Using Mandated Disclosures to Assess Transition Risk: Evidence from Climate Solutions*

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Abstract

We examine whether information in the 10-K Business Description section on firms' development and deployment of climate solution products and services can be used to assess climate transition risk through its implications for asset prices and firm performance. Using large language models to extract this information, we find that firms more engaged in climate solutions exhibit lower stock returns, higher valuation multiples, and more positive (negative) stock price reactions to climate-related events signaling increased (decreased) future demand for climate solutions. We then document that these firms also exhibit higher future profitability when regulatory uncertainty is high, climate concerns unexpectedly increase, and a larger share of sales is in states with climate plans and support for climate action. Overall, our results appear consistent with the hedging hypothesis (Pástor, Stambaugh, & Taylor, 2021, 2022): that firms with high exposure to climate solutions—identified via existing mandated disclosures—can hedge investors against climate transition risks.

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1. Introduction

As the world moves toward reduced carbon emissions, the development of new policies and regulations, advancements in technologies, and changes in market preferences will impose risks on some companies and offer opportunities to others. Several studies explore the former set of firms, focusing on climate transition risk for those exhibiting high carbon emissions and other pollutants.[1] We build on these papers by examining the latter. Specifically, we focus on climate solutions, defined as products and services that develop or deploy technologies in a transition to a low-carbon economy. For companies engaged in climate solutions, transition risks may present new business opportunities due to the rising demand for their products and services. Consequently, the business opportunities for firms with significant exposure of their product portfolio to climate solutions (hereafter "high-climate solution firms") suggest that these firms could act as a hedge against climate transition risk for investors (Pástor et al., 2021, 2022). Accordingly, this paper assesses the market pricing and financial performance implications of firms' exposure to climate solutions.

Building on prior research deriving text-based measures using accounting data (e.g., Brown & Tucker, 2011; Li, 2010; Loughran & Mcdonald, 2016; Lyle, Riedl, & Siano, 2023), we estimate firms' climate solutions using mandated accounting disclosures. Specifically, we apply large language models (LLMs) to analyze the "Business Description" (i.e., Item 1) in U.S. publicly listed firms' 10-K filings (Lu, Serafeim, Xu, & Awada, 2024). This section is particularly suitable for our analysis as it provides a legally mandated, detailed account of companies' products and services, reducing the likelihood of misinformation (i.e., greenwashing) and offering a standardized text for LLM analysis. To identify firms' climate solution products and services, this measure fine-tunes a Generative Pre-trained Transformer (GPT) model using a labeled dataset to identify sentences related to climate solutions. This data is available for 13 GICS industry groups with indicated exposure to climate solutions, where the model demonstrates higher accuracy in identifying climate solutions (Lu et al., 2024). Applying this process, we construct a variable, *CS measure*, defined as the ratio of climate solutions sentences to the total number of sentences in Item 1. This measure proxies for a firm's exposure to climate solutions-related opportunities in its product and service offerings.[2]

[1]Research indicates that assets with greater exposure to climate change news (Huynh & Xia, 2021), higher carbon emissions (Bolton & Kacperczyk, 2021, 2023), or increased toxic emissions (Hsu, Li, & Tsou, 2023) tend to yield higher expected returns, reflecting a positive risk premium as investors demand additional compensation for holding them.

[2]To illustrate, the average firm in our sample has a *CS measure* of 2.695, indicating 2.70% of sentences in Item 1 are classified as related to climate solutions. Of note, the *CS measure* also exhibits predictable

We predict that firms' climate solutions may affect stock returns and firm performance, as high-climate solution firms are better positioned to hedge against transition risks. In particular, we expect the products and services of such firms to be in greater demand during periods of heightened transition risk, allowing them to capitalize on new market opportunities (Pástor et al., 2021, 2022). Traditional theories of intertemporal hedging motives suggest that market participants pay more for firms with strong hedging potential (Campbell, 1993, 1996; Merton, 1973). Thus, we predict that high-climate solution firms exhibit higher stock prices today, resulting in lower expected returns: we denote this as the "hedging hypothesis." Related, we expect such firms to exhibit stronger financial performance when transition risk increases, consistent with elevated demand for climate solutions products and services. Our broad empirical findings support both expectations: we document that firms with greater exposure to climate solutions are associated with lower expected stock returns, and exhibit stronger financial performance following periods of elevated transition risk. Combined, we infer the evidence as consistent with the proposed hedging hypothesis.

Our empirical analyses proceed in five steps. First, we conduct portfolio level analyses by sorting firms into quintile portfolios based on their *CS measure*. Importantly, we sort firms relative to same industry peers, thus differentiating between firms with high versus low climate solutions while controlling for industry-specific effects. We find that firms with higher exposure to climate solutions (i.e., those with higher values of the *CS measure*) exhibit relatively lower subsequent stock returns. Specifically, a high-minus-low portfolio strategy reflecting a long (short) position in the quintile portfolio of the highest (lowest) *CS measure* yields a significant average annual return of -5.37%. We also conduct time-series regression analysis of the portfolios' excess returns on common risk factors to estimate alphas. We confirm that these risk factors cannot account for the negative cross-sectional return spread observed across portfolios sorted based on *CS measure*.

Second, we conduct firm-level analysis, employing pooled panel regressions to examine the cross-sectional relationship between individual stock returns and *CS measure*, while controlling for a comprehensive set of variables to account for industry group effects and other known return predictors. We find that *CS measure* consistently negatively predicts future stock returns across various control variables specifications. These effects remain economically significant: a one standard deviation increase in *CS measure* corresponds to lower future stock returns of 2.82% per annum. We also conduct pooled panel regressions to investigate the

variation: for example, the average *CS measure* is 57% and 11% for Tesla and General Motors, respectively. We detail the construction of this variable in Section 3.1.

relationship between firms' contemporaneous valuation ratios and *CS measure*. Our results indicate that high-climate solution firms exhibit higher valuation ratios, consistent with the market placing a valuation premium on these firms.

Third, we confirm the uniqueness of the proposed *CS measure* relative to other climate-related metrics, including those derived from alternative disclosure channels. Of note, Sautner, van Lent, Vilkov, and Zhang (2023a) derive a measure capturing climate opportunities as discussed in earnings conference calls, proposing this as a proxy for market participants' attention to a firm's climate opportunities. We confirm that all main results are robust to controlling for this latter climate opportunities exposure. Moreover, consistent with Sautner, van Lent, Vilkov, and Zhang (2023b), we fail to find significant market returns associated with their climate opportunities exposure measure, suggesting that our documented negative *CS measure*-return relationship applies more to firms offering climate solutions through their products and services (as captured by our measure) rather than those attracting market attention for climate opportunities (as captured by theirs). Related, we confirm that our *CS measure* differs from emissions-based metrics. Conceptually, climate solutions and emissions need not be strongly correlated: for instance, battery production helps other firms reduce emissions but it is not itself a high-emitting industry, especially if the battery is produced with low carbon electricity. Empirically, we find our inferences are unchanged to controlling for carbon footprint.

Fourth, after documenting a robust negative *CS measure*-return relationship, we examine whether the lower expected returns of high-climate solution firms stem from their ability to hedge against climate transition risks by examining two implications of the hedging hypothesis. First, this hypothesis suggests that the hedging value of climate solutions should increase when transition risk is higher. Accordingly, we analyze firms' short-window stock price reactions to five significant climate-related regulatory events capturing changes in transition risk. Results indicate that high-climate solution firms exhibit significantly higher 5-day cumulative abnormal returns (CAR) relative to low-climate solution firms to events designated as increasing demand for climate solutions through tighter regulations or increased incentives (such as the signing of the Paris Agreement), and lower CAR to decreased demand for climate solutions (captured in anticipated relaxation in regulatory stringency with the election of President Trump). These findings confirm that equity investors incorporate the expected benefits and costs associated with political and regulatory changes conditional on firms' engagement in climate solutions.

Fifth and related to the previous analysis, the hedging hypothesis suggests that the future profitability of high-climate solution firms should be higher when transition risk increases due to greater demand for climate solutions. Accordingly, we examine how firms' future profitability is influenced by the interaction between *CS measure* and three measures of transition risk. The first measure is the environmental and climate policy uncertainty index developed by Noailly, Nowzohour, and van den Heuvel (2022), which captures time-series variation in transition risk stemming from environmental regulatory uncertainty. The second measure, following Ardia, Bluteau, Boudt, and Inghelbrecht (2023), captures time-series variation in unexpected media climate change concerns, providing a more general indicator of transition risk. The third measure, which varies in both the cross-section and times-series, assesses firms' direct exposure to climate-related shocks by combining the geographical distribution of firms' operations based on state-level sales with climate-related shocks at the state level. We conduct pooled panel regressions of firms' future profitability on *CS measure* and its interactions with each of these three measures of transition risk. We test the joint hypothesis that (i) the linear *CS measure* term enters negatively, suggesting that high-climate solution firms exhibit lower future profitability when there is minimal transition risk, consistent with the costly investment required to provide climate solutions, and (ii) the interaction between *CS measure* and each measure of transition risk enters positively, indicating that the negative impact of *CS measure* on future profitability is mitigated during periods of heightened transition risk. Consistent with this joint hypothesis, the impact of *CS measure* on future profitability becomes less negative (and sometimes even positive) when transition risk reaches sufficiently high levels, as captured by each of the above three proxies.

Overall, we infer these results as consistent with the hedging hypothesis, since the expected cash flows and actual performance of high-climate solution firms are dependent on the level of transition risk. Of note, the hedging hypothesis posits that the future profitability of high-climate solution firms will covary positively with transition risk, indicating higher future profitability in states of the world characterized by elevated levels of transition risk.

We also assess two potential alternative explanations for our findings. First, the literature on attention and return predictability suggests that the market often underreacts to various types of value-relevant information, including industry news, demographic shifts, and upstream-downstream relationships (Cohen & Frazzini, 2008; DellaVigna & Pollet, 2007; Hong, Torous, & Valkanov, 2007). To the extent the market systematically underreacts to climate solutions information, this would suggest a similar negative association with returns. However, this latter prediction also suggests that the future profitability of high-climate solution firms should be unaffected by the level of transition risk. Thus, our empirical evidence regarding systematic differences in future profitability conditional on transition risk appears inconsistent with this "mispricing" notion.[3] Second, investors' preferences for so-called green assets may lead to increased demand for high-climate solution firms to the extent their products and services are perceived as environmentally friendly by investors. The theoretical literature suggests that such preferences, which reflect non-pecuniary motives, can lead to the stock prices of these firms trading at a premium (Baker, Bergstresser, Serafeim, & Wurgler, 2022; Fama & French, 2007; Friedman & Heinle, 2016; Pástor et al., 2021; Pedersen, Fitzgibbons, & Pomorski, 2021; Zerbib, 2022). Related, norm-constrained investors often engage in exclusionary ethical investing, leading to higher expected returns for brown firms due to reduced demand (Fernando, Sharfman, & Uysal, 2017; Heinkel, Kraus, & Zechner, 2001; Hong & Kacperczyk, 2009; Luo & Balvers, 2017). Thus, under this so-called "investor preference hypothesis," high-climate solution firms may reflect a price premium due to investor preferences for firms that provide green products and services, again resulting in lower expected returns. However, we find no evidence of either institutional investors or norm-contrained investors holding higher shares in firms with higher climate solutions. Combined, these latter results suggest that the investor preference hypothesis is unlikely to explain the negative *CS measure*-return relationship. We further note that a potential explanation is that while there has been significant societal pressure for institutional investors to avoid holding shares in high carbon emission firms, there has been limited pressure on investors to hold shares of high-climate solutions firms, consistent with negative screening being the most frequent ESG strategy (Amel-Zadeh & Serafeim, 2018).

We then conduct additional analyses. First, we demonstrate that the effectiveness of climate solutions as a hedge against transition risk is even stronger when firms also have a low carbon footprint, as the positive carbon premium may offset the negative return spread associated with the hedging potential of climate solutions. Second, we conduct a topic analysis on *CS measure* to assess the carbon abatement costs and potential of firms' climate solutions. We find that the hedging benefits are more pronounced for firms offering low-cost climate solutions, suggesting that investors perceive these firms as better positioned to manage transition risk effectively. Third, while the investor preference hypothesis predicts greater institutional ownership in high-climate solution firms regardless of transition risk, the hedging hypothesis suggests that a specific subgroup of investors—those with high hedging needs and

[3] We also examine analyst forecast errors by regressing them on the interaction between *CS measure* and the measures of transition risk, and find no evidence that high-climate solution firms are overvalued during periods of elevated transition risk.

the ability to hedge—will invest more in high-climate solution firms when transition risk is elevated. Consistent with this expectation, we find that only natural arbitrageurs, such as mutual funds and independent investment advisors, tilt their portfolios toward high-climate solution stocks in response to increased transition risk, indicating the active use of these stocks as a hedge. Finally, we confirm the robustness of our main findings through several approaches: using equal-weighted portfolio returns, conducting Fama-MacBeth regressions, controlling for firm innovation, accounting for ratings of a firm's greenness, and utilizing option-implied expected returns.

Our findings contribute to three key literatures. First, we build upon the literature on the informativeness of regulated disclosures in capital markets (Brown & Tucker, 2011; Li, Lundholm, & Minnis, 2013). Smith (2023) develops a theoretical model in which climate disclosure facilitates more efficient risk-sharing in financial markets by helping investors identify stocks that effectively hedge climate risk. We provide empirical evidence supporting this argument by showing that existing regulated filings already contain valuable information that LLMs can extract to generate measurable variations relevant to climate risk hedging. Further, while prior research raises concerns that 10-K filings have become increasingly boilerplate (Dyer, Lang, & Stice-Lawrence, 2017) or predominantly focus on risk-related content (Campbell, Chen, Dhaliwal, Lu, & Steele, 2014; Matsumura, Prakash, & Vera-Muñoz, 2024), we show that these filings provide information on business opportunities that is distinct from existing measures. For example, compared to textual analyses that primarily assess firms' exposure to climate risks (Berkman, Jona, & Soderstrom, 2024; Kölbel, Leippold, Rillaerts, & Wang, 2024; Li, Shan, Tang, & Yao, 2024; Sautner et al., 2023a), our approach emphasizes climate-related opportunities. Furthermore, relative to existing measures of climate opportunities (Leippold & Yu, 2023; Sautner et al., 2023a), our measure—derived from firms' 10-K Item 1 business descriptions—is more likely to capture products and services already integrated into a firm's operations rather than prospective opportunities discussed in voluntary disclosures or under development in patents.

Second, our work builds upon papers examining the impact of CSR reporting and regulation (e.g., Christensen, Hail, & Leuz, 2021) by demonstrating that climate-related informational content can be extracted from already existing (and non-CSR specific) mandated firm disclosures. That is, our findings suggest a complementary role for CSR and non-CSR disclosure channels in the identification and decision-usefulness of such signals. Related, our study contributes to the growing literature examining the pricing of assets in the context of climate transition risk.

Recent work examines this pricing in equities (Bolton & Kacperczyk, 2021, 2023; Hsu et al., 2023; Pástor et al., 2022; Sautner et al., 2023b), corporate bonds (Huynh & Xia, 2021; Seltzer, Starks, & Zhu, 2022), bank loans (Delis, de Greiff, Iosifidi, & Ongena, 2024; Ivanov, Kruttli, & Watugala, 2024; Kacperczyk & Peydró, 2022), and options (Ilhan, Sautner, & Vilkov, 2021). Of note, these studies predominantly adopt a left-tail risk perspective, viewing transition risks as challenges for firms with high carbon emissions, industrial pollution, stranded assets, or poor environmental profiles. In contrast, we adopt a business opportunity (i.e., right-tail risk) perspective, recognizing that firms engaged in climate solutions can benefit from transition risks, as heightened climate concerns can drive increased demand for their goods and services (Pástor et al., 2021).

Finally, our study contributes to the accounting literature on innovation and stock returns. In particular, Glaeser and Lang (2024) call for research to examine how well existing disclosures capture the existence and nature of green innovation. Earlier work finds that higher investments in R&D are associated with higher stock returns (Chambers, Jennings, & Thompson, 2002; Chan, Lakonishok, & Sougiannis, 2001; Lev & Sougiannis, 1996), with some attributing these returns to compensation for different types of risks (Lev & Sougiannis, 1999; Lin & Wang, 2016; Stoffman, Woeppel, & Yavuz, 2022; Tseng, 2022), while others argue they reflect mispricing (Eberhart, Maxwell, & Siddique, 2004; Lev, Sarath, & Sougiannis, 2005). We extend this literature in two ways. First, we show that climate solution firms, despite their active engagement in innovative technologies, exhibit lower expected returns. This finding contrasts with the conventional innovation premium, as high-climate solution firms can serve as a hedge against transition risk for investors. Second, our findings provide direct evidence that mandated reporting can provide useful signals relating to green innovation.

2. Literature review and conceptual underpinning

Empirical research provides support that climate-related risks influence expected returns. For example, Faccini, Matin, and Skiadopoulos (2023) document that risks arising from the U.S. climate-policy debate are priced in the U.S. stock market. Huynh and Xia (2021) demonstrate that corporate bonds with heightened exposure to climate change news risk exhibit higher expected returns, reflecting a positive risk premium. Bolton and Kacperczyk (2021, 2023) find that firms with higher carbon emissions have higher returns, as investors demand a carbon premium to compensate for potential regulatory risks. Hsu et al. (2023) document a similar pollution premium for firms with toxic emissions. Additionally, Leippold and Yu (2023) find that firms with more green patents earn a negative return premium and attract more institutional investor ownership.

Several studies document instances of mispricing related to climate change risks. For example, Hong, Li, and Xu (2019) find that stocks with greater exposure to drought risk have lower returns due to the market's underreaction to climate risk. Similarly, research shows that firms adversely affected by abnormal temperatures (Cuculiza, Kumar, Xin, & Zhang, 2024) and those with poor ESG practices (Glossner, 2021) experience lower returns because the market does not fully incorporate information about their poor future performance into stock prices. There is also evidence that carbon risk may be mispriced, as indicated by the positive abnormal returns generated by a long-short portfolio constructed from stocks with low versus high carbon emissions (Garvey, Iyer, & Nash, 2018; In, Park, & Monk, 2019; Kim & Kim, 2020).

An established literature documents that investors are more inclined to hold socially responsible firms due to social norms and preferences, which influence stock prices. For example, Hong and Kacperczyk (2009) demonstrate that "sin" stocks have higher expected returns due to lower demand from norm-constrained investors. More generally, ESG-sensitive investors' reluctance to invest in certain assets leads to higher expected returns for non-green companies (Fernando et al., 2017; Heinkel et al., 2001; Luo & Balvers, 2017). Additionally, research indicates that both retail and institutional investors' demand for socially responsible firms can increase prices and decrease the expected returns of these firms (Cao, Titman, Zhan, & Zhang, 2023; Chava, 2014; Gibson, Krueger, & Mitali, 2021; Riedl & Smeets, 2017).

Although each of the three hypotheses—hedging, mispricing, and investor preference—predicts that high-climate solution firms have lower expected stock returns, they offer different testable implications for the economic mechanism driving the relationship. The testable implications for the hedging hypothesis are derived from the equilibrium model developed by Pástor et al. (2021). In this model, stocks whose cash flows correlate positively with climate risk—i.e., performing well when there is an unexpected negative climate shock—serve as a climate-risk hedge and thus have a lower expected return. Conversely, stocks whose cash flows correlate negatively with climate risk—i.e., performing poorly when there is an unexpected negative climate shock—have a higher expected return. Accordingly, we proxy for firms' cash flows by examining their profitability (e.g., gross margin, return on assets, and return on sales), as the literature indicates that transition risk affects the profitability and operation of firms (Hsu et al., 2023; Ramadorai & Zeni, 2024).

Applying this framework to the context of climate solutions, we expect high-climate solution firms' cash flows to correlate positively with transition risk, given that their products and services are in highest demand during periods of greater urgency for decarbonization. Our prediction is related to research investigating the impact of carbon emissions on firm value. For example, Ramelli, Wagner, Zeckhauser, and Ziegler (2021) demonstrate that the Trump's 2016 election boosted carbon-intensive firms as it downshifted expectations regarding U.S. policy toward climate change. Monasterolo and de Angelis (2020) observe a decrease in the risk premia for low-carbon assets following the Paris Agreement. Thus, the hedging hypothesis predicts that (i) high climate solution firms exhibit lower expected returns (reflecting a price premium for their acting as a hedge against transition risk) and (ii) *conditional* on the level of transition risk, the future profitability of high-climate solution firms will increase with higher levels of transition risk.

In contrast, the mispricing hypothesis posits that investors systematically overvalue high-climate solution firms relative to their fundamental value, suggesting the cash flows of these firms should be unaffected by the level of transition risk. Thus, the mispricing hypothesis predicts that high-climate solution firms will exhibit lower future profitability *regardless* of the level of transition risk. Finally, the investor preference hypothesis does not reflect expectations regarding future profitability but rather changes in investors' holdings driven by their preference for holding stocks of high-climate solution firms. To examine testable implications of this hypothesis, we follow the existing literature and use institutional ownership to measure investor demand (Bolton & Kacperczyk, 2021; Hong & Kacperczyk, 2009; Pedersen et al., 2021). According to this hypothesis, we expect high-climate solution firms to be associated with higher institutional ownership, especially among norm-constrained investors.

3. Data, sample, and variables

3.1. Climate solutions large language model

To measure firms' focus on climate solution products and services, we use data that fine-tunes a GPT model to detect climate solutions sentences in the "Business Description" (i.e., Item 1) section of 10-K filings from the Securities and Exchange Commission's (SEC) EDGAR database (Lu et al., 2024). Our sample period spans fiscal years 2005 to 2022. We start in 2005 to coincide with the more stable SEC disclosure requirement for firms regarding their most significant risks in Item 1A. We retain 13 (out of 25) GICS industry groups that are central to climate solutions; this both ensures materiality of climate solutions as part of the underlying business model, and reflects where our model is more accurate in identifying climate solutions.

The climate solutions GPT model is fine-tuned using a training dataset of 3,508 sentences, each labeled as either a climate solutions sentence or not. These sentences are chosen from 10-K Item 1 sentences that are representative of each of the 13 industry groups, as well as sentences that the model deems more difficult to classify through an active learning approach.[4] The labeling for climate solution sentences is based on Project Drawdown, which contains a list of technologies that can reduce greenhouse gases in the atmosphere, and are compiled by a network of scientists and researchers. GPT is well-suited for this measure since separating climate solution sentences from other climate sentences requires more advanced context recognition than other methods such as lexicon-based approaches, and the fine-tuned GPT model is more capable of understanding contextual sentences.[5] Our fine-tuned climate solutions GPT model achieves an accuracy rate of 84.09% and an F1 score of 0.79, indicating a high level of precision and recall in its predictions.[6]

The climate solutions GPT model to applied to all sentences in 10-K Item 1. To capture the relative importance of climate solutions for a given firm-year, we create the variable *CS measure*, defined as the number of climate solutions sentences divided by the total number of sentences in the 10-K Item 1. We use this measure to proxy for a firm's economic activities relating to climate solution products and services. Previous research provides validation that this measure correlates with other measures of climate opportunities, such as green patents and green revenues, as well as with higher research and development investments required to commercialize climate solutions (Lu et al., 2024). The Internet Appendix presents a related extract on the LLM methodology section of Lu et al. (2024), which details the construction and labeling of the climate solutions GPT model.

3.2. Financial and accounting data

We obtain stock return data from Center for Research in Security Prices (CRSP) and accounting data from Compustat. To address backfilling bias, we require firms to be listed on Compustat

[4]In machine learning, active learning is a semi-supervised learning framework that selects the data points the model learns from with the aim of optimizing learning efficiency and model performance with less labeled data. We provide more details in the Internet Appendix.

