Pricing Climate Ambiguity*

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May 30, 2025

Abstract

The theoretical literature on climate finance advocates the existence of a tight relation between climate change uncertainty and the uncertainty about the probabilistic models (ambiguity) concerning future consumption opportunities and, by extension, asset prices. This paper provides empirical evidence for the relevance of this phenomenon to equity prices. It empirically identify a transmission channel—ambiguity (Knightian uncertainty)—through which climate change relates to the cross-section of expected stock returns. In particular, we find evidence of a so-far. undisclosed climate-ambiguity cross-sectional pricing anomaly. At a minimum, a portfolio-specific climate ambiguity factor explains alone 41% of the abnormal returns linked with the anomaly. The explanatory power rises to 92% when stocks are sorted according to their climate ambiguity level in a univariate portfolio analysis.

Keywords and Phrases: Ambiguity, Knightian Uncertainty, Asset Pricing, Factor Models, Climate Change.

JEL Classification Numbers: D81, D83, G11, G12, Q50

*We are grateful to Azi Ben-Rephael, Fernando Bernstein, Chris Brooks, Filippo Busetto, Simon Gervais, Cosmin Ilut, Pino Lopomo, Thierry Post, Adriano Rampini, David Robinson, Ana Sina, and Paolo Zaffaroni for helpful discussions. We also thank seminar participants at Aix-Marseille School of Economics, Bristol Business School, Banco de España, Duke University Fuqua School of Business, and Nazarbayev University for comments. Rocciolo is grateful to the Economics department at the University of Warwick for hospitality. Billio, Guidolin, and Rocciolo acknowledge the financial support of the Italian Ministry of Research PRIN 2020 PROT. 2020B2AKFW ("Fin4Green - Finance for a Sustainable, Green and Resilient Society"). Izhakian acknowledges hosting by the Stern School of Business, New York University.

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1 Introduction

Given the long-run nature of climate risk(Engle, Giglio, Kelly, Lee, and Stroebel, 2020), a large portion of the growing literature on climate finance stresses the necessity of considering further layers of uncertainty not already captured by standard notions of risk(Lemoine and Traeger, 2016; Heal and Millner, 2014; Heal, 2017; Giglio, Kelly, and Stroebel, 2021)). In particular, specific emphasis has been placed on ambiguity (Knightian uncertainty), that is, is the uncertainty on the probability of each future climate scenario (Barnett, Brock, and Hansen, 2020, 2021). Accordingly, the conjecture that part of the observable ambiguity in the economy may be due to climate change, has been employed as a foundational postulate in theoretical advances concerning a variety of models in financial economics.[1] Although widely investigated in the theoretical literature, the relationship between asset prices, ambiguity, and climate change has, to the best of our knowledge, not yet been tested empirically. Moreover, when pure climate risk (in the absence of ambiguity) is considered, the evidence on the predictive power for climate and ESG risks and the cross-section of stock returns remains blurred and, in some cases, mixed.[2] This paper, fills this gap by presenting empirical evidence of the significant impact of climate ambiguity on asset prices. Hence, we provide a first confirmation of the theoretical conjecture that a link between climate and asset market perceived ambiguity exists.

In consumption-based asset pricing models that consider ambiguity, prices are determined by discounting future payoffs using a stochastic discount factor which accounts for future consumption and their associated risk and ambiguity (Collard, Mukerji, Sheppard, and Tallon, 2018). Indeed, climate change may have consequences for future consumption and hence affect no-arbitrage prices through this classical channel. However, the probabilities of these

[1] Among others, such an assumption is employed in the analysis of the social cost of carbon (Barnett et al., 2020), optimal climate policy (Millner, Dietz, and Heal, 2013; Barnett et al., 2021), ESG uncertainty (Avramov, Cheng, Lioui, and Tarelli, 2022; Avramov, Lioui, Liu, and Tarelli, 2021), asset pricing (Barnett, 2023), sustainable portfolio investment (Billio, Guidolin, and Rocciolo, 2024), and catastrophe risk management (Berger, Emmerling, and Tavoni, 2017).

[2] For example, the evidence on transition risk affecting asset prices through carbon emissions is mixed (Bolton and Kacperczyk, 2021; Aswani, Raghunandan, and Rajgopal, 2024; Bolton and Kacperczyk, 2024). For instance, the coefficient estimates of the physical risk associated with temperature anomalies and cumulative carbon emissions in a regression explaining the market portfolio's risk premium turn out to be statistically insignificant, as reported in Table IA.1 of Internet Appendix IA, and graphically summarized in Figure 2.

consequences are also uncertain, generating *climate ambiguity* (Barnett et al., 2020). Therefore, the stochastic discount factor employed to determine asset prices is also likely to be affected by climate ambiguity. Since investors are on average ambiguity averse (Ellsberg, 1961), equilibrium asset prices are lower (and expected returns are higher), reflecting an ambiguity premium (Brenner and Izhakian, 2018). In particular, climate ambiguity should be reflected in a positive, significant premium observable in the cross-section of expected stock returns. However, differently from the traditional, multifactor asset pricing models under risk (of whichever type), where a set of common risk factors may be identifiable, such a premium is idiosyncratic by nature. In particular, consistent with the asset pricing under ambiguity literature, the ambiguity premium of each asset will be measured by an abnormal *alpha* component in the expected return-beta relation[3]

$$\mathbb{E}(R_i) - R^f \;=\; \alpha_i + \sum_{k=1}^{K} \beta_{i,k}\mathbb{E}(F_k), \tag{1}$$

where all of the relevant common pricing factors F_k, which in a pure risk environment (absence of ambiguity) would deliver a perfect pricing, are included. Therefore, an asset i, displaying higher comparative climate ambiguity, will imply a comparatively higher α.

To test the empirical implications of climate ambiguity for asset prices, we consider the cross-section of expected stock returns of all stocks listed on the NYSE, NASDAQ, and AMEX. We use a measure of ambiguity adapted from the ambiguity literature (Izhakian, 2017, 2020). Rooted in ambiguity theory, this measure quantifies the degree of daily *variation in outcome probabilities* (ambiguity) based on intraday realized returns available in the Trade and Quote (TAQ) database (Brenner and Izhakian, 2018; Augustin and Izhakian, 2020). [4] To estimate the climate ambiguity affecting firms, we regress each firm's estimated ambiguity

[3]The literature on asset pricing under ambiguity states the existence of a one-to-one correspondence between perceived ambiguity, ambiguity aversion, and the cross-section pricing errors (*alphas*). See, e.g., Maccheroni, Marinacci, and Ruffino (2013, Proposition 9), Hara and Honda (2022, Section 5), and Rocciolo (2024, Theorem 4)

[4]This ambiguity measure applies exclusively to the probabilities of events, independently of the outcomes associated with these events. Since the measure is outcome-independent, the degree of ambiguity does not change if the outcomes associated with events change while the induced partition of the state space into events remains unchanged. This approach to ambiguity measurement has generated active discussions. In a recent comment, Fu, Melenberg, and Schweizer (2023) challenges the theoretical foundations of this measure, arguing that it does not reflect preferences for ambiguity. However, Izhakian (2024) shows that this critique is flawed as it violates the axioms of the underlying model. Moreover, for what concerns our study, Fu et al. (2023) acknowledge that their claims do not invalidate the empirical efficacy of the measure.

on a sequence of variables commonly employed in the literature to measure climate change: the world surface temperature anomaly with respect to the pre-industrial level, the U.S. cumulative carbon emissions, each individual firms' carbon emissions, the aggregate cost of disasters that occurred in the U.S., and the yearly count of realized extreme weather conditions such as droughts, floodings, and cyclones. Then, we perform a standard portfolio analysis by allocating the stocks into quintile portfolios based on their climate ambiguity. In particular, we first perform a univariate analysis and sort stocks into five quintile climate ambiguity portfolios. Then, to check the robustness of our result against carbon risk (Bolton and Kacperczyk, 2021) we double sort the stocks to allocate them into 75 portfolios jointly based on their climate ambiguity and carbon emissions.[5]

Figure 1 sketches our main findings in the case of the univariate portfolio analysis by plotting the cumulative returns for the high (5^{th} quintile) and low (1^{st} quintile) climate ambiguity portfolios. The figure shows that the cumulative return on the high climate ambiguity portfolio almost always exceeded that on the low climate ambiguity portfolio, providing preliminary evidence of a climate ambiguity premium.

[Figure 1]

Using the portfolios obtained from the stocks sorting, we then estimate different specifications of Equation (1). In particular, we employ as risk factors the returns on the market portfolio, Fama and French (2015)'s SMB, HML, investment and profitability portfolios, Carhart (1997)'s momentum portfolio, and the classical q-factors (Hou, Xue, and Zhang, 2015).[6] The estimated *alphas* in Equation (1) and the GRS test (Gibbons, Ross, and Shanken, 1989) confirm the existence of climate ambiguity premium independently from the sequence of factors employed in Equation (1). This supports the empirical evidence derived from the portfolio sorting in Figure 1. Unconditionally of the multifactor model selected, all the portfolios, except those consisting of stocks issued by firms with an extremely low pollution index, display positive and statistically significant *alphas*, which are monotonically increasing as the

[5] We further perform alternative bivariate sorting experiments using alternative transition risk metrics. These analyses are reported in the Online Appendix.

[6] We further check the robustness of our result by also employing the GMB factor by Pástor, Stambaugh, and Taylor (2022), the WSJ index by Engle et al. (2020), and a variety of climate risk metrics by Ardia, Bluteau, Boudt, and Inghelbrecht (2023) and Faccini, Matin, and Skiadopoulos (2023). These analysis are reported in Section 4.

climate ambiguity of the portfolio increases. Moreover, a GRS test rejects all the considered multifactor models, including those that account for the risk factor that is conjectured to explain the anomaly obtained. This factor is built by taking a long position in the high climate ambiguity portfolio and a short position in the low climate ambiguity portfolio.

The idiosyncratic nature of ambiguity, given by the one-to-one correspondence in the cross-section between perceived ambiguity and pricing errors (Hara and Honda, 2022), does not allow for a formal test to confirm that the elicited premia, obtained from sorting stocks based on their climate ambiguity, are actually due to ambiguity rather than other omitted risk factors. Nevertheless, the persistence of the premia in their magnitude, statistical significance, and increasing pattern as measured climate ambiguity increases, despite the multifactor model used to estimate them, provides evidence against an omitted factor interpretation. Furthermore, regressing the cross-sectional *alphas* on the climate ambiguity of the portfolios, the adjusted R^2 span from 41% for the portfolios obtained from bivariate stocks sorting into climate ambiguity quintiles and scope 2 emissions, to 92% in the case of the univariate sorted portfolios. The residuals of these regressions, which quantify the pricing errors unexplained by climate ambiguity, are almost uniformly statistically insignificant and flat across alternative portfolios. Therefore, despite the unavailability of a formal test, our findings arguably discard the omitted factor hypothesis in favor of the existence of a climate ambiguity premium.

To further validate our findings, we employ a variety of robustness tests at both a design and at a methodological level. We test the robustness of the results across different specifications of the econometric model employed to estimate the firms' climate ambiguity from the aggregate ambiguity index. In addition, we explore other plausible explanations for the findings, including the possibility of climate ambiguity being another proxy for climate risk or other risk sources. Our findings prove to be robust across all these tests.

By introducing a new proxy for climate ambiguity, our paper nests into the branch of climate finance that aims to provide measures for the uncertainty induced by climate change both at market and individual firm level. Examples of such metrics include the Wall Street Journal Index (Engle et al., 2020), the Media Climate Change Concern Index (Ardia et al., 2023), the Textual Climate Change Risk Measures (Faccini et al., 2023), and the earnings announcement-based climate risk exposure (Sautner, Van Lent, Vilkov, and Zhang, 2023). In an asset pricing perspective, our paper relates the studies attempting to find the existence of abnormal returns due to climate change, including evidence of carbon (Bolton and Kacperczyk, 2021, 2023), pollution (Hsu, Li, and Tsou, 2023), and environmental scores (Avramov et al., 2022; Pástor et al., 2022) premia. This paper adds to the aforementioned studies the notion of ambiguity and one of its important determinants—climate change.

To summarize, we contribute to the finance literature in three ways. First, we introduces a measure of *climate ambiguity*, that we show to be priced in the cross-section of expected stock returns. Second, we provide new evidence at a firm level on how climate change affects equity prices. In particular, we show that climate change significantly affects stock prices through the channel of ambiguity rather than just through climate risk. Finally, since climate is strictly exogenous and hence cannot be affected by ambiguity or investors' attitudes toward it, our empirical findings provide an external validation to the ambiguity measure we employ, which has broadly used in the recent literature.

2 Research Design

This section details the data and methods involved in our analysis. To sketch the methodology employed to estimate climate ambiguity and verify its effectiveness, we present the results of our estimation taking as a benchmark the market portfolio. Note that this preliminary analysis also provides insights on the relationship between climate and the ambiguity perceived at market level.

2.1 Data

The firm-level dataset covers monthly returns on all stocks listed on NYSE, NASDAQ, and AMEX issued by non-financial firms, available in the Center for Research in Security Prices (CRSP) for over 12 thousand firms observed from January 1993 to December 2020. We match this dataset with firm-level yearly observations on carbon emissions from the Trucost database. To ensure that the emissions are known before sorting stocks into portfolios, we match the observations available in fiscal year-end $t-1$ with the returns for July year t to June year $t+1$. Trucost reports observations on scope 1, scope 2, and scope 3 (upstream) carbon emissions starting from 2002.[7] We employ these data in the bivariate sorting of the stocks by climate ambiguity and carbon emissions. Still, we keep the original dataset starting from 1993 for the univariate sorting for climate ambiguity to avoid unnecessary losses of observations. The two-way sorting by climate ambiguity and carbon emissions aims to disentangle their competing effects on asset prices of climate ambiguity and climate risk, which we proxy through carbon emissions following previous literature (Bolton and Kacperczyk, 2021, 2023).

For each stock in every month, we estimate the ambiguity, denoted $\mho^2$, as the expected probability-weighted average of the variances of return probabilities. To this end, we use intra-day returns data from TAQ and the methodology used in recent literature (Izhakian and Yermack, 2017; Brenner and Izhakian, 2018; Augustin and Izhakian, 2020; Izhakian, Yermack, and Zender, 2022), as detailed in Internet Appendix IA.1. Monthly returns on the market portfolio, size (SMB), value (HML) (Fama and French, 1996), momentum (UMD) (Carhart, 1997), profitability (RMW) and investment (CMA) factor portfolios (Fama and French, 2015) are taken from the Kenneth French data library, while the q-factors (Hou et al., 2015) are from the global-q.org website.

To estimate the effect of climate change dynamics on the economy, we follow the literature[8] and collect data from the National Oceanic and Atmospheric Administration (NOAA) monthly observations on the world's ocean surface temperature anomaly with respect to the pre-industrial level, yearly observations on the U.S. cumulative carbon emissions[9], yearly CPI-adjusted cost in billions of dollars of U.S. climate and weather disasters, and yearly counts of droughts, floodings, freezes, storms, cyclones, wildfires, and winter storms that

[7] A detailed description of the Trucost database is provided in Bolton and Kacperczyk (2021). The subdivision of carbon emissions into scopes 1 to 3 is in accordance with the Greenhouse Gas Protocol. Scope 1 covers direct emissions over one year from establishments that are owned or controlled by the firm. Scope 2 covers indirect emissions from the generation of purchased heat, steam, and electricity consumed by the firm. Scope 3 covers indirect emissions caused by the operations and products of the firm but occur from sources not owned or controlled by it. Following Bolton and Kacperczyk (2021), we employ just upstream emissions for scope 3 due to the significant data gap for downstream emissions in the Trucost database.

[8] According to Barnett et al. (2020), which is based on Matthews, Gillett, Stott, and Zickfeld (2009), climate change damages are primarily generated by the evolution in temperature anomaly and cumulative carbon emissions. While temperature anomaly is clearly correlated with cumulative carbon emissions, we consider both in order to capture the transition component of climate ambiguity on top of its physical one.

