high-frequency intraday data, future research equipped with such data could expand on these initial findings, potentially leading to more comprehensive insights into the behavior of the options market.

Third, the IV surface model from François et al. (2022), which relies on daily options data, highlighted a selection bias by excluding firms with inconsistent data availability. This exclusion is particularly significant as options trading volume and market size have been shown to influence stock returns and market dynamics (Zhou, 2022; Griffith et al., 2020). More so, in Table 5, I present results where the signs of the variables are consistent between the two datasets. Still, the strength of significance is weaker in my dataset compared to those reported in Ardia et al. (2023a). This raises a pertinent question: would a larger dataset encompassing more firms yield more statistically significant results? Addressing this gap by including a broader array of companies could enhance the applicability of the findings and offer a more nuanced understanding of the IV surface model's impact across different market segments.

Fourth, I applied Bayesian regularization to the regression factors before calculating the implied moments. This regularization made the results more coherent, smooth, and interpretable. However, it is reasonable to question whether this regularization significantly influenced the results' significance. Comparing these findings with those obtained without Bayesian regularization would be valuable to determine if the results differ substantially.

Finally, I employed the UMC index from Ardia et al. (2023b) as the primary proxy for unexpected variations in climate change concerns. However, exploring whether the results would be substantially different if using indices from other studies, such as those by Faccini et al. (2023) or Bua et al. (2024), would also be pertinent. This comparison could provide deeper insights into the robustness of the findings across different indices.

7 Conclusion

Climate finance is gaining traction in academic and corporate circles, yet many areas still need to be explored. Following the studies by Ardia et al. (2023a) and Pástor et al. (2021) that measure the link between climate change concerns and *realized* stock movements, my research aims to examine the link between climate change concerns and *option-implied* stock movements.

I use the volatility surface model proposed by François et al. (2022) to convert daily options data into forward-looking return distributions for individual firms. Subsequently, I apply the methodology of Breeden and Litzenberger (1978) to calculate the first four option-implied moments. These moments are then regressed against the daily changes in the unexpected climate change concerns (UMC) index by Ardia et al. (2023a), using two distinct methods: a panel regression approach and a green-minus-brown non-parametric approach. My results indicate that the relationship between the option-implied underlying first moment and unexpected variations in climate change concerns is weaker than that with the realized first moment. Moreover, I find that unexpected increases in climate change concerns are linked to higher implied volatility and skewness across all stocks, but more so for brown stocks. Lastly, the strength of the relationship between the implied moments and the UMC index varies among topical clusters.

References

Ameli, N., Drummond, P., Bisaro, A., Grubb, M., and Chenet, H. (2020). Climate finance and disclosure for institutional investors: why transparency is not enough. *Climatic Change*, 160(4):565–589.

Ardia, D., Bluteau, K., Boudt, K., and Inghelbrecht, K. (2023a). Climate change concerns and the performance of green vs. brown stocks. *Management Science*, 69(12):7607–7632.

Ardia, D., Bluteau, K., Lortie-Cloutier, G., and Tran, T. D. (2023b). Factor exposure heterogeneity in green and brown stocks. *Finance Research Letters*, 55:103900.

Baele, L., Bekaert, G., Inghelbrecht, K., and Wei, M. (2020). Flights to safety. *Review of Financial Studies*, 33(2):689–746.

Baker, M., Bergstresser, D., Serafeim, G., and Wurgler, J. (2018). Financing the response to climate change: The pricing and ownership of US green bonds. Technical report, National Bureau of Economic Research.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics*, 131(4):1593–1636.

Bakshi, G., Cao, C., and Chen, Z. (1997). Empirical performance of alternative option pricing models. *Journal of Finance*, 52(5):2003–2049.

Bansal, R., Kiku, D., and Ochoa, M. (2019). Climate change risk. *Federal Reserve Bank of San Francisco Working Paper*.

Bansal, S., Mani, S. P., Gupta, H., and Maurya, S. (2023). Sustainable development of the green bond markets in India: Challenges and strategies. *Sustainable Development*, 31(1):237–252.

Bauer, M. D., Huber, D., Rudebusch, G. D., and Wilms, O. (2022). Where is the carbon premium? Global performance of green and brown stocks. *Journal of Climate Finance*, 1:100006.

Black, F. (1976). The pricing of commodity contracts. *Journal of Financial Economics*, 3(1-2):167–179.

Blei, D. M., Ng, A. Y., and Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, 3(Jan):993–1022.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3):307–327.

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

Boudt, K., Peterson, B. G., and Croux, C. (2008). Estimation and decomposition of downside risk for portfolios with non-normal returns. *Journal of Risk*, 11(2):79–103.

Bouri, E., Iqbal, N., and Klein, T. (2022). Climate policy uncertainty and the price dynamics of green and brown energy stocks. *Finance Research Letters*, 47:102740.

Breeden, D. T. and Litzenberger, R. H. (1978). Prices of state-contingent claims implicit in option prices. *Journal of Business*, 51(4):621–651.

Brière, M. and Ramelli, S. (2023). Green sentiment, stock returns, and corporate behaviour. *Evolving Practices in Public Investment Management*, page 69.

Bryzgalova, S., Pavlova, A., and Sikorskaya, T. (2023). Retail trading in options and the rise of the big three wholesalers. *Journal of Finance*, 78(6):3465–3514.

Bua, G., Kapp, D., Ramella, F., and Rognone, L. (2024). Transition versus physical climate risk pricing in european financial markets: A text-based approach. *European Journal of Finance*, pages 1–35.

Busch, T., Johnson, M., and Pioch, T. (2022). Corporate carbon performance data: Quo vadis? *Journal of Industrial Ecology*, 26(1):350–363.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52(1):57–82.

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

Cheema-Fox, A., LaPerla, B. R., Serafeim, G., Turkington, D., and Wang, H. S. (2021). Decarbonization factors. *Journal of Impact and ESG Investing*, 2(1):47–73.

Duan, J.-C. and Wei, J. (2009). Systematic risk and the price structure of individual equity options. *Review of Financial studies*, 22(5):1981–2006.

Dutta, A., Bouri, E., Rothovius, T., and Uddin, G. S. (2023). Climate risk and green investments: New evidence. *Energy*, 265:126376.

Eccles, R. G. and Stroehle, J. C. (2018). Exploring social origins in the construction of ESG measures. *Available at SSRN 3212685*.

El Ghoul, S., Guedhami, O., Kwok, C. C., and Mishra, D. R. (2011). Does corporate social responsibility affect the cost of capital? *Journal of Banking & Finance*, 35(9):2388–2406.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., and Stroebel, J. (2020). Hedging climate change news. *Review of Financial Studies*, 33(3):1184–1216.

Faccini, R., Matin, R., and Skiadopoulos, G. (2023). Dissecting climate risks: Are they reflected in stock prices? *Journal of Banking & Finance*, 155(C).

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47(2):427–465.

Fama, E. F. and French, K. R. (2007). Disagreement, tastes, and asset prices. *Journal of Financial Economics*, 83(3):667–689.

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

Fernandez, V. (2008). Copula-based measures of dependence structure in assets returns. *Physica A: Statistical mechanics and its applications*, 387(14):3615–3628.

François, P., Galarneau-Vincent, R., Gauthier, G., and Godin, F. (2022). Venturing into uncharted territory: An extensible implied volatility surface model. *Journal of Futures Markets*, 42(10):1912–1940.

Fung, W. and Hsieh, D. A. (2004). Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal*, 60(5):65–80.

Gambhir, A., George, M., McJeon, H., Arnell, N. W., Bernie, D., Mittal, S., Köberle, A. C., Lowe, J., Rogelj, J., and Monteith, S. (2022). Near-term transition and longer-term physical climate risks of greenhouse gas emissions pathways. *Nature Climate Change*, 12(1):88–96.

Garvey, G. T., Iyer, M., and Nash, J. (2018). Carbon footprint and productivity: Does the "E" in ESG capture efficiency as well as environment. *Journal of Investment Management*, 16(1):59–69.

Gauthier, G. and Simonato, J.-G. (2012). Linearized Nelson-Siegel and Svensson models for the estimation of spot interest rates. *European Journal of Operational Research*, 219(2):442–451.

Gavriilidis, K. (2021). Measuring climate policy uncertainty. *Available at SSRN 3847388*.