[5]For example, "We produce electric vehicles" is considered a climate solutions sentence, but "We believe we have a responsibility and opportunity to play a role in the global economic transition to net zero emissions" is not. As a more challenging example, the sentence "Primary fleet EV competitors include Smith Electric, Azure Dynamics, Enova, and EnVision Motor Company" is classified as a climate solutions sentence but "Electric vehicle industry growth has accelerated in the past several years" is not. While both sentences refer to the climate solution electric vehicles (EV), the former implies the focal firm produces EV and has EV competitors, while the latter merely describes an industry trend without sufficient information to suggest the focal firm produces EV.

[6]The F1 score is calculated as the harmonic mean of precision (the percentage of predicted positives that are truly positive) and recall (the percentage of true positives that are predicted as positives).

for two years before we include them in our sample (Hsu et al., 2023). Our sample consists of firms with non-missing data for *CS measure*, stock returns, and whose domestic common shares (SHRCD = 10 or 11) are traded on the NYSE, AMEX, or NASDAQ. Following the literature, we exclude financial firms with four-digit standard industrial classification (SIC) codes ranging from 6000 to 6999.

3.3. Descriptive statistics

Table 1 provides descriptive statistics for the 2005-2023 firm-year sample. Our analysis includes control variables for firm fundamentals, including: the natural logarithm of market capitalization (*ME*); the natural logarithm of book-to-market ratio (*B/M*); investment rate (*I/K*); ratio of R&D to sales (*R&D/Sales*); return on assets (*ROA*); return on equity (*ROE*); book leverage (*Leverage*); operating leverage (*OL*); tangibility (*Tangibility*); and Whited-Wu index (*WW*). Additionally, we include controls for stock characteristics, such as the standard deviation of monthly stock returns over the past 12 months (*Volatility*) and the cumulative 12-month return of a stock, excluding the immediate past month (*Momentum*). Table A.1 of Appendix A presents the variable definitions.

Panel A of Table 1 presents the summary statistics for all variables used in this study. Our sample comprises 14,311 firm-year observations with non-missing values for *CS measure*. *CS measure* exhibits a mean of 2.695: i.e, 2.70% of the total sentences in a firm's 10-K Item 1 Business Description relate to climate solutions per our GPT model classification. The standard deviation is 6.12, signifying considerable variation across firms. Panel B presents the summary statistics of *CS measure* across 4-digit GICS industry groups: firms in "Utilities", "Automobiles & Components", and "Capital Goods" exhibit higher *CS measure*; those in "Transportation", "Consumer Durables & Apparel", and "Household & Personal Products" exhibit lower *CS measure*. Panel C presents the correlation coefficients for all Panel A variables. *CS measure* exhibits generally low correlations with other variables, except the three profitability ratios of *Gross margin* (-0.18), *ROS* (-0.20), and *ROA* (-0.25).

4. Empirical results

This section investigates the empirical relationship between firms' climate solutions and cross-sectional stock returns by: (i) conducting portfolio-level analysis to examine if firms' climate solutions negatively predict stock returns; (ii) confirming if this relationship remains after accounting for common risk factors through asset pricing tests; (iii) using firm-level analysis to control for other firm characteristics that may predict stock returns in the cross-section;

and (iv) performing valuation regressions to analyze if firms with more climate solutions trade at a valuation premium.

4.1. Portfolio analysis

First, we create quintile portfolios based on firms' *CS measure* overJuly 2006 to June 2023.[7] Specifically, we rebalance portfolios at the end of every June in year t by assigning sample firms into quintile groups within the corresponding 4-digit GICS industry group, based on their *CS measure* as of the fiscal yearend in calendar year $t-1$. Critically, this provides industry-specific breakpoints for quintile portfolios for each June, where the low (high) portfolio contains firms with the lowest (highest) *CS measure* in each industry group. We present the time-series average of the cross-sectional medians of firm characteristics for the five *CS measure*-sorted portfolios in Internet Appendix Table IA.1. Firms in the low (high) portfolio exhibit a mean *CS measure* of 0.42% (9.7%). After forming the five portfolios, we track their performance over the subsequent twelve months (i.e., July of year t to June of year $t+1$) by computing value-weighted monthly returns.[8] We then construct a high-minus-low portfolio, representing a zero-cost trading strategy taking a long (short) position in the high-*CS measure* (low-*CS measure*) portfolio.

Table 2 Panel A presents the average returns in excess of the risk-free rate in percentage, t-statistics,[9] standard deviations, and Sharpe ratios. The findings indicate that a firm's *CS measure* negatively predicts stock returns, with excess returns generally decreasing across the portfolios from low to high. Specifically, the low, 2, 3, 4, and high portfolios yield excess returns of 0.97%, 0.87%, 0.89%, 0.87%, and 0.52%, respectively. Notably, the high-minus-low portfolio exhibits a monthly excess return of -0.45% (t-statistic = -2.06). The equivalent annualized excess return is -5.37%, which is comparable in magnitude to the pollution premium of 4.42% per Hsu et al. (2023). Furthermore, Sharpe ratios tend to decrease from the low to high portfolio, with the magnitude of the annualized Sharpe ratio of the high-minus-low portfolio ($0.52 = \sqrt{12} \times 0.15$) being comparable to that of the equity risk premium.

We then confirm the robustness of our observed variation in the average returns of the *CS measure*-sorted portfolios to existing risk factors models. To adjust for risk exposure, we perform time-series regressions of portfolios' excess returns on risk factors to estimate each

[7]We only include firms with at least one non-zero *CS measure* during the sample period.

[8]Publicly traded companies in the U.S. are generally required by the SEC to file their 10-K reports within 90 days after the end of the fiscal year. The six-month minimum gap between the fiscal yearend and the return tests ensures that the values of *CS measure* are known before they are used to explain returns.

[9]Standard errors are calculated using the Newey-West correction for 12 lags.

portfolio's risk-adjusted return (i.e., alphas). We use five sets of risk factors (Hsu et al. (2023)). Panel B includes the market factor (MKT) based on the CAPM model; Panel C the Fama and French (1996) three factors (MKT, the size factor SMB, and the value factor HML); Panel D the Carhart (1997) four factors (MKT, SMB, HML, and the momentum factor UMD); Panel E the Fama and French (2015) five factors (MKT, SMB, HML, the profitability factor RMW, and the investment factor CMA); and Panel F the Hou, Xue, and Zhang (2015) q-factors (MKT, SMB, the investment factor I/A, and the profitability factor ROE). We find that the cross-sectional return spread across portfolios sorted on *CS measure* cannot be captured by these risk factors as the alphas in the high-minus-low portfolio remain statistically significant. In Figure 1, we illustrate the time-series of the cumulative abnormal returns from an initial investment of one dollar based on the risk-adjusted returns of the high-minus-low portfolio from Panel E of Table 2. Throughout most of the sample period, the high-minus-low portfolio consistently displays lower risk-adjusted returns. In summary, the above results suggest that the observed negative *CS measure*-return relationship cannot be ascribed to common risk exposure.

4.2. Firm-level analysis

To ensure that our results do not hinge solely on portfolio returns, we next run pooled panel regressions using individual stocks. This approach enables us to account for a comprehensive set of firm characteristics that are known predictors of stock returns, and to explore whether the negative *CS measure*-return relationship is influenced by other predictors at the firm level.

For each month from July of year t to June of year $t+1$, we regress individual stocks' monthly returns in excess of the risk-free rate on the *CS measure* from year $t-1$ and various control variables known by the end of June in year t. Following Hsu et al. (2023), we control for *log ME*, *log B/M*, *I/K*, *ROA*, *Leverage*, *Tangibility*, *WW*, *Volatility*, and *Momentum*. Given that climate solutions frequently involve innovative technologies and processes, firms with higher R&D expenditures may be more involved in the development and implementation of climate solutions. Thus, we also incorporate R&D to sales (*R&D/Sales*) to disentangle the effect of climate solutions on stock returns from the broader impact of innovation activities (Chambers et al., 2002; Chan et al., 2001). We use year-month fixed effects to capture cross-sectional variation in returns, and industry fixed effects to account for the impact of *CS measure* on individual stock returns relative to other peer firms within the same 4-digit GICS industry group (Bolton & Kacperczyk, 2021; Pedersen et al., 2021). Standard errors are clustered at the firm level. All independent variables are normalized to a zero mean and a one standard deviation after winsorization at the 1st and 99th percentiles to reduce the impact of outliers.

Table 3 presents the results. Column (1) includes only *CS measure*, which attains a significantly negative coefficient of -0.235 (t-statistic = -3.79). This finding suggests that a one standard deviation increase in *CS measure* corresponds to a decrease of 2.82% in the annualized stock return.[10] As the difference in the average *CS measure* between the low and high portfolios from Section 4.1 reflects 1.52 standard deviations, the coefficient estimate in column (1) implies an annual return spread of -4.29%, which aligns with the previous high-minus-low portfolio effect of -5.37%.

Results remain robust in Column (2) (which controls for firm characteristics known to predict stock returns in the cross-section), as well as Column (3) (which additionally controls for stock characteristics that are also known predictors of stock returns (Hsu et al., 2023)). Overall, these findings indicate that the negative *CS measure*-return relationship also holds at the firm level, and cannot be explained by other known firm-level predictors of stock returns.[11]

4.3. Controlling for other climate-related measures

We next demonstrate that *CS measure* both differs from other examined climate-related measures, and that our results are robust to controlling for these alternative measures. Specifically, we show how *CS measure* (which captures companies with products and services in climate solutions) differs from proxies based on voluntary disclosures reflecting investor attention on potential opportunities (Sautner et al., 2023a) and from measures of climate risk based on greenhouse gas emissions.

4.3.1. Controlling for climate change opportunity exposure

Sautner et al. (2023a) develop firm-level climate change exposure measures based on the relative frequency with which bigrams related to climate change occur in earnings conference call transcripts (*CCExposure*). The authors also construct similar exposure variables to capture opportunities ($CCExposure^{Opp}$), regulatory shocks ($CCExposure^{Reg}$), and physical shocks ($CCExposure^{Phy}$) related to climate change. Sautner et al. (2023a) describe their

[10]The magnitude of this effect is comparable to the carbon premium observed by Bolton and Kacperczyk (2021), where they demonstrate that a one standard deviation increase in the level of scope 1 and scope 2 emissions leads to a 1.8% and 2.9% increase in annualized returns, respectively.

[11]We further explore whether the negative *CS measure*-return relationship varies across industry groups, given the significant industry-level variation in firms' *CS measure* previously observed in Panel B of Table 1. Figure 2 plots the point estimates and corresponding 95% confidence intervals of the coefficients on *CS measure* using the specification in column (3) of Table 3, estimated separately for each GICS industry group. While the negative *CS measure*-return relationship persists in most industry groups, there are some exceptions. The coefficients on *CS measure* are statistically insignificant for the 'Transportation", "Consumer Durables & Apparel", and "Household & Personal Products" industry groups, consistent with these three industries exhibiting the lowest average *CS measure*.

measure as capturing "attention paid by earnings call participants to firms' climate change exposures"; in contrast, we argue that *CS measure* identifies firms with climate solutions in their product portfolio as reflected in the 10-K business description. Consistent with this distinction, a manual examination of firms with the largest gap between the two measures reveals that firms with low $CCExposure^{Opp}$ but high *CS measure* are more likely to already be offering climate solutions products and services. In contrast, firms with high $CCExposure^{Opp}$ but low *CS measure* are discussing climate opportunities without necessarily having them integrated into their business operations. Also supporting this notion, Lu et al. (2024) finds that the *CS measure* is associated with higher revenue growth, but not $CCExposure^{Opp}$.

To verify that our results are not driven by firms' climate change exposure variables, we perform double sorting on *CS measure* and *CCExposure*. Specifically, at the end of every June in year t, we assign firms into bottom and top groups based on the median value of the *CCExposure* measure in year $t-1$ and into quintile groups based on *CS measure* in year $t-1$, both relative to 4-digit GICS industry peers. This double sorting results in ten portfolios (2 $\times$ 5). We track the performance of these ten portfolios from July of year t to June of year $t+1$. If firms' climate change exposure is responsible for the negative *CS measure*-return relationship, then we would expect the return spread to be concentrated within the bottom or top groups. However, as shown in columns (1) to (6) of Table 4, the return spread on the high-minus-low *CS measure* portfolio remains significantly negative for both the bottom and top groups across all specifications presented in Panels A through F.

We also incorporate these variables as additional control variables in the pooled panel regressions. Table 5 Panel A demonstrates that the coefficient on *CS measure* again remains significantly negative, while none of the coefficients on Sautner et al.'s (2023a) climate change exposure variables exhibit statistical significance. These findings are consistent with those of Sautner et al. (2023b), who also report an insignificant unconditional risk premium associated with their climate change exposure variables based on realized returns.

4.3.2. Controlling for carbon emissions

We next control for firms' carbon emissions to address the potential concern that firms with a high *CS measure* may have lower carbon emissions. Lu et al. (2024) suggest this scenario is unlikely as there is a very low correlation between *CS measure* and greenhouse gas emissions. Nonetheless, we perform double sorting on *CS measure* and the natural logarithm of the sum of a firm's scope 1 and 2 greenhouse gas emissions (*log Scope 1 and 2*) using data from Trucost. Specifically, at the end of every June in year t, we assign firms into bottom and top groups based on the median value of the *log Scope 1 and 2* in year $t-1$ and into quintile groups based on *CS measure* in year $t-1$, both relative to industry peers. Table 4 columns (7) to (12) show that the return spread on the high-minus-low *CS measure* portfolio is significantly negative in both the bottom and top groups of carbon emissions. Thus, the negative *CS measure*-return relationship is not concentrated within either emissions group.

Table 5 Panel B then incorporates measures of carbon emissions in the pooled panel regressions. Columns (1) and (2) control for firms' natural logarithm of scope 1 (*log Scope 1*) and scope 2 (*log Scope 2*) emissions, respectively; while columns (3) and (4) control for firms' scope 1 (*Scope 1 int*) and scope 2 (*Scope 2 int*) carbon emission intensity, respectively.[12] The coefficients on *log Scope 1* and *log Scope 2* are both positive, although statistically significant only for the latter, indicating the presence of a carbon risk premium. Consistent with Bolton and Kacperczyk's (2021), the carbon premium appears unrelated to emission intensity as the coefficients on carbon emission intensity are insignificant. Importantly, across all four columns, the coefficients on *CS measure* remain significantly negative, confirming its predictive power beyond carbon emissions.

4.4. Valuation regressions

We now investigate the firm valuation implications of climate solutions by analyzing the relation between contemporaneous valuation ratios and *CS measure* (Pedersen et al., 2021). Similar to prior research (Hong & Kacperczyk, 2009), we consider three valuation ratios (all in natural logarithm form): market-to-book ratio (*log MB*), price-to-earnings ratio (*log PE*), and enterprise value to EBITDA ratio (*log EM*).[13] The first ratio reflects a balance sheet perspective, while the latter two offer an income statement perspective.

We conduct pooled panel regressions of these valuation ratios on firms' *CS measure* in the same year.[14] In addition to the control variables from the previous section, we introduce the additional controls of a firm's current and future three years' *ROE* (*ROE*, *F1ROE*, *F2ROE*, *F3ROE*) as per Hong and Kacperczyk (2009). Our baseline specification uses industry fixed effects and year fixed effects, with standard errors clustered at the firm level. However, given that industry-specific, time-varying competition, business cycles, or technological development can influence firm profits (and hence valuations) within each industry, we alternatively also

[12] Following Bolton and Kacperczyk (2021), we winsorize carbon emission intensity at the 2.5% level.

[13] The enterprise value of a firm represents the total value of debt and equity. Since EBITDA reflects profits to both debtholders and equityholders, the enterprise value to EBITDA ratio remains unaffected by changes in capital structure.

[14] Observations are dropped if the denominator of the valuation ratio is negative.

employ industry × year fixed effects, with standard errors clustered at the industry × year level to accommodate within-industry-year variation.

Table 6 presents the results. Across all specifications, firms with more climate solutions exhibit higher valuation ratios across all three measures. The magnitude of the valuation effects are also economically sizable. For example, in column (1), the coefficient on *CS measure* is 0.051, implying that a one standard deviation increase in a firm's *CS measure* corresponds to a 5% increase in its market-to-book ratio relative to industry peers. These findings show that firms with more climate solutions currently trade at a valuation premium, consistent with their observed negative future stock returns.

5. Economic mechanisms

The results thus far indicate that high-climate solution firms experience lower future stock returns and exhibit higher current market valuations. We now explore the potential mechanisms underlying these findings. Our main hypothesis is that high-climate solution firms represent a better hedge against climate transition risks. To provide evidence in support of the hedging hypothesis, we first examine how firms' stock prices react to salient climate-related regulatory events. Then, we analyze the relationship between firms' climate solutions and future profitability, conditional on environmental regulatory uncertainty, unexpected climate change concerns, and firm-level exposure to climate-related shocks.

5.1. Climate-related regulatory shocks

We investigate whether the *CS measure*-return relationship is driven by climate transition risk by examining the stock price reactions to major climate regulatory events. We predict that market valuations of firms with more climate solutions stand to benefit from events likely to increase demand for climate solutions (Pástor et al., 2021), and conversely be adversely affected by shocks that diminish demand for climate solutions through relaxed regulations.

Our analysis consists of five events posited as affecting demand for climate solutions. First, we consider the Massachusetts v. EPA Supreme Court case, decided on April 2, 2007. In this case, the EPA was mandated by Congress to regulate greenhouse gas emissions from motor vehicles; this signaled a tightening of environmental regulations (Sugar, 2007), and led to the EPA establishing emission standards for vehicles. The second event is the announcement of the Paris Agreement on December 12, 2015. This landmark event increased the likelihood of regulatory actions aimed at limiting carbon emissions and significantly elevated the importance of transition risks (Bolton & Kacperczyk, 2021, 2023; Monasterolo & de Angelis, 2020). The third event is Donald Trump's unexpected election victory on November 8, 2016. This event signaled a probable relaxation of environmental regulations, reflecting his stated pledges to dismantle climate regulations and withdraw from the Paris Agreement (Ramelli et al., 2021). The fourth event is the Congressional confirmation of President Biden's election results on December 14, 2020. This event signified a significant reversal in expectations regarding U.S. climate policy following the Trump administration, as Biden proposed to revoke several of his predecessor's executive orders and identified climate change as one of his top priorities (Pham, Hao, Truong, & Trinh, 2023). Lastly, we examine the announcement of the Inflation Reduction Act on July 27, 2022. This legislation benefits firms engaged in climate solutions by allocating substantial funds for the development of climate solutions, intended to expedite emission reductions in the U.S.

We examine shareholder reactions to the aforementioned events using a short-run event study methodology (MacKinlay, 1997). We estimate daily cumulative abnormal returns (CARs) based on the market model (using the CRSP value-weighted index) over a 5-day window from the event date, which we refer to as a $(0, +5)$ window.[15] Panels A to E of Table 7 present the mean CARs around each event for stocks sorted into quintile portfolios based on *CS measure* relative to their 4-digit GICS industry group peers. The CARs of the *CS measure*-sorted portfolios exhibit a predominantly monotonic increasing pattern from the low to high portfolios, and consistently significant positive high-minus-low portfolio CARs, for regulatory events expected to be advantageous for firms with more climate solutions (Panels A, B, D, and E). Conversely, for the event likely to signify negative news for high-climate solution firms (Panel C), the CAR of the high-minus-low portfolio is significantly negative. The impact of these regulatory shocks on shareholder wealth is also economically substantial. To illustrate, consider the Trump election event: with an average market capitalization of $6.4 billion for sample firms, the average difference in CARs between the high and low portfolios of -2.145% implies an estimated loss of approximately $137 million over the 5-day window. Conversely, the subsequent Biden election event translates to an estimated gain of around $342 million over the event window.[16]

In Panel F of Table 7, we conduct cross-sectional regressions of CARs on *CS measure*, allowing us to control for various firm and stock characteristics as well as industry fixed

[15]To estimate the benchmark model parameters for each firm-event date pair, we use 250 trading days of return data, with the window ending 20 days before the event date. We require a minimum of 120 non-missing observations within the estimation window. To mitigate the impact of outliers, we apply winsorization to all CARs at the 1st and 99th percentiles.

[16]The average market capitalization of sample firms used in the Biden election event is $10 billion.

effects. We obtain qualitatively similar results: firms with more climate solutions outperform (underperform) their industry peers in response to regulatory shocks signaling an increase (decrease) in the stringency of climate regulations. These results are consistent with the notion that high (low)-climate solution firms enjoy an expected profitability advantage (disadvantage) when regulations become more (less) stringent, reflected in positive (negative) stock price reactions. Importantly, these findings provide evidence that the observed *CS measure*-return relationship is associated with climate transition risk.

5.2. Future profitability

Given the observed stock price reactions to various regulatory events, we now investigate the impact of firms' climate solutions on future profitability, conditional on several measures of transition risk. We consider three profitability measures following prior literature (Hsu et al., 2023; Novy-Marx, 2013). First, gross margin (*Gross margin*), defined as revenue minus cost of goods sold over revenues, which quantifies how much each dollar of revenues goes to the firm after accounting for the cost of goods sold. Second, return on sales (*ROS*), defined as net income scaled by sales, which measures profitability after considering all expenses incurred in generating sales, such as operating expenses. Third, return on assets (*ROA*), defined as operating income scaled by total assets, which evaluates how efficiently a company utilizes its assets to generate profits.

5.2.1. Future profitability and environmental regulatory uncertainty

We hypothesize that periods characterized by high regulatory uncertainty trigger increased awareness of climate transition risks and heightened consumer concerns regarding climate issues, which prompts greater demand for goods and services offered by climate solution providers (Pástor et al., 2021, 2022). Thus, we anticipate that high-climate solution firms will experience positive cash flow shocks during periods of high regulatory uncertainty, resulting in higher future profitability in such states of the world.

We measure environmental regulatory uncertainty using the environmental and climate policy uncertainty (EnvPU) index developed by Noailly et al. (2022). This index, which is available from 2005 to 2019, is constructed from news articles extracted from ten leading U.S. newspapers and represents the share of environmental policy uncertainty articles over all environmental and climate policy articles in a given month. An increase in the index indicates a rise in the uncertainty surrounding environmental and climate policy. Thus, the EnvPU index captures the volatility (i.e., second moment) of environmental policy news rather than the level (i.e., first moment). Importantly, the EnvPU index is forward-looking, focusing solely on articles pertaining to changes in current and future environmental and climate policy uncertainty, while excluding those related to resolved or past uncertainties. Since our analysis is conducted at the yearly level, we aggregate the monthly index by computing the natural logarithm of the mean of the 12-month moving average of the EnvPU index for each year (*log EnvPU*). The time-series of *log EnvPU* is plotted in Internet Appendix Figure IA.1.