[9] An untabulated correlation analysis shows a pairways correlation between World and U.S. cumulative carbon emissions of approximately 99% making the use of either one similar.

occurred in the U.S. over the observation period. We complement our dataset with observations on variables employed as controls on a variety of robustness checks. These include the climate change news index based on the Wall Street Journal (WSJI, Engle et al., 2020), the Media Climate Change Concerns Index (MCCI, Ardia et al., 2023), the Textual Climate Change Risk Measures (TCRM, Faccini et al., 2023), and the Green-minus-Brown factor portfolio returns (GMB, Pástor et al., 2022). All of these variables are available online.

Table 1 provides a description of the data used in our pilot analysis on the market portfolio. Panel A presents summary statistics. Over our sample, the equity premium on the market portfolio is a textbook-level 8.3% per year with an annualized volatility of 14.7%, implying an annualized Sharpe ratio of 0.56. Equity index returns are left-skewed and characterized by non-negligible excess kurtosis, as expected. While the summary statistics of the 1-month T-bill rate appear typical (the annualized mean is just above 2% with very modest volatility, positive skewness but platikurticity), the ambiguity index $\mho^2$ appears to be small but also substantially variable (e.g., its coefficient of variation exceeds one, $0.048/0.046 \simeq 1.043$), and characterized by massive positive skewness and excess kurtosis. Finally, in light of the green finance literature on climate change, the temperature anomaly T^* is always positive ($0.46C^\circ$ on average), positively skewed, but displays tails thinner than a normal distribution. The variables measuring the environmental damages deriving from the existence of a temperature anomaly (droughts, floodings, freezing, etc.), all pick up the very same statistical features. Panel B of Table 1 reports correlations. It shows that while market portfolio excess returns are weakly correlated with all explanatory factors taken separately (including $\mho^2$), the climate-related variables and the associated damages are positively (and generally significantly) correlated with the ambiguity index. However, these correlations are never extreme (the highest is 0.55, between $\mho^2$ and cumulative $CO2$ emissions in the U.S.). Of course, given their very nature, the environmental damage variables and T^* correlate substantially.

[Table 1]

Figure 2 plots the key time-series variables. The second plot in the first row shows that the market portfolio realized variance is subject to classical clustering and visible regimes.

Realized variance has two visible troughs, in correspondence to the 2005-2007 and 2011-2019 periods, when it declines to less than half the overall sample mean. $\mho^2$ exhibits remarkable time variation with notable peaks corresponding to the economic crises as well as periods of market turmoil (2008-2009, 2017, and 2020-201) and troughs (like 2009-2010 and 2022). However, $\mho^2$ seems to possibly contain a weak, increasing trend that may be related to increasing climate change concerns. The two bottom rows of Figure 2 show that in naive, univariate regressions, T^* and cumulative carbon emissions hardly explain excess stock returns, display a negative relation with market volatility, but are positively related to $\mho^2$. The negative relation between climate change and volatility and its positive relation with ambiguity suggests that the evolution of climate change reduces risk but increases the uncertainty of probabilities (ambiguity) about the future states of the economy. This provides preliminary evidence of the importance of considering climate ambiguity in asset pricing and portfolio allocation problems.

[Figure 2]

2.2 Climate Ambiguity

By Barnett et al. (2020), climate change ambiguity is generated by the uncertainty about the distribution of: *i*) carbon dynamic, which maps carbon emissions into carbon in the atmosphere, *ii*) temperature dynamic, which maps carbon in the atmosphere into temperature changes, *iii*) consumption damages, which convert temperature changes into contractions of consumption levels, and *iv*) tipping points, which determine thresholds at which higher order of damages begin to occur. Accordingly, to estimate climate ambiguity, we relate the degree of ambiguity, $\mho^2$, to the following observable climate change variables: temperature anomaly, cumulative carbon emissions, firm-level carbon emission, and aggregate climate change damages. To account for the possible resolution of uncertainty by the realization of adverse climate scenarios, in some of the econometric specifications we further control for the yearly counts of extreme weather events (such as droughts and cyclones), which may reduce climate ambiguity. For every stock i, we estimate various specifications of the following time series regression

$$\mho_{i,t}^2 = \beta_{i,0} + \overbrace{\beta_{i,T}T_t^* + \beta_{i,C}CCO2_t + \sum_{k=1}^{3}\beta_{i,s_k}Scope(k)_{i,t} + \beta_{i,CD}CD_t + B_{i,cnt}Cnt_t}^{\mho_t^c} + B_{i,ctr}Ctr_t + \nu_t, \quad (2)$$

where T_t^* is the temperature anomaly, $CCO2_t$ is the level of cumulative carbon emissions in the U.S. atmosphere, $Scope(k)$ is the level of carbon emissions (scope 1, scope 2, and scope 3) produced by firm i, CD_t is the aggregate cost of disasters occurred in the U.S., Cnt_t is the $m \times N$ vector of disasters occurrences, and Ctr_t is a $j \times N$ matrix of control variables that includes WSJI, MCCI, and TCRM. The climate ambiguity, denoted $\mho^c$, is then estimated as the post-estimation values of $\mho_i^2$ predicted by the climate change variables in Equation (2).

2.3 Market Climate Ambiguity

As discussed above, we first focus on the market climate ambiguity and report the results of our analysis of what concerns the market portfolio, a proxy for the state economy. Table 2 reports the findings of estimating climate ambiguity for the market portfolio.[10] In a variety of regression specifications, it shows that a substantial portion of $\mho^2$ is explained by climate variables, in particular T^*, the cumulative CO2 emissions in the U.S., the number of cyclones, and the occurrence of wildfires. When either only T^* or a very few variables are included, the temperature anomaly explains a moderate portion of $\mho^2$, with adjusted R^2s between 25% and 44%. Extended models that add climate events and further controls produce R^2s spanning from 51% to 61%; yet, for such models, T^* tends to be insignificant. The cumulative CO2 emissions always enter the regressions with a positive and significant coefficient that turns out to be rather stable, always in the range of 0.12-0.18, irrespective of the inclusion of controls. Finally, note that the regression models in Columns (6)-(9) of Table 2 show that adding WSJI, MCCI, and TCRM, separately or together, increases only marginally the resulting explanatory power.[11]

[Table 2]

[10] Note that the estimation of Equation (2) for the market portfolio does not involve firm-level carbon emissions.

[11] Such additions may decrease the adjusted R^2 not only due to the complexity of a bigger penalization but also because the additional regressors may shorten the estimation sample.

Since the specification of Equation (2) in Column (5) delivers, excluding the models that add control variables, the highest adjusted R^2, we estimate the market climate ambiguity by employing the specification in Column (5). In particular, we employ the following:

$$\mho^C_{mkt,t} = \hat{\beta}_{mkt,T} T^*_t + \hat{\beta}_{mkt,C} CCO2_t + \hat{\beta}_{mkt,CD} CD_t + \hat{B}_{mkt,cnt} Cnt_t, \tag{3}$$

where $\hat{\beta}_{mkt,T}, \hat{\beta}_{mkt,C}, \hat{\beta}_{mkt,CD}$, and $\hat{B}_{mkt,cnt}$ are the estimates obtained from the model in Column (5) of Table 2. Throughout the rest of the paper, we refer to the latter as our *benchmark model* for estimating climate ambiguity.[12] In particular, we employ the same specification, augmented by individual carbon emissions, to estimate the firm-level climate ambiguity used in our cross-sectional analysis. Our robustness tests show that adopting climate ambiguity specifications based on the models augmented by controls in Columns (6)-(9) hardly affects our empirical findings. Nevertheless, it is reassuring that even when a large number of controls are included in Column (9), the maximum adjusted R^2 is 61 percent, rather close to the 52 percent achieved by Column (5), and that the coefficient estimates associated with cumulative emissions, temperature anomaly, and occurrence of wildfires remain generally precisely estimated.

Figure 3 depicts the time series of estimated market climate ambiguity by our benchmark model. We point out the main climate-related political events during the observation period. These are the Kyoto Protocol; the U.S. withdraws from the latter, the effective Kyoto Protocol date, the G8 Climate Agreement, the Doha Climate Change Conference, the EPA Tier 3, Paris Agreement and following the withdrawal of the U.S. from it, and the date in which the U.S. rejoin the agreement. Remarkably, the time-series climate market ambiguity shows peaks in response to each of these events and a generally increasing pattern, consistent with the increasing temperature anomaly and cumulative carbon emissions, and the consequently overall concern about climate change.

[Figure 3]

[12]Figure IA.1 in Internet Appendix IA.4 plots the estimated climate ambiguity for the specifications in Column (1)-(5) of Table 2. It shows that the specific model used to explain $\mho^2$ does not play a first-order role. In particular, Columns (2)-(5) all imply similar and highly correlated estimates of $\mho^c$ despite the heterogeneous underlying regression R^2.

3 Empirical Findings

3.1 Cross-Sectional Analysis

To perform the cross-sectional analysis, in June of each year, we sort all stocks into quintiles of climate ambiguity and carbon emissions. To determine the breakpoints for climate ambiguity, we follow Fama and French (1992) and subsequent literature and consider just the stocks listed on the NYSE.[13] However, to determine the portfolio breakpoints for scope 1, scope 2, and scope 3 emissions, we prioritize avoiding loss of information and consider all of the stocks in our CRSP database for which data on carbon emissions are available in Trucost.[14] The sorting induced by these breakpoints delivers 80 portfolios (our test portfolios), divided in the following way: 5 portfolios are obtained through the univariate sorting of the stocks into quintiles of climate ambiguity, and 75 portfolios (25 for each emission scope) are obtained through bivariate independent sorting into quintiles of climate ambiguity and carbon emissions. After sorting firms into the corresponding portfolio in June of each year (t), we compute the equal-weighted returns and climate ambiguity for the following 12 months, from July t to June $t+1$. At the end of June $t+1$, a new sorting and allocation take place.

We test a variety of multifactor models on the 80 portfolio returns, extract from each model the unexplained abnormal returns (*alphas*), and investigate whether there exists an asset pricing anomaly confirming our conjecture of a positive climate ambiguity premium. Recall that, according to the asset pricing under ambiguity literature (Maccheroni et al., 2013; Hara and Honda, 2022), the climate ambiguity premium directly relates with the alphas of the portfolios, provided that the employed sequence of pricing factors represent a fairly good candidate for a perfect pricing model under conditions of risk. To select such a candidate, we look at the average absolute cross-section pricing errors produced by each considered model and select the one reaching the minimum. According to the results of our estimations, such choice falls to the Fama and French (1996) three-factor model.[15]

[13]Untabulated results show that using breakpoints obtained by considering all the NYSE, NASDAQ and AMEX stocks do not produce material differences in the subsequent analyses.

[14]The use of NYSE breakpoints for carbon emissions delivers unbalanced portfolios in which most of the stocks are allocated in low carbon portfolio quintiles.

[15]We report the findings for the three-factor model as it delivers the lowest average absolute pricing error (Table 4). The findings for alternative models are reported in Internet Appendix IA.4

[Table 3]

Panel A.1 of Table 3 reports the summary statistics for the 5 portfolios obtained through univariate sorting of the stocks by their climate ambiguity. As expected, the average returns are increasing with respect to climate ambiguity quintiles, confirming the conjectured positive relation between climate ambiguity and expected stock returns (i.e., a positive climate ambiguity premium). In particular, relative to the 1$^{\text{st}}$ quintile, the 5$^{\text{th}}$ quintile portfolio displays an average excess return of 0.40 percent with a t-statistic of 6.12. Panel B.1 reports the *alphas* and associated t-statistics for the 5 univariate portfolios estimated from the Fama-French three-factor model. Consistent with our conjecture, the *alpha* of the low climate ambiguity portfolio is statistically insignificant. In contrast, for all other four portfolios the *alphas* are positive, statistically significant, and increasing in climate ambiguity. For the difference portfolio (high minus low climate ambiguity), the average abnormal return is 0.99 percent and is significant at the 99% level.

Panels A.2-A.4 of Table 3 provide the summary statistics for the 75 portfolios obtained by bivariate sortings of stocks into quintiles of climate ambiguity and carbon emissions. Overall, average returns tend to increase with respect to climate ambiguity, although not without exceptions. For scope 1 emissions portfolios, the average returns increase in the climate ambiguity only for the 3$^{\text{rd}}$ - 5$^{\text{th}}$ quintiles, while for the two lowest carbon portfolios, the average return displays a decreasing pattern with respect to climate ambiguity. This inverted pattern between returns and climate ambiguity for the low carbon portfolios is persistent and also displayed by portfolios sorting stocks by scope 2 and scope 3 emissions. The increasing pattern between average returns and climate ambiguity is instead consistent in the two upper quintiles of carbon, independent of the emissions type.

Panels B.2-B.4 of Table 3 report the estimated *alphas* and associated t-statistics for the 75 bivariate portfolios. Independently of the emission type used to perform the sorting, all the *alphas*, except those in the 1$^{\text{st}}$ carbon quintile in Panel B.2, are increasing with respect to climate ambiguity. Also, consistent with the theory, the t-statistics increase in climate ambiguity, with the high climate ambiguity quintile presenting the highest value. In most cases, the difference portfolios display positive and statistically significant *alphas*, at least at 90% confidence level.

The GRS test (Gibbons et al., 1989), reported in Table 4, rejects any multifactor model involving different combinations of market portfolio, size, value, investment, profitability, momentum, and the q factors, at any significance level. The lowest average absolute pricing error is achieved by the Fama-French three-factor model, with values spanning from 0.32 for the climate ambiguity-scope 3 bivariate portfolios to 0.48 for the univariate climate ambiguity portfolios. Table 4 further reports the GRS test and average absolute *alphas* for models considering a traded common *Climate Ambiguity Factor*, obtained as

$$\begin{aligned} CAF_{s,t} &= \frac{HighBrown_s + HighMedium_s + HighGreen_s}{3} \\ &\quad - \frac{LowBrown_s + LowMedium_s + LowGreen_s}{3}, \end{aligned} \tag{4}$$

where s is the scope type. All the models that include the CAF are statistically rejected at any level of confidence, which is not surprising if we consider the idiosyncratic nature of ambiguity, which therefore cannot be explain with a common risk factor as is done for traditional risks exposures. This is further discussed in what follows.

[Table 4]

3.2 Climate Risk vs Climate Ambiguity Premia

The evidence thus far suggests the existence of an asset pricing anomaly linked to climate ambiguity that is not explained by any of the common risk factors employed in the literature. Ideally, when a new anomaly is discovered, it should be possible to form a mimicking risk factor portfolio that explains it. However, the idiosyncratic nature of the climate ambiguity premium makes the substance of such an attempt void. In fact, since ambiguity premia are by definition firm-specific and may not be diversified (Izhakian, 2019), a common factor that explains them in the cross-section should, in principle, not exist (Maccheroni et al., 2013; Rocciolo, 2024).

Given the one-to-one correspondence between ambiguity and the *alphas*, which can also arise because of omitted risk factors, the standard asset pricing econometrics toolkit does not allow a decisive conclusion on the discovered anomaly. To test for the counterargument that the discovered *alphas* are due to omitted factors, we corroborate our analysis by looking at the cross-sectional relation between the *alphas* and the portfolios' average climate ambiguity, our cross-sectional candidate firm-specific pricing factor. To this end, for each set of portfolios, we estimate the following cross-section regression

$$a_i \;=\; \gamma \overline{\mho_i^c} + \xi_i, \tag{5}$$

where a_i are the *alphas* estimated through the time-series Fama-French three-factor regressions, and $\overline{\mho_i^c}$ is the time series average of the climate ambiguity of portfolio i, computed as the equal-weighted average of the climate ambiguity of the stocks in the portfolio. Note that we force the intercept of the regression in Equation (5) to zero in order to challenge, at most, our conjecture.[16] If the *alphas* quantify the climate ambiguity premium, we should observe from estimating Equation (5) a sufficiently high goodness of fit and a sensible reduction of the residual abnormal returns ξ_i compared to the original *alphas*, both in terms of magnitude and significance.

Table 5 reports the findings of estimating Equation (5). For the univariate portfolios sorted on climate ambiguity (Panel A), the evidence strongly supports the ambiguity premium conjecture. The cross-sectional adjusted R^2 is 92%, highlighting an almost linear relation between the abnormal returns and portfolio climate ambiguity. Further, all of the residual unexplained *alphas* (ξ_i) are statistically insignificant, except for the high climate ambiguity portfolio, which, in any case, is significant just at the 10% confidence level. For the bivariate portfolios, the evidence is less overwhelming but still supports our conjecture. The adjusted R^2s span from 41% for the scope 2 portfolios to the 53% for the scope 1 portfolios, exhibiting a good fit of the model in Equation (5) for any of the considered family of bivariate test assets.