Griffith, T., Roseman, B., and Shang, D. (2020). The effects of an increase in equity tick size on stock and option transaction costs. *Journal of Banking & Finance*, 114:105782.

GSIA (2018). Global sustainable investment review. Technical report, Global Sustainable Investment Alliance, Sydney, New South Wales, Australia.

Halcoussis, D. and Lowenberg, A. D. (2019). The effects of the fossil fuel divestment campaign on stock returns. *The North American Journal of Economics and Finance*, 47:669–674.

Han, H. and Park, M. D. (2013). Comparison of realized measure and implied volatility in forecasting volatility. *Journal of Forecasting*, 32(6):522–533.

Hansen, J., Sato, M., Kharecha, P., Von Schuckmann, K., Beerling, D. J., Cao, J., Marcott, S., Masson-Delmotte, V., Prather, M. J., Rohling, E. J., et al. (2017). Young people's burden: Requirement of negative CO2 emissions. *Earth System Dynamics*, 8(3):577–616.

Hu, L. (2006). Dependence patterns across financial markets: A mixed copula approach. *Applied Financial Economics*, 16(10):717–729.

Hui-Min, L., Xue-Chun, W., Xiao-Fan, Z., and Ye, Q. (2021). Understanding systemic risk induced by climate change. *Advances in Climate Change Research*, 12(3):384–394.

Huij, J., Laurs, D., Stork, P. A., and Zwinkels, R. C. (2022). Carbon beta: A market-based measure of climate risk. *Available at SSRN 3957900*.

Huynh, T. D. and Xia, Y. (2021). Climate change news risk and corporate bond returns. *Journal of Financial and Quantitative Analysis*, 56(6):1985–2009.

Ilhan, E., Sautner, Z., and Vilkov, G. (2021). Carbon tail risk. *Review of Financial Studies*, 34(3):1540–1571.

Infante, J. and Estevez-Mendoza, C. (2024). Investor attitudes and preferences toward climate change and sustainable investments: A bibliometric analysis. In *Climate Change and Finance: Navigating the Challenges and Opportunities in Capital Markets*, pages 75–101. Springer.

Jagannathan, R., Ravikumar, A., and Sammon, M. (2018). Environmental, social, and governance criteria: Why investors should care. *Journal of Investment Management*, 16(1):18–31.

Lafferty, J. and Blei, D. (2005). Correlated topic models. *Advances in neural information processing systems*, 18.

Lai, K. K., Yu, L., and Wang, S. (2006). Mean-variance-skewness-kurtosis-based portfolio optimization. In *First International Multi-Symposiums on Computer and Computational Sciences (IMSCCS'06)*, volume 2, pages 292–297. IEEE.

Li, H., Bouri, E., Gupta, R., and Fang, L. (2023). Return volatility, correlation, and hedging of green and brown stocks: Is there a role for climate risk factors? *Journal of Cleaner Production*, pages 137–594.

Lin, T.-C. and Liu, X. (2018). Skewness, individual investor preference, and the cross-section of stock returns. *Review of Finance*, 22(5):1841–1876.

Long, S., Lucey, B., Kumar, S., Zhang, D., and Zhang, Z. (2022). Climate finance: What we know and what we should know? *Journal of Climate Finance*, 1:100005.

Madan, D. B. and McPhail, G. S. (2000). Investing in skews. *Journal of Risk Finance*, 2(1):10–18.

Mahani, R. S. and Poteshman, A. M. (2008). Overreaction to stock market news and misevaluation of stock prices by unsophisticated investors: Evidence from the option market. *Journal of Empirical Finance*, 15(4):635–655.

Malevergne, Y. and Sornette, D. (2003). Testing the gaussian copula hypothesis for financial assets dependences. *Quantitative Finance*, 3(4):231.

Monetary, I. M. F. and Department, C. M. (2004). *Global Financial Stability Report, April 2004: Market Developments and Issues*. International Monetary Fund.

Myung, I. J. (2003). Tutorial on maximum likelihood estimation. *Journal of Mathematical Psychology*, 47(1):90–100.

Newey, W. K. and West, K. D. (1987). Hypothesis testing with efficient method of moments estimation. *International Economic Review*, pages 777–787.

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

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

Pham, L., Hao, W., Truong, H., and Trinh, H. H. (2023). The impact of climate policy on us environmentally friendly firms: A firm-level examination of stock return, volatility, volume, and connectedness. *Energy Economics*, 119:106564.

Poteshman, A. M. (2001). Underreaction, overreaction, and increasing misreaction to information in the options market. *Journal of Finance*, 56(3):851–876.

Rogach, O. I., Shnyrkov, O. I., Dziuba, P. V., et al. (2019). Skewness-based portfolio selection: Implications for international investing in frontier markets. *Journal Transition Studies Review*, 26(2):23–28.

Salisu, A. A., Ndako, U. B., and Vo, X. V. (2023). Transition risk, physical risk, and the realized volatility of oil and natural gas prices. *Resources Policy*, 81:103383.

Santi, C. (2023). Investor climate sentiment and financial markets. *International Review of Financial Analysis*, 86:102490.

Stan, K., Watt, G. A., and Sanchez-Azofeifa, A. (2021). Financial stability in response to climate change in a northern temperate economy. *Nature Communications*, 12(1):7161.

Stephens, J. C. and Markusson, N. (2018). 503Technological Optimism in Climate Mitigation: The Case of Carbon Capture and Storage. In *Oxford Handbook of Energy and Society*. Oxford University Press.

Stroebel, J. and Wurgler, J. (2021). What do you think about climate finance? *Journal of Financial Economics*, 142(2):487–498.

Xiong, J. X. (2021). The impact of ESG risk on stocks. *Journal of Impact and ESG Investing*, 2(1):7–18.

Zhang, S. Y. (2022). Are investors sensitive to climate-related transition and physical risks? evidence from global stock markets. *Research in International Business and Finance*, 62:101710.

Zhou, Y. (2022). Option trading volume by moneyness, firm fundamentals, and expected stock returns. *Journal of Financial Markets*, 58:100648.

Appendix

In this appendix, I provide the individual results for the panel and GMB regressions for each combination of the implied moments, topical clusters, and control sets. The results for CTRL-15 are the same as those found in Section 5. The panel regression results are presented in Tables A1-A4, while the GMB results are presented in Tables A5-A24.

Table A1: Panel Regression Results - IM1
Refer to Table 4 but only for the first moment, and to Section 4.3 for a detailed description of the individual control sets.

Cluster	Control Set	$lGHG$	UMC	$lGHG \times UMC$
Aggregate	CTRL-1	-0.001 (0.002)	0.005* (0.003)	-0.007* (0.004)
	CTRL-3	-0.001 (0.002)	0.005 (0.003)	-0.006 (0.004)
	CTRL-6	-0.001 (0.002)	0.005* (0.003)	-0.006 (0.004)
	CTRL-15	-0.002 (0.002)	0.004 (0.003)	-0.006 (0.004)
BI	CTRL-1	-0.001 (0.002)	0.005* (0.003)	-0.008** (0.004)
	CTRL-3	-0.001 (0.002)	0.005 (0.003)	-0.007* (0.004)
	CTRL-6	-0.001 (0.002)	0.005* (0.003)	-0.008* (0.004)
	CTRL-15	-0.002 (0.002)	0.004 (0.003)	-0.007* (0.004)
EI	CTRL-1	-0.002 (0.002)	0.005* (0.003)	-0.002 (0.004)
	CTRL-3	-0.001 (0.002)	0.005 (0.003)	-0.002 (0.004)
	CTRL-6	-0.001 (0.002)	0.005* (0.003)	-0.001 (0.004)
	CTRL-15	-0.002 (0.002)	0.003 (0.003)	-0.002 (0.004)
R	CTRL-1	-0.001 (0.002)	0.001 (0.003)	-0.004 (0.004)
	CTRL-3	-0.001 (0.002)	0.001 (0.003)	-0.004 (0.004)
	CTRL-6	-0.001 (0.002)	0.002 (0.003)	-0.003 (0.004)
	CTRL-15	-0.002 (0.002)	0.001 (0.003)	-0.003 (0.004)
SD	CTRL-1	-0.001 (0.002)	0.003 (0.003)	-0.008** (0.003)
	CTRL-3	-0.001 (0.002)	0.003 (0.003)	-0.007** (0.003)
	CTRL-6	-0.001 (0.002)	0.004 (0.003)	-0.006* (0.003)
	CTRL-15	-0.002 (0.002)	0.003 (0.003)	-0.007* (0.003)

Table A2: Panel Regression Results - IM2
Refer to Table 4 but only for the second moment, and to Section 4.3 for a detailed description of the individual control sets.