To examine whether the future profitability of high-climate solution firms increases more during periods of greater regulatory uncertainty, we conduct the following pooled panel regression following Hsu et al. (2023):

$$\begin{aligned}\overline{Profit}_{i,t+1\rightarrow t+10} &= \beta_0 + \beta_1 CS\ measure_{i,t} + \beta_2 CS\ measure_{i,t} \times log\ EnvPU_t \\ &+ \beta_3 X_{i,t} + Fixed\ effects + \varepsilon_{i,t},\end{aligned} \tag{1}$$

where the outcome variables are future profitability, measured as the moving-average from year $t+1$ to $t+10$ of gross margin ($\overline{Gross\ margin}_{i,t+1\rightarrow t+10}$), return on sales ($\overline{ROS}_{i,t+1\rightarrow t+10}$), and return on assets ($\overline{ROA}_{i,t+1\rightarrow t+10}$).[17] $CS\ measure_{i,t}$ is firm i's climate solutions as of year t. The vector $X_{i,t}$ contains baseline control variables as well as the values of the profitability measures in year t (*Gross margin*, *ROS*, and *ROA*) and their changes from year $t-1$ (Δ*Gross margin*, Δ*ROS*, and Δ*ROA*). We employ either industry fixed effects and year fixed effects with standard errors clustered at the firm level, or industry $\times$ year fixed effects with standard errors clustered at the industry $\times$ year level, following Hsu et al. (2023). We interact $CS\ measure_{i,t}$ and $log\ EnvPU_t$ to examine the prediction that high-climate solution firms are more likely to benefit from increased environmental regulatory uncertainty.[18]

Table 8 presents the results. We find that the relation between firms' climate solutions and future profitability is contingent upon the state of the world determined by the degree of regulatory uncertainty. For each profitability measure, the coefficient estimate on *CS measure* is significantly negative, indicating that during periods of low regulatory uncertainty, high-climate solution firms experience reduced future cash flows. In untabulated analysis, we find that the *CS measure* is positively associated with both Selling, General, and Administrative expenses (SG&A) and Cost of Goods Sold (COGS), consistent with the additional operational and investment costs required to deliver climate solutions. In contrast, the estimated coefficient on the interaction term is significantly positive, indicating that during periods of high regulatory

[17] We calculate the moving average for up to 10 years ahead. If a firm has less than 10 years of data available, we calculate the moving average using the available uninterrupted stream of future years.

[18] There is no main effect for *log EnvPU* because it is absorbed by the year fixed effects.

uncertainty, the reduced cash flows of high-climate solution firms are offset, leading to improved future profitability.

To illustrate the economic magnitude of the non-linear effects of climate solutions on future profitability, we plot the marginal effects of *CS measure* on future profitability conditional on sample values of *log EnvPU* in Figure 3. The solid line represents the point estimates, while the dashed lines indicate the 95% confidence intervals. We divide the sample into quartiles based on *log EnvPU*, denoted as Q1, Q2, and Q3. Across all panels, we find that the marginal effect of climate solutions on future profitability increases with the level of regulatory uncertainty. Moreover, among the top quartile of regulatory uncertainty, we observe some evidence of a reversal in the sign of the marginal effect from negative to positive. This finding suggests that the impact of climate solutions on future profitability becomes less negative, and sometimes even positive, when regulatory uncertainty reaches sufficiently high levels.

5.2.2. Future profitability and unexpected climate change concerns

We now extend our analysis beyond environmental regulatory uncertainty to encompass shocks to climate change concerns, which serve as a broader indicator of transition risk. An *unexpected* increase in climate change concerns is likely to shift consumer preferences toward climate solution products and services, thereby boosting the net cash flows of high-climate solution firms and ultimately leading to greater future profitability for these firms (Ardia et al., 2023; Pástor et al., 2021).

We quantify climate change concerns using the Media Climate Change Concerns (MCCC) index developed by Ardia et al. (2023), which extracts data from news articles about climate change from major U.S. newspapers. The latter paper assigns each article a "concerns score" based on the levels of negativity and risk discussed. Thus, the MCCC index is a daily measure that tracks changes in climate change concerns by aggregating these article-level scores while adjusting for heterogeneity across newspapers. In our analysis, we use the monthly MCCC index to facilitate aggregation to the yearly level.

To differentiate between expected and unexpected shifts in climate change concerns that may influence preferences for climate solution products and services, we follow Ardia et al. (2023) and use the prediction error of an AR(1) model calibrated on the MCCC index as a proxy for unexpected changes. Specifically, we estimate the following model:

$$MCCC_t = \mu + \rho MCCC_{t-1} + \gamma X_{t-1} + \varepsilon_{i,t}, \tag{2}$$

where $MCCC_t$ is the MCCC index in month t and X_{t-1} denotes a vector of control variables used to mitigate the potential impact of various confounding factors on the MCCC index. This vector includes financial-market, energy-related, and macroeconomic variables as detailed in Ardia et al. (2023).[19] To calculate the prediction error in month t, we estimate the above AR(1) model using a rolling window spanning the previous 60 months from January 2008 to September 2022, and define the prediction error as the actual realization of the MCCC index in month t minus the AR(1) model's forecast.[20] The estimation results are presented in Internet Appendix Table IA.2. Following Ardia et al. (2023), we refer to the prediction errors as unexpected media climate change concerns (UMC). We aggregate UMC to the yearly level by taking the mean of the 12-month moving-average of the unexpected climate change concerns in year t.

We estimate the following pooled panel regression to assess the relationship between climate solutions and future profitability following an unexpected shock to climate change concerns:

$$\begin{aligned}\overline{Profit}_{i,t+1\rightarrow t+10} &= \beta_0 + \beta_1 CS\ measure_{i,t} + \beta_2 CS\ measure_{i,t} \times UMC_t \\ &+ \beta_3 X_{i,t} + Fixed\ effects + \varepsilon_{i,t},\end{aligned} \tag{3}$$

where the specification is the same as in Equation (1). We interact $CS\ measure_{i,t}$ and UMC_t to examine the prediction that high-climate solution firms are more likely to benefit from unexpected increases in climate change concerns.[21]

Table 9 presents the results. Columns (1), (4), and (7) show that during periods of low unexpected climate change concerns, high-climate solution firms experience a decline in future profitability, likely due to reduced demand for their products and services. However, as unexpected climate change concerns increase, the future profitability of high-climate solution firms improves. In the remaining columns, we utilize the UMC derived from the topic model of Ardia et al. (2023), focusing on two transition risk themes: "Business Impact" (UMC^{BI}) and "Societal Debate" (UMC^{SD}).[22] The coefficients on the interaction term using these thematic

[19] The control variables include the term spread factor ($TERM$) and default spread factor ($DFLT$) of Fung and Hsieh (2004), the economic policy uncertainty index (EPU) of Baker, Bloom, and Davis (2016), the CBOE volatility index (VIX), the crude oil return (WTI), the propane return ($PROP$), the natural gas return (NG), the excess market return (MKT), the small-minus-big factor (SMB) and the high-minus-low factor (HML) of Fama and French (1996), the robust-minus-weak factor (RMW) and the conservative-minus-aggressive factor (CMA) of Fama and French (2015), and the momentum factor (MOM) of Carhart (1997).

[20] The data for the MCCC index begins in January 2003. However, due to the 60-month rolling window, our sample can only start from January 2008 onwards.

[21] There is no main effect for UMC because it is absorbed by the year fixed effects.

[22] The Business Impact theme encompasses topics surrounding climate summits, agreements/actions, and climate-related legislation/regulations. The Societal Debate theme involves topics such as political campaigns, social events, and controversies.

UMC measures are all significantly positive, indicating that high-climate solution firms are less adversely affected by unexpected climate change concerns related to transition risk. Figure 4 plots the marginal effect of *CS measure* on future profitability across sample values of *UMC*, revealing that the marginal effect increases with unexpected climate change concerns. Overall, the evidence in this section suggests that high-climate solution firms possess a better ability to hedge against transition risk driven by unexpected shifts in climate change concerns.

5.2.3. Future profitability and firm-level exposure to climate-related shocks

So far, we have focused on changes in transition risk using solely time series variation in climate-related shocks. Now, we examine a firm's direct exposure to such shocks by combining the geographical distribution of its operations with climate-related shocks that vary at the state level. Specifically, we use location-related business data from Infogroup to determine the sales volume of each firm in every state.[23] Then, we compute a weighted average of four different measures of state-level climate-related shocks, where each state's measure is weighted by the firm's share of sales volume in that state as follows:

$$\mathit{Sales\ (Exposure)}_{i,t} = \frac{\sum_s Sales_{i,s,t} \times Exposure_{s,t}}{\sum_s Sales_{i,s,t}}, \tag{4}$$

where $Sales_{i,s,t}$ is firm i's sales in state s in year t and $Exposure_{s,t}$ denotes one of four measures of climate-related shocks in state s in year t discussed below. Thus, $\mathit{Sales\ (Exposure)}_{i,t}$ represents firm i's exposure to climate-related shocks in year t based on state-level sales. This variable captures variation in exposure to climate-related shocks not only in the time series but also across different firms in the cross-section.

We explore four measures of climate-related shocks that vary across states. First, we use the staggered adoption of state-led climate plans.[24] As these plans encompass both mitigation and adaptation strategies, and transition risk predominantly stems from mitigation-related actions rather than adaptation, we solely focus on the subset of mitigation plans enacted by states.[25] Although these plans differ in their scopes and strategies from state to state, they

[23]Infogroup aggregates data from diverse sources including telephone white page directories, utility connections, real estate property data, credit card billing statements, and public records.

[24]Data is obtained from the Georgetown Climate Center.

[25]We manually review each plan to determine whether it is an adaptation or mitigation plan by analyzing its details. For instance, California EO B-30-15 outlines a statewide greenhouse gas emission reduction target aiming to decrease emissions to 40 percent below 1990 levels by 2030, with the ultimate goal of achieving an 80 percent reduction below 1990 levels by 2050. This is categorized as a mitigation plan because it focuses on reducing the emission of greenhouse gases that contribute to climate change. In contrast, Florida Senate Bill (S.B.) 1954 aims to assess flooding risks associated with increased precipitation, extreme weather events, and sea-level rise, and to initiate a coordinated statewide effort to adapt to these risks. As this plan primarily

all reflect commitments to mitigating climate risks. The implementation of these mitigation plans increases the likelihood of new climate-related regulations within the state, presenting new opportunities for high-climate solution firms that primarily operate within these states. To account for the cumulative impact of multiple plans implemented over time, we define $Exposure_{s,t}$ as the number of plans finalized in state s as of year t ($SCAP_{s,t}$).

Second, we use three measures derived from the Yale Program on Climate Change Communication (YPCCC) survey, which assesses public opinion regarding climate change across states (Howe, Mildenberger, Marlon, & Leiserowitz, 2015). Public opinion plays a critical role in influencing policy decisions and consumer behavior related to climate change mitigation efforts. We focus on three specific questions aimed at understanding consumer preferences in response to climate change. Specifically, we define $Exposure_{s,t}$ as the percentage of the adult population in a given state s during year t who support regulating CO2 as a pollutant ($\textit{YPCCC Regulate}_{s,t}$), think global warming is happening ($\textit{YPCCC Happening}_{s,t}$), or are worried about global warming ($\textit{YPCCC Worried}_{s,t}$). These data are available from 2008 to 2022. We anticipate that states with a higher percentage of adults holding these views will offer increased business opportunities for high-climate solution firms, given the expected rise in consumer demand for their goods and services and citizen support for climate policies.

To examine the relationship between climate solutions and future profitability conditional on firm-level exposure to climate-related shocks, we estimate the following pooled panel regression:

$$\begin{aligned}\overline{Profit}_{i,t+1\rightarrow t+10} &= \beta_0 + \beta_1 \textit{CS measure}_{i,t} + \beta_2 \textit{Sales (Exposure)}_{i,t} \\ &+ \beta_3 \textit{CS measure}_{i,t} \times \textit{Sales (Exposure)}_{i,t} + \beta_4 X_{i,t} + \textit{Fixed effects} + \varepsilon_{i,t},\end{aligned} \tag{5}$$

where the specification is the same as in Equation (1).[26]

Table 10 presents the results. Across all three panels, we observe a significantly negative coefficient on *CS measure*, and a significantly positive coefficient on the interaction between *CS measure* and each of the four measures of firm-level exposure to climate-related shocks. This result suggests that high-climate solution firms tend to experience lower future profitability if their sales are in regions with fewer climate-related shocks. However, an increase in sales in areas with more climate-related shocks leads to improved future profitability. The economic magnitude of this relationship is also sizable. For example, in column (2) of Panel C, if *Sales*

addresses adapting to potential sea-level rise, it falls into the category of adaptation plans and is therefore excluded from our consideration.

[26]There is now a main effect for *Sales (Exposure)* because it is not subsumed by year fixed effects.

(YPCCC Regulate) increases from the 25th to the 75th percentile, then the marginal effect of *CS measure* on the average return on assets over the next 10 years increases by 0.06%, representing a 1.8% increase relative to the sample mean.[27] Overall, the results in this section, which directly link regions with climate-related shocks to where firms make sales and future profitability, suggest that high-climate solution firms hedge against transition risk.

5.3. Mispricing

The evidence presented so far suggests that the documented negative *CS measure*-return relationship appears consistent with high-climate solution firms having a better capacity to hedge against transition risk, rather than investors mispricing these firms. Specifically, mispricing would imply that high-climate solution firms should consistently exhibit lower future profitability *independent* of the level of transition risk, resulting in lower subsequent stock returns due to systematic overvaluation relative to their fundamental value. However, the profitability regression results in the previous sections reveal that (1) the linear *CS measure* term enters negatively and (2) the interaction between *CS measure* and each measure of transition risk—environmental regulatory uncertainty, unexpected climate change concerns, and firm-level exposure to climate-related shocks—enters positively. Thus, the fact that the relationship between firms' climate solutions and future profitability is *conditional* on the level of transition risk suggests that the market places a valuation premium on climate solutions because they serve as a hedge against transition risk, rather than due to mispricing.

To further rule out the mispricing hypothesis, we examine whether investors overvalue high-*CS measure* firms when transition risk is high. Since investor expectations are not directly observable, we use analysts' earnings forecasts as a proxy for informed market participants' views. Specifically, we examine analyst forecast errors by estimating the following pooled regression:

$$\begin{aligned} \textit{Forecast error}_{i,t+1} = \beta_0 + \beta_1 \textit{CS measure}_{i,t} + \beta_2 \textit{Transition risk}_{i,t} \\ + \beta_3 \textit{CS measure}_{i,t} \times \textit{Transition risk}_{i,t} + \beta_4 X_{i,t} + \textit{Fixed effects} + \varepsilon_{i,t}, \end{aligned} \tag{6}$$

where *Forecast error*$_{i,t+1}$ is the one-year analyst earnings forecast error of firm i in fiscal year $t+1$, *CS measure*$_{i,t}$ is measured at the end of fiscal year t, *Transition risk*$_{i,t}$ is one of the transition risk measures used previously, and $X_{i,t}$ is a vector of control variables. The one-year

[27] The 25th and 75th percentile of the normalized variable *Sales (YPCCC Regulate)* are 0.15 and 0.43, respectively. Thus, the coefficient of 0.002 implies an increase of $0.002 \times (0.43 - 0.15) = 0.06\%$, which is approximately $0.0006/0.032 = 1.8\%$ of the sample mean of the outcome variable.

analyst earnings forecast error is calculated as the difference between the actual earnings per share for a given fiscal year and the median analyst consensus forecast, scaled by the stock price at the end of the fiscal year.[28] The consensus forecast is taken from the month following the firm's 10-K filing, ensuring that information on the *CS measure* is available to analysts before they make their estimates.

The results are presented in Internet Appendix Table IA.3. If analysts overvalue high-*CS measure* firms during periods of elevated transition risk, we would expect to observe systematic negative forecast errors in these periods. However, the coefficients on the interaction term *CS measure* × *Transition risk* are statistically insignificant across all measures of transition risk, suggesting that mispricing is unlikely to explain our results.

5.4. Investor preferences

In this section, we investigate whether the negative *CS measure*-return relationship can be attributed to investor preferences for firms offering climate solutions. Pedersen et al. (2021) demonstrate that stronger investor demand for stocks with superior environmental performance leads to higher contemporaneous prices and lower future returns. If investors' preferences for stocks with better environmental performance extend to a preference for firms offering climate solutions, this may explain the lower returns observed in high-climate solution firms, even in the absence of explicit hedging against transition risks.

We examine this hypothesis using institutional ownership data from Thomson Reuters Institutional Holdings (specifically, form 13F data). Formally, we estimate the following pooled panel regression at the firm-investor-quarter level:

$$\overline{IO}_{j,i,t+1\rightarrow t+4} = \beta_0 + \beta_1 CS\ measure_{i,t} + \beta_2 X_{i,t} + \beta_3 Y_{j,t} + Fixed\ effects + \varepsilon_{i,t}, \tag{7}$$

where $IO_{j,i,t}$ represents the fraction of shares of firm i held by investor j in quarter t (expressed as a percentage). Following Pedersen et al. (2021), we use the moving-average from quarter $t+1$ to $t+4$ of *IO* as the outcome variable so that *CS measure* is known before observing institutional holdings. $X_{i,t}$ includes baseline control variables, while $Y_{j,t}$ includes controls for institutional investors, such as portfolio size (measured by the market value of the institutional investor's portfolio) and portfolio concentration (measured by the Herfindahl-Hirschman index computed using portfolio weights). We incorporate institutional investor, firm, and year-quarter fixed effects, with standard errors clustered at the firm level. The coefficient on *CS*

[28]We remove all observations that have a forecast error of larger than 10% of the stock price.

measure signifies the extent of institutional investors' demand for firms with more climate solutions.

In column (1) of Table 11, we present the results using the sample of all institutional investors. The coefficient on *CS measure* is insignificant, suggesting that institutional investors do not alter their portfolio holdings based on firms' climate solutions. However, pooling all institutional investors may obscure potential effects on institutional ownership, as different investors may have different preferences. For instance, norm-constrained institutions such as insurance companies or pension funds are more susceptible to public pressure and tend to avoid poor sustainability firms, whereas mutual funds and hedge funds often act as natural arbitrageurs (Bolton & Kacperczyk, 2021; Hong & Kacperczyk, 2009). In column (2), we focus on the subsample of institutions classified as mutual funds or independent investment advisors, while column (3) uses the subsample of institutions categorized as banks, insurance companies, or others, including pension plans, endowments, and employee-ownership plans. Across both subsamples, we fail to document significance on *CS measure*. Overall, the absence of increased investor demand for firms offering climate solutions—despite the high power of the regression, reflected in the large number of observations and high explanatory power—is inconsistent with the investor preference hypothesis providing a primary explanation for the negative *CS measure*-return relationship.

6. Additional analyses

6.1. Interaction between climate solutions and carbon emissions

In this section, we investigate whether the hedging effectiveness of climate solutions depends on firms' carbon emissions. This analysis is motivated by our findings for the "Energy" industry in Figure 2, where we do not observe a significant negative relationship between *CS measure* and returns, despite this industry's relatively high average *CS measure* of 1.725 (Panel B, Table 1). One possible explanation is that many firms classified in this industry group are oil and gas companies that emit significant amounts of carbon. On the one hand, these firms are often key innovators in the green patent landscape (Cohen, Gurun, & Nguyen, 2020), which explains their engagement in climate solutions. On the other hand, their substantial carbon emissions lead to a carbon premium, as investors demand compensation for exposure to carbon emission risk (Bolton & Kacperczyk, 2021). Consequently, while such firms may benefit from increased demand for certain products and services due to transition risk, they may also incur costs due to their carbon footprint (Bolton & Kacperczyk, 2021, 2023). Accordingly, we hypothesize that the hedging effectiveness of climate solutions is more pronounced for firms with lower carbon emissions (and thus, having lower carbon premiums).[29]

To formally investigate the interaction effect between climate solutions and carbon emissions, we conduct pooled panel regressions and incorporate measures of carbon emissions and their interactions with *CS measure*. Table 12 presents the results. With the exception of column (2), the coefficients on the interaction terms are significantly positive, while those on the linear *CS measure* term are always significantly negative. These findings suggest that for firms with high engagement in climate solutions and minimal carbon footprint, the hedging effectiveness of climate solutions is maximized. However, as the firm's carbon emissions increase, the positive carbon premium offsets the hedging effectiveness of climate solutions.

6.2. Topic analysis: Carbon abatement costs and potential

A firm's climate solutions can differ in terms of carbon abatement costs and potential, depending on the technology employed, which may affect the firm's ability to hedge transition risks. To explore this, we conduct a topic analysis of the firm's climate solutions (Lu et al., 2024). For each sentence related to climate solutions in 10-K Item 1, the topic analysis uses the fine-tuned GPT model to assign the sentence to one of 88 topics based on technologies from Project Drawdown. Each topic is then scaled by the total number of sentences in 10-K Item 1. We decompose *CS measure* into high and low categories based on two dimensions: carbon abatement costs and abatement potential. Specifically, *CS measure (High abatement cost)* (*CS measure (Low abatement cost)*) is the sum of climate solution topics where the net initial cost to implement the climate solution is classified as high (low) according to the Project Drawdown 2020 report. Similarly, *CS measure (High abatement potential)* (*CS measure (Low abatement potential)*) is the sum of climate solution topics where the abatement potential of the climate solution is classified as high (low) according to the Project Drawdown 2020 report. Lastly, *CS measure (High cost per potential)* (*CS measure (Low cost per potential)*) is the sum of climate solution topics where the net initial implementation cost per abatement potential of the climate solution is classified as high (low) according to the Project Drawdown 2020 report.

We then run similar pooled panel regressions as in Table 3, but using the decomposed *CS measure* categories. In column (1) of Internet Appendix Table IA.4, the coefficient

[29] Preliminary evidence supporting this hypothesis appears in the double sorting analysis in Table 4. Although the return spread on the high-minus-low *CS measure* portfolio is negative and statistically significant in both the bottom and top carbon emission groups, the spread is consistently larger in magnitude for firms in the bottom carbon emissions group. This pattern suggests that while climate solutions hedge against transition risk across all levels of carbon emissions, the hedging effectiveness is stronger for firms with lower carbon footprints.

on *CS measure (Low abatement cost)* is significantly negative, while the coefficient on *CS measure (High abatement cost)* is insignificant. This result suggests that firms with low carbon abatement cost technologies are better able to hedge against transition risks. Column (2) shows that both high and low abatement potential technologies act as hedges, while column (3) indicates that only low cost per potential technologies serve as effective hedges. These findings are consistent with the notion that firms utilizing low-cost climate solutions are better positioned to profit from an increased demand for sustainable products. Such firms can offer competitive pricing while maintaining profit margins, making them more adaptable to changes in consumer preferences. As a result, investors may perceive them as less vulnerable to climate transition risks.

6.3. Climate solutions, institutional ownership, and transition risk

Given that cash flows of high-climate solution firms tend to improve precisely when there is heightened transition risk, we investigate whether certain institutional investors tilt their portfolios towards these firms during such periods to hedge against transition risk. Specifically, we estimate a regression model similar to Equation (7), but with additional interaction terms between *CS measure* and the various measures of transition risk utilized in previous sections.

We present the results in Internet Appendix Table IA.5. Following the categorization in Hong and Kacperczyk (2009), Panel A consists of institutions classified as mutual funds or independent investment advisors, while Panel B comprises institutions classified as banks, insurance companies, or others. We find that only mutual funds or independent investment advisors adjust their holdings to increase exposure to high-climate solution firms in response to elevated transition risk, as indicated by the significantly positive coefficients on the interaction terms in Panel A. In contrast, we find no evidence of norm-constrained investors adjusting their portfolio, as none of the interaction terms are significant in Panel B. These results are consistent with the notion that investors in Panel A are natural arbitrageurs in the market and benefit the most from hedging against transition risk (Bolton & Kacperczyk, 2021). Conversely, investors in Panel B often have longer-term investment horizons and lower turnover ratios, reducing the need to rebalance their portfolio holdings to hedge against transition risk.

6.4. Robustness tests

6.4.1. Equal-weighted portfolio returns

We perform the same univariate portfolio sorting analysis as in Table 2, except we compute equal-weighted excess returns across the portfolios instead of value-weighted returns. This approach ensures that our results are not driven by extremely large or small firms. Internet Appendix Table IA.6 demonstrates that the high-minus-low portfolio continues to yield a negative return spread across all asset pricing factor tests, with the magnitude being slightly larger than that observed using value-weighted returns.