The residual pricing errors, ξ_i, reported in Table 5, are in general closer to zero and less significant than their counterpart a_i in Table 3. For instance, for the 25 bivariate climate ambiguity scope 1 portfolios (Panel B), 16 out of 25 portfolios exhibit ξ_i lower than a_i in absolute values, while the remaining 9 have either close or slightly higher values than a_i. Out of 14 portfolios displaying significant *alphas* at a 95% confidence level in Table 3, only 2 remain significant after accounting for climate ambiguity. The evidence for the remaining 50 portfolios is similar. For the bivariate climate ambiguity scope 2 portfolios,

[16]The inclusion of a constant in Equation (5) delivers results that are even better aligned with our interpretation.

out of 11 portfolios showing unconditional pricing errors significant at least at the 95% level of confidence, at most one remains unexplained by the portfolios climate ambiguity, and the same holds true for the bivariate climate ambiguity scope 3 portfolios. Finally, both for the 5 univariate portfolios and the 75 bivariate portfolios, the residual pricing errors lose the increasing pattern in $\mho^c$ that is displayed by the *alphas* in Table 3, which further support the conjecture that those *alphas* reflect climate ambiguity premium.

[Table 5]

4 Alternative Hypotheses and Robustness Tests

The lack of a formal test for our claim that the pricing errors reported in Table 3 consist entirely of climate ambiguity premia leaves the door open to other possible explanations. To further validate our interpretation, we test in this section our conjecture against other possible risk factors, as well as climate risk proxies other than carbon emissions.

4.1 Alternative Risk Factors

The first alternative factor we consider is the Green-minus-Brown portfolio (GMB, Pástor et al., 2022). This factor portfolio is constructed by taking the difference between the returns on the portfolio of stocks classified as *green* and the return on the portfolio of stocks classified as *brown* according to their MSCI Environmental Pillar Score. Being based on environmental scores rather than carbon emissions only, the GMB factor aims to price a wider range of climate risk exposure types. The monthly returns on the GMB portfolio are available starting from January 2009 because of insufficient observations in the MSCI database for the preceding years.

Table IA.2 in Internet Appendix IA.4 reports the GRS test on the 80 portfolios for all the previously considered multifactor models, each augmented by the GMB factor. There is no sensible difference compared to the tests in Table 4 for the univariate portfolios. For these portfolios, the best model is the GMB-augmented CAPM, demonstrating an absolute average α of 0.38, marginally better than the GMB-augmented Fama-French three-factor model. The GRS test rejects all the models at any significance level, exactly as for the non-augmented models in Table 4. For the bivariate portfolios, the augmented models seem to perform better. For the scope 1 and scope 2 bivariate portfolios, the GRS test does not reject many of the augmented models at any significance level, while for scope 3, it rejects the hypothesis of jointly null pricing errors at least at the 90% confidence level. However, despite these statistical results, which appear to be in favor of interpreting the *alphas* in terms of *greenium*, a closer look shows that the evidence lacks economic significance. In fact, whenever the GRS test does not reject a model in Table IA.2, it does so with an associated $A|a_i|$ which is sensibly higher than that displayed by the corresponding non-augmented model in Table 4. This provides evidence that the statistical conclusion of the test is driven by higher standard errors displayed by the *alphas* rather than by a contraction of the latter, falsifying the alternative interpretation.

Next, we consider other proxies for climate risk that are not strictly related to carbon emissions or the firms' environmental scores but instead relate to the overall concerns of the market about climate change. These factors are the Wall Street Journal Index (WSJI), aggregate Media Climate Concern Index (MCCI), and aggregate Textual Climate Change Risk Measures (TCRM). Since these factors are not traded, we test their impact on the cross-section by examining their capacity to explain the *alphas* from our benchmark model (Cochrane, 2009). To this end, we estimate the following variation of Equation (5)

$$a_i \quad = \quad \gamma_{0,i}\overline{\mho_i^c} + \gamma_{WSJI} b_{i,WSJI} + \gamma_{MCCI} b_{i,MCCI} + \gamma_{TCRM} b_{i,TCRM} + \xi_i, \tag{6}$$

where $b_{i,WSJI}$, $b_{i,MCCI}$ and $b_{i,TCRM}$ are the estimated sensitivities of stock i's returns to WSJI, MCCI and TCRM from the time series regression tests of the stock returns on MKT, SMB, HML (our benchmark model in Table 4) augmented by the three indexes. The *alphas* a_i are determined according to two distinct methods: the first considers the *alphas* previously determined by employing the Fama-French three-factor model (benchmark model), and the second, for better consistency, those generated by the time-series regression tests on the augmented model.

Table IA.3 in Internet Appendix IA.4 reports the estimated ξ and associated t-statistics from Equation (6) with a_i estimated from the benchmark model. It shows that adding the climate concern risk factors is not informative. The adjusted R^2 spans from -12% for the bivariate climate ambiguity-scope 1 portfolios to 27% for the univariate portfolios, with an overall higher cross-sectional mispricing than that obtained by employing the climate ambiguity portfolios as the sole explanatory variable. In contrast, the climate concern factors perform well when the *alphas* are extracted from the augmented Fama-French three-factor model. As reported in Table IA.4 in Internet Appendix IA.4, the climate concern factors display a good performance with a minimum of 73% adjusted R^2 for the univariate portfolios and an overall reduced mispricing for portfolios in the bottom quintiles of climate ambiguity. However, for portfolios in the upper two quintiles of climate ambiguity, the inclusion of climate concerns factors worsens the mispricing, with higher residual pricing errors than those obtained in our univariate regression in Table 5. Moreover, the increasing pattern between pricing errors and climate ambiguity is preserved, suggesting that the remaining unexplained part of the residual is due to climate ambiguity. Indeed, the estimation of the full specification in Equation (6), which therefore includes the portfolios' average climate ambiguity, confirms our last conjecture, as reported in Table IA.5. For the univariate portfolios, the adjusted R^2 is 99% with essentially null residual and associated standard errors. For the bivariate portfolios, the adjusted R^2 is never lower than 93% with residual pricing errors that are mostly insignificant. This test highlights that, while climate concerns must be considered, they do not entirely absorb climate ambiguity. Therefore, the latter should be considered as it remains a substantial determinant of expected stock returns.

4.2 Methodological Robustness Checks

Throughout the analysis, we make a sequence of methodological choices, including the econometric specification for estimating climate ambiguity in Equation (2) and the use of $\mho^2$ as a metric for the aggregate ambiguity. This section explores the robustness of our main results across alternative methodological choices.

First, we test the robustness of our results across the following different models for determining $\mho^c$ from Equation (2): Model (1) only T^*, Model (2) only $CCO2$, (3) both T^* and $CCO2$, (4) Model (3) augmented by the aggregate cost of disasters, (5) our benchmark model, from (6) to (8) the benchmark model augmented by the WSJI, the MCCI, and the TCRM, respectively, and (9) the full model which considers all the variables listed above. All models are augmented by scope 1, scope 2, and scope 3 carbon emissions. Figure IA.2

in Internet Appendix IA.3 depicts the difference in the cumulative returns of the high and the low climate ambiguity portfolios for the eight alternative models. Independent of the model, each series displays a similar pattern to that obtained from our benchmark in model Figure 1. In all cases, the high climate ambiguity portfolio almost everywhere dominates the low climate ambiguity portfolio in terms of cumulative returns, generating an almost everywhere positive difference. Next, for each $\mho^c$ model, we replicate our baseline analysis: we first sort the stocks according to the new estimated climate ambiguity, allocate the stocks into portfolios, and estimate the pricing errors from the Fama-French three-factor model. The empirical findings are reported in Table IA.5 to Table IA.9 in Internet Appendix IA.4. For any $\mho^c$ specification, the evidence remains substantially equivalent to that in our main analysis, except for 8 out of the 640 portfolios generated by the new sorting operations.

Next, we consider alternative proxies of ambiguity employed in earlier studies: the volatility of mean (*VolMean*) and the volatility of volatility (*VolVol*).[17] We replicate our time series analysis in Table 2 by replacing $\mho^2$ with *VolMean* and *VolVol*. The findings reported in Table IA.10 and Table IA.11 in Internet Appendix IA.4 show the absence of any meaningful relation of both *VolMean* and *VolVol* with the climate variables. For instance, a simple model that considers either only T^* or only CCO2 displays a negative and statistically significant coefficient estimate for *VolMean* and an insignificant coefficient for *VolVol*. Adding other climate variables or combining T^* and CCO2 does not improve the model in any meaningful way. Furthermore, the adjusted R^2 of the baseline models without climate controls displays sensibly lower values than in our main analysis, spanning from 0.1% to 10.8%. Finally, untabulated analysis finds a lack of any pattern in expected stock returns arising from sorting stocks on either *VolMean* or *VolVol*. Overall, the evidence suggests that *VolMean* and *VolVol* may capture other aspects of uncertainty, but these are unrelated to climate change.

5 Conclusion

In a theoretical perspective, climate change uncertainty has long been recognized as a mechanism that induces ambiguity—the uncertainty on the probabilities of payoff-relevant

[17] See, for example, Garlappi, Uppal, and Wang (2007).

outcomes—in the economy. However, to date, empirical support for this theoretical conjecture has been sparse. This paper fills this gap between theory and data, providing empirical evidence that validates the relevance of climate ambiguity in asset pricing. We examine the relationship between climate change and ambiguity in the economy by investigating its impact on the cross-section of expected stock returns. First, we extract firm-specific climate ambiguity from the total ambiguity based upon an exhaustive family of climate-change proxies. Next, we sort a standard universe of U.S. stocks into portfolios according to their estimated exposure to climate ambiguity and carbon emissions, with the aim to disentangle possible common effects. The resulting portfolios display unexplained abnormal returns, which are increasing in their climate ambiguity, both in their magnitude and statistical significance. A cross-sectional idiosyncratic climate ambiguity factor explains up to 92% of the abnormal returns, providing evidence consistent with the existence of a climate ambiguity premium. The pricing errors and their correlation with the portfolios' climate ambiguity are persistent and robust across different climate risk metrics, estimation methodologies for climate ambiguity, and multifactor models employed in the cross-section analysis.

In conclusion, we provide novel broad-market evidence that climate change affects asset prices through the channel of ambiguity, adding to recent work on the consequences of climate change for the economy and the stock market. Undoubtedly, other mechanisms are important for how climate change affects financial markets. Nevertheless, we provide robust evidence on the importance of considering further layers of uncertainty, such as ambiguity, when attempting to price climate change uncertainty, as predicted by the theoretical literature.

References

Ait-Sahalia, Y., Mykland, P. A., Zhang, L., 2005. How often to sample a continuous-time process in the presence of market microstructure noise. Review of Financial Studies 18, 351–416.

Andersen, T. G., Bollerslev, T., Diebold, F. X., Ebens, H., 2001. The distribution of realized stock return volatility. Journal of Financial Economics 61, 43–76.

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

Aswani, J., Raghunandan, A., Rajgopal, S., 2024. Are carbon emissions associated with stock returns? Review of Finance 28, 75–106.

Augustin, P., Izhakian, Y., 2020. Ambiguity, volatility, and credit risk. Review of Financial Studies 33, 1618–1672.

Avramov, D., Cheng, S., Lioui, A., Tarelli, A., 2022. Sustainable investing with esg rating uncertainty. Journal of Financial Economics .

Avramov, D., Lioui, A., Liu, Y., Tarelli, A., 2021. Dynamic esg equilibrium. SSRN eLibrary 3935174 .

Bandi, F. M., Russell, J. R., 2006. Separating microstructure noise from volatility. Journal of Financial Economics 79, 655–692.

Barnett, M., 2023. Climate change and uncertainty: An asset pricing perspective. Management Science 69, 7562–7584.

Barnett, M., Brock, W., Hansen, L. P., 2020. Pricing uncertainty induced by climate change. Review of Financial Studies 33, 1024–1066.

Barnett, M., Brock, W., Hansen, L. P., 2021. Confronting uncertainty in the climate change dynamics. Working Paper .

Bayes, T., Price, R., Canton, J., 1763. An essay towards solving a problem in the doctrine of chances. C. Davis, Printer to the Royal Society of London London, U. K.

Berger, L., Emmerling, J., Tavoni, M., 2017. Managing catastrophic climate risks under model uncertainty aversion. Management Science 63, 749–765.

Bernoulli, J., 1713. Ars Conjectandi (The Art of Conjecturing).

Billio, M., Guidolin, M., Rocciolo, F., 2024. Responsible investing under climate change uncertainty. Working Paper .

Bolton, P., Kacperczyk, M., 2021. Do investors care about carbon risk? Journal of Financial Economics .

Bolton, P., Kacperczyk, M., 2023. Global pricing of carbon-transition risk. Journal of Finance 78, 3677–3754.

Bolton, P., Kacperczyk, M., 2024. Are carbon emissions associated with stock returns? comment. Review of Finance 28, 107–109.

Brenner, M., Izhakian, Y., 2018. Asset pricing and ambiguity: Empirical evidence. Journal of Financial Economics 130, 503–531.

Carhart, M. M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

Cochrane, J. H., 2009. Asset pricing: Revised edition. Princeton university press.

Collard, F., Mukerji, S., Sheppard, K., Tallon, J., 2018. Ambiguity and the historical equity premium. Quantitative Economics 9, 945–993.

Ellsberg, D., 1961. Risk, ambiguity, and the savage axioms. Quarterly Journal of Economics 75, 643–669.

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

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

Fama, E. F., French, K. R., 1992. The cross-section of expected stock returns. Journal of Finance 47, 427–465.

Fama, E. F., French, K. R., 1996. Multifactor explanations of asset pricing anomalies. Journal of Finance 51, 55–84.

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

French, K. R., Schwert, G. W., Stambaugh, R. F., 1987. Expected stock returns and volatility. Journal of Financial Economics 19, 3–29.

Fu, R., Melenberg, B., Schweizer, N., 2023. Comment on "a theoretical foundation of ambiguity measurement"[j. econ. theory 187 (2020) 105001]. Journal of Economic Theory 207, 105573.

Garlappi, L., Uppal, R., Wang, T., 2007. Portfolio selection with parameter and model uncertainty: A multi-prior approach. Review of Financial Studies 20, 41–81.

Gibbons, M. R., Ross, S. A., Shanken, J., 1989. A test of the efficiency of a given portfolio. Econometrica pp. 1121–1152.

Giglio, S., Kelly, B., Stroebel, J., 2021. Climate finance. Annual Review of Financial Economics 13, 15–36.

Hara, C., Honda, T., 2022. Implied ambiguity: mean-variance inefficiency and pricing errors. Management Science 68, 4246–4260.

Heal, G., 2017. The economics of the climate. Journal of Economic Literature 55, 1046–63.

Heal, G., Millner, A., 2014. Reflections: Uncertainty and decision making in climate change economics. Review of Environmental Economics and Policy 8, 120–137.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. Review of Financial Studies 28, 650–705.

Hsu, P.-H., Li, K., Tsou, C.-Y., 2023. The pollution premium. Journal of Finance 78, 1343–1392.

Izhakian, Y., 2017. Expected utility with uncertain probabilities theory. Journal of Mathematical Economics 69, 91–103.

Izhakian, Y., 2019. Knight meets sharpe: Capital asset pricing under ambiguity. SSRN eLibrary 2007815.

Izhakian, Y., 2020. A theoretical foundation of ambiguity measurement. Journal of Economic Theory 187, 105001.

Izhakian, Y., 2024. A theoretical foundation of ambiguity measurement: A reply. SSRN eLibrary 4828038 .

Izhakian, Y., Yermack, D., 2017. Risk, ambiguity, and the exercise of employee stock options. Journal of Financial Economics 124, 65–85.

Izhakian, Y., Yermack, D., Zender, J. F., 2022. Ambiguity and the tradeoff theory of capital structure. Management Science 68, 4090–4111.

Jaynes, E. T., 1957. Information theory and statistical mechanics. Physical Review 106, 620.

Laplace, P. S., 1814. Théorie analytique des probabilitiés.