Cluster	Control Set	$lGHG$	UMC	$lGHG \times UMC$
Aggregate	CTRL-1	0.002 (0.002)	0.015*** (0.004)	0.007 (0.005)
	CTRL-3	0.002 (0.002)	0.014*** (0.004)	0.007 (0.005)
	CTRL-6	0.002 (0.002)	0.014*** (0.004)	0.007 (0.005)
	CTRL-15	0.002 (0.003)	0.023*** (0.004)	0.007 (0.005)
BI	CTRL-1	0.002 (0.002)	0.018*** (0.004)	0.005 (0.005)
	CTRL-3	0.002 (0.002)	0.018*** (0.004)	0.004 (0.005)
	CTRL-6	0.002 (0.002)	0.018*** (0.004)	0.004 (0.005)
	CTRL-15	0.002 (0.003)	0.023*** (0.004)	0.004 (0.005)
EI	CTRL-1	0.002 (0.002)	0.003 (0.003)	0.006 (0.004)
	CTRL-3	0.002 (0.002)	0.003 (0.003)	0.006 (0.004)
	CTRL-6	0.002 (0.002)	0.003 (0.003)	0.006 (0.004)
	CTRL-15	0.002 (0.003)	0.014*** (0.003)	0.006 (0.004)
R	CTRL-1	0.002 (0.002)	0.020*** (0.003)	0.007 (0.005)
	CTRL-3	0.002 (0.002)	0.019*** (0.003)	0.006 (0.005)
	CTRL-6	0.002 (0.002)	0.020*** (0.003)	0.006 (0.005)
	CTRL-15	0.002 (0.003)	0.027*** (0.003)	0.006 (0.005)
SD	CTRL-1	0.002 (0.002)	0.009*** (0.003)	0.006 (0.004)
	CTRL-3	0.002 (0.002)	0.007** (0.003)	0.006 (0.004)
	CTRL-6	0.002 (0.002)	0.007** (0.003)	0.006 (0.004)
	CTRL-15	0.002 (0.003)	0.014*** (0.003)	0.006 (0.004)

Table A3: Panel Regression Results - IM3

Refer to Table 4 but only for the third moment, and to Section 4.3 for a detailed description of the individual control sets.

Cluster	Control Set	$lGHG$	UMC	$lGHG \times UMC$
Aggregate	CTRL-1	0.000 (0.002)	0.012*** (0.004)	0.005 (0.005)
	CTRL-3	0.000 (0.002)	0.012*** (0.004)	0.004 (0.005)
	CTRL-6	0.000 (0.002)	0.012*** (0.004)	0.004 (0.005)
	CTRL-15	-0.001 (0.003)	0.012*** (0.004)	0.005 (0.005)
BI	CTRL-1	0.000 (0.002)	0.012*** (0.004)	0.005 (0.005)
	CTRL-3	0.000 (0.002)	0.012*** (0.004)	0.005 (0.005)
	CTRL-6	0.000 (0.002)	0.012*** (0.004)	0.005 (0.005)
	CTRL-15	-0.001 (0.003)	0.012*** (0.004)	0.005 (0.005)
EI	CTRL-1	0.001 (0.002)	0.006* (0.003)	0.000 (0.004)
	CTRL-3	0.000 (0.002)	0.007* (0.003)	0.000 (0.004)
	CTRL-6	0.001 (0.002)	0.006* (0.003)	0.000 (0.004)
	CTRL-15	-0.001 (0.003)	0.005 (0.003)	0.000 (0.004)
R	CTRL-1	0.000 (0.002)	0.009** (0.004)	0.004 (0.005)
	CTRL-3	0.000 (0.002)	0.008** (0.004)	0.003 (0.005)
	CTRL-6	0.000 (0.002)	0.008** (0.004)	0.003 (0.005)
	CTRL-15	-0.001 (0.003)	0.008** (0.004)	0.003 (0.005)
SD	CTRL-1	0.000 (0.002)	0.013*** (0.003)	0.006 (0.004)
	CTRL-3	0.000 (0.002)	0.013*** (0.003)	0.006 (0.004)
	CTRL-6	0.000 (0.002)	0.013*** (0.003)	0.005 (0.004)
	CTRL-15	-0.001 (0.003)	0.011*** (0.003)	0.006 (0.004)

Table A4: Panel Regression Results - IM4
Refer to Table 4 but only for the fourth moment, and to Section 4.3 for a detailed description of the individual control sets.

Cluster	Control Set	$lGHG$	UMC	$lGHG \times UMC$
Aggregate	CTRL-1	0.000 (0.002)	0.001 (0.003)	0.004 (0.004)
	CTRL-3	0.000 (0.002)	0.001 (0.003)	0.004 (0.004)
	CTRL-6	0.000 (0.002)	0.001 (0.003)	0.003 (0.004)
	CTRL-15	0.000 (0.003)	0.000 (0.003)	0.003 (0.005)
BI	CTRL-1	0.000 (0.002)	0.006* (0.003)	-0.001 (0.005)
	CTRL-3	0.000 (0.002)	0.006 (0.003)	-0.001 (0.005)
	CTRL-6	0.000 (0.002)	0.006 (0.003)	-0.001 (0.005)
	CTRL-15	0.000 (0.003)	0.005 (0.004)	-0.001 (0.005)
EI	CTRL-1	-0.001 (0.002)	-0.004 (0.003)	0.008* (0.004)
	CTRL-3	-0.001 (0.002)	-0.004 (0.003)	0.008* (0.004)
	CTRL-6	0.000 (0.002)	-0.004 (0.003)	0.008* (0.004)
	CTRL-15	0.000 (0.003)	-0.003 (0.003)	0.008* (0.004)
R	CTRL-1	0.000 (0.002)	0.011*** (0.003)	0.006 (0.004)
	CTRL-3	0.000 (0.002)	0.010*** (0.003)	0.006 (0.004)
	CTRL-6	0.000 (0.002)	0.011*** (0.003)	0.005 (0.004)
	CTRL-15	0.000 (0.003)	0.011*** (0.003)	0.006 (0.004)
SD	CTRL-1	0.000 (0.002)	0.002 (0.003)	0.000 (0.004)
	CTRL-3	0.000 (0.002)	0.001 (0.003)	0.000 (0.004)
	CTRL-6	0.000 (0.002)	0.002 (0.003)	0.000 (0.004)
	CTRL-15	0.000 (0.003)	0.001 (0.003)	0.000 (0.004)

Table A5: GMB, Green, Brown, and Neutral Portfolios – IM1 – Aggregate
Refer to Table 6, but specifically for the first moment, and for the aggregate index.

	GMB	Green	Brown	Neutral
Intercept	0.046	0.062***	0.016	0.034*
	(0.039)	(0.022)	(0.031)	(0.020)
UMC	0.031	0.017	-0.014	0.009
	(0.033)	(0.020)	(0.027)	(0.016)
MKT	0.053**	-0.924***	-0.871**	0.923**
	(0.015)	(0.009)	(0.013)	(0.010)
HML	0.082***	0.145***	0.063**	-0.050***
	(0.030)	(0.020)	(0.022)	(0.017)
SMB	-0.003	-0.039***	-0.036	0.006
	(0.028)	(0.015)	(0.023)	(0.013)
CMA	-0.396***	-0.060*	0.337*	0.144**
	(0.048)	(0.031)	(0.036)	(0.024)
RMW	-0.244**	-0.106***	0.138**	0.123**
	(0.039)	(0.025)	(0.029)	(0.021)
MOM	0.048**	-0.030**	-0.078***	-0.048***
	(0.019)	(0.013)	(0.015)	(0.012)
$PROP$	-1.494***	-0.370	1.124**	0.135
	(0.467)	(0.294)	(0.387)	(0.207)
WTI	-4.455***	-2.722***	1.733**	0.643*
	(0.704)	(0.430)	(0.549)	(0.363)
NG	-0.196	-0.185	0.011	-0.066
	(0.249)	(0.155)	(0.178)	(0.090)
EPU	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
VIX	-0.003	-0.003**	0.000	-0.001
	(0.002)	(0.001)	(0.002)	(0.001)
FTS	0.113	0.080	-0.033	0.112
	(0.116)	(0.075)	(0.099)	(0.088)
$TERM$	2.189***	0.754***	-1.435***	-0.275***
	(0.267)	(0.147)	(0.212)	(0.137)
$DFLT$	0.165	0.239	0.073	-0.047
	(0.537)	(0.267)	(0.453)	(0.247)
TED	-0.054	-0.034	0.020	-0.021
	(0.078)	(0.042)	(0.065)	(0.045)

Table A6: GMB, Green, Brown, and Neutral Portfolios – IM1 – BI

Refer to Table 6, but specifically for the first moment, and for the Business Impact cluster.