6.4.2. More granular GICS industry classification

To account for more granular differences in the *CS measure* between firms in different industries, we replicate our main analysis using 6-digit GICS industries rather than 4-digit GICS industry groups. Internet Appendix Table IA.7 presents the results of the univariate portfolio sorting within 6-digit GICS industries. Internet Appendix Table IA.8 displays the panel regression results using 6-digit GICS industry fixed effects. In both tables, our main results remain qualitatively unchanged with the use of finer industry classifications.

6.4.3. Fama-MacBeth regressions

We examine the relationship between climate solutions and individual stock returns, similar to the analysis in Table 3, but employ Fama-MacBeth regressions instead of pooled panel regressions. Specifically, we conduct cross-sectional regressions for each month from July of year t to June of year $t+1$. In each month, monthly returns of individual stocks in excess of the risk-free rate are regressed on *CS measure* in year $t-1$, different sets of control variables known by the end of June in year t, and industry dummies based on 4-digit GICS industry groups. We then compute the time-series mean and standard errors of the coefficient estimates from these monthly regressions, using the Newey-West correction for 12 lags. The results, presented in Internet Appendix Table IA.9, continue to demonstrate a robust negative *CS measure*-return relationship, with similar coefficient magnitudes as observed using pooled panel regressions.

6.4.4. Alternative controls for innovation

While we incorporate the ratio of R&D expenses to sales as a control for firms' innovation activities in our analyses, we also explore alternative measures of innovation as robustness tests. One potential issue with using R&D expenses is that they represent a flow variable. However, climate solutions often require continuous and substantial investment in R&D to develop new technologies or enhance existing ones, leading to tangible outcomes such as new products and services over the long term. Therefore, controlling for a firm's accumulated stock of R&D may be more appropriate.

To measure a firm's stock of R&D, we employ two models that capitalize R&D. First, we utilize the *Knowledge capital* measure proposed by Ewens, Peters, and Wang (2024), which estimates the capital value of R&D using market prices and purchase price allocations in acquisitions and bankruptcy recovery data to estimate industry-level R&D depreciation rates. Second, we utilize the *RDC* measure introduced by Iqbal, Rajgopal, Srivastava, and Zhao (2024), which estimates the capital value of R&D based on industry-year regressions of R&D investment and future revenues. We scale both *Knowledge capital* and *RDC* by sales so that they are comparable across firms.

As R&D expense primarily reflects innovation inputs, we explore two measures that measure innovation outputs. First, we examine trade secrecy, which is one of the most prevalent methods of protecting innovation. Following Glaeser (2018), we define *Trade secret* as a dummy variable indicating whether a firm's 10-K filings in a given year include references to trade secrets, and zero otherwise. Second, we utilize a patent-based measure of innovation output known as *RETech*, introduced by Bowen, Frésard, and Hoberg (2023). This measure is a continuous variable that gauges the intensity with which the vocabulary of a given patent is growing in use across the entire corpus of patents, encompassing both public and private firms. Higher (lower) levels of *RETech* correspond to patents in technology areas that are likely to substitute (complement) existing technologies. Since a firm's innovation output may be intermittent and unevenly spread over time, we define *RETech stock* as the average *RETech* across all of the firm's patent applications over the prior five years while applying a 20% yearly rate of depreciation, scaled by the number of patents (Bowen et al., 2023).[30]

Internet Appendix Table IA.10 incorporates the aforementioned innovation measures as controls in the pooled panel regressions from Table 3. Among these measures, only *Trade secret* shows statistical significance, while the coefficients for the other innovation measures are all statistically insignificant. Importantly, including these measures as control variables does not alter the negative relationship between the *CS measure* and returns. Thus, our findings are robust to controlling for these alternative measures of firms' overall innovation activities.

6.4.5. Controlling for greenness

A potential concern is that a firm's *CS measure* might reflect the greenness of the stock as firms with more climate solutions may have better environmental ratings. However, even if this is the case, it cannot explain our results, since Pástor et al. (2022) observe a positive

[30]By construction, *RETech stock* is equal to zero when firms have no patent applications over the prior five years. Thus, we include a zero-patent dummy as a control variable. This variable captures a firm's "stock" of *RETech*, and scaling by the total number of patents ensures that this measure does not simply reflect the size of its patent portfolio, ensuring comparability across firms.

cross-sectional relationship between a stock's greenness and stock returns. Nevertheless, we control for the same proxy as in Pástor et al. (2022) to understand the implications for *CS measure*.

We follow Pástor et al. (2022) and measure a firm's greenness using the MSCI variables "Environmental pillar score" (*E_score*) and "Environmental pillar weight" (*E_weight*). While the environmental pillar includes themes related to environmental opportunities, the majority of its components capture various other themes related to a firm's operations, which are unrelated to the firm's products and services or non-climate focused environmental issues.[31] Indeed, the correlation between *CS measure* and the measure of firms' greenness (discussed below) is only 0.04. Thus, a firm's greenness is unlikely to be a substitute measure for a firm's climate solutions.

Specifically, the unadjusted greenness score for firm i in month t is calculated as

$$G_{i,t} = -(10 - E\_score_{i,t}) \times E\_weight_{i,t}/100 \tag{8}$$

where $E\_score_{i,t}$ and $E\_weight_{i,t}$ are from firm i's most recent MSCI ratings date as of month t, looking back no more than 12 months. The term $10 - E\_score_{i,t}$ quantifies how far the firm deviates from a perfect environmental score of 10. The product $(10 - E\_score_{i,t}) \times E\_weight_{i,t}$ measures the firm's brownness, capturing the interaction of how badly the firm scores on environmental issues and how large the environmental impacts are for the industry's typical firm ($E\_weight_{i,t}$). The negative sign at the beginning converts the measure from brownness to greenness. We define a firm's greenness as

$$Greenness_{i,t} = G_{i,t} - \overline{G}_{i,t} \tag{9}$$

where $\overline{G}_{i,t}$ is the value-weighted average of $G_{i,t}$ across all firms i. By subtracting $\overline{G}_{i,t}$, $Greenness_{i,t}$ measures the company's greenness relative to the market portfolio.

We control for firms' greenness in the pooled panel regressions presented in Table 3. The results are presented in Internet Appendix Table IA.11. Column (1) considers the sample period from July 2007 to June 2023, corresponding to the availability of MSCI data. Column (2) narrows down the sample period from November 2012 to June 2023, coinciding with MSCI's

[31] For example, other key themes include "Climate Change", encompassing issues such as carbon emissions, vulnerability to climate change, financing environmental impact, and product carbon footprint. "Natural Capital" addresses biodiversity and land use, raw material sourcing, and water stress. Lastly, "Pollution and Waste" covers aspects such as electronic waste, packaging materials and waste, as well as toxic emissions and waste.

expanded coverage starting in October 2012. In both columns, the coefficient on *Greenness* is significantly positive. This finding is consistent with Pástor et al. (2022), who observe a positive cross-sectional relationship between a stock's greenness and its return, attributed to unexpectedly strong increases in environmental concerns in recent years. Importantly, the coefficient on *CS measure* remains significantly negative in both columns, indicating the robustness of our main findings after accounting for firms' greenness.

6.4.6. Option-implied expected returns

A potential concern is whether realized returns accurately reflect expected returns over short sample periods. To address this concern, we utilize the generalized lower bounds (*GLB*) from Chabi-Yo, Dim, and Vilkov (2023) as a proxy for expected excess returns. The *GLB* provides a forward-looking, option-implied estimate of expected excess returns that accounts for the entire risk-neutral return distribution and implicitly considers all higher-order moments. We conduct the same univariate portfolio analysis as in Table 2, but now using *GLB* as the measure of expected returns. Internet Appendix Table IA.12 demonstrates that the high-minus-low portfolio continues to exhibit a negative return spread. Similarly, we perform the same pooled panel regression as in Table 3, but this time utilizing *GLB* as the outcome variable. The results in Internet Appendix Table IA.13 confirm that the negative *CS measure*-return relationship persists when using option-implied expected returns.

7. Conclusion

We employ a novel measure of climate solutions, leveraging LLMs trained on the business descriptions contained in publicly listed firms' 10-K filings to analyze the asset pricing implications of firms' engagement in climate solutions. A long-short portfolio constructed from firms with high versus low climate solutions within an industry group generates an average excess return of -5.37% per year from 2005 to 2023. This negative return spread cannot be explained by existing risk factors and continues to hold at the individual stock level after controlling for known predictors of returns. Furthermore, high-climate solution firms are valued at a premium by the stock market, evidenced by their higher contemporaneous valuation ratios.

Our findings suggest that high-climate solution firms are better positioned to hedge against transition risks, given the increased demand for their products and services during periods of heightened transition risk. This hypothesis is supported by event studies, which indicate that high-climate solution firms exhibit higher CARs following political and regulatory events, as well as international agreements, signaling increased future demand for climate solutions. Additionally, we observe that during periods of heightened transition risk, the future profitability of high-climate solution firms tends to improve, further supporting their effectiveness in hedging transition risks. These insights into how financial markets perceive and value firms engaged in climate solutions can guide policymakers, investors, and businesses in making informed decisions to transition towards a low-carbon economy.

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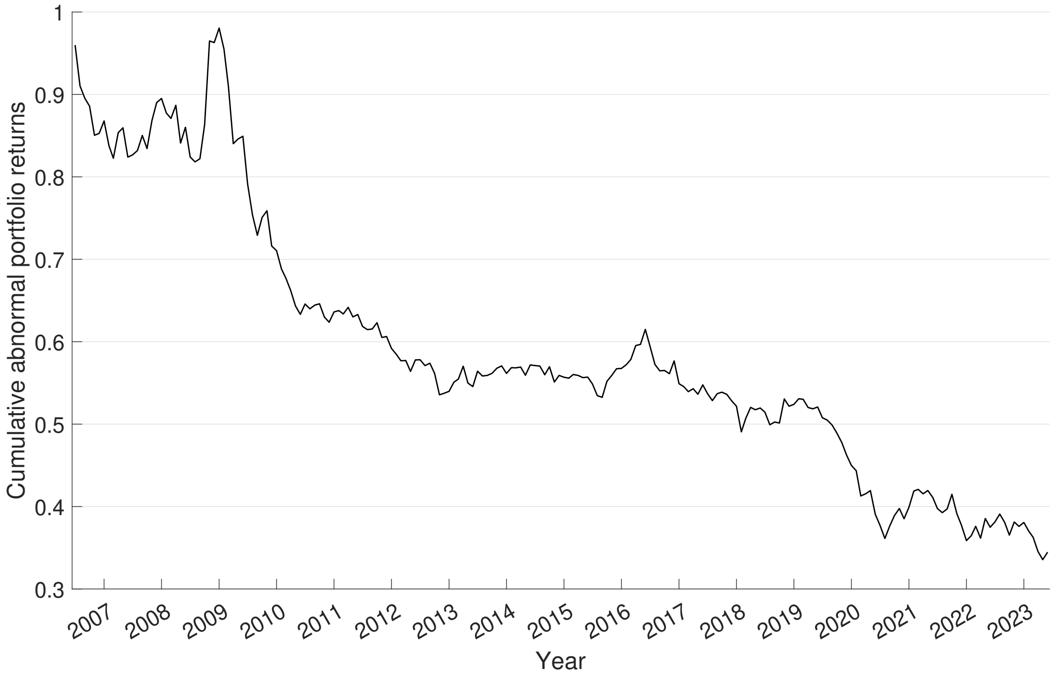
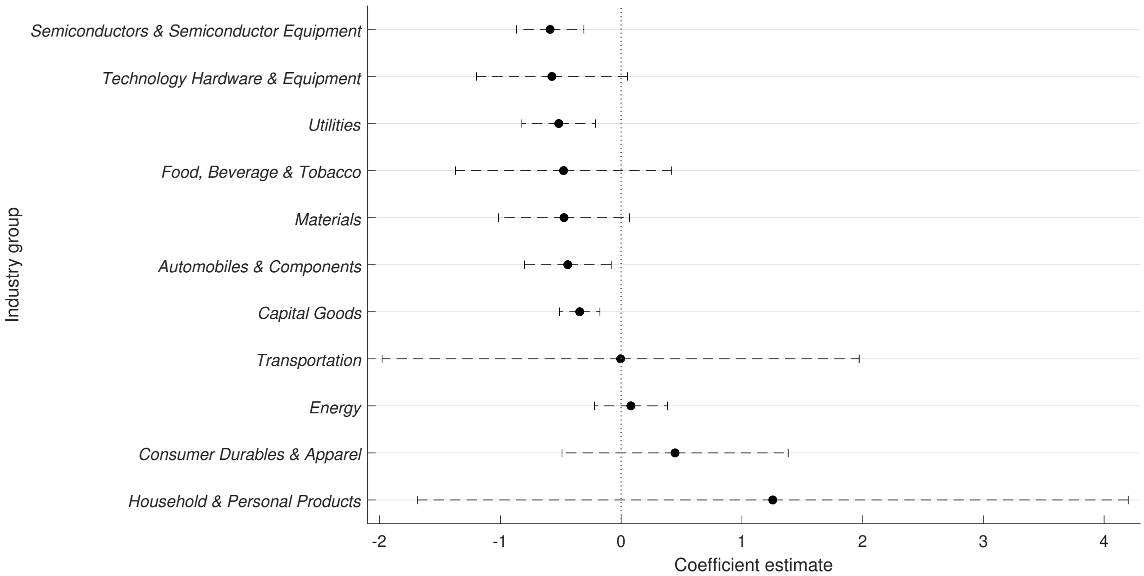
Figure 1
Cumulative abnormal returns of the high-minus-low portfolio using climate solutions.



This figure shows the time-series of the cumulative abnormal returns from an initial investment of one dollar based on the risk-adjusted returns of the high-minus-low portfolio in Panel E of Table 2. The sample period is July 2006 to June 2023.

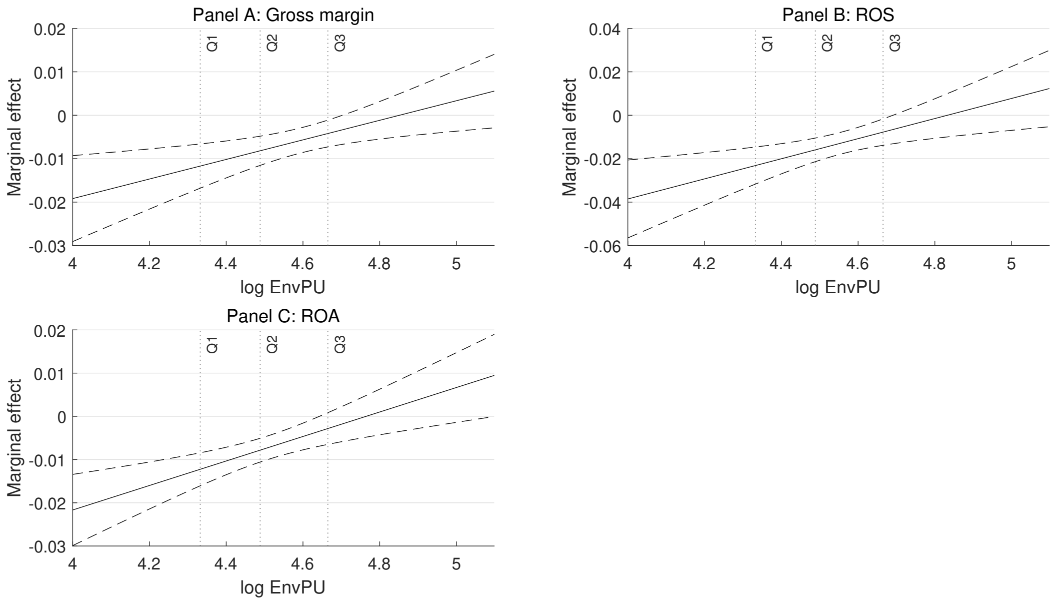
Figure 2
Climate solutions and individual stock returns by industry group.



This figure shows the point estimates (black dot) and 95% confidence intervals (dashed lines) of the coefficients on *CS measure* using the specification in column (3) of Table 3 by industry group. The vertical axis shows the 4-digit GICS industry groups.

Figure 3

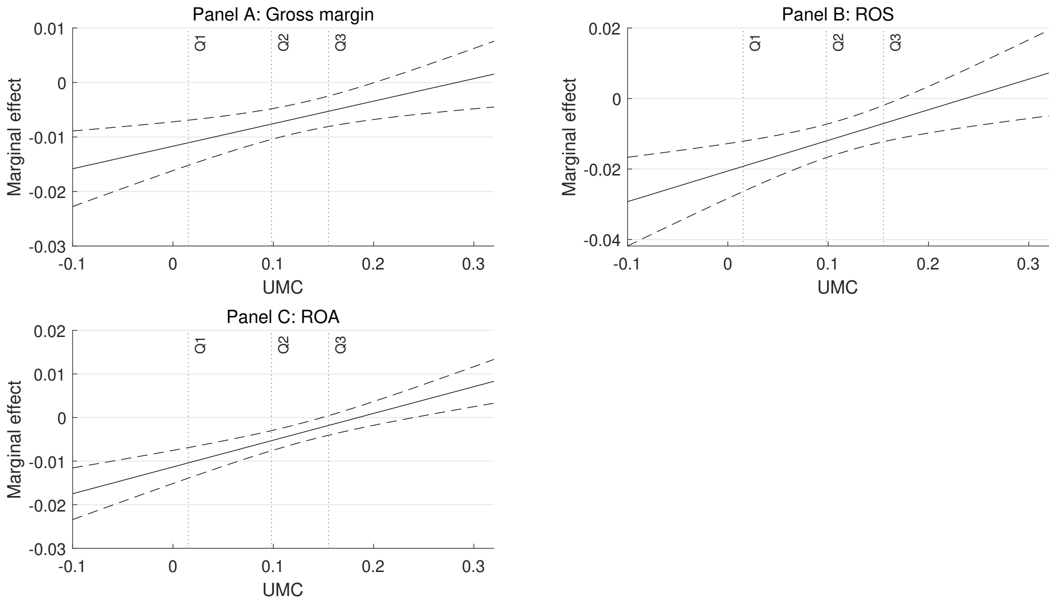
Marginal effects of climate solutions on future profitability conditional on environmental regulatory uncertainty.



This figure plots the marginal effects (solid line) and corresponding 95% confidence intervals (dashed line) of climate solutions on future profitability conditional on environmental regulatory uncertainty using the specification in columns (1), (3), and (5) of Table 8. The dependent variable in Panels A, B, and C are $\overline{Gross\ margin}_{i,t+1\rightarrow t+10}$, $\overline{ROS}_{i,t+1\rightarrow t+10}$, and $\overline{ROA}_{i,t+1\rightarrow t+10}$, respectively. *log EnvPU* is the natural logarithm of the mean of the 12-month moving-average of the EnvPU index in year t (Noailly et al., 2022). The dashed vertical lines split the sample into quartiles based on *log EnvPU*.

Figure 4

Marginal effects of climate solutions on future profitability conditional on unexpected climate change concerns.



This figure plots the marginal effects (solid line) and corresponding 95% confidence intervals (dashed line) of climate solutions on future profitability conditional on unexpected climate change concerns using the specification in columns (1), (4), and (7) of Table 9. The dependent variable in Panels A, B, and C are $\overline{Gross\ margin}_{i,t+1\rightarrow t+10}$, $\overline{ROS}_{i,t+1\rightarrow t+10}$, and $\overline{ROA}_{i,t+1\rightarrow t+10}$, respectively. *UMC* is the mean of the 12-month moving-average of the prediction error from a rolling AR(1) model applied to the MCCC index controlling for the potential effects of financial-market, energy-related, and macroeconomic variables in year t (Ardia et al., 2023). The dashed vertical lines split the sample into quartiles based on *UMC*.

Table 1
Descriptive statistics.

Panel A: Summary statistics

Variables	N	Mean	Median	P25	P75	Std. dev.
CS measure	14,311	2.695	0.615	0.000	2.174	6.124
log PE	10,434	2.983	2.931	2.585	3.312	0.751
log EM	12,542	2.310	2.259	1.949	2.591	0.653
Gross margin	14,311	0.327	0.312	0.205	0.444	0.208
ROS	14,311	0.016	0.044	-0.007	0.092	0.160
ROA	14,311	0.049	0.067	0.023	0.113	0.132
$\overline{Gross\ margin}_{t+1\rightarrow t+10}$	14,012	0.206	0.174	0.080	0.302	0.160
$\overline{ROS}_{t+1\rightarrow t+10}$	14,012	0.010	0.019	-0.008	0.053	0.086
$\overline{ROA}_{t+1\rightarrow t+10}$	14,012	0.032	0.032	0.007	0.069	0.076
log ME	13,930	7.011	7.103	5.562	8.410	2.081
log B/M	13,883	-0.659	-0.586	-1.109	-0.152	0.837
I/K	14,273	0.207	0.165	0.106	0.258	0.171
R&D/Sales	14,311	0.046	0.006	0.000	0.040	0.095
ROE	14,311	0.132	0.143	0.041	0.246	0.490
Leverage	14,262	0.247	0.236	0.083	0.366	0.204
OL	14,311	0.875	0.750	0.461	1.136	0.684
Tangibility	14,299	0.315	0.223	0.110	0.486	0.255
WW	13,455	-0.376	-0.383	-0.443	-0.315	0.104
Volatility	14,192	0.123	0.103	0.070	0.150	0.081
Momentum	13,811	1.179	1.078	0.822	1.348	0.840
log EnvPU	12,769	4.496	4.488	4.332	4.665	0.257
UMC	12,333	0.091	0.098	0.015	0.155	0.093
Sales (SCAP)	11,277	0.766	0.039	0.000	0.552	1.942
Sales (YPCCC Regulate)	9,960	65.584	71.549	68.672	74.610	20.996
Sales (YPCCC Happening)	9,960	60.806	66.045	61.790	70.340	19.812
Sales (YPCCC Worried)	9,960	51.813	55.450	50.838	61.252	17.400

Panel B: Summary statistics of CS measure by industry group

GICS industry group	N	Mean	Median	P25	P75	Std. dev.
(1010) Energy	1,776	1.725	0.257	0.000	0.847	5.223
(1510) Materials	1,895	2.320	0.962	0.000	2.339	4.764
(2010) Capital Goods	3,288	4.122	0.971	0.000	3.125	8.559
(2030) Transportation	603	0.657	0.418	0.000	1.039	0.794
(2510) Automobiles & Components	528	5.434	1.281	0.000	6.882	9.095
(2520) Consumer Durables & Apparel	911	0.784	0.000	0.000	1.000	1.602
(3020) Food, Beverage & Tobacco	690	1.415	0.338	0.000	1.058	3.053
(3030) Household & Personal Products	312	0.865	0.506	0.000	1.286	1.104
(4520) Technology Hardware & Equipment	1,811	1.032	0.303	0.000	1.003	2.508
(4530) Semiconductors & Semiconductor Equipment	1,284	3.093	0.645	0.000	1.969	7.178
(5510) Utilities	1,150	5.607	4.351	1.190	7.947	5.749