Lemoine, D., Traeger, C. P., 2016. Ambiguous tipping points. Journal of Economic Behavior & Organization 132, 5–18.

Liu, L. Y., Patton, A. J., Sheppard, K., 2015. Does anything beat 5-minute rv? a comparison of realized measures across multiple asset classes. Journal of Econometrics 187, 293–311.

Maccheroni, F., Marinacci, M., Ruffino, D., 2013. Alpha as ambiguity: Robust mean-variance portfolio analysis. Econometrica 81, 1075–1113.

Matthews, H. D., Gillett, N. P., Stott, P. A., Zickfeld, K., 2009. The proportionality of global warming to cumulative carbon emissions. Nature 459, 829–832.

Millner, A., Dietz, S., Heal, G., 2013. Scientific ambiguity and climate policy. Environmental and Resource Economics 55, 21–46.

Pástor, L., Stambaugh, R. F., Taylor, L. A., 2022. Dissecting green returns. Journal of Financial Economics 146, 403–424.

Rocciolo, F., 2024. Arbitrage pricing under ambiguity. SSRN eLibrary 3804478 .

Sautner, Z., Van Lent, L., Vilkov, G., Zhang, R., 2023. Firm-level climate change exposure. Journal of Finance 78, 1449–1498.

Scholes, M., Williams, J., 1977. Estimating betas from nonsynchronous data. Journal of Financial Economics 5, 309–327.

Sheppard, W. F., 1897. On the calculation of the most probable values of frequency-constants, for data arranged according to equidistant division of a scale. Proceedings of the London Mathematical Society 1, 353–380.

Stuart, A., Ord, K., 2010. Kendall's advanced theory of statistics, distribution theory, vol. 1. John Wiley & Sons.

Figure 1: Cumulative returns for the high and low climate ambiguity portfolios

The figure plots the monthly cumulative returns for the high (5^{th} quintile) and low (1^{st} quintile) climate ambiguity portfolios, obtained by the unconditional sorting of al stocks listed at NYSE, NASDAQ, and AMEX on their climate ambiguity into quintiles. The period the variables are observed spans from January 1993 to December 2020.

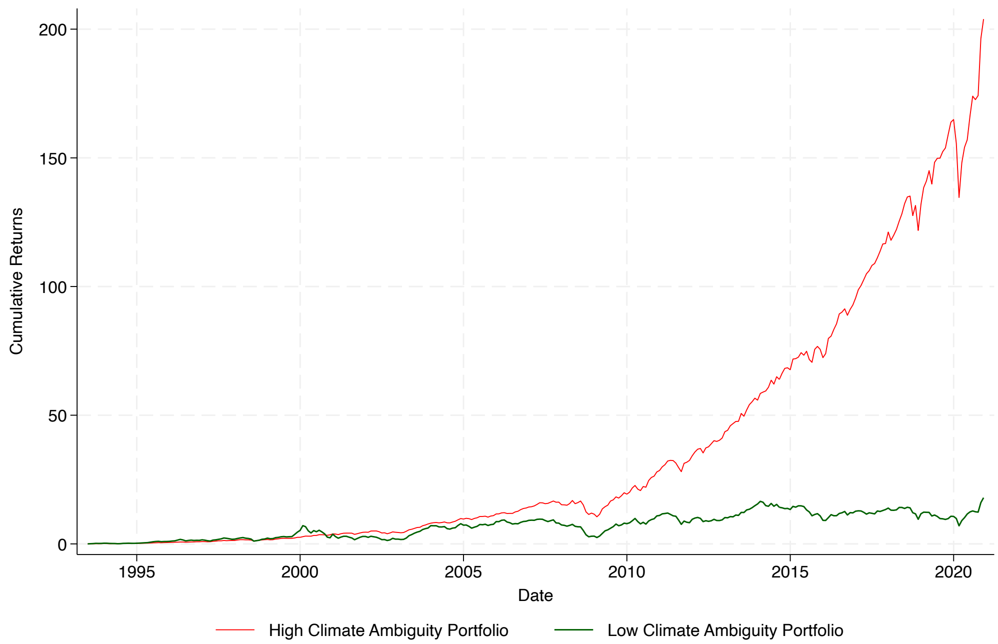


Figure 2: Baseline findings graphical summary

Graphical summary for returns, risk, ambiguity, and their estimated linear relations with temperature anomaly and cumulative carbon emissions. The plots on the first row depicts the monthly time series of the market portfolio's excess returns (left), estimated volatility (center), and the (total) ambiguity (right). The scatter plots on the second and third rows report on the x-axis the temperature anomaly and cumulative carbon emissions, respectively, and the market portfolio returns (left), estimated volatility (center) and estimated ambiguity (right) on the y-axis. Each plot reports the univariate OLS regression line with 95% confidence bands. The period the variables are observed spans from January 1993 to December 2020.

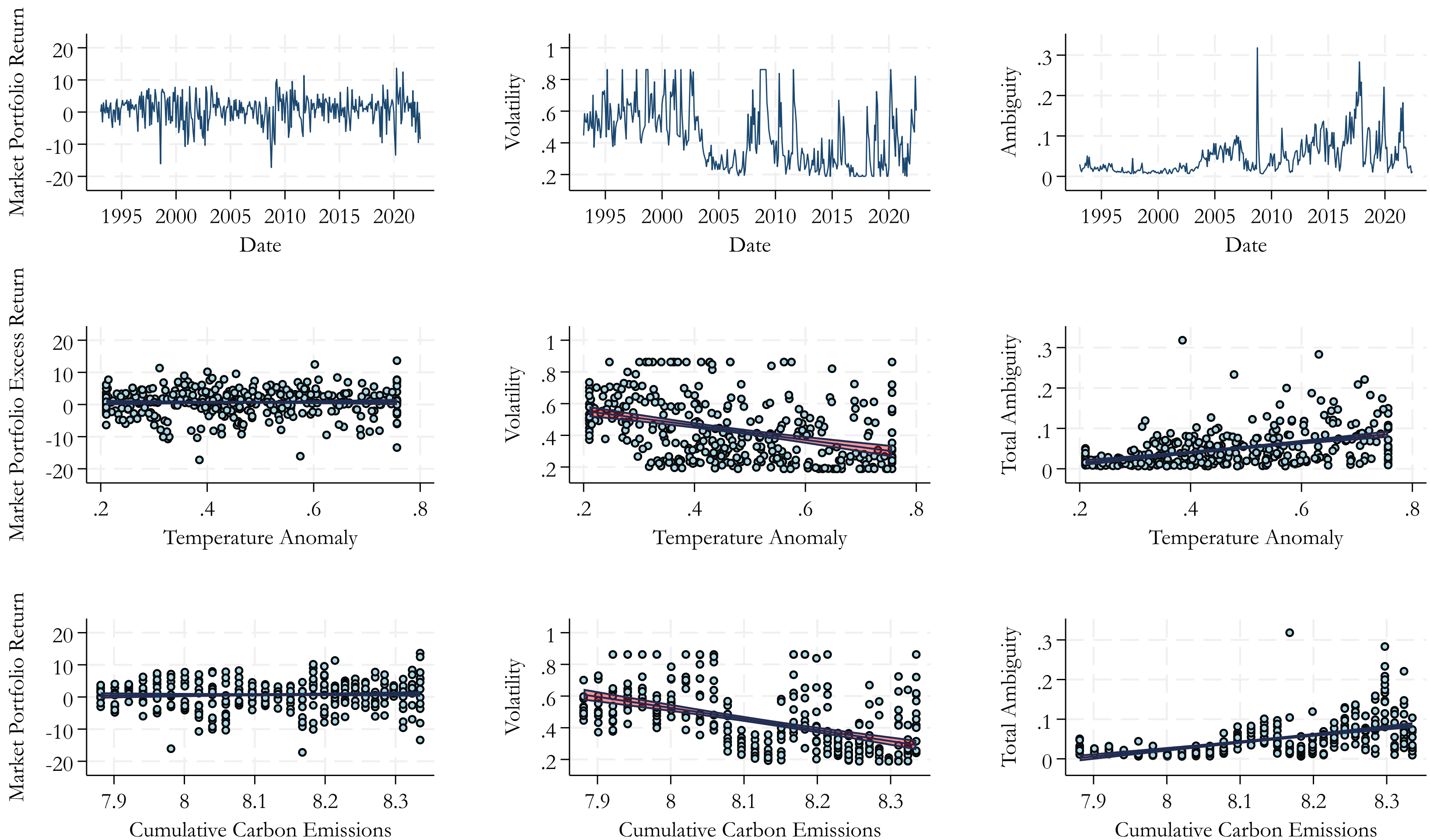


Figure 3: Estimated climate ambiguity from the benchmark model

Fitted time series of the market portfolio's climate ambiguity, estimated from the linear combination of temperature anomaly, cumulative carbon emissions, aggregate cost of disasters, and yearly counts of extreme weather events byEquation (2). the following climate change related events are highlighted: Kyoto Protocol (KP, 11 December 1997), U.S. withdrawals from KP (1 March 2001), KP effective start date (16 February 2005), G8 Climate Agreement (6 July 2005), Doha Climate Change Conference (26 November 2012), EPA Tier 3 Initiative (18 April 2014), Paris Agreement (12 December 2015), U.S. withdrawals from Paris Agreement (1 June 2017). The period the variables are observed spans from January 1993 to December 2020.

Table 1: Summary statistics

Summary statistics for the main variables employed in the analysis. Mkt-RF and R^f are the market portfolio excess returns and the 4 weeks T-Bill rates from the Kenneth French data library. $\mho^2$ is the ambiguity degree obtained by employing the methodology described in Internet Appendix IA.1. σ is the market monthly volatility computed using intraday returns on the SPDR50 adjusted for the Scholes and Williams (1977) correction as detailed in Internet Appendix IA.2. T^* is the monthly temperature anomaly measured in C° relative to the average temperature in the period 1901-2010. CCO2 is the annual cumulative carbon emissions in the U.S. measured in log billion tonnes. Drought, Flooding, Freeze, Storm, Cyclone, Wildfire, and Winter Storm, are the annual number of occurrences of each of these disasters in the U.S., and the Cost of Disasters is the annual CPI-adjusted cost in billions of dollars of the sum of all the climate disasters in the U.S. over a year. The period the variables are observed spans from January 1993 to December 2020.

Panel A: Descriptive Statistics

	Obs.	Mean	Median	St.Dev	Skewness	Kurtosis	Min	Max
Mkt-RF	335	0.689	1.290	4.412	-0.645	4.258	-17.230	13.650
R^f	335	0.182	0.140	0.174	0.442	1.677	0.000	0.560
σ	335	0.434	0.410	0.192	0.610	2.455	0.189	0.863
$\mho^2$	335	0.048	0.033	0.046	2.114	9.335	0.006	0.318
T^*	335	0.463	0.448	0.162	0.204	1.990	0.210	0.756
CCO2	335	8.129	8.151	0.137	-0.207	1.809	7.881	8.335
Drought	335	0.796	1.000	0.404	-1.469	3.159	0.000	1.000
Flooding	335	1.051	1.000	1.018	0.868	3.450	0.000	4.000
Freeze	335	0.136	0.000	0.431	3.277	13.040	0.000	2.000
Storm	335	4.824	4.000	3.586	0.476	2.120	0.000	13.000
Cyclone	335	1.598	1.000	1.691	1.177	4.328	0.000	7.000
Wildfire	335	0.609	1.000	0.489	-0.447	1.200	0.000	1.000
Winter Storm	335	0.541	0.000	0.722	0.943	2.508	0.000	2.000
Cost of Disasters	335	66.660	32.900	77.625	2.394	8.832	10.000	366.700

Panel B: Correlations

Variables	Mkt-RF	$\mho^2$	T^*	CCO2	Flooding	Storm	Cyclone	Cost of Disasters
Mkt-RF	1.000							
$\mho^2$	0.055	1.000						
T^*	0.012	0.449	1.000					
CCO2	0.033	0.549	0.748	1.000				
Flooding	0.100	0.323	0.345	0.293	1.000			
Storm	0.053	0.462	0.685	0.857	0.334	1.000		
Cyclone	0.029	0.144	0.256	0.198	-0.206	0.400	1.000	
Cost of Disasters	0.031	0.517	0.292	0.370	0.021	0.421	0.565	1.000

Table 2: Estimated market climate ambiguity

The table reports the time series coefficient estimates of different specifications of the following econometric model for the market degree of ambiguity, $\mho_t^2$

$$\mho_t^2 = \beta_0 + \beta_T T_t^* + \beta_C CCO2_t + \beta_{CD} CD_t + B_{cnt} Cnt_t + B_{ctr} Ctr_t + \nu_t,$$

where T^* is the world ocean surface temperature anomaly relative to the period 1901-2010, $CCO2$ is the U.S. level of cumulative carbon emissions, and CD is the aggregate cost of disasters occurred in the U.S. measured in CPI adjusted billion dollars. Cnt controls for the disaster events: the count variables Drought, Flooding, Freeze, Storm, Cyclone, Wildfire, and Winter Storm. Ctr controls for WSJI (Engle et al., 2020),MCCI (Ardia et al., 2023) and TCRMI (Faccini et al., 2023). All the reported standard errors are Newey-West adjusted for heteroskedasticity. The period the variables are observed spans from January 1993 to December 2020.Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T*	0.115***		0.025*	0.024*	0.022	0.019	0.028	0.041*	0.053**
	(0.011)		(0.014)	(0.014)	(0.015)	(0.016)	(0.023)	(0.021)	(0.026)
CCO2 US		0.167***	0.145***	0.118***	0.128***	0.126***	0.180*	0.167***	0.164
		(0.012)	(0.015)	(0.016)	(0.024)	(0.025)	(0.101)	(0.048)	(0.116)
Cost of Disasters				0.000***	0.000***	0.000***	0.000***	0.000***	0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Drought					0.003	0.005	0.001	0.011*	0.010
					(0.004)	(0.004)	(0.009)	(0.006)	(0.010)
Flooding					0.005**	0.004	0.004	0.004	0.000
					(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
Freeze					0.005*	0.004	0.009*	0.007	0.012*
					(0.003)	(0.003)	(0.005)	(0.005)	(0.007)
Storm					-0.001	-0.001	-0.000	0.001	0.003
					(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Cyclone					-0.004***	-0.004*	-0.007***	-0.003	-0.002
					(0.001)	(0.002)	(0.002)	(0.002)	(0.004)
Wildfire					-0.007**	-0.008**	-0.020**	-0.022***	-0.035***
					(0.004)	(0.004)	(0.008)	(0.005)	(0.010)
Winter Storm					-0.003	-0.003	-0.004	-0.008**	-0.008
					(0.002)	(0.002)	(0.004)	(0.003)	(0.005)
Constant	-0.007*	-1.309***	-1.143***	-0.935***	-1.013***	-0.996***	-1.424*	-1.331***	-1.320
	(0.004)	(0.097)	(0.119)	(0.122)	(0.188)	(0.196)	(0.807)	(0.384)	(0.933)
N. Obs.	353	335	335	335	335	293	216	239	174
Adj. R^2	0.251	0.376	0.381	0.442	0.513	0.489	0.501	0.562	0.611
WSJI	NO	NO	NO	NO	NO	YES	NO	NO	YES
MCCI	NO	NO	NO	NO	NO	NO	YES	NO	YES
TCRMI	NO	NO	NO	NO	NO	NO	NO	YES	YES

Table 3: Summary statistics and estimated *alphas* for the 80 test portfolios

The table reports the summary statistics (Panel A) and *alphas* obtained from the three-factor regression test (Panel B)

$$R_{i,t} = a_i + b_i \mathrm{MKT}_t + s_i \mathrm{SMB}_t + h_i \mathrm{HML}_t + \varepsilon_{i,t},$$

where MKT, SMB, and HML are the Fama and French (1996) three-factor portfolios: market, size, and value, respectively. Low to high refer to the climate ambiguity quintiles of the sorted stocks, and green to brown refer to their carbon emissions. Panel A reports the average historical return and standard deviation of the 5 portfolios formed on climate ambiguity (Panel A.1), and the 75 portfolios formed by bivariate sorting in quintiles by climate ambiguity and scope 1 (Panel A.2), scope 2 (Panel A.3), and scope 3 emissions (Panel A.4). For the same portfolios, Panel B reports their estimate for a_i (pricing errors) and associated t-statistics. The period the variables are observed spans from January 1993 to December 2020.