	GMB	Green	Brown	Neutral
Intercept	0.049	0.062***	0.013	0.034***
	(0.039)	(0.022)	(0.031)	(0.020)
UMC	0.007	0.014	0.007	0.016
	(0.033)	(0.021)	(0.027)	(0.016)
MKT	0.053***	0.924***	0.871***	0.923***
	(0.015)	(0.009)	(0.013)	(0.011)
HML	0.082***	0.145***	0.063***	-0.050***
	(0.030)	(0.020)	(0.022)	(0.017)
SMB	-0.003	-0.039***	-0.036	0.006
	(0.028)	(0.015)	(0.023)	(0.013)
CMA	-0.396***	-0.059*	0.336***	0.141***
	(0.048)	(0.032)	(0.036)	(0.024)
RMW	-0.244*	-0.106*	0.138***	0.123***
	(0.039)	(0.025)	(0.029)	(0.021)
MOM	0.048***	-0.030**	-0.078***	-0.048***
	(0.019)	(0.013)	(0.015)	(0.012)
$PROP$	-1.494***	-0.367	1.127***	0.139
	(0.468)	(0.295)	(0.388)	(0.208)
WTI	-4.446***	-2.722***	1.739***	0.645***
	(0.703)	(0.430)	(0.550)	(0.362)
NG	-0.202	-0.187	0.015	-0.066
	(0.248)	(0.155)	(0.177)	(0.099)
EPU	0.000	0.000	0.000	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.003	-0.003***	0.000	-0.001
	(0.002)	(0.001)	(0.002)	(0.001)
FTS	0.112	0.078	-0.034	0.111
	(0.116)	(0.076)	(0.099)	(0.088)
$TERM$	2.185***	0.753***	-1.432***	-0.276***
	(0.267)	(0.147)	(0.212)	(0.137)
$DFLT$	0.169	0.237	0.068	-0.051
	(0.538)	(0.268)	(0.453)	(0.246)
TED	0.052	-0.033	0.019	-0.021
	(0.078)	(0.042)	(0.065)	(0.045)

Table A7: GMB, Green, Brown, and Neutral Portfolios – IM1 – EI
Refer to Table 6, but specifically for the first moment, and for the Environmental Impact cluster.

	GMB	Green	Brown	Neutral
Intercept	0.045	0.061***	0.016	0.036***
	(0.039)	(0.022)	(0.032)	(0.020)
UMC	0.036	0.020	-0.016	0.001
	(0.030)	(0.018)	(0.025)	(0.015)
MKT	0.053***	0.924***	0.871***	0.923***
	(0.015)	(0.009)	(0.013)	(0.011)
HML	0.082***	0.145***	0.063***	-0.050***
	(0.030)	(0.020)	(0.022)	(0.017)
SMB	-0.003	-0.039***	-0.036	0.006
	(0.028)	(0.015)	(0.023)	(0.013)
CMA	-0.396***	-0.06*	0.337***	0.141***
	(0.048)	(0.032)	(0.036)	(0.024)
RMW	-0.244***	-0.107*	0.138***	0.123***
	(0.039)	(0.025)	(0.029)	(0.021)
MOM	0.047***	-0.03**	-0.077***	-0.048***
	(0.019)	(0.013)	(0.015)	(0.012)
$PROP$	-1.497***	-0.372	1.125***	0.134
	(0.467)	(0.293)	(0.388)	(0.208)
WTI	-4.463***	-2.726***	1.739***	0.645***
	(0.706)	(0.430)	(0.551)	(0.362)
NG	-0.202	-0.187	0.009	-0.066
	(0.248)	(0.155)	(0.177)	(0.089)
EPU	0.000	0.000	0.000	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.003	-0.003***	0.000	-0.001
	(0.002)	(0.001)	(0.002)	(0.001)
FTS	0.116	0.082	-0.034	0.112
	(0.116)	(0.076)	(0.099)	(0.088)
$TERM$	2.194***	0.757***	-1.437***	-0.277***
	(0.266)	(0.147)	(0.211)	(0.137)
$DFLT$	0.175	0.244	0.069	-0.045
	(0.537)	(0.268)	(0.453)	(0.246)
TED	-0.057	-0.036	0.021	-0.021
	(0.078)	(0.041)	(0.065)	(0.045)

Table A8: GMB, Green, Brown, and Neutral Portfolios – IM1 – R

Refer to Table 6, but specifically for the first moment, and for the Research cluster.

	GMB	Green	Brown	Neutral
Intercept	0.047	0.063***	0.016	0.034***
	(0.039)	(0.022)	(0.032)	(0.020)
UMC	0.022	0.003	-0.019	0.001
	(0.034)	(0.019)	(0.031)	(0.016)
MKT	0.053***	0.924***	0.871***	0.923***
	(0.015)	(0.009)	(0.013)	(0.011)
HML	0.082***	0.145***	0.064***	-0.050***
	(0.030)	(0.020)	(0.022)	(0.017)
SMB	-0.003	-0.039***	-0.036	0.006
	(0.028)	(0.015)	(0.023)	(0.013)
CMA	-0.396***	-0.059*	0.337***	0.140***
	(0.048)	(0.031)	(0.036)	(0.024)
RMW	-0.244***	-0.107*	0.138***	0.123***
	(0.039)	(0.025)	(0.029)	(0.021)
MOM	0.048***	-0.030**	-0.077***	-0.048***
	(0.019)	(0.013)	(0.015)	(0.012)
$PROP$	-1.501***	-0.372	1.129***	0.132
	(0.468)	(0.296)	(0.388)	(0.208)
WTI	-4.454***	-2.725***	1.739***	0.645***
	(0.704)	(0.431)	(0.552)	(0.363)
NG	-0.195	-0.187	0.007	-0.064
	(0.249)	(0.156)	(0.179)	(0.089)
EPU	0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.003	-0.003***	0.000	-0.001
	(0.002)	(0.001)	(0.002)	(0.001)
FTS	0.114	0.082	-0.034	0.112
	(0.116)	(0.076)	(0.099)	(0.088)
$TERM$	2.187***	0.757***	-1.435***	-0.276***
	(0.266)	(0.147)	(0.212)	(0.137)
$DFLT$	0.172	0.244	0.069	-0.045
	(0.538)	(0.268)	(0.454)	(0.246)
TED	-0.053	-0.033	0.021	-0.021
	(0.078)	(0.041)	(0.065)	(0.045)

Table A9: GMB, Green, Brown, and Neutral Portfolios – IM1 – SD

Refer to Table 6, but specifically for the first moment, and for the Societal Debate cluster.