Table 1 continued

Panel C: Correlation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
(1) *CS measure*	1																									
(2) *log PE*	0.02	1																								
(3) *log EM*	0.05	0.62	1																							
(4) *Gross margin*	-0.18	0.14	0.15	1																						
(5) *ROS*	-0.20	-0.33	-0.12	0.37	1																					
(6) *ROA*	-0.25	-0.24	-0.27	0.35	0.75	1																				
(7) $\overline{ROA}_{t+1\rightarrow t+10}$	-0.15	0.08	0.07	0.50	0.22	0.23	1																			
(8) $\overline{ROS}_{t+1\rightarrow t+10}$	-0.18	0.00	0.01	0.11	0.46	0.50	0.36	1																		
(9) $\overline{Gross\ margin}_{t+1\rightarrow t+10}$	-0.24	-0.03	-0.07	0.10	0.45	0.62	0.42	0.79	1																	
(10) *log ME*	-0.09	0.01	0.02	0.15	0.41	0.44	0.15	0.40	0.39	1																
(11) *log B/M*	0.01	-0.26	-0.32	-0.20	-0.13	-0.20	-0.15	-0.16	-0.20	-0.32	1															
(12) *I/K*	0.01	0.02	0.04	0.16	-0.04	-0.06	0.13	-0.15	-0.11	-0.09	-0.13	1														
(13) *R&D/Sales*	0.13	0.23	0.26	0.18	-0.33	-0.41	0.14	-0.24	-0.32	-0.18	-0.16	0.23	1													
(14) *ROE*	-0.13	-0.08	-0.13	0.12	0.35	0.46	0.09	0.26	0.32	0.27	-0.32	-0.04	-0.20	1												
(15) *Leverage*	0.01	-0.07	0.02	-0.10	-0.06	-0.03	-0.14	0.05	0.03	0.19	-0.08	-0.17	-0.24	0.11	1											
(16) *OL*	-0.04	-0.09	-0.13	-0.33	-0.12	-0.03	-0.19	-0.03	0.07	-0.25	-0.05	0.08	-0.06	0.02	-0.15	1										
(17) *Tangibility*	0.03	-0.10	-0.14	-0.08	0.03	-0.04	-0.13	-0.03	-0.08	0.17	0.24	-0.23	-0.34	-0.02	0.29	-0.31	1									
(18) *WW*	0.08	0.09	0.09	-0.05	-0.37	-0.41	-0.05	-0.35	-0.34	-0.82	0.08	0.17	0.30	-0.37	-0.33	0.24	-0.25	1								
(19) *Volatility*	0.14	-0.08	0.01	-0.13	-0.38	-0.36	-0.17	-0.32	-0.29	-0.44	0.11	0.05	0.15	-0.20	0.03	0.09	-0.04	0.32	1							
(20) *Momentum*	0.01	-0.04	0.02	0.03	0.13	0.14	-0.02	0.02	0.04	0.08	-0.18	0.04	0.00	0.07	-0.03	0.01	-0.04	-0.01	0.11	1						
(21) *log EnvPU*	0.03	0.03	0.06	0.02	0.03	-0.01	-0.16	0.01	-0.05	0.05	-0.04	-0.09	-0.04	0.01	0.06	-0.06	0.01	-0.06	-0.01	0.14	1					
(22) *UMC*	-0.01	0.10	0.12	-0.02	-0.02	-0.04	-0.17	0.01	-0.04	0.08	-0.05	-0.06	-0.02	0.00	0.09	-0.05	0.02	-0.08	0.01	-0.11	0.09	1				
(23) *Sales (SCAP)*	0.01	0.08	0.12	0.09	-0.02	-0.06	-0.06	-0.01	-0.09	-0.02	-0.05	0.08	0.19	-0.04	-0.05	-0.02	-0.13	0.05	0.03	0.03	0.17	0.16	1			
(24) *Sales (YPCCC Regulate)*	-0.05	0.01	0.04	0.02	0.10	0.08	-0.15	0.02	-0.02	0.15	-0.07	0.02	-0.03	0.06	0.08	-0.01	-0.02	-0.09	-0.28	0.13	0.17	-0.15	0.13	1		
(25) *Sales (YPCCC Happening)*	-0.04	0.02	0.06	0.03	0.09	0.06	-0.17	0.02	-0.04	0.14	-0.08	0.03	-0.01	0.04	0.07	-0.02	-0.03	-0.08	-0.26	0.12	0.11	-0.14	0.19	0.98	1	
(26) *Sales (YPCCC Worried)*	-0.04	0.02	0.07	0.03	0.08	0.05	-0.20	0.01	-0.06	0.14	-0.08	0.02	0.00	0.04	0.07	-0.02	-0.03	-0.08	-0.23	0.13	0.14	-0.11	0.23	0.97	0.99	1

This table presents descriptive statistics for the firm-year sample. Panel A presents summary statistics for the variables used in this paper. Panel B presents summary statistics of the firm-year observations of *CS measure* across 4-digit GICS industry groups. Panel C presents the correlation matrix. The sample period is 2005 to 2023 at annual frequency. Variable definitions are presented in Table A.1 in Appendix A.

Table 2
Univariate portfolio sorting based on climate solutions.

	L	2	3	4	H	H-L
Panel A: Excess returns						
Excess return	0.97***	0.87**	0.89**	0.87**	0.52*	-0.45**
	(2.81)	(2.55)	(2.48)	(2.39)	(1.90)	(-2.06)
Standard deviation	5.41	5.05	5.16	5.30	4.78	2.96
Sharpe ratio	0.18	0.17	0.17	0.16	0.11	-0.15
Panel B: CAPM						
α_{CAPM}	0.26*	-0.04	-0.08	-0.08	-0.30	-0.55***
	(1.84)	(-0.27)	(-0.50)	(-0.37)	(-1.37)	(-2.64)
Panel C: FF3						
α_{FF3}	0.24	0.00	-0.08	-0.02	-0.26	-0.50***
	(1.64)	(0.02)	(-0.48)	(-0.10)	(-1.37)	(-2.64)
Panel D: FF4						
α_{FF4}	0.24*	0.01	-0.08	-0.02	-0.28	-0.53***
	(1.66)	(0.04)	(-0.53)	(-0.11)	(-1.56)	(-2.81)
Panel E: FF5						
α_{FF5}	0.10	-0.11	-0.19	-0.16	-0.39*	-0.48**
	(0.73)	(-0.67)	(-1.29)	(-0.81)	(-1.93)	(-2.42)
Panel F: HXZ						
α_{HXZ}	0.18	-0.04	-0.06	-0.25	-0.36*	-0.53**
	(1.34)	(-0.24)	(-0.40)	(-1.52)	(-1.69)	(-2.36)

This table shows the average excess returns and asset pricing factor tests for five portfolios sorted on *CS measure* relative to the 4-digit GICS industry group peers. The sample period is July 2006 to June 2023. We rebalance portfolios at the end of every June in year t by assigning firms into quintile groups based on *CS measure* in year $t-1$ and track the performance of the five portfolios from July of year t to June of year $t+1$. Portfolio returns are value-weighted by firms' market capitalization. Panel A reports the average excess returns over the risk-free rate, standard deviations, and Sharpe ratios. The remaining panels present the alphas obtained from time-series regressions of *CS measure*-sorted portfolios' excess returns on asset pricing factors. Panel B includes the market factor (MKT) based on the CAPM model. Panel C includes the Fama and French (1996) three factors (MKT, the size factor SMB, and the value factor HML). Panel D includes the Carhart (1997) four factors (MKT, SMB, HML, and the momentum factor UMD). Panel E includes the Fama and French (2015) five factors (MKT, SMB, HML, the profitability factor RMW, and the investment factor CMA). Panel F includes the Hou et al. (2015) q-factors (MKT, SMB, the investment factor I/A, and the profitability factor ROE). t-statistics based on standard errors using the Newey-West correction for 12 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 3
Climate solutions and individual stock returns.

Dep. variable: $R_{i,t}$	(1)	(2)	(3)
CS measure$_{i,t-1}$	-0.235***	-0.197***	-0.378***
	(-3.79)	(-3.28)	(-6.20)
log ME		-0.518***	0.411***
		(-3.17)	(3.33)
log B/M		0.090	0.088
		(1.25)	(1.34)
I/K		-0.171***	-0.272***
		(-3.08)	(-4.49)
R&D/Sales		0.073	-0.006
		(1.04)	(-0.08)
ROA		0.161**	0.615***
		(2.08)	(7.78)
Leverage		0.061	-0.168***
		(1.03)	(-2.89)
Tangibility		-0.069	-0.217***
		(-1.12)	(-3.15)
WW		-0.448**	-0.205
		(-2.48)	(-1.58)
Volatility			2.401***
			(20.32)
Momentum			-0.490***
			(-5.97)
Industry F.E.	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes
Observations	165,637	155,788	152,794
R^2	0.18	0.19	0.21

This table reports pooled panel regressions of individual excess stock returns on their *CS measure* and other firm characteristics. In each month from July of year t to June of year $t+1$, monthly returns over the risk-free rate of individual stocks ($R_{i,t}$) are regressed on *CS measure* in year $t-1$, different sets of control variables known by the end of June in year t, and industry fixed effects. Control variables include the natural logarithm of market capitalization (*ME*), the natural logarithm of book-to-market ratio (*B/M*), investment rate (*I/K*), ratio of R&D to sales (*R&D/Sales*), return on assets (*ROA*), book leverage (*Leverage*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), stock return momentum (*Momentum*), and industry dummies based on 4-digit GICS industry groups. All independent variables are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample period is July 2006 to June 2023. Robust t-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 4

Double portfolio sorting.

	Sautner et al.'s (2023a) *CCExposure*						Carbon emissions					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	L	2	3	4	H	H-L	L	2	3	4	H	H-L
Panel A: Excess return												
Bottom	0.89**	0.79**	0.67*	0.93**	0.21	-0.63***	0.94**	0.68	0.71*	0.57*	0.21	-0.73*
	(2.42)	(2.10)	(1.85)	(2.38)	(0.48)	(-2.79)	(2.35)	(1.29)	(1.81)	(1.89)	(0.42)	(-1.80)
Top	1.45***	0.84**	0.80*	0.71*	0.46	-0.99***	1.16***	0.81**	0.72*	0.78**	0.49*	-0.66***
	(3.34)	(2.17)	(1.93)	(1.79)	(1.61)	(-2.99)	(3.10)	(2.23)	(1.69)	(2.05)	(1.70)	(-2.70)
Panel B: CAPM												
Bottom	0.03	-0.05	-0.17	-0.01	-0.64***	-0.63***	0.10	-0.19	-0.15	-0.15	-0.67*	-0.78*
	(0.19)	(-0.21)	(-1.08)	(-0.02)	(-2.77)	(-2.72)	(0.60)	(-0.62)	(-0.65)	(-0.99)	(-1.78)	(-1.83)
Top	0.58***	0.01	-0.06	-0.11	-0.23	-0.81**	0.28*	-0.01	-0.10	-0.01	-0.22	-0.50**
	(2.63)	(0.03)	(-0.28)	(-0.41)	(-0.93)	(-2.49)	(1.68)	(-0.06)	(-0.59)	(-0.03)	(-0.90)	(-2.10)
Panel C: FF3												
Bottom	0.07	0.03	-0.12	-0.01	-0.58**	-0.63**	0.13	-0.19	-0.12	-0.10	-0.69*	-0.82**
	(0.54)	(0.14)	(-0.85)	(-0.02)	(-2.50)	(-2.60)	(0.75)	(-0.61)	(-0.54)	(-0.78)	(-1.95)	(-2.06)
Top	0.53**	0.04	-0.06	-0.04	-0.20	-0.73**	0.24	0.05	-0.10	0.03	-0.18	-0.43**
	(2.37)	(0.24)	(-0.29)	(-0.17)	(-0.90)	(-2.50)	(1.44)	(0.24)	(-0.63)	(0.12)	(-0.86)	(-2.12)
Panel D: FF4												
Bottom	0.08	0.04	-0.12	0.00	-0.58**	-0.63***	0.14	-0.17	-0.11	-0.11	-0.70**	-0.84**
	(0.58)	(0.19)	(-0.81)	(0.02)	(-2.51)	(-2.64)	(0.76)	(-0.54)	(-0.52)	(-0.92)	(-2.03)	(-2.15)
Top	0.53**	0.03	-0.08	-0.05	-0.23	-0.75**	0.25	0.04	-0.11	0.02	-0.20	-0.45**
	(2.35)	(0.16)	(-0.39)	(-0.19)	(-1.06)	(-2.59)	(1.46)	(0.23)	(-0.69)	(0.07)	(-1.00)	(-2.22)
Panel E: FF5												
Bottom	-0.05	-0.09	-0.23*	-0.10	-0.67**	-0.59**	-0.02	-0.16	-0.23	-0.30*	-0.68*	-0.66*
	(-0.40)	(-0.44)	(-1.70)	(-0.47)	(-2.52)	(-2.44)	(-0.13)	(-0.53)	(-0.99)	(-1.82)	(-1.83)	(-1.68)
Top	0.38*	-0.05	-0.18	-0.20	-0.33	-0.71**	0.12	-0.10	-0.22	-0.16	-0.33	-0.45**
	(1.79)	(-0.32)	(-0.89)	(-0.80)	(-1.46)	(-2.36)	(0.76)	(-0.52)	(-1.46)	(-0.68)	(-1.57)	(-2.19)
Panel F: HXZ												
Bottom	0.02	-0.03	-0.16	-0.09	-0.62***	-0.60***	0.09	-0.08	-0.08	-0.16	-0.51	-0.60
	(0.14)	(-0.14)	(-1.16)	(-0.41)	(-2.76)	(-2.77)	(0.54)	(-0.24)	(-0.34)	(-1.10)	(-1.47)	(-1.58)
Top	0.47**	-0.01	-0.04	-0.33	-0.29	-0.77**	0.18	-0.04	-0.11	-0.22	-0.31	-0.49**
	(2.18)	(-0.08)	(-0.17)	(-1.53)	(-1.18)	(-2.27)	(1.14)	(-0.18)	(-0.63)	(-1.09)	(-1.31)	(-2.02)

This table shows average excess returns and asset pricing factor tests for ten portfolios independently double sorted. In columns (1) through (6), double sorting is based on five portfolios for the *CS measure* and two portfolios for Sautner et al.'s (2023a) *CCExposure* measure, relative to 4-digit GICS industry group peers. We rebalance portfolios at the end of every June in year t by assigning firms into bottom and top groups based on the median value of the *CCExposure* measure in year $t-1$ and into quintile groups based on *CS measure* in year $t-1$. In columns (7) through (13), we present results from double sorting into five portfolios based on the *CS measure* and two portfolios based on the natural logarithm of the sum of a firm's scope 1 and 2 greenhouse gas emissions (*log Scope 1 and 2*), each relative to its 4-digit GICS industry group peers. We rebalance portfolios at the end of every June in year t by assigning firms into bottom and top groups based on the median value of *log Scope 1 and 2* in year $t-1$ and into quintile groups based on *CS measure* in year $t-1$. The sample period is July 2006 to June 2023. We track the performance of the ten portfolios from July of year t to June of year $t+1$. Portfolio returns are value-weighted by firms' market capitalization. We present the excess returns and alphas obtained from time-series regressions of the portfolio's excess returns on asset pricing factors. Panel A reports the average excess returns over the risk-free rate. Panel B includes the market factor (MKT) based on the CAPM model. Panel C includes the Fama and French (1996) three factors (MKT, the size factor SMB, and the value factor HML). Panel D includes the Carhart (1997) four factors (MKT, SMB, HML, and the momentum factor UMD). Panel E includes the Fama and French (2015) five factors (MKT, SMB, HML, the profitability factor RMW, and the investment factor CMA). Panel F includes the Hou et al. (2015) q-factors (MKT, SMB, the investment factor I/A, and the profitability factor ROE). t-statistics based on standard errors using the Newey-West correction for 12 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 5
Panel regressions with controls for other climate-related measures.

Panel A: Sautner et al.'s (2023a) CCExposure				
Dep. variable: $R_{i,t}$	(1)	(2)	(3)	(4)
CS measure$_{i,t-1}$	-0.170**	-0.170**	-0.326***	-0.322***
	(-2.18)	(-2.31)	(-4.51)	(-4.59)
CCExposure	-0.004		-0.016	
	(-0.06)		(-0.25)	
CCExposure^{Opp}		-0.035		-0.034
		(-0.66)		(-0.62)
CCExposure^{Reg}		0.072		0.014
		(1.50)		(0.29)
CCExposure^{Phy}		-0.022		0.003
		(-0.61)		(0.09)
Controls	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes
Observations	143,213	143,213	132,683	132,683
R^2	0.20	0.20	0.23	0.23

Panel B: Carbon emissions				
Dep. variable: $R_{i,t}$	(1)	(2)	(3)	(4)
CS measure$_{i,t-1}$	-0.270***	-0.274***	-0.272***	-0.269***
	(-4.07)	(-4.04)	(-4.11)	(-4.07)
log Scope 1	0.133			
	(1.37)			
log Scope 2		0.243***		
		(3.00)		
Scope 1 int			-0.077	
			(-1.10)	
Scope 2 int				-0.057
				(-1.05)
Controls	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes
Observations	83,025	83,025	83,025	83,025
R^2	0.27	0.27	0.27	0.27

This table reports pooled panel regressions of individual excess stock returns on their *CS measure* and controls for other climate-related measures. In Panel A, we include controls for Sautner et al.'s (2023a) measure in year $t-1$ and in Panel B, we include controls for carbon emissions in year $t-1$. In each month from July of year t to June of year $t+1$, monthly returns over the risk-free rate of individual stocks ($R_{i,t}$) are regressed on *CS measure* in year $t-1$, other climate-related measures in year $t-1$, control variables known by the end of June in year t, and industry fixed effects. We use Sautner et al.'s (2023a) firm-level exposure measures related to climate change (*CCExposure*), opportunity (*CCExposure*^{Opp}), regulatory (*CCExposure*^{Reg}), and physical (*CCExposure*^{Phy}) shocks. *log Scope 1* and *log Scope 2* are the natural logarithm of a firm's scope 1 and 2 greenhouse gas emissions, respectively. *Scope 1 int* and *Scope 2 int* are a firm's scope 1 and scope 2 carbon emission intensity, respectively. Both emission intensity measures are winsorized at the 2.5% level. Control variables include the natural logarithm of market capitalization (*ME*), the natural logarithm of book-to-market ratio (*B/M*), investment rate (*I/K*), ratio of R&D to sales (*R&D/Sales*), return on assets (*ROA*), book leverage (*Leverage*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), stock return momentum (*Momentum*), and industry dummies based on 4-digit GICS industry groups. All independent variables are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample period is July 2006 to June 2023. Robust t-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 6
Contemporaneous valuation regressions.

Dep. variable:	$log\ MB_{i,t}$		$log\ PE_{i,t}$		$log\ EM_{i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
CS measure$_{i,t}$	0.051**	0.052***	0.040**	0.036**	0.047**	0.046***
	(2.43)	(4.60)	(2.03)	(2.28)	(2.20)	(3.17)
I/K	0.127***	0.126***	-0.020	-0.012	0.009	0.014
	(8.92)	(9.67)	(-1.39)	(-0.84)	(0.70)	(1.29)
R&D/Sales	0.265***	0.266***	0.338***	0.331***	0.289***	0.291***
	(8.50)	(14.34)	(9.32)	(13.24)	(5.45)	(8.86)
ROE	0.268***	0.272***	-0.170***	-0.162***	-0.206***	-0.193***
	(6.60)	(7.01)	(-4.95)	(-4.85)	(-6.84)	(-8.19)
F1ROE	0.117***	0.113***	0.018	0.015	0.025*	0.022
	(7.33)	(4.52)	(0.85)	(0.63)	(1.70)	(1.57)
F2ROE	0.066***	0.063***	0.052***	0.048**	0.029***	0.024**
	(4.20)	(3.04)	(2.88)	(2.44)	(2.69)	(2.11)
F3ROE	0.056***	0.058***	-0.005	-0.008	0.017	0.019
	(4.32)	(4.51)	(-0.27)	(-0.46)	(1.30)	(1.44)
Leverage	0.067***	0.065***	0.007	0.010	0.071***	0.070***
	(3.11)	(4.36)	(0.42)	(0.79)	(4.79)	(7.26)
OL	0.043**	0.044***	-0.049***	-0.046***	-0.080***	-0.076***
	(2.35)	(4.01)	(-3.68)	(-4.25)	(-5.64)	(-7.69)
Tangibility	-0.068***	-0.066***	-0.019	-0.017	-0.089***	-0.087***
	(-2.74)	(-5.27)	(-0.83)	(-1.09)	(-4.51)	(-7.41)
WW	-0.004	-0.005	0.112***	0.110***	0.101***	0.099***
	(-0.19)	(-0.35)	(7.11)	(8.68)	(6.80)	(10.82)
Volatility	-0.139***	-0.137***	-0.092***	-0.088***	-0.056***	-0.046***
	(-8.57)	(-7.69)	(-4.63)	(-4.33)	(-3.78)	(-3.21)
Momentum	0.097***	0.091***	0.053***	0.047***	0.047***	0.040***
	(9.59)	(6.34)	(4.05)	(3.02)	(5.08)	(3.64)
Industry F.E.	Yes	No	Yes	No	Yes	No
Year F.E.	Yes	No	Yes	No	Yes	No
Industry × Year F.E.	No	Yes	No	Yes	No	Yes
Observations	10,755	10,749	8,261	8,251	9,672	9,667
R^2	0.35	0.36	0.15	0.17	0.23	0.25

This table reports pooled panel regressions of a stock's contemporaneous valuation on its *CS measure* and various control variables. The three valuation measures are *log MB*, the natural logarithm of market-to-book ratio, *log PE*, the natural logarithm of price-to-earnings ratio, and *log EM*, the natural logarithm of enterprise value to EBITDA ratio. Observations are dropped if the denominator of the valuation ratio is negative. Control variables include the investment rate (*I/K*), ratio of R&D to sales (*R&D/Sales*), return on equity (*ROE*), returns on equity for the next three years (*F1ROE*, *F2ROE*, and *F3ROE*), book leverage (*Leverage*), operating leverage (*OL*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), and stock return momentum (*Momentum*). We omit control variables that are related to the valuation ratios by construction (i.e., *log ME* and *log B/M*). Industry and Industry × Year fixed effects are based on 4-digit GICS industry groups. All independent variables are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample period is 2005 to 2023. Robust t-statistics based on standard errors clustered at the firm level (columns (1), (3), and (5)) and industry × year level (columns (2), (4), and (6)) are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 7

Event study around climate-related regulatory shocks.