	Low	2	3	4	High	High-Low	Low	2	3	4	High	High-Low
Panel A: Summary Statistics												
	Mean						Std. Deviation					
Panel A.1: Univariate												
All	1.31	1.34	1.25	1.24	1.71	0.40	9.14	6.63	5.46	4.62	4.04	6.12
Panel A.2: Bivariate Scope 1												
Green	2.04	1.69	1.37	1.20	1.61	-0.43	8.47	6.93	5.42	4.99	5.14	6.40
2	1.43	1.20	1.40	1.30	1.30	-0.13	8.58	6.79	5.79	5.09	4.09	6.01
3	1.00	1.31	1.31	1.16	1.14	0.14	10.36	7.92	6.03	4.97	3.73	7.95
4	0.88	1.28	1.16	0.87	0.97	0.09	9.74	7.45	6.14	4.99	3.51	7.65
Brown	0.68	1.06	0.97	0.96	0.94	0.26	11.01	8.27	6.83	5.20	3.47	8.91
Panel A.3: Bivariate Scope 2												
Green	1.86	1.63	1.40	1.32	1.36	-0.51	8.29	6.55	5.19	4.44	3.52	6.75
2	0.91	1.19	1.23	1.13	1.22	0.31	9.72	7.17	5.85	5.00	3.83	7.35
3	1.39	1.07	1.21	1.03	1.09	-0.29	10.53	7.79	6.25	5.04	3.82	8.08
4	0.75	1.18	1.02	0.95	1.07	0.32	10.48	8.75	6.78	5.36	3.67	8.37
Brown	0.80	1.23	1.09	0.92	0.81	0.01	11.17	8.50	6.71	5.72	3.62	8.79
Panel A.4: Bivariate Scope 3												
Green	2.07	1.70	1.51	1.39	1.58	-0.49	24.40	13.87	10.83	8.78	8.73	6.33
2	1.12	1.08	1.25	1.34	1.53	0.41	21.90	13.16	9.89	7.94	6.85	8.14
3	1.13	0.91	1.07	1.29	1.24	0.11	25.52	13.69	10.20	8.17	6.44	12.46
4	0.88	0.93	0.93	1.06	1.25	0.37	21.16	14.69	10.67	8.32	6.13	9.64
Brown	0.71	0.70	0.81	0.88	1.04	0.33	18.13	14.40	10.46	8.26	6.07	9.82
Panel B: Pricing Errors												
	a						$t(a)$					
Panel B.1: Univariate												
All	0.00	0.35	0.40	0.51	1.00	0.99	0.40	3.11	4.58	6.64	15.30	4.76
Panel B.2: Bivariate Scope 1												
Green	0.78	0.56	0.40	0.36	0.57	-0.21	3.01	3.70	3.86	3.54	3.48	-0.69
2	-0.09	0.35	0.34	0.34	0.55	0.64	-0.24	2.03	2.66	4.09	4.65	1.51
3	-0.39	0.01	0.17	0.36	0.45	0.84	-0.78	0.05	1.15	3.14	4.39	1.62
4	-0.27	0.07	-0.13	0.23	0.34	0.61	-0.52	0.26	-0.78	2.18	3.35	1.17
Brown	-0.35	0.00	-0.01	0.28	0.41	0.76	-0.55	0.01	-0.03	1.74	2.93	1.27
Panel B.3: Bivariate Scope 2												
Green	0.55	0.55	0.48	0.58	0.85	0.29	2.52	3.22	4.69	4.58	5.44	1.03
2	-0.46	0.08	0.27	0.28	0.56	1.02	-1.50	0.42	2.23	2.52	4.94	2.98
3	-0.04	-0.11	0.23	0.19	0.44	0.48	-0.13	-0.51	1.60	1.63	4.15	1.36
4	-0.45	-0.09	0.00	0.09	0.44	0.89	-1.09	-0.33	0.00	0.60	4.24	2.02
Brown	-0.50	-0.06	0.07	0.04	0.21	0.71	-1.09	-0.19	0.31	0.28	2.13	1.60
Panel B.4: Bivariate Scope 3												
Green	0.50	0.45	0.46	0.46	0.87	0.37	2.11	3.08	4.25	3.93	4.99	1.24
2	-0.39	0.19	0.32	0.30	0.65	1.04	-1.25	0.94	2.47	2.90	5.66	2.96
3	-0.15	-0.23	0.21	0.16	0.41	0.57	-0.39	-1.10	1.51	1.41	3.96	1.34
4	-0.63	-0.07	0.02	0.22	0.44	1.07	-1.49	-0.28	0.10	1.42	3.74	2.46
Brown	0.19	-0.26	0.05	0.09	0.23	0.04	0.40	-0.70	0.20	0.64	2.43	0.09

Table 4: Summary of the GRS test for the 80 test portfolios

The table reports the GRS statistics and associated p-values for the hypothesis test that the intercept in the multifactor model that include the factors listed in first column are jointly null. $A|a_i|$ is the average absolute intercept obtained from each model. MKT is the market portfolio excess return, SMB and HML are the Fama-French factor portfolios for size and value, UMD is the momentum factor portfolio. RMW and CMA are the Fama and French (2015) factor portfolios for profitability and investments. Full+Consumption Factors model augment the Fama and French (2015) five-factor model with UMD, and with the q factors by Hou et al. (2015). CAF is the portfolio of a long position on the high climate ambiguity portfolio and a short position on the low climate ambiguity portfolio, computed by Equation (4). The period the variables are observed spans from January 1993 to December 2020.

	Univariate			Bivariate - Scope 1			Bivariate- Scope 2			Bivariate - Scope 3		
	GRS	p(GRS)	$A\|a_i\|$	GRS	p(GRS)	$A\|a_i\|$	GRS	p(GRS)	$A\|a_i\|$	GRS	p(GRS)	$A\|a_i\|$
MKT	49.29	0.00	0.50	3.18	0.00	0.37	2.87	0.00	0.34	3.29	0.00	0.35
MKT,SMB,HML	52.85	0.00	0.48	3.31	0.00	0.34	3.06	0.00	0.30	3.62	0.00	0.32
MKT,SMB,HML,UMD	53.45	0.00	0.62	3.56	0.00	0.35	3.15	0.00	0.30	3.76	0.00	0.32
MKT,SMB,HML,CMA,RMW	44.81	0.00	0.49	3.87	0.00	0.36	3.67	0.00	0.33	4.42	0.00	0.33
MKT,SMB,HML,CMA,RMW,UMD	45.75	0.00	0.60	4.00	0.00	0.36	3.69	0.00	0.32	4.44	0.00	0.33
MKT+ q factors	42.73	0.00	0.70	3.79	0.00	0.47	3.63	0.00	0.44	4.25	0.00	0.44
Full + q factors	40.67	0.00	0.65	4.08	0.00	0.38	3.67	0.00	0.33	4.56	0.00	0.36
MKT,CAF	44.74	0.00	0.84	2.85	0.00	0.43	2.69	0.00	0.34	3.17	0.00	0.34
MKT,SMB,HML,CAF	45.12	0.00	0.74	3.03	0.00	0.39	2.92	0.00	0.32	3.54	0.00	0.33
Full + CAF	40.34	0.00	0.68	4.05	0.00	0.41	3.64	0.00	0.33	4.51	0.00	0.34

Table 5: Cross-sectional test on the 80 test portfolios: pricing errors summary

The table reports the estimated residuals and associated t-statistics of the cross-section regression test

$$a_i = \gamma \overline{\mho_i^c} + \xi_i,$$

where, a_i is the average returns on the test portfolio i left unexplained by the Fama-French three-factor model and $\overline{\mho_i^c}$ is its time-series average climate ambiguity. The portfolios are the 80 portfolios obtained by sorting stocks on climate ambiguity and firm-level carbon emissions, as described in Section 2. The period the variables are observed spans from January 1993 to December 2020.

			ξ					$t(\xi)$			Adj. R^2
	Low	2	3	4	High	Low	2	3	4	High	
Panel A: Univariate											
All	0.08	0.21	0.17	0.13	-0.10	0.49	1.31	1.03	0.84	-1.66	92%
Panel B: Bivariate Scope 1											
Green	0.57	0.37	0.18	-0.02	0.38	2.12	1.38	0.67	-0.08	1.49	53%
2	0.09	-0.10	0.17	0.09	0.10	0.33	-0.38	0.63	0.33	0.39	
3	-0.47	-0.02	0.09	-0.02	0.05	-1.76	-0.08	0.32	-0.07	0.18	
4	-0.37	0.06	-0.02	-0.30	-0.11	-1.38	0.22	-0.06	-1.14	-0.44	
Brown	-0.65	-0.24	-0.22	-0.14	-0.10	-2.43	-0.90	-0.81	-0.54	-0.38	
Panel C: Bivariate Scope 2											
Green	0.49	0.42	0.28	0.30	0.45	1.69	1.45	0.98	1.04	1.62	41%
2	-0.52	-0.05	0.07	-0.01	0.16	-1.80	-0.17	0.25	-0.02	0.57	
3	-0.10	-0.24	0.03	-0.10	0.04	-0.36	-0.83	0.10	-0.35	0.13	
4	-0.51	-0.22	-0.20	-0.20	0.03	-1.76	-0.76	-0.70	-0.71	0.11	
Brown	-0.56	-0.19	-0.13	-0.25	-0.21	-1.93	-0.66	-0.46	-0.89	-0.75	
Panel D: Bivariate Scope 3											
Green	0.44	0.32	0.26	0.17	0.46	1.56	1.13	0.92	0.62	1.72	44%
2	-0.45	0.06	0.12	0.01	0.24	-1.60	0.20	0.41	0.02	0.88	
3	-0.22	-0.36	0.00	-0.14	0.00	-0.77	-1.29	0.01	-0.49	-0.01	
4	-0.70	-0.21	-0.19	-0.08	0.02	-2.46	-0.73	-0.67	-0.29	0.08	
Brown	0.12	-0.39	-0.16	-0.21	-0.20	0.42	-1.40	-0.57	-0.77	-0.75	

IA Internet Appendix

IA.1 Estimating ambiguity

Our empirical measure of ambiguity is extracted from a firm's equity. Intuitively, ambiguity represents the uncertainty in future outcome *probabilities*, as opposed to risk, which measures the uncertainty in future *outcomes*. Utilizing the EUUP framework (Izhakian, 2017), the degree of ambiguity can be measured by the volatility of uncertain *probabilities*, just as the degree of risk can be measured by the volatility of uncertain *outcomes*. In particular, the degree of ambiguity can be measured by the expected probability-weighted average variance of probabilities (across the relevant events). Formally, the measure of ambiguity is given by (Izhakian, 2020)

$$\mho^2 [X] \quad = \quad \int \mathrm{E}[\varphi(x)] \, \mathrm{Var}[\varphi(x)] \, dx. \tag{7}$$

This statistic can be estimated using trading data. The measure of ambiguity in Equation (7) is distinct from aversion to ambiguity. The former is a matter of beliefs (or information) and estimated from data, while the latter is a matter of subjective attitudes and endogenously determined by empirical estimations. Risk independence represents another major advantage of $\mho^2$; in contrast to risk measures, $\mho^2$ does not depend upon the magnitudes of the outcomes associated with the events, only upon the partition they induce over the state space (Brenner and Izhakian, 2018).

We proceed with the empirical implementation under the following assumptions. As investors share the same information set, all have an identical set of priors over the intraday return distribution. Each prior in the set is represented by the observed daily intraday returns, and the number of priors in the set depends on the number of trading days in the month. The set of priors thus consists of 18–22 realized distributions over a month. For practical implementations, we discretize return distributions into n bins $B_j = (r_{j-1}, r_j]$ of equal size, such that each distribution is represented as a histogram. The height of the bar of a particular bin is computed as the frequency of daily intraday returns observed in that bin, and thus represents the probability of the returns in that bin. Equipped with these 18–22 daily return histograms, we compute the expected probability of being in a particular bin across the daily return distributions, $\mathrm{E}[\mathrm{P}(B_j)]$, as well as the variance of these probabilities, $\mathrm{Var}[\mathrm{P}(B_j)]$. We assign an equal likelihood to each histogram.[18] Using these values, the monthly degree of ambiguity of firm i is then computed as follows:

$$\mho^2 [r_i] \quad \equiv \quad \frac{1}{\sqrt{w(1-w)}} \sum_{j=1}^{n} \mathrm{E}[\mathrm{P}_i(B_j)] \, \mathrm{Var}[\mathrm{P}_i(B_j)]. \tag{8}$$

To minimize the impact of bin size on the scale of ambiguity, we apply a variation of Sheppard (1897)'s correction and scale the probability weighted-average variance of probabilities to the

[18] Equal weighting is consistent with the *principle of insufficient reason*, which states that given n possibilities that are indistinguishable except for their names, each possibility should be assigned a probability equal to $\frac{1}{n}$ (Bernoulli, 1713; Laplace, 1814); with the idea of the simplest non-informative prior in Bayesian probability (Bayes, Price, and Canton, 1763), which assigns equal probabilities to all possibilities; and with the principle of maximum entropy (Jaynes, 1957), which states that the probability distribution which best describes the current state of knowledge is the one with the largest entropy.

size of the bins by $\frac{1}{\sqrt{w(1-w)}}$, where $w = r_j - r_{j-1}$.

We follow recent studies and estimate the empirical degree of firm-level ambiguity using intraday stock data from the *TAQ* database (e.g., Izhakian and Yermack, 2017; Augustin and Izhakian, 2020; Izhakian et al., 2022). We compute the degree of ambiguity for each stock each month. In our implementation, we sample five-minute stock returns from 9:30 to 16:00 to mitigate microstructure effects (Andersen, Bollerslev, Diebold, and Ebens, 2001; Ait-Sahalia, Mykland, and Zhang, 2005; Bandi and Russell, 2006; Liu, Patton, and Sheppard, 2015). Thus, we obtain daily histograms of up to 78 intraday returns. If we observe no trade in a specific time point for a given stock, we compute returns based on the volume-weighted average of the nearest trading prices within 150 seconds distance from that time point. If there is no price change within this distance, we drop this five-minute observation of the given stock. We ignore returns between closing and next-day opening prices to eliminate the impact of overnight price changes and dividend distributions. We drop all days with fewer than 10 different five-minute returns; then we drop months with fewer than 10 intraday return distributions. We also drop extreme returns ($\pm 5\%$ log returns over five minutes), as many such returns are due to improper orders that are often later canceled by the stock exchange. In addition, we use the book value of total debt and the market value of equity estimated at every five-minute interval to unlever the intraday returns.[19] Finally, we normalize the intraday five-minute rates of return to daily returns.

For the bin formation, we divide the range of daily returns into 1002 intervals. We form a grid of 1000 bins, from -100% to $+100\%$, each of width 0.2%, in addition to the left and right tails, defined as $(-\infty, -100\%]$ and $(+100\%, +\infty)$, respectively. We compute the mean and the variance of probabilities for each interval, assigning equal likelihood to each distribution (i.e., all histograms are equally likely).[20] Some bins may not be populated with return realizations. Therefore, we assume a normal return distribution and use its moments to extrapolate return probabilities. That is, $\mathrm{P}_i(B_j) = \Phi(r_j; \mu_i, \sigma_i) - \Phi(r_{j-1}; \mu_i, \sigma_i)$, where $\Phi(\cdot)$ denotes the cumulative normal probability distribution, characterized by its mean μ_i and the variance σ_i^2 of the returns. As in French, Schwert, and Stambaugh (1987), we apply the Scholes and Williams (1977) adjustment for nonsynchronous trading to estimate the variance of returns.[21] This adjustment further eliminates any microstructure effects caused by bid-ask bounce, although our use of five-minute returns minimizes microstructure effects.

An important characteristic of our measure of ambiguity is that it is outcome independent up to a state-space partition, which allows for a risk-independent examination of the impact of ambiguity on financial decisions. Specifically, the measure of ambiguity $\mho^2$ captures the variation in the frequencies (probabilities) of outcomes but ignores the magnitudes of outcomes (returns). In contrast, the measure of risk captures the variation in the magnitudes

[19]The correlation between the ambiguity measure computed using unlevered returns and the one computed using (levered) stock returns is very high, so unlevering the returns does not alter our findings.