	GMB	Green	Brown	Neutral
Intercept	0.046	0.061***	0.015	0.034
	(0.039)	(0.022)	(0.031)	(0.021)
UMC	0.031	0.024	-0.007	0.012
	(0.029)	(0.018)	(0.024)	(0.013)
MKT	0.053***	0.924***	0.871***	0.923***
	(0.015)	(0.009)	(0.013)	(0.011)
HML	0.082***	0.145***	0.064***	-0.050***
	(0.030)	(0.020)	(0.022)	(0.017)
SMB	-0.004	-0.039***	-0.036	0.005
	(0.028)	(0.015)	(0.023)	(0.013)
CMA	-0.395***	-0.059*	0.336***	0.141***
	(0.048)	(0.032)	(0.036)	(0.024)
RMW	-0.244***	-0.107***	0.138***	0.123***
	(0.039)	(0.025)	(0.029)	(0.021)
MOM	0.048***	-0.030***	-0.078***	-0.048***
	(0.019)	(0.013)	(0.015)	(0.012)
$PROP$	-1.500***	-0.374	1.126***	0.133
	(0.466)	(0.293)	(0.387)	(0.207)
WTI	-4.456***	-2.721***	1.735***	0.643***
	(0.703)	(0.429)	(0.549)	(0.362)
NG	-0.204	-0.19	0.015	-0.069
	(0.248)	(0.155)	(0.177)	(0.099)
EPU	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
VIX	-0.003	-0.003***	0	-0.001
	(0.002)	(0.001)	(0.002)	(0.001)
FTS	0.111	0.079	-0.032	0.111
	(0.116)	(0.076)	(0.099)	(0.088)
$TERM$	2.186***	0.753***	-1.433***	-0.276***
	(0.267)	(0.147)	(0.212)	(0.137)
$DFLT$	0.167	0.238	0.072	-0.047
	(0.537)	(0.267)	(0.453)	(0.247)
TED	-0.055	-0.035	0.02	-0.021
	(0.078)	(0.042)	(0.065)	(0.045)

Table A10: GMB, Green, Brown, and Neutral Portfolios – IM2 – Aggregate
Refer to Table 6, but specifically for the second moment, and for the aggregate index.

	GMB	Green	Brown	Neutral
Intercept	0.421	0.390***	-0.032	0.026
	(0.279)	(0.202)	(0.311)	(0.192)
UMC	-0.138	0.059	0.197	0.084
	(0.180)	(0.162)	(0.210)	(0.155)
MKT	-0.027	-1.084***	-1.057***	-1.085***
	(0.098)	(0.096)	(0.126)	(0.085)
HML	-0.037	0.091	0.128	0.051
	(0.167)	(0.149)	(0.202)	(0.157)
SMB	-0.172	0.174	0.345***	0.208*
	(0.105)	(0.124)	(0.153)	(0.126)
CMA	0.298	-0.031	-0.329	-0.083
	(0.242)	(0.200)	(0.284)	(0.204)
RMW	0.317*	0.434***	0.117	0.188
	(0.185)	(0.176)	(0.201)	(0.147)
MOM	0.160	-0.004	-0.164	-0.120
	(0.113)	(0.082)	(0.128)	(0.089)
$PROP$	1.234	3.798	2.563	2.911
	(3.399)	(2.392)	(3.633)	(2.068)
WTI	8.022**	-2.030	-10.052***	-5.116
	(3.209)	(3.372)	(3.633)	(3.331)
NG	-0.660	1.435	2.095	0.509
	(1.300)	(0.989)	(1.393)	(0.845)
EPU	-0.001	0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.019	0.014	0.033**	0.037***
	(0.012)	(0.013)	(0.018)	(0.012)
FTS	0.718	0.065	-0.653	-0.362
	(0.497)	(0.575)	(0.698)	(0.637)
$TERM$	0.766	1.833	1.067	2.074**
	(1.434)	(1.158)	(1.622)	(1.103)
$DFLT$	3.010	8.517***	5.507	5.689**
	(2.760)	(2.311)	(3.557)	(2.248)
TED	-1.258**	-0.299	0.959	-0.478
	(0.582)	(0.375)	(0.605)	(0.393)

Table A11: GMB, Green, Brown, and Neutral Portfolios – IM2 – BI

Refer to Table 6, but specifically for the second moment, and for the Business Impact cluster

	GMB	Green	Brown	Neutral
Intercept	0.041	0.383***	-0.029	0.021
	(0.278)	(0.202)	(0.311)	(0.191)
UMC	-0.079	0.113	0.192	0.141
	(0.192)	(0.176)	(0.214)	(0.164)
MKT	-0.026	-1.084***	-1.058***	-1.085***
	(0.098)	(0.096)	(0.127)	(0.085)
HML	-0.037	0.091	0.128	0.051
	(0.167)	(0.149)	(0.202)	(0.157)
SMB	-0.173*	0.174	0.346***	0.208***
	(0.105)	(0.124)	(0.154)	(0.126)
CMA	0.297	-0.031	0.336***	0.141***
	(0.242)	(0.200)	(0.284)	(0.204)
RMW	0.317*	0.436***	0.119	0.191
	(0.185)	(0.176)	(0.201)	(0.148)
MOM	0.158	-0.003	-0.161	-0.118
	(0.113)	(0.082)	(0.127)	(0.069)
$PROP$	1.219	3.828	2.608	2.948
	(3.404)	(2.397)	(3.641)	(2.082)
WTI	8.034***	-2.011	-10.045***	-5.096
	(3.206)	(3.366)	(3.635)	(3.322)
NG	0.112	1.435	2.075	0.506
	(1.301)	(0.992)	(1.397)	(0.852)
EPU	-0.001	0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.003	0.014	0.033***	0.037***
	(0.012)	(0.013)	(0.018)	(0.012)
FTS	0.112	0.052	-0.034	0.124
	(0.116)	(0.076)	(0.099)	(0.088)
$TERM$	2.185***	0.753***	-1.432***	2.071***
	(0.267)	(0.147)	(0.212)	(0.137)
$DFLT$	0.169	2.289	5.471	4.327
	(0.538)	(2.308)	(3.929)	(2.239)
TED	-1.266***	-0.295	0.971	-0.473
	(0.582)	(0.375)	(0.603)	(0.424)

Table A12: GMB, Green, Brown, and Neutral Portfolios – IM2 – EI
Refer to Table 6, but specifically for the second moment, and for the Environmental Impact cluster.

	GMB	Green	Brown	Neutral
Intercept	0.421	0.394***	-0.027	0.031
	(0.278)	(0.202)	(0.311)	(0.191)
UMC	-0.144	0.030	0.175	0.047
	(0.173)	(0.140)	(0.198)	(0.136)
MKT	-0.026	-1.084***	-1.058***	-1.085***
	(0.098)	(0.096)	(0.127)	(0.085)
HML	-0.038	0.091	0.129	0.051
	(0.167)	(0.149)	(0.202)	(0.157)
SMB	-0.173**	0.174	0.347***	0.209***
	(0.105)	(0.124)	(0.154)	(0.126)
CMA	0.299	-0.031	-0.330	-0.018
	(0.242)	(0.200)	(0.284)	(0.204)
RMW	0.318**	0.434***	0.116	0.187
	(0.185)	(0.176)	(0.201)	(0.148)
MOM	0.161	-0.004	-0.165	-0.118
	(0.113)	(0.082)	(0.128)	(0.089)
$PROP$	1.245	3.793	2.548	2.905
	(3.402)	(2.393)	(3.637)	(2.071)
WTI	8.059***	-2.045	-10.104***	-5.139
	(3.205)	(3.374)	(3.632)	(3.331)
NG	-0.068	1.434	2.114	0.506
	(1.301)	(0.992)	(1.402)	(0.851)
EPU	-0.001	0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.019	0.014	0.033***	0.037***
	(0.012)	(0.013)	(0.018)	(0.012)
FTS	0.708	0.066	-0.642	-0.359
	(0.497)	(0.575)	(0.699)	(0.638)
$TERM$	0.748	1.832	-1.209	2.074***
	(1.427)	(1.159)	(1.619)	(1.104)
$DFLT$	2.968	8.532***	5.564	5.711***
	(2.753)	(2.316)	(3.955)	(2.253)
TED	-1.247***	-0.299	0.947	-0.479
	(0.583)	(0.376)	(0.605)	(0.395)

Table A13: GMB, Green, Brown, and Neutral Portfolios – IM2 – R
Refer to Table 6, but specifically for the second moment, and for the Research cluster.