	L	2	3	4	H	H-L
Panel A: MA vs EPA (April 2, 2007)						
$CAR(0,+5)$	-1.084*	-0.228	-0.896	0.163	0.693	1.777*
	(-2.00)	(-0.56)	(-1.64)	(0.14)	(0.66)	(2.07)
Panel B: Paris Agreement (December 12, 2015)						
$CAR(0,+5)$	-2.399*	-1.249	-0.610	0.251	3.679*	6.078***
	(-2.13)	(-1.30)	(-1.11)	(0.28)	(1.93)	(4.01)
Panel C: Trump election (November 8, 2016)						
$CAR(0,+5)$	3.745***	3.618*	3.152*	2.974*	1.600	-2.145**
	(3.40)	(2.07)	(2.03)	(1.99)	(1.04)	(-2.57)
Panel D: Biden election (December 14, 2020)						
$CAR(0,+5)$	-1.631**	-1.371	-0.839	-0.500	1.777*	3.408**
	(-2.62)	(-1.26)	(-1.14)	(-0.64)	(2.09)	(2.71)
Panel E: IRA (July 27, 2022)						
$CAR(0,+5)$	-1.880**	-1.392**	-0.560	1.554	6.229**	8.109***
	(-2.26)	(-2.34)	(-0.74)	(1.28)	(2.91)	(4.76)

Panel F: Cross-sectional regressions

	MA vs EPA	Paris Agreement	Trump election	Biden election	IRA
Dep. variable: $CAR(0,+5)$	(1)	(2)	(3)	(4)	(5)
CS measure	0.609***	1.392***	-1.441***	1.415**	1.755**
	(3.07)	(3.60)	(-5.19)	(2.44)	(3.04)
log ME	0.127	0.048	-0.830**	-0.040	0.038
	(0.77)	(0.15)	(-3.05)	(-0.87)	(0.63)
log B/M	0.719*	-0.310	0.271	-0.980**	-0.570
	(2.07)	(-1.05)	(0.68)	(-3.06)	(-1.14)
I/K	-0.262	0.016	-0.263	-0.296	-0.493
	(-0.71)	(0.19)	(-1.05)	(-0.53)	(-1.48)
R&D/Sales	-0.533	0.364	2.930**	1.702	0.208*
	(-1.25)	(0.21)	(2.58)	(1.24)	(2.17)
ROA	0.348	-1.101	0.900	-1.127	-0.584
	(0.93)	(-1.04)	(1.52)	(-1.72)	(-1.11)
Leverage	-0.204	-0.497	-1.543**	-0.639	-0.148
	(-0.78)	(-1.12)	(-3.02)	(-1.55)	(-0.31)
Tangibility	-0.156	-0.272	-0.192	-0.432*	0.206
	(-0.47)	(-0.32)	(-0.41)	(-1.87)	(0.45)
WW	-0.108	-0.281	0.105	0.094	0.130
	(-0.95)	(-1.11)	(0.17)	(0.17)	(0.94)
Volatility	0.286	-0.373	2.375**	0.290	0.994
	(0.34)	(-0.52)	(2.88)	(0.76)	(1.45)
Momentum	-0.442	-2.211***	-2.408***	0.102	-1.884***
	(-1.63)	(-3.36)	(-4.57)	(0.35)	(-4.33)
Industry F.E.	Yes	Yes	Yes	Yes	Yes
Observations	1,074	1,197	1,141	1,064	1058
R^2	0.02	0.16	0.20	0.13	0.13

Panels A to E present mean cumulative abnormal returns (%) around various climate-related regulatory events for stocks sorted on *CS measure* relative to the 4-digit GICS industry group peers. We report daily cumulative abnormal returns based on the market model over a 5-day window from the event date, which we refer to as a $(0,+5)$ window. Panel F presents cross-sectional regressions of $CAR(0,+5)$ on stocks' known value of *CS measure* at the time of the event. Control variables include the natural logarithm of market capitalization (*ME*), the natural logarithm of book-to-market ratio (*B/M*), investment rate (*I/K*), ratio of R&D to sales (*R&D/Sales*), return on assets (*ROA*), book leverage (*Leverage*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), stock return momentum (*Momentum*), and industry dummies based on 4-digit GICS industry groups. All independent variables are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. Robust t-statistics based on standard errors clustered at the industry level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 8
Climate solutions, future profitability, and environmental regulatory uncertainty.

Dep. variable:	$\overline{Gross\ margin}_{i,t+1\rightarrow t+10}$		$\overline{ROS}_{i,t+1\rightarrow t+10}$		$\overline{ROA}_{i,t+1\rightarrow t+10}$	
	(1)	(2)	(3)	(4)	(5)	(6)
CS measure$_{i,t}$	-0.094**	-0.087**	-0.168**	-0.199***	-0.098***	-0.119***
	(-2.29)	(-2.34)	(-2.16)	(-2.64)	(-3.90)	(-3.75)
CS measure$_{i,t}$ × *log EnvPU*$_t$	0.019**	0.018**	0.034**	0.041**	0.020***	0.025***
	(2.14)	(2.18)	(1.97)	(2.47)	(3.73)	(3.51)
Gross margin	0.077***	0.079***				
	(16.54)	(17.08)				
Δ*Gross margin*	-0.015***	-0.015***				
	(-6.05)	(-5.03)				
ROS			0.078***	0.082***		
			(11.11)	(15.69)		
Δ*ROS*			-0.017***	-0.018***		
			(-5.55)	(-4.98)		
ROA					0.044***	0.046***
					(15.52)	(24.03)
Δ*ROA*					-0.007***	-0.008***
					(-7.61)	(-6.06)
log ME	0.024***	0.023***	0.028***	0.027***	0.015***	0.015***
	(6.13)	(6.22)	(4.56)	(5.73)	(7.68)	(9.13)
log B/M	-0.016***	-0.016***	-0.006	-0.007**	-0.008***	-0.008***
	(-4.95)	(-5.66)	(-1.19)	(-2.04)	(-3.96)	(-6.73)
I/K	-0.007***	-0.007***	-0.011***	-0.009***	-0.005***	-0.004***
	(-3.19)	(-3.62)	(-2.96)	(-2.66)	(-4.16)	(-3.77)
R&D/Sales	-0.004	-0.003	-0.022***	-0.020***	-0.012***	-0.012***
	(-0.90)	(-1.47)	(-3.55)	(-5.14)	(-5.52)	(-7.47)
ROE	-0.014***	-0.013***	-0.000	-0.000	-0.008***	-0.008***
	(-3.50)	(-3.65)	(-0.07)	(-0.06)	(-3.22)	(-4.50)
Leverage	-0.015***	-0.014***	0.005	0.006***	0.002	0.003**
	(-4.60)	(-8.01)	(1.37)	(3.02)	(1.17)	(2.60)
OL	-0.014***	-0.013***	0.011***	0.012***	0.007***	0.007***
	(-3.94)	(-6.18)	(4.08)	(5.37)	(4.80)	(8.84)
Tangibility	-0.006	-0.007**	-0.008	-0.007	-0.003	-0.003
	(-1.43)	(-2.36)	(-1.55)	(-1.48)	(-1.31)	(-1.36)
WW	0.000	-0.000	0.000	0.001	-0.001	-0.001
	(0.08)	(-0.05)	(0.00)	(0.19)	(-0.82)	(-0.54)
Volatility	-0.010***	-0.013***	-0.015***	-0.018***	-0.006***	-0.008***
	(-4.07)	(-7.11)	(-3.79)	(-6.10)	(-4.21)	(-6.27)
Momentum	0.001	0.002	0.002	0.004*	-0.001	-0.001
	(0.44)	(0.84)	(1.07)	(1.77)	(-1.13)	(-0.62)
Industry F.E.	Yes	No	Yes	No	Yes	No
Year F.E.	Yes	No	Yes	No	Yes	No
Industry × Year F.E.	No	Yes	No	Yes	No	Yes
Observations	11,404	11,394	11,404	11,394	11,404	11,394
R^2	0.49	0.50	0.42	0.45	0.52	0.54

This table reports pooled panel regressions of a stock's future profitability on its *CS measure*, environmental regulatory uncertainty, and their interactions, together with other control variables in year t. The future profitability measures are the moving-average from year $t+1$ to $t+10$ of gross margin ($\overline{Gross\ margin}_{i,t+1\rightarrow t+10}$), return on sales ($\overline{ROS}_{i,t+1\rightarrow t+10}$), and return on assets ($\overline{ROA}_{i,t+1\rightarrow t+10}$). We measure environmental regulatory uncertainty using the natural logarithm of the mean of the 12-month moving-average of the EnvPU index in year t (Noailly et al., 2022). Control variables include the values of the profitability measures in year t (*Gross margin*, *ROS*, and *ROA*) and their changes from year $t-1$ (Δ*Gross margin*, Δ*ROS*, and Δ*ROA*), natural logarithm of market capitalization (*ME*), the natural logarithm of book-to-market ratio (*B/M*), investment rate (*I/K*), ratio of R&D to sales (*R&D/Sales*), return on equity (*ROE*), book leverage (*Leverage*), operating leverage (*OL*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), and stock return momentum (*Momentum*). Industry and Industry × Year fixed effects are based on 4-digit GICS industry groups. All independent variables (except for *log EnvPU*) are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample period is 2005 to 2019. Robust t-statistics based on standard errors clustered at the firm level (columns (1), (3), and (5)) and industry × year level (columns (2), (4), and (6)) are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 9
Climate solutions, future profitability, and unexpected climate change concerns.

Dep. variable:	$\overline{Gross\ margin}_{i,t+1\to t+10}$			$\overline{ROS}_{i,t+1\to t+10}$			$\overline{ROA}_{i,t+1\to t+10}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$CS\ measure_{i,t}$	-0.011***	-0.010***	-0.011***	-0.021***	-0.019***	-0.020***	-0.011***	-0.009***	-0.010***
	(-3.81)	(-3.63)	(-3.77)	(-3.67)	(-3.70)	(-3.55)	(-5.17)	(-5.00)	(-4.94)
$CS\ measure_{i,t} \times UMC_t$	0.041***			0.070**			0.050***		
	(2.59)			(2.50)			(4.71)		
$CS\ measure_{i,t} \times UMC_t^{BI}$		0.023**			0.054**			0.034***	
		(2.03)			(2.45)			(4.28)	
$CS\ measure_{i,t} \times UMC_t^{SD}$			0.031***			0.049**			0.038***
			(2.58)			(2.12)			(4.30)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,041	11,041	11,041	11,041	11,041	11,041	11,041	11,041	11,041
R^2	0.52	0.52	0.52	0.39	0.39	0.39	0.48	0.48	0.48

This table reports pooled panel regressions of a stock's future profitability on its *CS measure*, unexpected media climate change concerns, and their interactions, together with other control variables in year t. The future profitability measures are the moving-average from year $t+1$ to $t+10$ of gross margin ($\overline{Gross\ margin}_{i,t+1\to t+10}$), return on sales ($\overline{ROS}_{i,t+1\to t+10}$), and return on assets ($\overline{ROA}_{i,t+1\to t+10}$). We measure unexpected climate change concerns as the prediction error from a rolling AR(1) model applied to the MCCC index controlling for the potential effects of financial-market, energy-related, and macroeconomic variables (Ardia et al., 2023). *UMC* is the mean of the 12-month moving-average of the unexpected climate change concerns in year t. UMC^{BI} and UMC^{SD} are the *UMC* computed based on the themes "Business Impact" and "Societal Debate", respectively (Ardia et al., 2023). Control variables include the values of the profitability measures in year t (*Gross margin*, *ROS*, and *ROA*) and their changes from year $t-1$ (Δ*Gross margin*, Δ*ROS*, and Δ*ROA*), natural logarithm of market capitalization (*ME*), the natural logarithm of book-to-market ratio (*B/M*), investment rate (*I/K*), ratio of R&D to sales (*R&D/Sales*), return on equity (*ROE*), book leverage (*Leverage*), operating leverage (*OL*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), stock return momentum (*Momentum*), and industry dummies based on 4-digit GICS industry groups. All independent variables (except for the *UMC* variables) are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample period is 2008 to 2022. Robust t-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 10
Climate solutions, future profitability, and firm-level exposure to climate-related shocks.

	(1)	(2)	(3)	(4)
Panel A: $\overline{\text{Gross margin}}_{i,t+1\rightarrow t+10}$				
CS measure$_{i,t}$	-0.007***	-0.007***	-0.007***	-0.007***
	(-3.21)	(-3.15)	(-3.15)	(-3.15)
Sales (SCAP)$_{i,t}$	-0.006***			
	(-3.73)			
Sales (YPCCC Regulate)$_{i,t}$		-0.005		
		(-1.34)		
Sales (YPCCC Happening)$_{i,t}$			-0.005	
			(-1.32)	
Sales (YPCCC Worried)$_{i,t}$				-0.005
				(-1.34)
CS measure$_{i,t}$ × *Sales (SCAP)*$_{i,t}$	0.003*			
	(1.85)			
CS measure$_{i,t}$ × *Sales (YPCCC Regulate)*$_{i,t}$		0.003**		
		(2.12)		
CS measure$_{i,t}$ × *Sales (YPCCC Happening)*$_{i,t}$			0.003**	
			(2.28)	
CS measure$_{i,t}$ × *Sales (YPCCC Worried)*$_{i,t}$				0.003**
				(2.40)
Controls	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Observations	10,468	8,650	8,650	8,650
R^2	0.63	0.60	0.60	0.60
Panel B: $\overline{ROS}_{i,t+1\rightarrow t+10}$				
CS measure$_{i,t}$	-0.015***	-0.004	-0.005	-0.005
	(-3.44)	(-1.20)	(-1.25)	(-1.21)
Sales (SCAP)$_{i,t}$	-0.000			
	(-0.15)			
Sales (YPCCC Regulate)$_{i,t}$		-0.003		
		(-1.28)		
Sales (YPCCC Happening)$_{i,t}$			-0.003	
			(-1.15)	
Sales (YPCCC Worried)$_{i,t}$				-0.003
				(-0.99)
CS measure$_{i,t}$ × *Sales (SCAP)*$_{i,t}$	0.004*			
	(1.95)			
CS measure$_{i,t}$ × *Sales (YPCCC Regulate)*$_{i,t}$		0.003*		
		(1.66)		
CS measure$_{i,t}$ × *Sales (YPCCC Happening)*$_{i,t}$			0.004*	
			(1.71)	
CS measure$_{i,t}$ × *Sales (YPCCC Worried)*$_{i,t}$				0.004*
				(1.72)
Controls	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Observations	10,468	8,650	8,650	8,650
R^2	0.40	0.38	0.38	0.38

Table 10 continued

Panel C: $\overline{ROA}_{i,t+1\rightarrow t+10}$				
CS measure$_{i,t}$	-0.007***	-0.005***	-0.005***	-0.005***
	(-4.20)	(-3.61)	(-3.58)	(-3.58)
Sales (SCAP)$_{i,t}$	-0.000			
	(-0.25)			
Sales (YPCCC Regulate)$_{i,t}$		-0.003		
		(-1.04)		
Sales (YPCCC Happening)$_{i,t}$			-0.003	
			(-1.03)	
Sales (YPCCC Worried)$_{i,t}$				-0.003
				(-1.07)
CS measure$_{i,t}$ × *Sales (SCAP)*$_{i,t}$	0.002**			
	(2.19)			
CS measure$_{i,t}$ × *Sales (YPCCC Regulate)*$_{i,t}$		0.002*		
		(1.87)		
CS measure$_{i,t}$ × *Sales (YPCCC Happening)*$_{i,t}$			0.002**	
			(2.06)	
CS measure$_{i,t}$ × *Sales (YPCCC Worried)*$_{i,t}$				0.002**
				(2.09)
Controls	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Observations	10,468	8,650	8,650	8,650
R^2	0.51	0.49	0.49	0.49

This table reports pooled panel regressions of a stock's future profitability on its *CS measure*, firm-level exposure to climate-related shocks, and their interactions, together with other control variables in year t. The future profitability measures are the moving-average from year $t+1$ to $t+10$ of gross margin ($\overline{Gross\ margin}_{i,t+1\rightarrow t+10}$) in Panel A, return on sales ($\overline{ROS}_{i,t+1\rightarrow t+10}$) in Panel B, and return on assets ($\overline{ROA}_{i,t+1\rightarrow t+10}$) in Panel C. We measure firm-level exposure to climate-related shocks using the weighted-average (based on the firm's state-level sales) of cumulative state-level climate plans, focusing exclusively on mitigation strategies (*Sales (SCAP)*) and YPCCC's survey questions on the percentage of the adult population in a given state who support regulating CO2 as a pollutant (*Sales (YPCCC Regulate)*), think global warming is happening (*Sales (YPCCC Happening)*), and are worried about global warming (*Sales (YPCCC Worried)*). See text for the details of the construction of these variables. Control variables include the values of the profitability measures in year t (*Gross margin*, *ROS*, and *ROA*) and their changes from year $t-1$ (Δ*Gross margin*, ΔROS, and ΔROA), natural logarithm of market capitalization (*ME*), the natural logarithm of book-to-market ratio (*B/M*), investment rate (*I/K*), ratio of R&D to sales (*R&D/Sales*), return on equity (*ROE*), book leverage (*Leverage*), operating leverage (*OL*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), stock return momentum (*Momentum*), and industry dummies based on 4-digit GICS industry groups. All independent variables are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample period is 2005 to 2023 for column (1) and 2008 to 2022 for columns (2) to (4). Robust t-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 11
Climate solutions and institutional ownership.

	All institutional investors	Natural arbitrageurs (mutual funds, independent investment advisors)	Norm-constrained (banks, insurance, others)
Dep. variable: $\overline{IO}_{j,i,t+1\rightarrow t+4}$	(1)	(2)	(3)
CS measure$_{i,t}$	-0.001	-0.006	0.001
	(-0.27)	(-1.16)	(0.56)
Firm and Institutional Investor Controls	Yes	Yes	Yes
Institutional Investor F.E.	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes
Observations	11,357,779	3,413,784	7,943,718
Adj R^2	0.49	0.51	0.48

This table reports the results of panel regressions at the investor-firm-quarter level of investor demand on *CS measure* and other control variables in quarter t. Investor demand is measured as the moving-average from quarter $t+1$ to $t+4$ of the institutional ownership (obtained from 13F reports) held by investor j in firm i ($\overline{IO}_{j,i,t+1\rightarrow t+4}$). Column (1) uses the full sample of institutional investors. Column (2) uses the subsample of institutions classified as mutual funds or independent investment advisors. Column (3) uses the subsample of institutions classified as banks, insurance companies, or others including pension plans, endowments, and employee-ownership plans. Control variables include the natural logarithm of market capitalization (*ME*), the natural logarithm of book-to-market ratio (*B/M*), investment rate (*I/K*), ratio of R&D to sales (*R&D/Sales*), return on equity (*ROE*), book leverage (*Leverage*), operating leverage (*OL*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), stock return momentum (*Momentum*), and investors' portfolio size (*Portfolio size*) and portfolio concentration (*Portfolio concentration*). All independent variables are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample period is 2005 to 2023. Robust t-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table 12
Interaction between climate solutions and carbon emissions.

Dep. variable: $R_{i,t}$	(1)	(2)	(3)	(4)
CS measure$_{i,t-1}$	-0.137**	-0.225***	-0.229***	-0.274***
	(-2.15)	(-3.46)	(-3.47)	(-3.95)
log Scope 1	0.106			
	(1.07)			
log Scope 2		0.220***		
		(2.63)		
Scope 1 int			-0.146*	
			(-1.70)	
Scope 2 int				-0.068
				(-1.24)
CS measure$_{i,t-1}$ × *log Scope 1*	0.169***			
	(3.35)			
CS measure$_{i,t-1}$ × *log Scope 2*		0.066		
		(1.40)		
CS measure$_{i,t-1}$ × *Scope 1 int*			0.212***	
			(2.84)	
CS measure$_{i,t-1}$ × *Scope 2 int*				0.095*
				(1.66)
Controls	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes
Observations	83,025	83,025	83,025	83,025
R^2	0.27	0.27	0.27	0.27

This table reports pooled panel regressions of individual excess stock returns on *CS measure* and their interactions with carbon emissions. In each month from July of year t to June of year $t+1$, monthly returns over the risk-free rate of individual stocks ($R_{i,t}$) are regressed on *CS measure* in year $t-1$, carbon emissions in year $t-1$, their interactions, control variables known by the end of June in year t, and industry fixed effects. *log Scope 1* and *log Scope 2* are the natural logarithm of a firm's scope 1 and 2 greenhouse gas emissions, respectively. *Scope 1 int* and *Scope 2 int* are a firm's scope 1 and scope 2 carbon emission intensity, respectively. Both emission intensity measures are winsorized at the 2.5% level. Control variables include the natural logarithm of market capitalization (*ME*), the natural logarithm of book-to-market ratio (*B/M*), investment rate (*I/K*), ratio of R&D to sales (*R&D/Sales*), return on assets (*ROA*), book leverage (*Leverage*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), stock return momentum (*Momentum*), and industry dummies based on 4-digit GICS industry groups. All independent variables are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample period is July 2006 to June 2023. Robust t-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

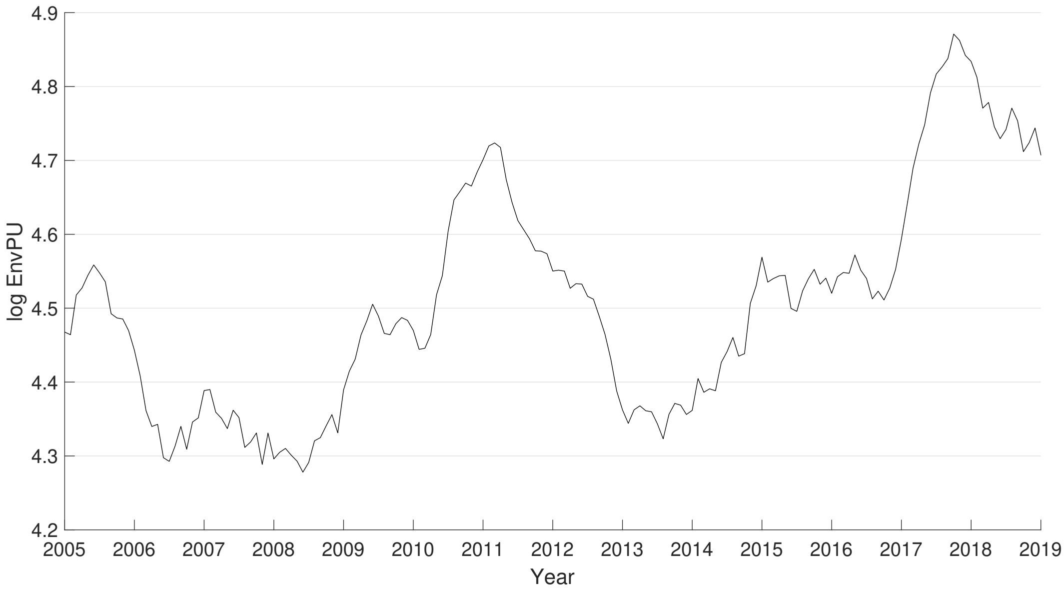
Appendix A: Variable definitions

Table A.1
Variable definitions.