[20]The assignment of equal likelihoods is equivalent to assuming that the daily ratios $\frac{\mu}{\sigma}$ are Student's-t distributed. When $\frac{\mu}{\sigma}$ is Student's t-distributed, cumulative probabilities are uniformly distributed (e.g., Stuart and Ord, 2010, Proposition 1.27, page 21).

[21]Scholes and Williams (1977) suggest adjusting the volatility of returns for nonsynchronous trading as $\sigma_t^2 = \frac{1}{N_t}\sum_{\ell=1}^{N_t}(r_{t,\ell} - \mathrm{E}[r_{t,\ell}])^2 + 2\frac{1}{N_t - 1}\sum_{\ell=2}^{N_t}(r_{t,\ell} - \mathrm{E}[r_{t,\ell}])(r_{t,\ell-1} - \mathrm{E}[r_{t,\ell-1}])$.

of outcomes but ignores the variation in the frequencies with which outcomes are observed. Thus, the measure of ambiguity is risk independent, just as standard measures of risk are ambiguity independent, implying that these two measures capture distinct and different aspects of uncertainty.[22]

IA.2 Estimating risk

For consistency, with our ambiguity estimation, we estimate risk using the same (unlevered) five-minute returns that we use to compute ambiguity. For each firm on each day, we estimate the variance of five-minute intraday returns, applying the Scholes and Williams (1977) correction for nonsynchronous trading. Each month, we estimate risk as the mean of the daily variance estimates.

[22]Brenner and Izhakian (2018) and Augustin and Izhakian (2020) conduct extensive tests to validate the ambiguity measure we utilize and to address concerns that it may capture other well-known dimensions of uncertainty and (variation of) distributional moments. Thereby, these tests also address the concern that our measure of ambiguity captures time-varying distributional moments.

IA.3 Supplementary Figures

Figure IA.1: Estimated climate ambiguity from different specifications of Equation (2)

Fitted time series of the market portfolio's climate ambiguity estimated from different linear combinations of temperature anomaly, cumulative carbon emissions, aggregate cost of disasters and yearly counts of extreme weather events by Equation (2). Model (1) considers only T^*, Model (2) only $CCO2$, Model (3) both T^* and $CCO2$, Model (4) augments Model (3) by the aggregate cost of disasters, and Model (5) is our benchmark model. The period the variables are observed spans from January 1993 to December 2020.

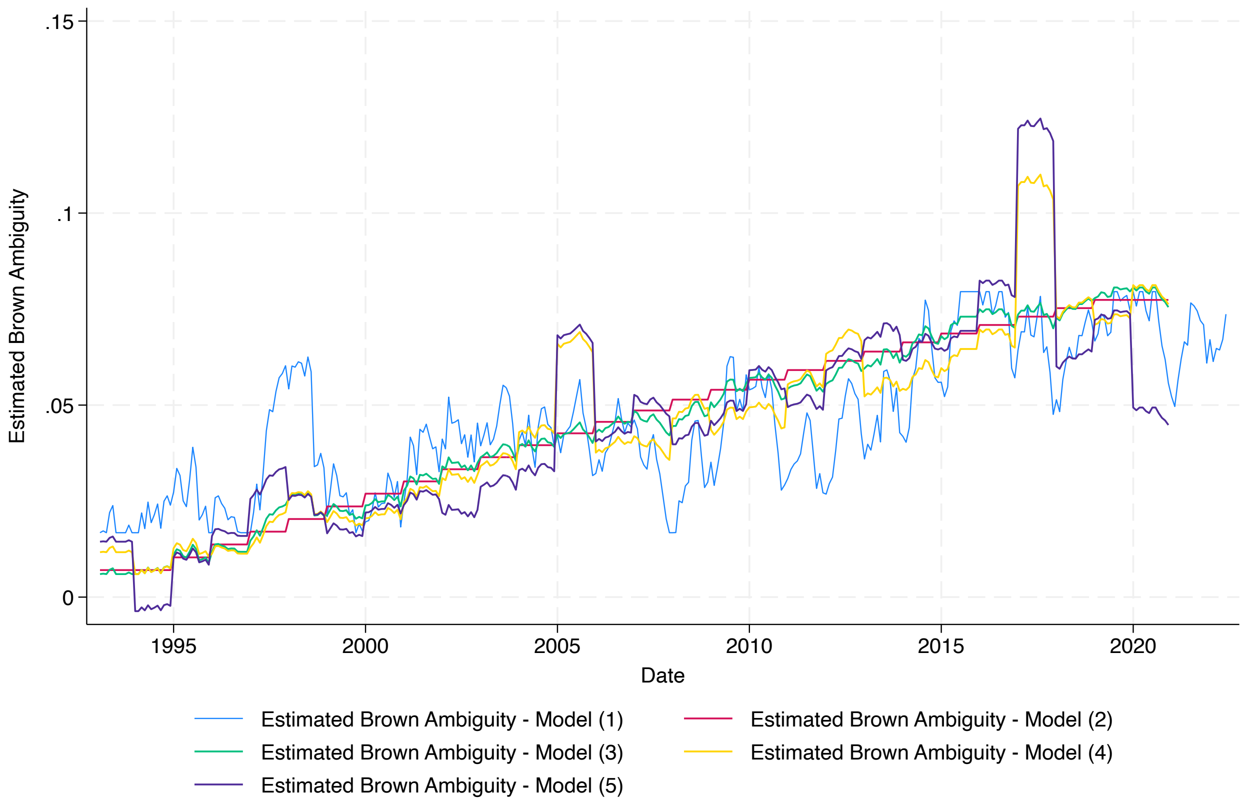
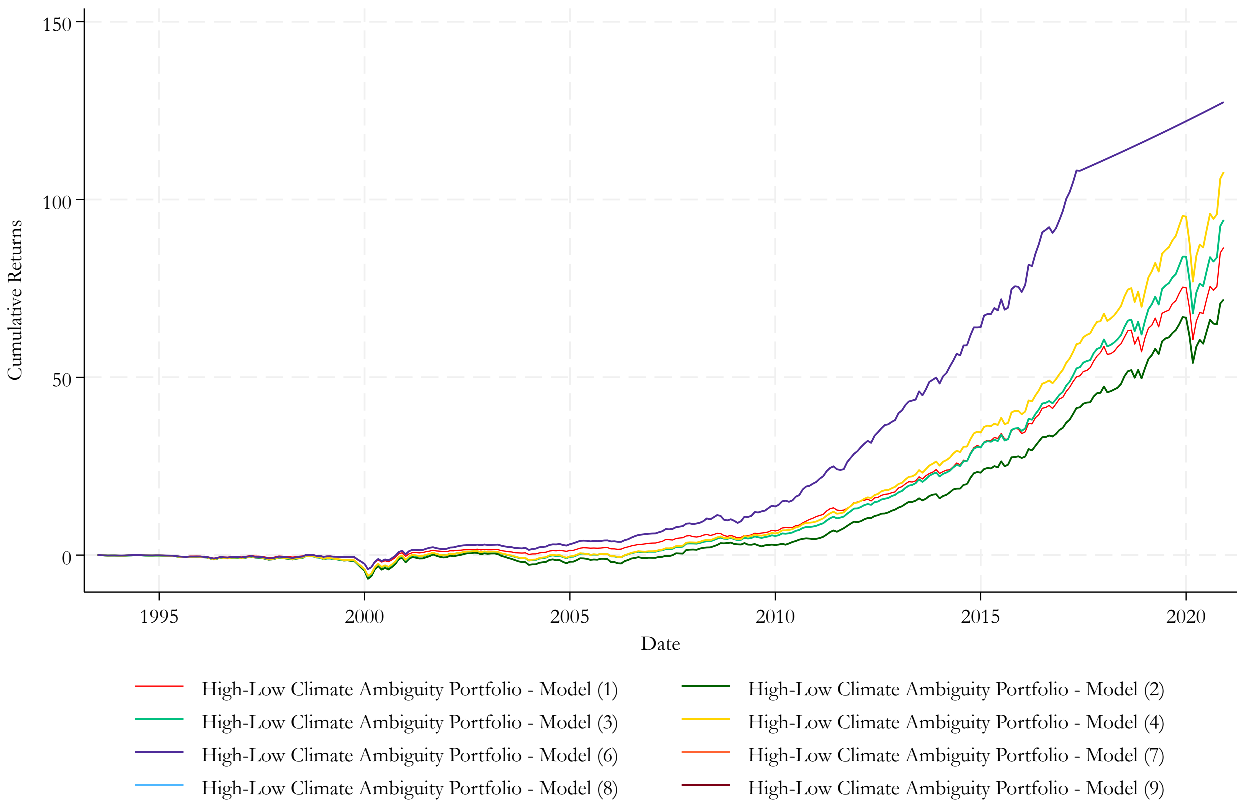


Figure IA.2: Difference in cumulative returns of High-Low climate ambiguity portfolios with $\mho^c$ obtained from alternative specifications of Equation (2)

The figure plots the differences in the monthly cumulative returns for the high (5^{th} quintile) and low (1^{st} quintile) climate ambiguity portfolios, obtained by the unconditional sorting of all stocks listed at NYSE, NASDAQ, and AMEX on their climate ambiguity into quintiles. The firm-level climate ambiguity is estimated according to the 8 alternatives to our benchmark model as in Table 2. The period the variables are observed spans from January 1993 to December 2020.



IA.4 Supplementary Tables

Table IA.1: Market portfolio's excess returns and climate change

The table reports the time series estimates of different specifications of the following econometric model for the excess returns on the market portfolio

$$\text{MKT}_t = \beta_0 + \beta_T T^*_t + \beta_C CCO2_t + \beta_{CD} CD_t + B_D D_t + B_{ctr} Ctr_t + \nu_t,$$

where T^* is the world ocean surface temperature anomaly relative to the period 1901-2010, $CCO2$ is the U.S. level of cumulative carbon emissions, and CD is the aggregate cost of disasters occurred in the U.S. measured in CPI adjusted billion dollars. Cnt controls for the disaster events: the count variables Drought, Flooding, Freeze, Storm, Cyclone, Wildfire, and Winter Storm. Ctr controls for WSJI (Engle et al., 2020),MCCI (Ardia et al., 2023) and TCRMI (Faccini et al., 2023). All the reported standard errors are Newey-West adjusted for heteroskedasticity. The period the variables are observed spans from January 1993 to December 2020.Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)
T^*	0.315		0.218	0.219	-1.356
	(1.447)		(2.553)	(2.557)	(2.695)
CCO2 US		1.048	0.858	0.896	-4.813
		(1.665)	(2.873)	(2.916)	(4.102)
Cost of Disasters				-0.000	-0.000
				(0.002)	(0.003)
Drought					-0.069
					(0.645)
Flooding					0.140
					(0.310)
Freeze					0.535
					(0.530)
Storm					0.411**
					(0.180)
Cyclone					-0.216
					(0.248)
Wildfire					-1.636***
					(0.549)
Winter Storm					-0.462
					(0.360)
Constant	0.543	-7.786	-6.341	-6.639	40.013
	(0.691)	(13.514)	(22.407)	(22.747)	(32.430)
Observations	335	335	335	335	335
R-squared	0.000	0.001	0.001	0.001	0.037

Table IA.2: Summary of the GRS test for GMB-augmented multifactor models

The table reports the GMB statistics and associated $p4$-values the hypothesis test that the intercept in the multifactor model that include the factors listed in first column are jointly null. The considered multifactor models augments the models considered in Table 4 with the GMB factor (Pástor et al., 2022). $A|a_i|$ is the average absolute intercept obtained from each model. MKT is the market portfolio excess return, SMB and HML are the Fama-French factor portfolios for size and value, UMD is the momentum factor portfolio. RMW and CMA are the Fama and French (2015) factor portfolios for profitability and investments. Full+Consumption Factors model augment the Fama and French (2015) five-factor model with UMD, and with the q factors by Hou et al. (2015). CAF is the portfolio of a long position on the high climate ambiguity portfolio and a short position on the low climate ambiguity portfolio, computed by Equation (4). The period the variables are observed spans from January 1993 to December 2020.

	Univariate			Bivariate - Scope 1			Bivariate- Scope 2			Bivariate - Scope 3		
	GRS	p(GRS)	$A\|a_i\|$	GRS	p(GRS)	$A\|a_i\|$	GRS	p(GRS)	$A\|a_i\|$	GRS	p(GRS)	$A\|a_i\|$
GMB,MKT	23.54	0.00	0.38	1.45	0.09	0.51	1.22	0.22	0.52	1.54	0.06	0.55
GMB,MKT,SMB,HML	21.3	0.00	0.41	1.28	0.18	0.41	1.15	0.29	0.37	1.54	0.06	0.44
GMB,MKT,SMB,HML,UMD	21.07	0.00	0.40	1.27	0.19	0.42	1.14	0.31	0.40	1.53	0.06	0.46
GMB,MKT,SMB,HML,CMA,RMW	20.19	0.00	0.38	1.45	0.09	0.42	1.26	0.19	0.38	1.79	0.02	0.44
GMB,MKT,SMB,HML,CMA,RMW,UMD	19.92	0.00	0.36	1.43	0.10	0.44	1.26	0.20	0.42	1.79	0.02	0.47
GMB,MKT+ q factors	21.12	0.00	0.43	1.51	0.07	0.37	1.21	0.23	0.32	1.71	0.02	0.39
Full + GMB + q factors	19.67	0.00	0.40	1.33	0.15	0.31	1.03	0.44	0.29	1.63	0.04	0.36
GMB,MKT,CAF	18.64	0.00	0.70	1.66	0.03	0.46	1.55	0.05	0.40	1.76	0.02	0.42
GMB,MKT,SMB,HML,CAF	15.93	0.00	0.62	1.36	0.13	0.41	1.47	0.08	0.40	1.69	0.03	0.41
Full + GMB + CAF	16.67	0.00	0.50	1.40	0.11	0.29	1.27	0.19	0.29	1.74	0.02	0.30

Table IA.3: Robustness check on the cross-sectional test: climate concerns indexes

The table reports the estimated residuals and associated t-statistics obtained from the cross-section regression

$$a_i = \gamma_{WSJI} b_{i,WSJI} + \gamma_{MCCI} b_{i,MCCI} + \gamma_{TCRM} b_{i,TCRM} + \xi_i,$$

where a_i is the average returns on test portfolio i left unexplained by the Fama-French three-factor model, and $b_{i,WSJI}, b_{i,MCCI}$, and $b_{i,TCRMI}$ are the coefficient estimates for each test portfolio i from the following time-series regression

$$R_{i,t} = a_i + b_i \text{MKT}_t + s_i \text{SMB}_t + h_i \text{HML}_t + b_{i,WSJI} \text{WSJI}_t + b_{i,MCCI} \text{MCCI} + b_{i,TCRM} \text{TCRM} + \varepsilon_{i,t}.$$

The 80 test portfolios are formed by bivariate sorting stocks on climate ambiguity and firm-level carbon emissions, as described in Section 2. The period the variables are observed spans from January 1993 to December 2020.