	GMB	Green	Brown	Neutral
Intercept	0.425	0.387***	-0.038	0.021
	(0.282)	(0.201)	(0.311)	(0.189)
UMC	-0.202	0.089	0.291	0.151
	(0.193)	(0.147)	(0.213)	(0.155)
MKT	-0.028	-1.083***	-1.055***	-1.084***
	(0.098)	(0.096)	(0.126)	(0.085)
HML	-0.035	0.090	0.125	0.049
	(0.167)	(0.150)	(0.202)	(0.157)
SMB	-0.172***	0.174	0.346***	0.208***
	(0.104)	(0.124)	(0.153)	(0.125)
CMA	0.300	-0.031	-0.331	-0.084
	(0.242)	(0.200)	(0.284)	(0.204)
RMW	0.314***	0.435***	0.121	0.191
	(0.185)	(0.166)	(0.202)	(0.147)
MOM	0.162	-0.005	-0.167	-0.121
	(0.113)	(0.082)	(0.128)	(0.089)
$PROP$	1.286	3.775	2.489	2.874
	(3.396)	(2.382)	(3.627)	(2.055)
WTI	7.982***	-2.012	-9.993***	-5.081
	(3.214)	(3.368)	(3.628)	(3.332)
NG	-0.706	1.455	2.161	0.547
	(1.305)	(0.992)	(1.397)	(0.848)
EPU	-0.001	0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.019	0.014	0.033***	0.037***
	(0.012)	(0.013)	(0.018)	(0.012)
FTS	0.707	0.070	-0.637	-0.353
	(0.496)	(0.574)	(0.697)	(0.636)
$TERM$	0.763	1.835	1.072	2.084***
	(1.143)	(1.152)	(1.612)	(1.099)
$DFLT$	2.979	8.532***	5.555	5.708***
	(2.755)	(2.315)	(3.554)	(2.251)
TED	-1.259***	-0.298	0.947	-0.479
	(0.583)	(0.374)	(0.605)	(0.395)

Table A14: GMB, Green, Brown, and Neutral Portfolios – IM2 – SD
Refer to Table 6, but specifically for the second moment, and for the Societal Debate cluster.

	GMB	Green	Brown	Neutral
Intercept	0.408	0.390***	-0.018	0.034
	(0.276)	(0.202)	(0.308)	(0.191)
UMC	-0.041	0.055	0.096	0.027
	(0.156)	(0.148)	(0.187)	(0.128)
MKT	-0.026	-1.084***	-1.058***	-1.085***
	(0.098)	(0.096)	(0.127)	(0.085)
HML	-0.037	0.090	0.127	0.051
	(0.167)	(0.150)	(0.203)	(0.157)
SMB	-0.172***	0.173	0.345***	0.209***
	(0.104)	(0.124)	(0.153)	(0.126)
CMA	0.296	-0.028	-0.324	-0.081
	(0.243)	(0.201)	(0.285)	(0.205)
RMW	0.318***	0.434***	0.115	0.187
	(0.185)	(0.176)	(0.201)	(0.147)
MOM	0.159	-0.004	-0.163	-0.119
	(0.113)	(0.082)	(0.128)	(0.089)
$PROP$	1.248	3.787	2.539	2.903
	(3.399)	(2.390)	(3.638)	(2.068)
WTI	8.050***	-2.034	-10.084***	-5.133
	(3.205)	(3.377)	(3.636)	(3.334)
NG	-0.204	1.420	2.050	0.491
	(1.304)	(0.997)	(1.399)	(0.847)
EPU	-0.001	0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.018	0.014	0.032***	0.037***
	(0.012)	(0.013)	(0.018)	(0.012)
FTS	0.722	0.062	-0.660	0.122
	(0.496)	(0.576)	(0.699)	(0.637)
$TERM$	2.186***	1.828	-1.433***	2.062***
	(1.434)	(1.154)	(1.620)	(1.499)
$DFLT$	2.988	8.520***	5.533	5.703***
	(2.755)	(2.315)	(3.923)	(2.254)
TED	-1.263***	-0.299	0.964	-0.475
	(0.583)	(0.374)	(0.606)	(0.392)

Table A15: GMB, Green, Brown, and Neutral Portfolios – IM3 – Aggregate
Refer to Table 6, but specifically for the third moment, and for the aggregate index.

	GMB	Green	Brown	Neutral
Intercept	0.043	0.524***	0.481***	0.344***
	(0.114)	(0.125)	(0.145)	(0.139)
UMC	-0.312	0.136	0.448***	0.107
	(0.227)	(0.191)	(0.193)	(0.141)
MKT	0.012	-1.679***	-1.691***	-1.439***
	(0.122)	(0.091)	(0.125)	(0.069)
HML	-0.108	0.022	0.129	0.306***
	(0.169)	(0.153)	(0.169)	(0.121)
SMB	-0.464***	0.098	0.558***	0.135
	(0.146)	(0.118)	(0.132)	(0.096)
CMA	0.388	0.146	-0.242	-0.019
	(0.267)	(0.235)	(0.288)	(0.189)
RMW	0.553***	0.276***	-0.274	0.128
	(0.230)	(0.166)	(0.200)	(0.148)
MOM	-0.016	0.067	0.083	0.078
	(0.101)	(0.084)	(0.094)	(0.069)
$PROP$	-0.483	1.804	2.287	-0.235
	(2.642)	(2.326)	(2.571)	(1.633)
WTI	9.436***	10.058***	0.622	6.727***
	(3.874)	(3.628)	(3.865)	(3.285)
NG	0.169	0.785	0.616	0.817
	(1.221)	(0.952)	(1.210)	(0.899)
EPU	0.000	0.001	0.001	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.004	-0.030***	-0.026***	-0.021***
	(0.008)	(0.008)	(0.009)	(0.008)
FTS	-0.131	1.032	1.163	0.774
	(0.560)	(0.691)	(0.885)	(0.726)
$TERM$	-3.983***	1.611	5.594***	1.947***
	(1.569)	(1.114)	(1.405)	(0.978)
$DFLT$	-0.659	0.977	1.636	-0.539
	(2.852)	(2.260)	(3.007)	(2.180)
TED	0.007	-0.177	-0.184	-0.087
	(0.215)	(0.237)	(0.264)	(0.249)

Table A16: GMB, Green, Brown, and Neutral Portfolios – IM3 – BI

Refer to Table 6, but specifically for the third moment, and for the Business Impact cluster

	GMB	Green	Brown	Neutral
Intercept	0.049	0.529***	0.479***	0.335***
	(0.114)	(0.122)	(0.148)	(0.139)
UMC	-0.386***	0.111	0.497***	0.187
	(0.230)	(0.201)	(0.212)	(0.143)
MKT	0.014	-1.684***	-1.694***	-1.439***
	(0.122)	(0.091)	(0.125)	(0.069)
HML	-0.107	0.022	0.129	0.306***
	(0.169)	(0.153)	(0.169)	(0.121)
SMB	-0.461***	0.099	0.564***	0.135
	(0.146)	(0.118)	(0.132)	(0.095)
CMA	0.386	0.147	-0.240	-0.018
	(0.266)	(0.236)	(0.290)	(0.189)
RMW	0.546***	0.277**	-0.269	0.131
	(0.229)	(0.167)	(0.200)	(0.148)
MOM	-0.020	0.069	0.089	0.080
	(0.101)	(0.084)	(0.093)	(0.069)
$PROP$	-0.579	1.829	2.408	-0.186
	(2.657)	(2.333)	(2.595)	(1.683)
WTI	9.434***	10.056***	0.655	6.756***
	(3.875)	(3.631)	(3.876)	(3.272)
NG	0.192	0.768	0.576	0.814
	(1.222)	(0.951)	(1.213)	(0.899)
EPU	0.000	0.001	0.001	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.004	0.014	0.033***	0.037***
	(0.008)	(0.013)	(0.014)	(0.012)
FTS	-0.084	0.052	-0.034	0.124
	(0.560)	(0.688)	(0.873)	(0.726)
$TERM$	3.967***	1.597	5.556***	1.943***
	(1.563)	(1.113)	(1.401)	(1.108)
$DFLT$	-0.657	0.961	1.531	-0.591
	(2.846)	(2.261)	(2.998)	(2.174)
TED	-1.266***	-0.295	0.971	-0.473
	(0.582)	(0.374)	(0.603)	(0.424)

Table A17: GMB, Green, Brown, and Neutral Portfolios – IM3 – EI
Refer to Table 6, but specifically for the third moment, and for the Environmental Impact cluster.