Variable	Definitions	Data source
CS measure	The percentage of sentences identified as climate solutions to the total number of sentences in a firm's 10-K Item 1 Business Description.	10-K filings
$R_{i,t}$	Monthly returns (t) over the risk-free rate of individual stocks (i).	CRSP
PE	Price-to-earnings ratio defined as market capitalization (ME) divided by equity income ($ib - dvp + txdi$).	CRSP; Compustat
EM	Enterprise value to EBITDA ratio defined as enterprise value ($ME + dlc + dltt + pstkrv - che$) divided by operating income before depreciation ($oibdp$).	CRSP; Compustat
Gross margin	Gross margin defined as revenue ($revt$) minus cost of goods sold ($cogs$) divided by revenue ($revt$).	Compustat
ROS	Return on sales defined as net income (ni) divided by sales ($sale$).	Compustat
ROA	Return on assets defined as operating income after depreciation ($oiadp$) divided by total assets (at).	Compustat
$\overline{Gross\ margin}_{t+1\to t+10}$	The moving-average from year $t+1$ to $t+10$ of *Gross margin*.	Compustat
$\overline{ROS}_{t+1\to t+10}$	The moving-average from year $t+1$ to $t+10$ of *ROS*.	Compustat
$\overline{ROA}_{t+1\to t+10}$	The moving-average from year $t+1$ to $t+10$ of *ROA*.	Compustat
ME	Market capitalization ($abs(prc) \times shrout$).	CRSP
B/M	Book-to-market ratio defined as book value of equity ($seq + txdb + itcb - pstkrv$) divided by market value of equity ($prcc\_f \times csho$).	Compustat
I/K	Investment rate defined as capital expenditures ($capx$) divided by property, plant and equipment ($ppent$).	Compustat
R&D/Sales	Ratio of R&D to sales defined as research and development expense (xrd) divided by sales ($sale$).	Compustat
ROE	Return on equity defined as operating income after depreciation ($oiadp$) divided by book value of equity ($seq + txdb + itcb - pstkrv$).	Compustat
Leverage	Book leverage defined as total liabilities ($dltt + dlc$) divided by total assets (at).	Compustat
OL	Operating leverage defined as sum of cost of goods sold ($cogs$) and selling, general, and administrative expenses (xsga) divided by total assets (at).	Compustat
Tangibility	Tangibility defined as property, plant and equipment ($ppent$) divided by total assets (at).	Compustat
WW	Whited-Wu index defined as $-0.091[(ib + dp)/at] - 0.062\text{dividend indicator} + 0.021[dltt/at] - 0.044\log(at) + 0.102\text{three-digit SIC industry sales growth} - 0.035\text{sales growth}$.	Compustat
Volatility	Stock return volatility defined as the standard deviation of monthly stock returns over the past 12 months.	CRSP
Momentum	Stock return momentum defined as the cumulative 12-month return of a stock, excluding the immediate past month.	CRSP
log EnvPU	The natural logarithm of the mean of the 12-month moving-average of the EnvPU index in year t. The EnvPU index represents the share of articles about environmental policy that cover environmental policy uncertainty.	Noailly et al. (2022)
UMC	The mean of the 12-month moving-average of the unexpected climate change concerns in year t. We measure unexpected climate change concerns as the prediction error from a rolling AR(1) model applied to the MCCC index controlling for the potential effects of financial-market, energy-related, and macroeconomic variables.	Ardia et al. (2023)
UMC^x	*UMC* computed based on the themes $x = BI$ ("Business impact") or SD ("Societal debate").	Ardia et al. (2023)
Sales (SCAP)	The weighted-average (based on the firm's state-level sales) of cumulative state-level climate plans, focusing exclusively on mitigation strategies.	Infogroup; Georgetown Climate Center
Sales (YPCCC Regulate)	The weighted-average (based on the firm's state-level sales) of YPCCC's survey question on the percentage of the adult population in a given state who support regulating CO2 as a pollutant.	Infogroup; Yale Climate Opinion Maps
Sales (YPCCC Happening)	The weighted-average (based on the firm's state-level sales) of YPCCC's survey question on the percentage of the adult population in a given state who think global warming is happening.	Infogroup; Yale Climate Opinion Maps
Sales (YPCCC Worried)	The weighted-average (based on the firm's state-level sales) of YPCCC's survey question on the percentage of the adult population in a given state who are worried about global warming.	Infogroup; Yale Climate Opinion Maps
$\overline{IO}_{j,i,t+1\to t+4}$	The moving-average from quarter $t+1$ to $t+4$ of the institutional ownership held by investor j in firm i.	Thomson 13F

Internet Appendix

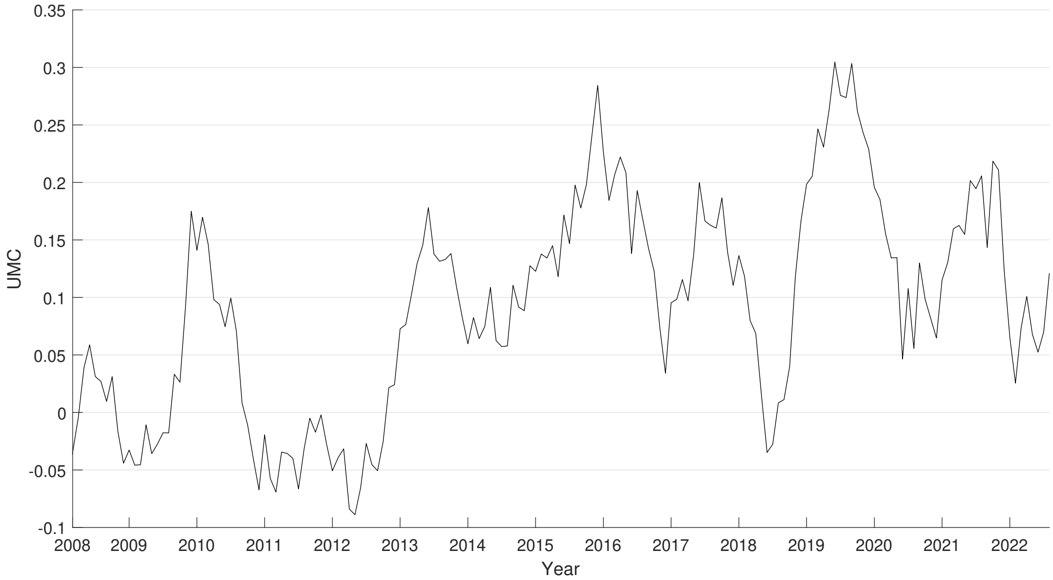
Figure IA.1
Time-series of environmental policy uncertainty index.



This figure shows the time-series of the natural logarithm of the 12-month moving-average of the EnvPU index from 2005 to 2019.

Figure IA.2

Time-series of unexpected climate change concerns.



This figure shows the time-series of the 12-month moving-average of the unexpected climate change concerns from 2008 to 2022.

Table IA.1
Portfolio characteristics.

	L	2	3	4	H
CS measure	0.420	0.815	1.453	2.801	9.701
log ME	14.029	14.352	14.400	14.629	13.567
log B/M	-0.573	-0.614	-0.539	-0.602	-0.577
I/K	0.167	0.163	0.159	0.160	0.162
R&D/Sales	0.006	0.009	0.009	0.010	0.018
ROA	0.068	0.073	0.069	0.073	0.042
Leverage	0.261	0.243	0.239	0.239	0.190
Tangibility	0.220	0.229	0.249	0.259	0.255
WW	-0.386	-0.393	-0.396	-0.407	-0.357
Volatility	0.108	0.100	0.100	0.100	0.124
Momentum	1.061	1.077	1.082	1.082	1.022
Observations	110	107	107	107	102

This table reports the time-series average of the cross-sectional median of firm characteristics for five portfolios sorted on *CS measure* relative to the 4-digit GICS industry group peers. The sample period is July 2006 to June 2023. We rebalance portfolios at the end of every June in year t by assigning firms into quintile groups based on *CS measure* in year $t-1$. Firm characteristics include the natural logarithm of market capitalization (*ME*), the natural logarithm of book-to-market ratio (*B/M*), investment rate (*I/K*), ratio of R&D to sales (*R&D/Sales*), return on assets (*ROA*), book leverage (*Leverage*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), and stock return momentum (*Momentum*). Variable definitions are presented in Table A.1 in Appendix A.

Table IA.2
Rolling AR(1) model regression coefficients.

	Mean	P25	Median	P75	%+	%−
Constant	0.688	0.533	0.670	0.832	100.00%	0.00%
MCCC	0.495	0.416	0.475	0.608	100.00%	0.00%
TERM	-0.060	-0.114	-0.034	0.008	0.00%	0.00%
DFLT	0.208	0.084	0.187	0.262	9.04%	0.00%
EPU	-0.075	-0.164	-0.114	0.046	0.56%	25.99%
VIX	-0.003	-0.012	-0.002	0.007	16.95%	2.82%
WTI	0.266	-0.058	0.203	0.615	4.52%	0.00%
PROP	0.213	0.045	0.204	0.364	0.56%	0.00%
NG	-0.097	-0.261	-0.145	0.085	0.00%	9.04%
MKT	0.005	-0.001	0.007	0.015	16.38%	0.00%
SMB	-0.016	-0.031	-0.017	-0.003	0.00%	31.64%
HML	0.004	-0.014	-0.002	0.025	8.47%	11.86%
RMW	0.010	-0.006	0.006	0.019	6.21%	0.00%
CMA	0.008	-0.013	0.023	0.030	2.26%	0.56%
MOM	0.002	-0.003	0.002	0.005	0.00%	0.00%

This table reports summary statistics on the regression coefficients from the rolling AR(1) model applied to the MCCC index. The coefficients are estimated over 177 rolling windows from January 2008 to September 2022 (each window is 60 months). We report the mean, median, and the 25th and 75th percentiles of the estimates. %+ and %− denote the percentage of time an estimate is significantly positive or negative, respectively, at the 10% significance level. *MCCC* is the autoregressive coefficient. Control variables include the term spread factor (*TERM*) and default spread factor (*DFLT*) of Fung and Hsieh (2004), the economic policy uncertainty index (*EPU*) of Baker et al. (2016), the CBOE volatility index (*VIX*), the crude oil return (*WTI*), the propane return (*PROP*), the natural gas return (*NG*), the excess market return (*MKT*), the small-minus-big factor (*SMB*) and the high-minus-low factor (*HML*) of Fama and French (1996), the robust-minus-weak factor (*RMW*) and the conservative-minus-aggressive factor (*CMA*) of Fama and French (2015), and the momentum factor (*MOM*) of Carhart (1997).

Table IA.3

Climate solutions, analyst forecast error, and transition risks.

Forecast error$_{i,t+1}$	(1)	(2)	(3)	(4)	(5)	(6)
CS measure	-1.212	-0.103	-0.026	-0.015	-0.016	-0.016
	(-0.97)	(-1.48)	(-0.47)	(-0.24)	(-0.25)	(-0.26)
CS measure$_{i,t}$ × *log EnvPU*$_t$	0.262					
	(0.94)					
CS measure$_{i,t}$ × *UMC*$_t$		0.534				
		(1.10)				
CS measure$_{i,t}$ × *Sales (SCAP)*$_{i,t}$			0.041			
			(0.79)			
CS measure$_{i,t}$ × *Sales (YPCCC Regulate)*$_{i,t}$				-0.027		
				(-0.58)		
CS measure$_{i,t}$ × *Sales (YPCCC Happening)*$_{i,t}$					-0.042	
					(-0.89)	
CS measure$_{i,t}$ × *Sales (YPCCC Worried)*$_{i,t}$						-0.051
						(-1.07)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,270	8,953	8,708	7,243	7,243	7,243
R^2	0.07	0.08	0.15	0.14	0.14	0.14

This table reports pooled panel regressions of analyst forecast errors on *CS measure*, measures of transition risks, and their interactions, together with other control variables in year t. *Forecast error* is the difference between the actual earnings per share for a given fiscal year and the median analyst consensus forecast, scaled by the stock price at the end of the fiscal year. We measure transition risks using environmental regulatory uncertainty, unexpected climate change concerns, and firm-level exposure to climate-related shocks. Control variables include the natural logarithm of market capitalization (*ME*), the natural logarithm of book-to-market ratio (*B/M*), investment rate (*I/K*), ratio of R&D to sales (*R&D/Sales*), return on equity (*ROE*), book leverage (*Leverage*), operating leverage (*OL*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), stock return momentum (*Momentum*), and industry dummies based on 4-digit GICS industry groups. All independent variables (except for *log EnvPU* and *UMC*) are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample period is 2005 to 2023. Robust t-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table IA.4
Climate solutions, carbon abatement costs and potential, and individual stock returns.

Dep. variable: $R_{i,t}$	(1)	(2)	(3)
CS measure (High abatement cost)$_{i,t-1}$	-0.065		
	(-1.20)		
CS measure (Low abatement cost)$_{i,t-1}$	-0.163***		
	(-2.99)		
CS measure (High abatement potential)$_{i,t-1}$		-0.123**	
		(-2.21)	
CS measure (Low abatement potential)$_{i,t-1}$		-0.117**	
		(-2.54)	
CS measure (High cost per potential)$_{i,t-1}$			-0.082
			(-1.52)
CS measure (Low cost per potential)$_{i,t-1}$			-0.151***
			(-2.87)
Controls	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes
Observations	152,794	152,794	152,794
R^2	0.20	0.20	0.20

This table reports pooled panel regressions of individual excess stock returns on their decomposed *CS measure* and other firm characteristics. We decompose *CS measure* into high and low categories based on two dimensions: the carbon abatement costs and the abatement potential of the firm's climate solutions. *CS measure (High abatement cost)* (*CS measure (Low abatement cost)*) is the sum of climate solution topics where the net initial cost to implement the climate solution is classified as high (low) according to the Project Drawdown 2020 report. *CS measure (High abatement potential)* (*CS measure (Low abatement potential)*) is the sum of climate solution topics where the abatement potential of the climate solution is classified as high (low) according to the Project Drawdown 2020 report. *CS measure (High cost per potential)* (*CS measure (Low cost per potential)*) is the sum of climate solution topics where the implementation cost per abatement potential of the climate solution is classified as high according to the Project Drawdown 2020 report. In each month from July of year t to June of year $t+1$, monthly returns over the risk-free rate of individual stocks ($R_{i,t}$) are regressed on decomposed *CS measure* in year $t-1$, different sets of control variables known by the end of June in year t, and industry fixed effects. Control variables include the natural logarithm of market capitalization (ME), the natural logarithm of book-to-market ratio (B/M), investment rate (I/K), ratio of R&D to sales (*R&D/Sales*), return on assets (ROA), book leverage (*Leverage*), tangibility (*Tangibility*), Whited-Wu index (WW), stock return volatility (*Volatility*), stock return momentum (*Momentum*), and industry dummies based on 4-digit GICS industry groups. All independent variables are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample period is July 2006 to June 2023. Robust t-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table IA.5

Climate solutions, institutional ownership, and transition risks.

Dep. variable: $\overline{IO}_{j,i,t+1\rightarrow t+4}$	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Natural arbitrageurs (mutual funds, independent investment advisors)						
CS measure$_{i,t}$	-0.088*	-0.011**	-0.008	-0.007	-0.007	-0.007
	(-1.95)	(-2.41)	(-1.40)	(-1.45)	(-1.46)	(-1.46)
Sales (SCAP)$_{i,t}$			-0.003*			
			(-1.82)			
Sales (YPCCC Regulate)$_{i,t}$				-0.005		
				(-0.81)		
Sales (YPCCC Happening)$_{i,t}$					-0.005	
					(-0.71)	
Sales (YPCCC Worried)$_{i,t}$						-0.006
						(-1.01)
CS measure$_{i,t}$ × *log EnvPU*$_t$	0.018*					
	(1.80)					
CS measure$_{i,t}$ × *UMC*$_t$		0.043***				
		(3.56)				
CS measure$_{i,t}$ × *Sales (SCAP)*$_{i,t}$			0.000			
			(0.19)			
CS measure$_{i,t}$ × *Sales (YPCCC Regulate)*$_{i,t}$				0.003***		
				(2.61)		
CS measure$_{i,t}$ × *Sales (YPCCC Happening)*$_{i,t}$					0.003***	
					(2.68)	
CS measure$_{i,t}$ × *Sales (YPCCC Worried)*$_{i,t}$						0.003**
						(2.49)
Firm and Institutional Investor Controls	Yes	Yes	Yes	Yes	Yes	Yes
Institutional Investor F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,610,465	3,269,864	2,996,462	2,882,800	2,882,800	2,882,800
Adj R^2	0.53	0.53	0.52	0.54	0.54	0.54
Panel B: Norm-constrained (banks, insurance companies, all other institutions)						
CS measure$_{i,t}$	0.046	-0.001	0.001	-0.001	-0.001	-0.001
	(1.38)	(-0.43)	(0.52)	(-0.29)	(-0.29)	(-0.27)
Sales (SCAP)$_{i,t}$			-0.001			
			(-1.55)			
Sales (YPCCC Regulate)$_{i,t}$				-0.002		
				(-0.59)		
Sales (YPCCC Happening)$_{i,t}$					-0.002	
					(-0.67)	
Sales (YPCCC Worried)$_{i,t}$						-0.003
						(-0.92)
CS measure$_{i,t}$ × *log EnvPU*$_t$	-0.010					
	(-1.35)					
CS measure$_{i,t}$ × *UMC*$_t$		0.011				
		(1.60)				
CS measure$_{i,t}$ × *Sales (SCAP)*$_{i,t}$			-0.000			
			(-0.41)			
CS measure$_{i,t}$ × *Sales (YPCCC Regulate)*$_{i,t}$				0.001		
				(0.93)		
CS measure$_{i,t}$ × *Sales (YPCCC Happening)*$_{i,t}$					0.001	
					(1.25)	
CS measure$_{i,t}$ × *Sales (YPCCC Worried)*$_{i,t}$						0.001
						(1.63)
Firm and Institutional Investor Controls	Yes	Yes	Yes	Yes	Yes	Yes
Institutional Investor F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,743,435	6,987,148	6,879,775	6,124,693	6,124,693	6,124,693
Adj R^2	0.47	0.51	0.49	0.52	0.52	0.52

Table IA.5 continued

This table reports the results of panel regressions at the investor-firm-quarter level of investor demand on *CS measure*, measures of transition risks, and their interactions, together with other control variables in quarter t. Investor demand is measured as the moving-average from quarter $t+1$ to $t+4$ of the institutional ownership (obtained from 13F reports) held by investor j in firm i ($\overline{IO}_{j,i,t+1\rightarrow t+4}$). Panel A uses the subsample of institutions classified as mutual funds or independent investment advisors. Panel B uses the subsample of institutions classified as banks, insurance companies, or others including pension plans, endowments, and employee-ownership plans. We measure transition risks using environmental regulatory uncertainty, unexpected climate change concerns, and firm-level exposure to climate-related shocks. Control variables include the natural logarithm of market capitalization (*ME*), the natural logarithm of book-to-market ratio (*B/M*), investment rate (*I/K*), ratio of R&D to sales (*R&D/Sales*), return on equity (*ROE*), book leverage (*Leverage*), operating leverage (*OL*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), stock return momentum (*Momentum*), and investors' portfolio size (*Portfolio size*) and portfolio concentration (*Portfolio concentration*). All independent variables (except for *log EnvPU* and *UMC*) are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample period is 2005 to 2023. Robust t-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table IA.6
Equal-weighted excess return and factor alpha.

	L	2	3	4	H	H-L
Panel A: Excess return						
Excess return	0.77	0.66	0.78	0.83*	0.18	-0.59*
	(1.42)	(1.20)	(1.57)	(1.68)	(0.33)	(-1.95)
Panel B: CAPM						
α_{CAPM}	-0.27	-0.34*	-0.22	-0.17	-0.88***	-0.62**
	(-1.01)	(-1.74)	(-0.92)	(-0.65)	(-2.64)	(-2.06)
Panel C: FF3						
α_{FF3}	0.01	-0.10	0.04	0.02	-0.74**	-0.75***
	(0.07)	(-0.56)	(0.30)	(0.14)	(-2.36)	(-2.61)
Panel D: FF4						
α_{FF4}	0.01	-0.10	0.04	0.02	-0.74**	-0.75**
	(0.07)	(-0.57)	(0.31)	(0.14)	(-2.40)	(-2.60)
Panel E: FF5						
α_{FF5}	-0.06	-0.09	-0.00	-0.01	-0.63**	-0.57**
	(-0.34)	(-0.48)	(-0.01)	(-0.05)	(-2.08)	(-2.07)
Panel F: HXZ						
α_{HXZ}	0.09	-0.02	0.09	0.09	-0.55*	-0.65**
	(0.55)	(-0.11)	(0.54)	(0.44)	(-1.88)	(-2.23)

This table shows equal-weighted excess returns and asset pricing factor tests for five portfolios sorted on *CS measure* relative to the 4-digit GICS industry group peers. The sample period is July 2006 to June 2023. We rebalance portfolios at the end of every June in year t by assigning firms into quintile groups based on *CS measure* in year $t-1$ and track the performance of the five portfolios from July of year t to June of year $t+1$. Portfolio returns are equal-weighted. We present the excess returns and alphas obtained from time-series regressions of *CS measure*-sorted portfolios' excess returns on asset pricing factors. Panel A reports the average excess returns over the risk-free rate. Panel B includes the market factor (MKT) based on the CAPM model. Panel C includes the Fama and French (1996) three factors (MKT, the size factor SMB, and the value factor HML). Panel D includes the Carhart (1997) four factors (MKT, SMB, HML, and the momentum factor UMD). Panel E includes the Fama and French (2015) five factors (MKT, SMB, HML, the profitability factor RMW, and the investment factor CMA). Panel F includes the Hou et al. (2015) q-factors (MKT, SMB, the investment factor I/A, and the profitability factor ROE). t-statistics based on standard errors using the Newey-West correction for 12 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table IA.7
Univariate portfolio sorting using 6-digit GICS industry.

	L	2	3	4	H	H-L
Panel A: Excess returns						
Excess return	0.97**	0.92***	0.68*	0.82**	0.46*	-0.51***
	(2.60)	(2.91)	(1.90)	(2.12)	(1.72)	(-2.61)
Panel B: CAPM						
α_{CAPM}	0.05	0.10	-0.01	-0.19	-0.24	-0.29*
	(0.28)	(0.62)	(-0.02)	(-1.34)	(-1.46)	(-1.77)
Panel C: FF3						
α_{FF3}	0.09	0.15	0.03	-0.17	-0.24	-0.34**
	(0.56)	(0.90)	(0.09)	(-1.41)	(-1.49)	(-1.97)
Panel D: FF4						
α_{FF4}	0.10	0.15	0.03	-0.18	-0.27*	-0.36**
	(0.59)	(0.89)	(0.08)	(-1.53)	(-1.68)	(-2.08)
Panel E: FF5						
α_{FF5}	0.01	0.01	-0.10	-0.29**	-0.34*	-0.35**
	(0.07)	(0.06)	(-0.31)	(-2.44)	(-1.88)	(-2.24)
Panel F: HXZ						
α_{HXZ}	0.08	0.12	-0.18	-0.26	-0.26	-0.34**
	(0.59)	(0.65)	(-1.31)	(-1.15)	(-1.49)	(-2.31)

This table shows the average excess returns and asset pricing factor tests for five portfolios sorted on *CS measure* relative to the 6-digit GICS industry peers. The sample period is July 2006 to June 2023. We rebalance portfolios at the end of every June in year t by assigning firms into quintile groups based on *CS measure* in year $t-1$ and track the performance of the five portfolios from July of year t to June of year $t+1$. Portfolio returns are value-weighted by firms' market capitalization. Panel A reports the average excess returns over the risk-free rate. The remaining panels present the alphas obtained from time-series regressions of *CS measure*-sorted portfolios' excess returns on asset pricing factors. Panel B includes the market factor (MKT) based on the CAPM model. Panel C includes the Fama and French (1996) three factors (MKT, the size factor SMB, and the value factor HML). Panel D includes the Carhart (1997) four factors (MKT, SMB, HML, and the momentum factor UMD). Panel E includes the Fama and French (2015) five factors (MKT, SMB, HML, the profitability factor RMW, and the investment factor CMA). Panel F includes the Hou et al. (2015) q-factors (MKT, SMB, the investment factor I/A, and the profitability factor ROE). t-statistics based on standard errors using the Newey-West correction for 12 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table IA.8
Panel regressions using 6-digit GICS industry fixed effects.

Dep. variable: $R_{i,t}$	(1)	(2)	(3)
CS measure$_{i,t-1}$	-0.245***	-0.203***	-0.351***
	(-3.81)	(-3.20)	(-5.11)
log ME		-0.536***	0.401***
		(-3.20)	(3.08)
log B/M		0.113	0.111*
		(1.54)	(1.66)
I/K		-0.166***	-0.272***
		(-3.00)	(-4.51)
R&D/Sales		0.070	0.000
		(0.96)	(0.00)
ROA		0.158**	0.623***
		(2.02)	(7.66)
Leverage		0.062	-0.185***
		(1.00)	(-3.10)
Tangibility		-0.086	-0.267***
		(-1.29)	(-3.65)
WW		-0.464**	-0.231*
		(-2.49)	(-1.67)
Volatility			2.451***
			(20.71)
Momentum			-0.507***
			(-6.10)
6-digit GICS Industry F.E.	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes
Observations	165,637	155,788	152,794
R^2	0.18	0.19	0.21

This table reports pooled panel regressions of individual excess stock returns on their *CS measure* and other firm characteristics using 6-digit GICS industry fixed effects. In each month from July of year t to June of year $t+1$, monthly returns over the risk-free rate of individual stocks ($R_{i,t}$) are regressed on *CS measure* in year $t-1$, different sets of control variables known by the end of June in year t, and 6-digit GICS industry fixed effects. Control variables include the natural logarithm of market capitalization (*ME*), the natural logarithm of book-to-market ratio (*B/M*), investment rate (*I/K*), ratio of R&D to sales (*R&D/Sales*), return on assets (*ROA*), book leverage (*Leverage*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), stock return momentum (*Momentum*), and industry dummies based on 6-digit GICS industries. All independent variables are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample period is July 2006 to June 2023. Robust t-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table IA.9
Fama-MacBeth regressions.