	ξ					$t(\xi)$					Adj. R^2
	Low	2	3	4	High	Low	2	3	4	High	
Panel A: Univariate											
All	0.07	-0.41	-0.10	0.24	0.51	1.41	-1.14	-0.24	0.95	1.41	27%
Panel B: Bivariate Scope 1											
Green	0.64	0.53	0.4	0.26	0.88	1.61	1.40	0.95	0.64	2.17	-12%
2	0.10	-0.01	0.41	0.45	0.56	0.36	-0.04	0.99	1.09	1.35	
3	-0.33	0.08	0.39	0.33	0.53	-0.96	0.21	1.00	0.81	1.28	
4	-0.36	0.15	0.19	0.01	0.37	-0.99	0.41	0.48	0.03	0.88	
Brown	-0.54	-0.09	-0.04	0.12	0.38	-1.53	-0.23	-0.09	0.32	0.92	
Panel C: Bivariate Scope 2											
Green	0.56	0.60	0.47	0.44	0.81	1.51	1.58	1.20	1.25	2.07	-7%
2	-0.47	-0.01	0.33	0.3	0.62	-1.27	-0.03	0.93	0.78	1.65	
3	0.13	-0.16	0.32	0.26	0.34	0.38	-0.43	0.86	0.70	0.90	
4	-0.25	-0.07	0.02	0.14	0.41	-0.73	-0.19	0.05	0.37	1.05	
Brown	-0.37	-0.23	-0.07	0.04	0.25	-1.08	-0.77	-0.19	0.12	0.63	
Panel D: Bivariate Scope 3											
Green	0.51	0.50	0.51	0.38	0.88	1.36	1.30	1.31	1.00	2.29	-8%
2	-0.18	0.11	0.20	0.35	0.69	-0.56	0.31	0.55	0.90	1.77	
3	-0.27	-0.32	0.33	0.11	0.32	-0.81	-0.90	0.91	0.28	0.84	
4	-0.52	-0.02	0.14	0.11	0.39	-1.50	-0.06	0.39	0.32	1.01	
Brown	0.13	-0.26	0.03	0.09	0.24	0.53	-0.70	0.09	0.24	0.61	

Table IA.4: Robustness check on the cross-sectional test: climate concerns indexes, α from benchmark model

The table reports the estimated residuals and associated t-statistics obtained from the cross-section regression

$$a_i = \gamma_{WSJI} b_{i,WSJI} + \gamma_{MCCI} b_{i,MCCI} + \gamma_{TCRM} b_{i,TCRM} + \xi_i,$$

where a_i, $b_{i,WSJI}, b_{i,MCCI}$, and $b_{i,TCRMI}$ are estimated for each test portfolio i by the following time-series regression

$$R_{i,t} = a_i + b_i \mathrm{MKT}_t + s_i \mathrm{SMB}_t + h_i \mathrm{HML}_t + b_{i,WSJI} \mathrm{WSJI}_t + b_{i,MCCI} \mathrm{MCCI} + b_{i,TCRM} \mathrm{TCRM} + \varepsilon_{i,t}.$$

The 80 test portfolios are formed by bivariate sorting stocks on climate ambiguity and firm-level carbon emissions, as described in Section 2. The period the variables are observed spans from January 1993 to December 2020.

	ξ					$t(\xi)$					Adj. R^2
	Low	2	3	4	High	Low	2	3	4	High	
Panel A: Univariate											
All	0.07	-0.41	-0.08	0.23	0.51	1.41	-1.17	-0.19	0.91	1.41	73%
Panel B: Bivariate Scope 1											
Green	0.50	0.59	0.42	0.16	0.51	1.42	1.75	1.15	0.43	1.42	82%
2	-0.08	-0.04	0.27	0.42	0.49	-0.31	-0.12	0.75	1.16	1.34	
3	-0.43	0.03	0.34	0.31	0.55	-1.39	0.07	1.00	0.86	1.48	
4	-0.39	0.18	0.17	0.04	0.40	-1.19	0.56	0.49	0.10	1.09	
Brown	-0.32	0.03	-0.03	0.23	0.46	-1.04	0.10	-0.08	0.68	1.25	
Panel C: Bivariate Scope 2											
Green	0.45	0.54	0.48	0.34	0.67	1.34	1.56	1.35	1.05	1.89	81%
2	-0.49	0.07	0.30	0.29	0.58	-1.46	0.20	0.91	0.82	1.69	
3	0.09	-0.10	0.21	0.24	0.39	0.30	-0.30	0.61	0.68	1.11	
4	-0.22	-0.03	0.08	0.14	0.43	-0.71	-0.09	0.23	0.40	1.21	
Brown	-0.28	-0.18	-0.12	0.00	0.33	-0.89	-0.68	-0.38	-0.01	0.93	
Panel D: Bivariate Scope 3											
Green	0.33	0.51	0.46	0.29	0.64	0.95	1.45	1.28	0.83	1.78	81%
2	-0.17	0.02	0.07	0.40	0.66	-0.57	0.07	0.21	1.12	1.84	
3	-0.27	-0.19	0.36	0.09	0.34	-0.88	-0.58	1.05	0.25	0.95	
4	-0.65	-0.07	0.15	0.10	0.46	-2.03	-0.19	0.43	0.30	1.28	
Brown	0.13	0.09	0.15	0.17	0.31	0.54	0.26	0.42	0.47	0.85	

Table IA.5: Robustness check on the cross-sectional test: climate concerns indexes and climate ambiguity

The table reports the estimated residuals and associated t-statistics obtained from the cross-section regression that follows

$$a_i = \gamma_{0,i}\overline{\mho_i^c} + \gamma_{WSJI} b_{i,WSJI} + \gamma_{MCCI} b_{i,MCCI} + \gamma_{TCRM} b_{i,TCRM} + \xi_i,$$

where a_i, $b_{i,WSJI}, b_{i,MCCI}$, and $b_{i,TCRMI}$ are estimated for each test portfolio i by the following time-series regression

$$R_{i,t} = a_i + b_i \mathrm{MKT}_t + s_i \mathrm{SMB}_t + h_i \mathrm{HML}_t + b_{i,WSJI}\mathrm{WSJI}_t + b_{i,MCCI}\mathrm{MCCI} + b_{i,TCRM}\mathrm{TCRM} + \varepsilon_{i,t}.$$

The 80 test portfolios are formed by bivariate sorting stocks on climate ambiguity and firm-level carbon emissions, as described in Section 2. The period the variables are observed spans from January 1993 to December 2020.

	ξ					$t(\xi)$					Adj. R^2
	Low	2	3	4	High	Low	2	3	4	High	
Panel A: Univariate											
All	0.00	-0.01	0.02	-0.01	0.00	1.00	-1.00	1.00	-1.00	1.00	99%
Panel B: Bivariate Scope 1											
Green	0.54	0.51	0.21	-0.14	0.02	2.55	2.57	0.96	-0.68	0.08	94%
2	0.02	-0.07	0.06	0.07	0.00	0.13	-0.35	0.30	0.34	0.02	
3	-0.36	0.05	0.11	-0.04	0.00	-1.94	0.22	0.57	-0.21	0.02	
4	-0.20	0.22	0.08	-0.28	-0.11	-1.03	1.10	0.39	-1.35	-0.55	
Brown	-0.19	0.07	-0.10	0.02	-0.03	-1.05	0.34	-0.47	0.12	-0.17	
Panel C: Bivariate Scope 2											
Green	0.51	0.51	0.29	0.18	0.18	2.43	2.35	1.33	0.88	0.89	93%
2	-0.35	0.10	0.03	-0.01	-0.01	-1.69	0.49	0.15	-0.05	-0.07	
3	0.17	-0.02	0.06	-0.10	-0.05	0.85	-0.12	0.28	-0.48	-0.24	
4	-0.23	0.07	-0.06	-0.11	-0.03	-1.18	0.34	-0.29	-0.54	-0.13	
Brown	-0.11	-0.19	-0.13	-0.15	-0.17	-0.60	-1.13	-0.66	-0.75	-0.83	
Panel D: Bivariate Scope 3											
Green	0.44	0.44	0.21	0.04	0.15	2.15	2.06	1.00	0.17	0.74	93%
2	-0.15	0.13	-0.01	0.00	0.09	-0.83	0.67	-0.06	0.00	0.48	
3	-0.06	-0.16	0.19	-0.19	-0.11	-0.34	-0.83	0.97	-0.89	-0.56	
4	-0.50	-0.04	-0.03	-0.08	-0.01	-2.64	-0.17	-0.15	-0.40	-0.07	
Brown	0.18	0.15	0.02	-0.09	-0.22	1.31	0.75	0.09	-0.44	-1.08	

Table IA.6: Estimated *alphas* for the 80 test portfolios: climate ambiguity Models (1) and (2)

The table reports the *alphas* and associated t-statistics obtained from the three-factor regressions on the 80 test portfolios returns. Low to high refer to the climate ambiguity quintiles of the sorted stocks, and green to brown refer to their carbon emissions. Portfolios' climate ambiguity is the fitted value of

$$\mho^2_{i,t} = \beta_{i,0} + \beta_{i,T} T^*_t + \sum_{k=1}^{3} \beta_{i,s_k} Scope(k)_{i,t} + \nu_t,$$

for Model (1) and of

$$\mho^2_{i,t} = \beta_{i,0} + \beta_{i,C} CCO2_t + \sum_{k=1}^{3} \beta_{i,s_k} Scope(k)_{i,t} \nu_t,$$

for Model (2). The period the variables are observed spans from January 1993 to December 2020.

	Low	2	3	4	High	High-Low	Low	2	3	4	High	High-Low
Panel A: Model (1)												
	a						$t(a)$					
Panel A.1: Univariate												
All	0.00	0.46	0.44	0.52	0.82	0.82	0.00	4.71	5.12	6.67	11.49	4.00
Panel A.2: Bivariate Scope 1												
Green	0.60	0.39	0.61	0.48	0.35	-0.25	2.46	2.38	4.41	4.00	2.19	-0.78
2	0.09	-0.06	0.14	0.43	0.60	0.51	0.43	-0.46	1.24	3.81	6.42	2.05
3	-0.30	0.05	0.09	0.29	0.48	0.79	-1.08	0.26	0.66	2.64	5.24	2.55
4	0.06	-0.06	0.15	0.12	0.27	0.21	0.16	-0.29	1.04	1.06	2.70	0.55
Brown	-0.19	0.03	0.18	0.29	0.33	0.53	-0.46	0.10	0.84	1.79	2.44	1.28
Panel A.3: Bivariate Scope 2												
Green	0.49	0.37	0.47	0.7	0.61	0.12	2.21	2.87	4.31	7.12	3.79	0.41
2	-0.2	-0.03	0.13	0.3	0.42	0.62	-0.68	-0.18	1.07	3.04	4.09	1.98
3	-0.15	-0.05	0.19	0.14	0.42	0.56	-0.48	-0.22	1.36	1.12	4.37	1.71
4	0.04	-0.23	0.1	0.09	0.4	0.35	0.07	-1.06	0.62	0.66	3.63	0.54
Brown	0.36	-0.06	0.1	0.19	0.22	-0.14	0.64	-0.2	0.49	1.17	2.26	-0.26
Panel A.4: Bivariate Scope 3												
Green	0.43	0.33	0.52	0.56	0.70	0.27	1.89	2.50	4.51	5.29	4.73	0.93
2	-0.29	0.01	0.18	0.45	0.5	0.79	-1.01	0.06	1.59	4.08	4.91	2.56
3	0.08	-0.23	0.07	0.15	0.38	0.30	0.18	-1.16	0.48	1.30	3.60	0.59
4	-0.39	-0.06	0.06	0.11	0.40	0.79	-1.02	-0.24	0.33	0.84	3.60	1.97
Brown	0.40	0.20	-0.02	0.11	0.22	-0.18	0.85	0.58	-0.07	0.69	2.33	-0.37
Panel B: Model (2)												
Panel B.1: Univariate												
All	.1	.38	.44	.5	.81	.72	.46	3.78	5.18	6.53	9.9	3.33
Panel B.2: Bivariate Scope 1												
Green	.6	.54	.52	.39	.41	-.19	2.56	3.7	3.65	2.85	2.43	-.63
2	.12	.09	.27	.36	.57	.45	.47	.68	2.37	3.22	5.2	1.58
3	-.18	.02	.24	.31	.47	.65	-.6	.13	1.83	2.76	5.15	1.98
4	-.17	.06	.13	.17	.31	.48	-.48	.23	.91	1.58	3.15	1.32
Brown	-.49	-.18	0	.23	.32	.81	-1.13	-.58	.01	1.43	2.37	1.89
Panel B.3: Bivariate Scope 2												
Green	.54	.52	.43	.6	.61	.08	2.36	3.87	4.02	5.56	3.83	.25
2	-.37	-.01	.29	.23	.46	.84	-1.25	-.07	2.35	2.26	4.46	2.56
3	0	-.1	.13	.19	.41	.41	-.01	-.52	.91	1.76	4.16	1.14
4	-.47	-.21	.01	.12	.37	.85	-1.13	-.87	.08	.9	3.53	1.92
Brown	-.56	-.09	.02	.15	.17	.73	-1.17	-.31	.09	.96	1.68	1.58
Panel B.4: Bivariate Scope 3												
Green	.43	.44	.52	.45	.72	.29	1.91	3.49	4.65	4.14	4.94	.99
2	-.3	.01	.28	.34	.47	.77	-1	.03	2.32	3.43	4.39	2.29
3	.05	-.24	-.04	.24	.44	.39	.14	-1.17	-.3	2.29	3.72	.97
4	-.51	-.03	.05	.16	.37	.88	-1.25	-.13	.31	1.14	3.34	2.1
Brown	-.01	-.31	-.08	.12	.2	.21	-.03	-.86	-.35	.81	2.05	.39

Table IA.7: Summary statistics and estimated *alphas* for the 80 test portfolios

The table reports the *alphas* and associated t-statistics obtained from the three-factor regressions on the 80 test portfolios returns. Low to high refer to the climate ambiguity quintiles of the sorted stocks, and green to brown refer to their carbon emissions. Portfolios' climate ambiguity is the fitted value of

$$\mho^2_{i,t} = \beta_{i,0} + \beta_{i,T} T^*_t + \beta_{i,C} CCO2_t + \sum_{k=1}^{3} \beta_{i,s_k} Scope(k)_{i,t} + \nu_t,$$

for Model (3) and of

$$\mho^2_{i,t} = \beta_{i,0} + \beta_{i,T} T^*_t + \beta_{i,C} CCO2_t + \sum_{k=1}^{3} \beta_{i,s_k} Scope(k)_{i,t} + \beta_{i,CD} CD_t + \nu_t,$$

for Model (4). The period the variables are observed spans from January 1993 to December 2020.

	Low	2	3	4	High	High-Low	Low	2	3	4	High	High-Low
Panel A: Model (3)												
	a						$t(a)$					
Panel A.1: Univariate												
All	.07	.4	.44	.5	.87	.8	.33	4.06	5.32	6.57	11.3	3.84
Panel A.2: Bivariate Scope 1												
Green	.6	.54	.45	.52	.43	-.17	2.55	3.55	3.35	3.5	2.54	-.54
2	.1	.03	.38	.27	.63	.53	.41	.18	3.32	2.45	5.66	1.84
3	-.2	-.03	.18	.34	.48	.68	-.67	-.17	1.4	2.96	5.3	2.09
4	-.29	.12	.08	.18	.29	.59	-.82	.52	.54	1.6	2.84	1.56
Brown	-.49	-.16	.03	.14	.32	.81	-1.13	-.54	.12	.89	2.38	1.9
Panel A.3: Bivariate Scope 2												
Green	.51	.5	.46	.61	.6	.08	2.29	3.86	4.55	5.35	3.69	.28
2	-.37	.01	.22	.24	.51	.88	-1.25	.03	1.93	2.4	4.91	2.68
3	-.08	-.16	.19	.13	.43	.51	-.24	-.82	1.37	1.14	4.42	1.44
4	-.49	-.31	.04	.12	.38	.87	-1.17	-1.31	.23	.87	3.37	1.95
Brown	-.38	-.07	-.05	.1	.16	.54	-.79	-.22	-.23	.63	1.6	1.16
Panel A.4: Bivariate Scope 3												
Green	.42	.43	.5	.5	.71	.29	1.84	3.38	4.6	4.52	4.91	1
2	-.39	.02	.31	.3	.48	.86	-1.29	.09	2.49	3.03	4.61	2.59
3	-.1	-.23	-.04	.2	.48	.58	-.27	-1.22	-.29	1.8	4.25	1.45
4	-.37	-.28	.09	.12	.4	.77	-.91	-1.26	.55	.85	3.49	1.83
Brown	.11	-.24	-.11	.08	.17	.06	.22	-.63	-.49	.56	1.75	.12
Panel B: Model (4)												
Panel B.1: Univariate												
All	.08	.36	.42	.51	.9	.83	.38	3.7	4.87	6.94	11.33	3.95
Panel B.2: Bivariate Scope 1												
Green	.59	.54	.41	.45	.48	-.11	2.52	3.61	2.88	3.26	2.72	-.36
2	.11	.05	.29	.34	.6	.5	.46	.37	2.45	3.07	5.37	1.78
3	-.13	-.06	.2	.31	.51	.65	-.45	-.3	1.52	2.95	5.62	1.97
4	-.3	.09	.14	.14	.31	.62	-.86	.39	.91	1.28	2.99	1.67
Brown	-.5	-.21	.06	.15	.3	.81	-1.15	-.73	.29	.94	2.2	1.89
Panel B.3: Bivariate Scope 2												
Green	.51	.49	.4	.65	.61	.1	2.31	3.94	3.88	5.69	3.75	.33
2	-.37	.05	.18	.24	.5	.87	-1.23	.32	1.41	2.49	4.63	2.64
3	-.11	-.15	.21	.15	.44	.55	-.34	-.82	1.48	1.41	4.5	1.61
4	-.51	-.31	.07	.06	.41	.91	-1.22	-1.32	.41	.42	3.46	2.05
Brown	-.33	-.29	.07	.07	.16	.49	-.69	-1.03	.3	.47	1.61	1.06
Panel B.4: Bivariate Scope 3												
Green	.42	.39	.46	.56	.74	.31	1.9	3.2	4.12	5.22	4.92	1.07
2	-.35	.03	.26	.27	.56	.91	-1.18	.18	1.97	2.87	5.32	2.72
3	-.13	-.16	-.02	.19	.43	.56	-.33	-.79	-.18	1.77	3.75	1.36
4	-.36	-.4	.17	.09	.4	.76	-.91	-1.75	1	.67	3.47	1.87
Brown	.09	-.23	-.06	.07	.16	.06	.19	-.65	-.24	.45	1.63	.13