	GMB	Green	Brown	Neutral
Intercept	0.007	0.532***	0.525***	0.358***
	(0.112)	(0.127)	(0.146)	(0.141)
UMC	-0.050	0.083	0.134	0.006
	(0.187)	(0.162)	(0.175)	(0.134)
MKT	0.015	-1.684***	-1.694***	-1.444***
	(0.122)	(0.091)	(0.126)	(0.077)
HML	-0.108	0.022	0.131	0.306***
	(0.169)	(0.153)	(0.169)	(0.122)
SMB	-0.464***	0.099	0.563***	0.137
	(0.146)	(0.118)	(0.133)	(0.096)
CMA	0.386	0.146	-0.240	-0.018
	(0.267)	(0.235)	(0.288)	(0.189)
RMW	0.553***	0.275**	-0.278	0.127
	(0.229)	(0.166)	(0.199)	(0.147)
MOM	-0.018	0.067	0.085	0.079
	(0.101)	(0.084)	(0.093)	(0.069)
$PROP$	-0.463	1.795	2.257	-0.242
	(2.628)	(2.333)	(2.587)	(1.686)
WTI	9.518***	10.021***	0.503	6.699***
	(3.844)	(3.631)	(3.882)	(3.293)
NG	0.215	0.785	0.570	0.797
	(1.301)	(0.959)	(1.226)	(0.899)
EPU	0.000	0.001	0.001	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.003	0.014	0.033***	0.037***
	(0.008)	(0.013)	(0.014)	(0.012)
FTS	-0.084	0.052	-0.034	0.124
	(0.559)	(0.693)	(0.973)	(0.731)
$TERM$	3.945***	1.612	5.557***	1.931***
	(1.559)	(1.113)	(1.401)	(1.098)
$DFLT$	-0.729	1.013	1.742	-0.516
	(2.853)	(2.263)	(3.498)	(2.173)
TED	-1.247***	-0.299	0.947	-0.479
	(0.583)	(0.376)	(0.605)	(0.395)

Table A18: GMB, Green, Brown, and Neutral Portfolios – IM3 – R

Refer to Table 6, but specifically for the third moment, and for the Research cluster.

	GMB	Green	Brown	Neutral
Intercept	0.018	0.529***	0.511***	0.345***
	(0.113)	(0.125)	(0.143)	(0.136)
UMC	-0.148	0.121	0.269	0.116
	(0.216)	(0.184)	(0.198)	(0.142)
MKT	0.013	-1.679***	-1.692***	-1.438***
	(0.122)	(0.091)	(0.125)	(0.077)
HML	-0.107	0.021	0.127	0.305***
	(0.169)	(0.153)	(0.169)	(0.121)
SMB	-0.463***	0.099	0.562***	0.136
	(0.146)	(0.118)	(0.133)	(0.096)
CMA	0.387	0.145	-0.241	-0.019
	(0.267)	(0.236)	(0.289)	(0.189)
RMW	0.554***	0.277**	-0.278	0.129
	(0.230)	(0.166)	(0.199)	(0.147)
MOM	-0.016	0.067	0.083	0.078
	(0.101)	(0.084)	(0.093)	(0.069)
$PROP$	-0.432	1.770	2.202	-0.267
	(2.622)	(2.334)	(2.575)	(1.678)
WTI	9.462***	-2.012	-9.993***	-5.081
	(3.856)	(3.625)	(3.628)	(3.285)
NG	0.178	0.801	0.623	0.837
	(1.229)	(0.956)	(1.224)	(0.911)
EPU	0.000	0.001	0.001	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.019	0.014	0.033***	0.037***
	(0.012)	(0.013)	(0.018)	(0.012)
FTS	0.707	0.070	-0.637	-0.353
	(0.496)	(0.574)	(0.697)	(0.636)
$TERM$	3.945***	1.604	5.554***	1.944***
	(1.566)	(1.111)	(1.408)	(1.099)
$DFLT$	-0.726	2.262	1.732	-0.515
	(2.855)	(2.267)	(3.033)	(2.153)
TED	-1.259***	-0.298	0.947	-0.479
	(0.582)	(0.239)	(0.606)	(0.392)

Table A19: GMB, Green, Brown, and Neutral Portfolios – IM3 – SD
Refer to Table 6, but specifically for the third moment, and for the Societal Debate cluster.

	GMB	Green	Brown	Neutral
Intercept	0.055	0.523***	0.468***	0.342***
	(0.112)	(0.126)	(0.146)	(0.141)
UMC	-0.388***	0.143	0.530***	0.116
	(0.212)	(0.189)	(0.197)	(0.117)
MKT	0.010	-1.678***	-1.689***	-1.438***
	(0.121)	(0.091)	(0.125)	(0.069)
HML	-0.102	0.020	0.122	0.304***
	(0.169)	(0.153)	(0.168)	(0.121)
SMB	-0.453***	0.096	0.549***	0.134
	(0.145)	(0.118)	(0.131)	(0.096)
CMA	0.372	0.152	-0.220	-0.014
	(0.265)	(0.235)	(0.285)	(0.189)
RMW	0.551***	0.275***	-0.276	0.127
	(0.231)	(0.166)	(0.201)	(0.148)
MOM	0.159	-0.004	-0.163	-0.119
	(0.113)	(0.082)	(0.128)	(0.089)
$PROP$	1.248	3.787	2.539	2.903
	(3.651)	(2.390)	(3.638)	(2.068)
WTI	9.437***	-2.034	-10.084***	-5.133
	(3.879)	(3.627)	(3.636)	(3.286)
NG	0.255	0.748	0.493	0.788
	(1.215)	(0.951)	(1.199)	(0.893)
EPU	0.001	0.001	0.001	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.005	0.014	0.032***	0.037***
	(0.008)	(0.008)	(0.010)	(0.008)
FTS	0.722	0.062	-0.660	0.122
	(0.496)	(0.576)	(0.699)	(0.637)
$TERM$	2.186***	1.828	-1.433***	2.062***
	(1.434)	(1.151)	(1.620)	(1.499)
$DFLT$	2.988	8.520***	5.533	5.703***
	(2.755)	(2.315)	(3.923)	(2.254)
TED	-1.263***	-0.299	0.964	-0.475
	(0.583)	(0.374)	(0.606)	(0.392)

Table A20: GMB, Green, Brown, and Neutral Portfolios – IM4 – Aggregate
Refer to Table 6, but specifically for the fourth moment, and for the aggregate index.

	GMB	Green	Brown	Neutral
Intercept	-0.008	0.141	0.149	0.011
	(0.158)	(0.212)	(0.232)	(0.193)
UMC	0.091	-0.065	-0.157	0.051
	(0.241)	(0.234)	(0.264)	(0.216)
MKT	-0.158	-0.018	0.140	-0.125
	(0.107)	(0.115)	(0.154)	(0.111)
HML	0.093	-0.057	-0.149	0.005
	(0.219)	(0.188)	(0.228)	(0.185)
SMB	0.134	0.155	0.021	0.134
	(0.200)	(0.160)	(0.220)	(0.162)
CMA	-0.691*	0.462	1.153***	0.601***
	(0.373)	(0.313)	(0.395)	(0.291)
RMW	-0.323	0.162	0.486	0.049
	(0.282)	(0.200)	(0.312)	(0.194)
MOM	-0.018	-0.408***	-0.228	-0.327***
	(0.158)	(0.118)	(0.167)	(0.105)
$PROP$	2.713	5.305	2.592	2.758
	(4.195)	(3.399)	(4.795)	(3.057)
WTI	-4.025	-11.243***	-7.218	-11.894***
	(5.660)	(4.441)	(6.843)	(5.054)
NG	0.112	-0.478	-0.590	0.063
	(1.942)	(1.280)	(2.162)	(1.053)
EPU	0.000	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.001	0.006	0.008	0.007
	(0.009)	(0.013)	(0.014)	(0.012)
FTS	-0.063	0.037	0.026	0.124
	(0.722)	(1.103)	(0.966)	(1.035)
$TERM$	2.414	1.194	-1.221	2.318
	(1.644)	(1.520)	(1.883)	(1.502)
$DFLT$	-2.483	2.289	4.772	4.327
	(4.142)	(3.261)	(3.929)	(3.131)
TED	0.271	-0.312	-0.583	-0.162
	(0.294)	(0.449)	(0.512)	(0.424)

Table A21: GMB, Green, Brown, and Neutral Portfolios – IM4 – BI
Refer to Table 6, but specifically for the fourth moment, and for the Business Impact cluster