Table IA.8: Summary statistics and estimated *alphas* for the 80 test portfolios

The table reports the *alphas* and associated t-statistics obtained from the three-factor regressions on the 80 test portfolios returns. Low to high refer to the climate ambiguity quintiles of the sorted stocks, and green to brown refer to their carbon emissions. Portfolios' climate ambiguity is the fitted value of

$$\mho^2_{i,t} = \beta_{i,0} + \beta_{i,T} T^*_t + \beta_{i,C} CCO2_t + \sum_{k=1}^{3} \beta_{i,s_k} Scope(k)_{i,t} + \beta_{i,CD} CD_t + B_{i,cnt} Cnt_t + b_{i,WSJI} \mathrm{WSJI}_t + \nu_t,$$

for Model (6) and of

$$\mho^2_{i,t} = \beta_{i,0} + \beta_{i,T} T^*_t + \beta_{i,C} CCO2_t + \sum_{k=1}^{3} \beta_{i,s_k} Scope(k)_{i,t} + \beta_{i,CD} CD_t + B_{i,cnt} Cnt_t + b_{i,MCCI} \mathrm{MCCI}_t + \nu_t,$$

for Model (7). The period the variables are observed spans from January 1993 to December 2020.

	Low	2	3	4	High	High-Low	Low	2	3	4	High	High-Low
Panel A: Model (6)												
	a						$t(a)$					
Panel A.1: Univariate												
All	.2	.43	.43	.52	1.08	.88	.76	2.36	2.85	4.21	9.59	4.08
Panel A.2: Bivariate Scope 1												
Green	.7	.48	.61	.35	.67	-.04	2.59	2.68	4.6	2.29	4.25	-.12
2	.13	.08	.38	.5	.43	.3	.48	.46	2.7	4.39	4.06	.94
3	-.3	.23	.32	.36	.52	.82	-.77	1.08	2.21	2.91	4.25	1.93
4	.07	.12	.26	.21	.42	.35	.17	.51	1.48	1.77	3.82	.85
Brown	-.15	.17	.09	.35	.51	.66	-.29	.55	.35	2	3.55	1.29
Panel A.3: Bivariate Scope 2												
Green	.65	.56	.54	.59	.82	.17	2.64	2.94	4.59	4.65	5.13	.53
2	-.2	.16	.3	.42	.5	.7	-.61	.82	2.29	3.84	4.01	1.84
3	.15	.13	.26	.28	.44	.29	.45	.6	1.71	2.21	3.95	.77
4	-.04	-.13	.16	.25	.5	.54	-.08	-.5	.85	1.78	4.41	1.07
Brown	-.26	0	.06	.19	.31	.57	-.54	.02	.26	1.32	2.66	1.21
Panel A.4: Bivariate Scope 3												
Green	.54	.55	.53	.52	.67	.13	1.99	3.23	4.43	3.93	4.83	.4
2	-.07	.15	.35	.42	.58	.65	-.22	.8	2.36	3.83	4.77	1.74
3	.31	-.03	.35	.17	.5	.18	.73	-.16	2.21	1.42	4.43	.4
4	-.38	-.11	.12	.41	.51	.89	-.87	-.44	.67	2.77	4.01	1.95
Brown	.26	.33	.14	.28	.33	.06	.53	.97	.59	2.15	3.01	.13
Panel B: Model (7)												
Panel B.1: Univariate												
All	-.09	.03	.24	.44	.89	.98	-.4	.19	2.13	4.79	11.66	4.55
Panel B.2: Bivariate Scope 1												
Green	.71	.4	.35	.54	.9	.19	3.15	1.57	2.25	3.68	3.65	.57
2	-.06	.15	.39	.48	.49	.55	-.23	.63	2.68	3.44	3.72	1.82
3	-.08	.31	.16	.23	.6	.68	-.23	1.14	.86	1.38	4.62	1.77
4	-.16	.07	.46	.27	.31	.47	-.45	.23	2.1	1.77	2.93	1.29
Brown	-.18	-.02	.1	.44	.38	.56	-.38	-.06	.44	2.07	2.79	1.2
Panel B.3: Bivariate Scope 2												
Green	.55	.49	.41	.72	.92	.37	2.47	3.07	2.71	4.6	5.48	1.24
2	-.43	.08	.31	.48	.43	.86	-1.47	.42	2.08	4.22	3.82	2.63
3	-.11	.16	.16	.21	.5	.62	-.35	.72	1.08	1.41	3.84	1.73
4	-.3	-.08	.28	.39	.47	.77	-.74	-.29	1.44	2.2	4	1.78
Brown	-.1	.03	0	.16	.26	.35	-.21	.11	0	.92	2.28	.78
Green	.45	.34	.29	.62	.84	.39	1.92	2.47	1.79	4.53	4.19	1.24
2	-.22	.17	.41	.48	.55	.77	-.75	.89	2.45	4.17	4.7	2.27
3	.1	.02	.09	.29	.44	.34	.27	.1	.46	1.89	3.73	.86
4	-.1	-.2	-.01	.43	.5	.6	-.23	-.9	-.05	1.79	3.92	1.27
Brown	-.18	.04	.39	.17	.24	.42	-.39	.11	1.69	1.18	2.23	.87

Table IA.9: Summary statistics and estimated *alphas* for the 80 test portfolios

The table reports the *alphas* and associated t-statistics obtained from the three-factor regressions on the 80 test portfolios returns. Low to high refer to the climate ambiguity quintiles of the sorted stocks, and green to brown refer to their carbon emissions. Portfolios' climate ambiguity is the fitted value of

$$\mho^2_{i,t} = \beta_{i,0} + \beta_{i,T} T^*_t + \beta_{i,C} CCO2_t + \sum_{k=1}^{3} \beta_{i,s_k} Scope(k)_{i,t} + \beta_{i,CD} CD_t + B_{i,cnt} Cnt_t + b_{i,TCRM} \mathrm{TCRM}_t + \nu_t,$$

for Model (8) and of

$$\mho^2_{i,t} = \beta_{i,0} + \beta_{i,T} T^*_t + \beta_{i,C} CCO2_t + \sum_{k=1}^{3} \beta_{i,s_k} Scope(k)_{i,t} + \beta_{i,CD} CD_t + B_{i,cnt} Cnt_t + B_{ctr} Ctr_t + \nu_t,$$

for Model (9). The period the variables are observed spans from January 1993 to December 2020.

	Low	2	3	4	High	High-Low	Low	2	3	4	High	High-Low
Panel A: Model (8)												
	a						$t(a)$					
Panel A.1: Univariate												
All	-.19	.35	.6	.74	1.34	1.53	-.65	1.45	3.4	5.28	10.99	6.45
Panel A.2: Bivariate Scope 1												
Green	.57	.48	.55	.27	.68	.12	2.27	2.64	4.24	1.99	4.11	.37
2	.01	.09	.28	.52	.52	.51	.04	.52	2.26	4.68	4.55	1.58
3	-.36	-.05	.24	.28	.51	.87	-1.13	-.24	1.76	2.51	4.34	2.54
4	-.42	.16	.08	.15	.35	.77	-1.17	.66	.51	1.31	3.38	2.04
Brown	-.48	-.19	.05	.24	.35	.83	-1.04	-.6	.22	1.26	2.66	1.83
Panel A.3: Bivariate Scope 2												
Green	.46	.55	.49	.55	.73	.27	1.74	3.03	4.17	4.42	4.95	.86
2	-.44	-.07	.28	.35	.48	.92	-1.17	-.34	2.13	3.38	4.17	2.23
3	-.02	-.06	.14	.23	.47	.49	-.06	-.33	.9	1.95	4.05	1.22
4	-.3	-.16	-.05	.2	.42	.72	-.65	-.62	-.29	1.45	3.83	1.48
Brown	-.56	-.4	-.05	-.01	.22	.78	-1.16	-1.28	-.22	-.07	2.12	1.67
Panel A.4: Bivariate Scope 3												
Green	.39	.44	.56	.47	.78	.38	1.42	2.49	5.02	3.91	5.51	1.16
2	-.24	.06	.18	.43	.56	.8	-.68	.35	1.4	3.62	5.17	2.06
3	.61	-.23	.05	.18	.45	-.16	.66	-.96	.34	1.58	3.92	-.17
4	-.65	-.3	.01	.25	.43	1.08	-1.55	-1.14	.04	1.84	3.5	2.46
Brown	-.18	-.1	-.1	.05	.24	.42	-.35	-.28	-.41	.31	2.47	.81
Panel B: Model (9)												
Panel B.1: Univariate												
All	.18	.33	.43	.56	1.02	.84	.58	1.32	2.17	3.26	6.61	3.88
Panel B.2: Bivariate Scope 1												
Green	.75	.41	.81	.49	.73	-.01	3.03	1.97	4.74	3.09	2.69	-.04
2	-.02	.15	.53	.59	.57	.59	-.06	.79	3.82	4.34	3.25	1.64
3	.18	.21	.49	.61	.38	.21	.5	.9	3.22	4.08	2.64	.54
4	.27	.07	.46	.34	.42	.15	.71	.28	2.5	2.52	3.58	.36
Brown	.12	.33	.4	.66	.57	.45	.24	.93	1.69	3.54	3.77	.9
Panel B.3: Bivariate Scope 2												
Green	.51	.59	.86	.79	.85	.33	2.1	3.3	4.85	4.56	4.62	1.02
2	.02	.04	.57	.59	.65	.63	.05	.18	4.09	4.47	4.17	1.75
3	.33	.09	.32	.5	.48	.15	.98	.42	2.16	3.17	2.92	.38
4	.03	.28	.4	.47	.47	.44	.08	.97	2.1	3.41	3.3	.97
Brown	-.27	.18	.13	.46	.41	.68	-.59	.58	.61	3.05	3.59	1.51
Panel B.4: Bivariate Scope 3												
Green	.49	.53	.78	.72	.96	.47	1.78	3.28	5.1	4.99	2.45	.94
2	.22	.27	.58	.49	.71	.49	.66	1.31	4.25	3.83	4.59	1.28
3	.12	.5	.22	.44	.44	.32	.29	2.38	1.11	2.67	3.17	.77
4	-.12	.27	.32	.68	.5	.62	-.3	1.06	1.52	3.91	3.62	1.47
Brown	.19	.46	.37	.47	.36	.17	.39	1.31	1.59	3.21	3.06	.35

Table IA.10: Estimated climate ambiguity trough *VolMean*

The table reports the time series coefficient estimates of different specifications of the following econometric model for the market volatility of mean, $VolMean_t$

$$VolMean_t = \beta_0 + \beta_T T^*_t + \beta_C CCO2_t + \beta_{CD} CD_t + B_{cnt} Cnt_t + B_{ctr} Ctr_t + \nu_t,$$

where T^* is the world ocean surface temperature anomaly relative to the period 1901-2010, $CCO2$ is the U.S. level of cumulative carbon emissions, and CD is the aggregate cost of disasters occurred in the U.S. measured in CPI adjusted billion dollars. Cnt controls for the disaster events: the count variables Drought, Flooding, Freeze, Storm, Cyclone, Wildfire, and Winter Storm. Ctr controls for WSJI (Engle et al., 2020),MCCI (Ardia et al., 2023) and TCRMI (Faccini et al., 2023). All the reported standard errors are Newey-West adjusted for heteroskedasticity. The period the variables are observed spans from January 1993 to December 2020.Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T^*	-0.000***		-0.000	-0.000	-0.000	-0.000*	-0.000*	-0.000	-0.000
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CCO2		-0.002***	-0.001	-0.000	-0.001	-0.001	0.003	-0.003*	0.012
		(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.002)	(0.009)
All Disasters Cost				-0.000***	-0.000***	-0.000***	-0.000	-0.000**	-0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Drought					0.000	-0.000	0.000	0.000*	0.000
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Flooding					0.000	0.000	0.000	0.000	0.000
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Freeze					-0.000	-0.000	-0.000	-0.000	-0.000
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Severe Storm					0.000	0.000	-0.000	0.000	-0.000
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tropical Cyclone					0.000**	0.000**	0.000**	0.000**	0.000*
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wildfire					0.000***	0.000***	0.000*	0.000**	0.000**
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Winter Storm					-0.000	-0.000*	0.000	0.000	0.000
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.000***	-0.004***	-0.001	-0.001	-0.003	-0.001	0.008	-0.007*	0.030
	(0.000)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.010)	(0.004)	(0.022)
N Obs.	335	335	335	335	335	293	216	239	174
Adj. R^2	0.034	0.027	0.036	0.041	0.108	0.117	0.262	0.211	0.415
WSJI	NO	NO	NO	NO	NO	YES	NO	NO	YES
MCCI	NO	NO	NO	NO	NO	NO	YES	NO	YES
TCRM	NO	NO	NO	NO	NO	NO	NO	YES	YES

Table IA.11: Estimated climate ambiguity trough *VolVol*

The table reports the time series coefficient estimates of different specifications of the following econometric model for the market volatility of volatility, $VolVol_t$

$$VolVol_t = \beta_0 + \beta_T T_t^* + \beta_C CCO2_t + \beta_{CD} CD_t + B_{cnt} Cnt_t + B_{ctr} Ctr_t + \nu_t,$$

where T^* is the world ocean surface temperature anomaly relative to the period 1901-2010, $CCO2$ is the U.S. level of cumulative carbon emissions, and CD is the aggregate cost of disasters occurred in the U.S. measured in CPI adjusted billion dollars. Cnt controls for the disaster events: the count variables Drought, Flooding, Freeze, Storm, Cyclone, Wildfire, and Winter Storm. Ctr controls for WSJI (Engle et al., 2020),MCCI (Ardia et al., 2023) and TCRMI (Faccini et al., 2023). All the reported standard errors are Newey-West adjusted for heteroskedasticity.. The period the variables are observed spans from January 1993 to December 2020.Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T^*	-0.000		0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CCO2		-0.000	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
All Disasters Cost				-0.000	-0.000*	-0.000	-0.000	-0.000	-0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Drought					0.000	-0.000	0.000	-0.000	0.000
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Flooding					-0.000	0.000	0.000	0.000	0.000
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Freeze					-0.000	-0.000	0.000	-0.000	-0.000
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Severe Storm					0.000	0.000	0.000	0.000	-0.000
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tropical Cyclone					0.000	0.000	0.000	0.000	0.000
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wildfire					-0.000	-0.000	0.000	0.000	0.000
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Winter Storm					-0.000*	-0.000	-0.000	-0.000	0.000
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.000*	0.000	0.000	0.000	0.000	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. Obs.	353	335	335	335	335	293	216	239	174
Adj. R^2	0.001	0.002	0.003	0.003	0.045	0.037	0.160	0.046	0.252
WSJI	NO	NO	NO	NO	NO	YES	NO	NO	YES
MCCI	NO	NO	NO	NO	NO	NO	YES	NO	YES
TCRM	NO	NO	NO	NO	NO	NO	NO	YES	YES