	GMB	Green	Brown	Neutral
Intercept	-0.031	0.122	0.152	-0.007
	(0.156)	(0.213)	(0.233)	(0.193)
UMC	0.281	0.084	-0.197	0.191
	(0.249)	(0.238)	(0.291)	(0.204)
MKT	-0.158	-0.017	0.141	-0.125
	(0.107)	(0.115)	(0.154)	(0.111)
HML	0.092	-0.057	-0.149	0.005
	(0.219)	(0.188)	(0.230)	(0.185)
SMB	0.133	0.154	0.021	0.133
	(0.200)	(0.160)	(0.220)	(0.162)
CMA	-0.691***	0.461	1.152***	0.600***
	(0.373)	(0.313)	(0.395)	(0.291)
RMW	0.546***	0.277**	-0.269	0.131
	(0.282)	(0.201)	(0.310)	(0.195)
MOM	-0.178	-0.408***	-0.230	-0.326***
	(0.158)	(0.117)	(0.168)	(0.105)
$PROP$	2.791	5.334	2.543	2.812
	(4.214)	(3.409)	(4.798)	(3.068)
WTI	-3.964	-11.201***	-7.237	-11.850***
	(5.568)	(4.422)	(6.799)	(5.031)
NG	0.122	-0.456	-0.578	0.073
	(1.301)	(1.280)	(2.149)	(1.053)
EPU	0.000	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.004	0.007	0.008	0.007
	(0.009)	(0.014)	(0.014)	(0.012)
FTS	-0.095	0.052	0.050	0.124
	(0.722)	(1.094)	(0.973)	(1.025)
$TERM$	2.420	1.211	-1.209	2.324
	(1.644)	(1.515)	(1.879)	(1.497)
$DFLT$	-2.577	2.242	4.819	4.261
	(4.135)	(3.249)	(3.969)	(3.113)
TED	0.276	-0.316	-0.592	-0.159
	(0.276)	(0.316)	(0.512)	(0.424)

Table A22: GMB, Green, Brown, and Neutral Portfolios – IM4 – EI
Refer to Table 6, but specifically for the fourth moment, and for the Environmental Impact cluster.

	GMB	Green	Brown	Neutral
Intercept	0.006	0.152	0.146	0.024
	(0.158)	(0.214)	(0.232)	(0.196)
UMC	-0.008	-0.151	-0.143	-0.052
	(0.223)	(0.204)	(0.251)	(0.195)
MKT	-0.159	-0.019	0.140	-0.126
	(0.107)	(0.115)	(0.154)	(0.112)
HML	0.093	-0.057	-0.149	0.005
	(0.219)	(0.189)	(0.228)	(0.185)
SMB	0.135	0.155	0.020	0.135
	(0.200)	(0.160)	(0.220)	(0.162)
CMA	-0.691***	0.463	1.153***	0.602***
	(0.373)	(0.314)	(0.395)	(0.291)
RMW	0.553***	0.275**	-0.278	0.127
	(0.229)	(0.166)	(0.199)	(0.147)
MOM	-0.018	0.067	0.085	0.079
	(0.101)	(0.084)	(0.093)	(0.069)
$PROP$	-0.463	1.795	2.257	2.755
	(2.628)	(2.333)	(2.587)	(1.686)
WTI	-4.049	-11.225***	-7.716	-11.908***
	(5.662)	(4.452)	(6.834)	(5.055)
NG	0.091	-0.516	-0.606	0.035
	(1.953)	(1.287)	(2.149)	(1.053)
EPU	0.000	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.003	0.007	0.008	0.007
	(0.009)	(0.014)	(0.014)	(0.012)
FTS	-0.065	0.066	-0.034	0.119
	(0.723)	(1.102)	(0.966)	(1.038)
$TERM$	2.397	1.162	-1.209	2.074***
	(1.632)	(1.515)	(1.879)	(1.497)
$DFLT$	-2.465	2.262	4.727	4.261
	(4.135)	(3.249)	(3.969)	(3.113)
TED	0.278	-0.316	-0.592	-0.159
	(0.296)	(0.449)	(0.515)	(0.425)

Table A23: GMB, Green, Brown, and Neutral Portfolios – IM4 – R
Refer to Table 6, but specifically for the fourth moment, and for the Research cluster.

	GMB	Green	Brown	Neutral
Intercept	0.032	0.120	0.088	-0.000
	(0.158)	(0.209)	(0.231)	(0.191)
UMC	-0.238	0.109	0.347	0.185
	(0.243)	(0.203)	(0.256)	(0.185)
MKT	-0.162	-0.016	0.146	-0.123
	(0.108)	(0.114)	(0.153)	(0.111)
HML	0.095	-0.058	-0.154	0.003
	(0.219)	(0.188)	(0.227)	(0.185)
SMB	0.137	0.154	0.021	0.133
	(0.199)	(0.160)	(0.220)	(0.162)
CMA	-0.687***	0.460	1.147***	0.602***
	(0.372)	(0.312)	(0.392)	(0.291)
RMW	-0.329	0.165	0.495	0.048
	(0.282)	(0.200)	(0.312)	(0.194)
MOM	-0.176	-0.408***	-0.229	-0.327***
	(0.158)	(0.117)	(0.167)	(0.105)
$PROP$	2.707	5.285	2.607	2.752
	(4.201)	(3.396)	(4.785)	(3.059)
WTI	-4.048	-11.185***	-7.186	-11.903***
	(5.565)	(4.441)	(6.819)	(5.047)
NG	0.093	-0.462	-0.555	0.052
	(1.943)	(1.284)	(2.165)	(1.055)
EPU	0.000	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.005	0.007	0.008	0.007
	(0.009)	(0.013)	(0.014)	(0.012)
FTS	-0.065	-0.035	0.051	0.122
	(0.722)	(1.100)	(0.969)	(0.725)
$TERM$	2.369	1.201	-1.198	2.311
	(1.642)	(1.515)	(1.875)	(1.499)
$DFLT$	-2.465	2.282	4.747	4.334
	(4.155)	(3.275)	(3.923)	(3.143)
TED	0.286	-0.313	-0.589	-0.161
	(0.295)	(0.450)	(0.514)	(0.422)

Table A24: GMB, Green, Brown, and Neutral Portfolios – IM4 – SD
Refer to Table 6, but specifically for the fourth moment, and for the Societal Debate cluster.

	GMB	Green	Brown	Neutral
Intercept	0.004	0.138	0.134	0.014
	(0.157)	(0.215)	(0.231)	(0.194)
UMC	0.005	-0.042	-0.047	0.022
	(0.247)	(0.216)	(0.256)	(0.185)
MKT	-0.159	-0.018	0.141	-0.125
	(0.107)	(0.115)	(0.153)	(0.111)
HML	0.093	-0.056	-0.149	0.005
	(0.219)	(0.189)	(0.228)	(0.185)
SMB	0.135	0.156	0.021	0.134
	(0.199)	(0.160)	(0.220)	(0.162)
CMA	-0.695*	0.460	1.149***	0.602***
	(0.372)	(0.313)	(0.393)	(0.291)
RMW	-0.324	0.163	0.487	0.048
	(0.282)	(0.200)	(0.312)	(0.194)
MOM	-0.179	-0.408***	-0.229	-0.327***
	(0.158)	(0.117)	(0.167)	(0.105)
$PROP$	2.707	5.314	2.607	2.752
	(4.201)	(3.396)	(4.785)	(3.059)
WTI	-4.048	-11.235***	-7.186	-11.903***
	(5.565)	(4.441)	(6.819)	(5.053)
NG	0.093	-0.462	-0.555	0.052
	(1.943)	(1.284)	(2.165)	(1.055)
EPU	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
VIX	-0.005	0.007	0.010	0.007
	(0.009)	(0.013)	(0.014)	(0.012)
FTS	-0.065	-0.035	0.030	0.122
	(0.722)	(1.100)	(0.969)	(0.638)
$TERM$	2.399	1.201	-1.198	2.333
	(1.642)	(1.515)	(1.875)	(1.497)
$DFLT$	-2.465	2.282	4.747	4.333
	(4.155)	(3.275)	(3.923)	(3.141)
TED	0.277	-0.313	-0.589	-0.161
	(0.294)	(0.448)	(0.606)	(0.422)