Dep. variable: $R_{i,t}$	(1)	(2)	(3)
CS measure$_{i,t-1}$	-0.238**	-0.190*	-0.291***
	(-2.04)	(-1.87)	(-2.85)
log ME		-0.607*	0.269
		(-1.95)	(1.42)
log B/M		-0.046	0.028
		(-0.43)	(0.31)
I/K		-0.091	-0.218***
		(-1.15)	(-2.80)
R&D/Sales		0.058	0.039
		(0.52)	(0.41)
ROA		0.144	0.535***
		(0.94)	(4.08)
Leverage		-0.101	-0.300***
		(-1.06)	(-3.67)
Tangibility		-0.077	-0.218**
		(-0.72)	(-2.31)
WW		-0.679**	-0.255
		(-2.35)	(-1.38)
Volatility			1.744***
			(5.38)
Momentum			-0.140
			(-0.82)
Industry F.E.	Yes	Yes	Yes
Observations	165,637	155,788	152,794
Adj R^2	0.07	0.11	0.16

This table reports Fama-MacBeth regressions of individual excess stock returns on their *CS measure* and other firm characteristics. We conduct cross-sectional regressions for each month from July of year t to June of year $t+1$. In each month, monthly returns over the risk-free rate of individual stocks ($R_{i,t}$) are regressed on *CS measure* in year $t-1$, different sets of control variables known by the end of June in year t, and industry fixed effects. Control variables include the natural logarithm of market capitalization (*ME*), the natural logarithm of book-to-market ratio (*B/M*), investment rate (*I/K*), ratio of R&D to sales (*R&D/Sales*), return on assets (*ROA*), book leverage (*Leverage*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), stock return momentum (*Momentum*), and industry dummies based on 4-digit GICS industry groups. All independent variables are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample period is July 2006 to June 2023. t-statistics based on standard errors using the Newey-West correction for 12 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table IA.10
Panel regressions with alternative controls for innovation.

Dep. variable: $R_{i,t}$	(1)	(2)	(3)	(4)
CS measure$_{i,t-1}$	-0.416***	-0.363***	-0.364***	-0.459***
	(-6.46)	(-5.57)	(-5.92)	(-6.10)
Knowledge capital/Sales	0.004			
	(0.05)			
RDC/Sales		0.077		
		(0.94)		
Trade secret			-0.209**	
			(-2.57)	
RETech stock				-0.022
				(-0.47)
log ME	0.486***	0.254*	0.417***	0.335**
	(4.07)	(1.94)	(3.44)	(2.16)
log B/M	0.025	0.029	0.086	0.102
	(0.38)	(0.40)	(1.35)	(1.35)
I/K	-0.257***	-0.261***	-0.279***	-0.244***
	(-4.19)	(-4.29)	(-4.52)	(-3.64)
ROA	0.629***	0.618***	0.610***	0.706***
	(7.93)	(6.34)	(8.65)	(6.88)
Leverage	-0.218***	-0.202***	-0.161***	-0.156**
	(-3.43)	(-3.22)	(-2.79)	(-2.04)
Tangibility	-0.296***	-0.326***	-0.247***	-0.363***
	(-3.85)	(-4.24)	(-3.63)	(-3.84)
WW	-0.140	-0.409***	-0.200	-0.176
	(-1.16)	(-3.05)	(-1.58)	(-1.08)
Volatility	2.457***	2.429***	2.411***	2.729***
	(17.84)	(20.13)	(20.10)	(16.35)
Momentum	-0.517***	-0.494***	-0.492***	-0.521***
	(-6.57)	(-5.80)	(-5.96)	(-5.12)
Industry F.E.	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes
Observations	130,151	131,402	151,993	96,898
R^2	0.21	0.22	0.21	0.22

This table reports pooled panel regressions of individual excess stock returns on their *CS measure* and other firm characteristics while controlling for alternative measures of innovation. In each month from July of year t to June of year $t+1$, monthly returns over the risk-free rate of individual stocks ($R_{i,t}$) are regressed on *CS measure* in year $t-1$, measures of innovation in year t, control variables known by the end of June in year t, and industry fixed effects. We include four measures of innovation. *Knowledge capital* is derived from industry-level R&D depreciation rates using the model by Ewens et al. (2024). This measure represents the capital value of R&D and covers the period from 2005 to 2019. We scale *Knowledge capital* by sales. *RDC* is calculated based on industry-year regressions of R&D investment and future revenues using the model by Iqbal et al. (2024). This measure also reflects the capital value of R&D and spans from 2005 to 2022. We scale *RDC* by sales. *Trade secret* is a dummy variable indicating whether a firm's 10-K filings in a given year include references to trade secrets, and zero otherwise, following the approach of Glaeser (2018). The sample period is from 2005 to 2023. *RETech stock* represents the average *RETech* metric from Bowen et al. (2023) across a firm's patent applications over the prior five years, with a 20% yearly depreciation rate applied and scaled by the number of patents. Higher (lower) levels of *RETech* correspond to patents in technology areas that are likely to substitute (complement) existing technologies. By construction, *RETech stock* is equal to zero when firms have no patent applications over the prior five years. Thus, we include a zero-patent dummy as a control variable. The sample period is from 2005 to 2019. Control variables include the natural logarithm of market capitalization (*ME*), the natural logarithm of book-to-market ratio (*B/M*), investment rate (*I/K*), return on assets (*ROA*), book leverage (*Leverage*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), stock return momentum (*Momentum*), and industry dummies based on 4-digit GICS industry groups. All independent variables (except for *Trade secret*) are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. Robust t-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table IA.11
Panel regressions with controls for greenness.

Sample period:	2007–2023	2012–2023
Dep. variable: $R_{i,t}$	(1)	(2)
CS measure$_{i,t-1}$	-0.167**	-0.145*
	(-2.21)	(-1.86)
Greenness$_{i,t-1}$	0.134***	0.105**
	(3.11)	(2.21)
log ME	0.185	0.236
	(1.07)	(1.31)
log B/M	-0.040	-0.059
	(-0.62)	(-0.86)
I/K	-0.214***	-0.217**
	(-2.62)	(-2.51)
R&D/Sales	0.031	0.005
	(0.38)	(0.06)
ROA	0.535***	0.494***
	(4.04)	(3.46)
Leverage	-0.060	-0.075
	(-0.97)	(-1.16)
Tangibility	-0.033	-0.061
	(-0.45)	(-0.78)
WW	-0.184	-0.181
	(-0.97)	(-0.92)
Volatility	1.930***	1.970***
	(12.62)	(11.69)
Momentum	-0.124	-0.088
	(-0.95)	(-0.63)
Industry F.E.	Yes	Yes
Year-Month F.E.	Yes	Yes
Observations	71,488	62,276
R^2	0.27	0.26

This table reports pooled panel regressions of individual excess stock returns on their *CS measure* and other firm characteristics while controlling for greenness. In each month from July of year t to June of year $t+1$, monthly returns over the risk-free rate of individual stocks ($R_{i,t}$) are regressed on *CS measure* in year $t-1$, greenness in year $t-1$, control variables known by the end of June in year t, and industry fixed effects. We measure a firm's greenness following Equation (9). Control variables include the natural logarithm of market capitalization (*ME*), the natural logarithm of book-to-market ratio (*B/M*), investment rate (*I/K*), ratio of R&D to sales (*R&D/Sales*), return on assets (*ROA*), book leverage (*Leverage*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), stock return momentum (*Momentum*), and industry dummies based on 4-digit GICS industry groups. All independent variables are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. Robust t-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Table IA.12
Factor alphas.

	L	2	3	4	H	H-L
Panel A: CAPM						
α_{CAPM}	0.80***	0.81***	0.85***	0.79***	0.75***	-0.06*
	(6.20)	(6.20)	(6.28)	(5.71)	(6.21)	(-1.93)
Panel B: FF3						
α_{FF3}	0.80***	0.80***	0.84***	0.78***	0.74***	-0.06**
	(6.43)	(6.41)	(6.46)	(5.95)	(6.46)	(-2.06)
Panel C: FF4						
α_{FF4}	0.81***	0.81***	0.85***	0.79***	0.75***	-0.06**
	(6.71)	(6.69)	(6.71)	(6.22)	(6.66)	(-2.12)
Panel D: FF5						
α_{FF5}	0.77***	0.77***	0.81***	0.75***	0.71***	-0.06**
	(6.50)	(6.41)	(6.50)	(6.00)	(6.48)	(-2.21)
Panel E: HXZ						
α_{HXZ}	0.82***	0.82***	0.86***	0.80***	0.76***	-0.06**
	(6.05)	(6.03)	(6.08)	(5.55)	(6.09)	(-2.03)

This table uses stock returns calculated using the generalized lower bounds of Chabi-Yo et al. (2023) and shows asset pricing factor tests for five portfolios sorted on *CS measure* relative to the 4-digit GICS industry group peers. The sample period is July 2006 to June 2023. We rebalance portfolios at the end of every June in year t by assigning firms into quintile groups based on *CS measure* in year $t-1$ and track the performance of the five portfolios from July of year t to June of year $t+1$. Portfolio returns are value-weighted by firms' market capitalization. We present the alphas obtained from time-series regressions of *CS measure*-sorted portfolios' returns on asset pricing factors. Panel A includes the market factor (MKT) based on the CAPM model. Panel B includes the Fama and French (1996) three factors (MKT, the size factor SMB, and the value factor HML). Panel C includes the Carhart (1997) four factors (MKT, SMB, HML, and the momentum factor UMD). Panel D includes the Fama and French (2015) five factors (MKT, SMB, HML, the profitability factor RMW, and the investment factor CMA). Panel E includes the Hou et al. (2015) q-factors (MKT, SMB, the investment factor I/A, and the profitability factor ROE). t-statistics based on standard errors using the Newey-West correction for 12 lags are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table IA.13

Panel regressions using option-implied expected returns.

Dep. variable: $GLB_{i,t}$	(1)	(2)
CS measure$_{i,t-1}$	-0.027***	-0.019**
	(-2.86)	(-2.03)
log ME	-0.397***	-0.398***
	(-18.92)	(-17.70)
log B/M	-0.012	-0.004
	(-1.10)	(-0.38)
I/K	-0.025***	-0.024**
	(-2.63)	(-2.52)
R&D/Sales	0.002	-0.001
	(0.15)	(-0.07)
ROA	0.016	-0.000
	(1.32)	(-0.04)
Leverage	-0.006	0.004
	(-0.56)	(0.40)
Tangibility	-0.000	0.005
	(-0.02)	(0.34)
WW	-0.099***	-0.073***
	(-5.05)	(-3.70)
Volatility		-0.079***
		(-5.78)
Momentum		-0.038***
		(-5.75)
Industry F.E.	Yes	Yes
Year-Month F.E.	Yes	Yes
Observations	122,473	121,995
R^2	0.54	0.55

This table reports pooled panel regressions of individual expected stock returns calculated using the generalized lower bounds of Chabi-Yo et al. (2023) on their *CS measure* and other firm characteristics. In each month from July of year t to June of year $t+1$, expected returns of individual stocks ($R_{i,t}$) are regressed on *CS measure* in year $t-1$, different sets of control variables known by the end of June in year t, and industry fixed effects. Control variables include the natural logarithm of market capitalization (*ME*), the natural logarithm of book-to-market ratio (*B/M*), investment rate (*I/K*), ratio of R&D to sales (*R&D/Sales*), return on assets (*ROA*), book leverage (*Leverage*), tangibility (*Tangibility*), Whited-Wu index (*WW*), stock return volatility (*Volatility*), stock return momentum (*Momentum*), and industry dummies based on 4-digit GICS industry groups. All independent variables are normalized to a zero mean and one standard deviation and winsorized at the 1st and 99th percentiles to reduce the impact of outliers. The sample period is July 2006 to June 2023. Robust t-statistics based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Variable definitions are presented in Table A.1 in Appendix A.

Extract from Lu et al. (2024) on the *CS measure* creation

Supplementary Note 1: Climate Solutions GPT Model

Data and Sample

Our primary data source is the SEC's EDGAR database, offering public access to 10K filings. A 10K filing is an annual report filed by publicly traded companies in the United States. As a regulatory document, filed with the Securities and Exchange Commission (SEC), companies are required to present factual information, which makes the report more reliable than other sources like sustainability reports and earnings conference calls. The report contains detailed information about a company's overall financial health, business practices, and strategy. Climate solutions are related to the product offering of companies therefore, for our analysis, we specifically targeted the business descriptions found in Part I, Item 1 (Business) of these filings.

Our sample starts with the universe of firms that report SEC 10-K filing in the EDGAR database from fiscal year 2005 to 2022. Our sample period begins in 2005 when the structure of 10-K is more stable. Starting 2005, the Securities and Exchange Commission (SEC) requires firms to disclose the most significant risks in Item 1A (Securities Offering Reform, Item 503(c) of Regulation S-K).

To ensure consistent firm identifiers over time, we use the WRDS-CIK linking tables to map the CIK in 10-K filings to GVKEY in Compustat (Hoberg & Phillips, 2016). This linking table allows us to match firms in Compustat to its historical CIK that could be different from the latest CIK due to firm name and structure changes (e.g., merger and acquisition, spin-offs, and bankruptcies). For example, General Motors filed for bankruptcy in 2009 and received a new CIK following that year. We are able to assign both CIK before and after the bankruptcy to the same GVKEY. We keep firm-year observations that are matched to Compustat as the majority of the firms not matched are funds, which we exclude together with financial institutions since we focus on climate solution products and services, but not the financing of them. Supplementary Table A1 shows the sample composition, where 37% of observations are excluded as a result of this requirement. We then use the Extractor API (Python) from the SEC API to retrieve the raw text of the Item 1 business description section of the 10-K filings. This process results in the loss of around 1% of observations where the API was not able to identify Item 1 or that the identified Item 1 contains fewer than 100 words.

We focus on industries that are pivotal to climate solutions, where our LLM is likely more accurate in identifying climate solutions. Based on reviewing Project Drawdown, we keep 13 (out of 25) GICS industry groups that are central to climate solutions: Energy, Materials, Capital Goods, Transportation, Automobiles & Components, Consumer Durables & Apparel, Food Beverage & Tobacco, Household & Personal Products, Technology Hardware & Equipment, Semiconductors & Semiconductor Equipment, Utilities, Equity Real Estate Investment Trusts (REITs), Real Estate Management & Development. This restriction reduces the sample by 35%. This process results in a final sample of 39,712 observations for 4,485 firms for fiscal years 2005 to 2022.

Climate Solutions Identification

The basis of our metric is a sentence-level binary classifier, designed to detect the presence of climate solutions within the text. This model was specifically developed for sentence-level classification (climate solution or not) due to two primary considerations. First, a sentence, as the fundamental unit of text, presents a clear and concise element for labelers to assess with high accuracy. Second, this method guarantees the precise extraction and identification of text segments specifically relevant to climate solutions.

Supplementary Table 1A: Sample Composition

Sample Composition		
	Sample Size	Ratio
Total 10K from edgar 2005-2022	146,718	
Firms not matched to Compustat	(53,894)	37%
Firms unable to extract item 1	(1,575)	1%
Firms not in relevant industries	(51,537)	35%
Final sample	39,712	

This table shows the sample composition.

Defining Climate Solutions

We define climate solutions as products and services that develop or deploy new technologies in a transition to a low-carbon economy. We identify climate solution technologies based on guidance from the Drawdown Project. The Drawdown Project contains a list of technologies that can reduce greenhouse gases in the atmosphere, and are compiled by a network of scientists and researchers.

While the Drawdown Project provides guidance on what decarbonization technology is considered a climate solution, when we label sentences, we need to decide for which firms the climate solution is a relevant product or service. Consider the following example with three companies involved in the climate solution technology of sustainable aviation fuel (SAF): an energy producer provides SAF to airlines to reduce its emissions and the airline sells flight tickets with lower carbon footprint to a consulting firm. We consider SAF a relevant climate solution for the energy producer since it is the developer of the technology. We also consider SAF a relevant climate solution for the airline since it deploys the technology. However, we do not consider SAF a relevant climate solution for the consulting firm since it engages in business as usual and neither develops nor deploys the climate solution technology.

Creating the training dataset

In the full dataset of almost nine million sentences from 10-K Item 1, only some of them pertain to climate solutions. Therefore, it is crucial to focus on the most representative sentences for efficient training of the model. We select sentences as our training dataset in two steps. In the first step, we select a sample of 100 sentences from each of the 13 industry groups based on sentences most confusing to the model using a one-shot BART model from Setfit. In the one-shot BART model, we predict whether a sentence is a climate solution sentence based on its alignment with Project Drawdown's Solutions Library. By using a BART model instead of randomly selecting sentences, we also ensure a better balance between positive and negative sentences. These chosen sentences go through a labeling process, which we describe in more detail in Supplementary Note 2.

In the second step, we conduct an iterative process to add sentences to the training set through an active learning approach. Active learning is a machine learning technique where the model identifies and selects specific data points for which it requires additional information (labels or annotations) to improve its performance. The technique often involves selecting data points where the model is uncertain. Thus, we identify common types of sentences that our model struggles to interpret or predicts as climate solutions (e.g., sentences considering climate regulations), and we include additional sentences on these confusing areas to further enhance the model. The objective of active learning is to select the data points from which the model learns better, aiming to improve learning efficiency and performance with less labeled data. This approach is particularly useful in scenarios where labeling data is expensive or time-consuming. By focusing on instances where the model's prediction is uncertain, active learning seeks to minimize the amount of required training data, thereby reducing costs and improving the model's accuracy and generalization capabilities.

We use a pre-trained ClimateBERT machine learning model as the base model for the active learning processes (Webersinke et al., 2022). A BERT model has the ability to capture rich contextual information, thus identifying and understanding ambiguous or uncertain cases. This capability enhances the effectiveness of the active learning process by ensuring that the most informative and challenging examples are selected for labeling. The ClimateBERT model's relatively compact size (in its number of weights/parameters) offers the advantage of requiring minimal computational power, enabling comparably quick fine-tuning. To mitigate the drawback of a smaller size model and less context encoded in its weights, the authors of ClimateBERT pre-trained it further on over 2 million paragraphs of climate-related texts to better respond to the domain-specific queries. Like any other binary classification model, ClimateBERT returns a logit, which can be transformed back to probabilities using a logistic function. Based on this output, we conduct the following iterative process:

1. Fine-tuned the model with the data.
2. Choose a decision boundary, that guarantees the highest F1 score.
3. Carefully examine the sentences whose predictions are close to the decision boundary.
4. Use these to guide the addition of new sentences into the dataset.

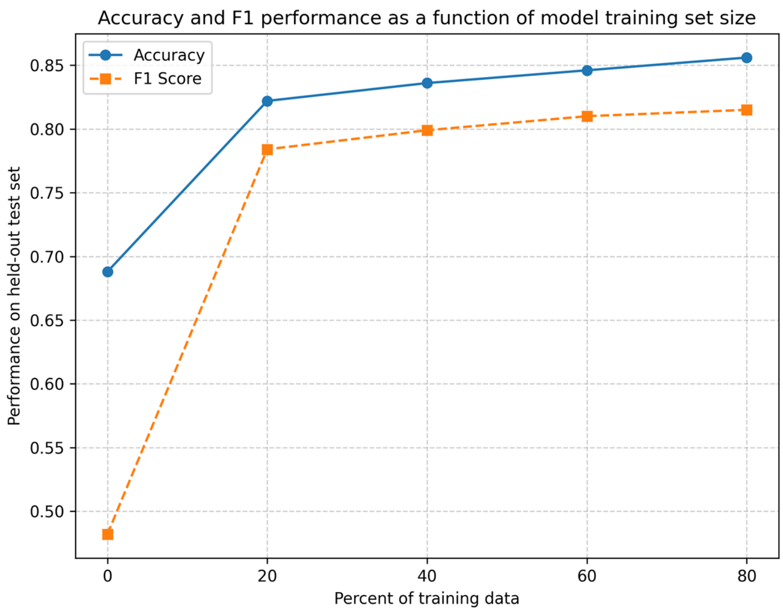
We underwent 8 rounds of active learning and generating training sets, as listed below. For each round, we identify the type of sentences causing confusion to the model and add around 200 sentences to the training set.

1. Sentences that contain "battery" or "electric" but are not related to climate solutions, such as those containing electric toothbrushes.
2. Sentences that describe climate policies or regulations faced by the firm, which does not mean the firm has products or services on climate solutions.
3. Sentences associated with buying carbon credits (e.g., renewable energy credits), but not the creation of carbon credits.
4. Sentences in the building/construction industry that likely needed more examples to properly inform the classifier's decision boundary, specifically when it relates to green buildings and LEED certifications.
5. Sentences containing ethanol, as the model initially does not consider most mentions of ethanol production as climate solution.
6. Sentences where the prefix 'bio' is present, where the model initially classifies as climate solutions but many are not, such as BiOmega-3.
7. Sentences containing generic agricultural products are sometimes misclassified as climate solutions, whereas sentences related to nutrient management and plant-based protein are climate solutions.
8. Sentences containing supporting products to other climate solutions are sometimes not classified as climate solutions. For example, products that enable existing cars to transition to a less carbon-intensive fuel.

This process results in a final training set of 3,508 sentences. The training set statistics are presented in Supplementary Table A2. The size of our dataset is benchmarked to Stammbach et al., 2023, where they annotated 3000 sentences to fine-tune transformer models for climate claim detection (Stammbach, Webersinke, Bingler, Kraus, & Leippold, 2023). Additionally, we evaluate the sufficiency of our training set size by examining how model performance changes as we increase the size of the training dataset. Specifically, we keep a held-out dataset using 20% of the training set, and examine the model performance on this held-out set when we train a GPT-3.5-turbo-1106 model using 0%, 20%, 40%, 60%, and 80% of the training set. Figure A2 shows the largest increase in model performance when the model is fine-tuned with 20% of the training set, compared to the non-fine-tuned model when 0% training data is provided. This increase reflects the value of fine-tuning the GPT model for the specific task of identifying climate solutions sentences. As the proportion of training set increases from 20% to 80%, we do not observe large improvements in model performance, which provides comfort that our training set is sufficient and that we do not anticipate large improvements in model performance if we were to annotate additional sentences.

Supplementary Table A2: Composition of the training data

Industry Name	Count in Training Set	Number of Positives	% of Positives	Count Overall	% of the Training Set	% of Overall Set
Automobiles and Components	291	168	0.577	180,942	8.640	1.984
Capital Goods	405	139	0.343	1,238,834	12.025	13.588
Consumer Durables and Apparel	178	45	0.253	494,283	5.285	5.421
Energy	181	74	0.409	1,769,351	5.374	19.406
Equity Real Estate Investment Trusts	188	57	0.303	492,869	5.582	5.406
Food, Beverage and Tobacco	451	163	0.361	412,178	13.391	4.521
Household and Personal Products	146	18	0.123	220,420	4.335	2.418
Materials	301	71	0.236	896,885	8.937	9.837
Real Estate Management and Development	134	40	0.299	492,869	3.979	5.406
Semiconductors and Semiconductor Equipment	178	69	0.388	460,569	5.285	5.052
Technology Hardware and Equipment	158	33	0.209	917,277	4.691	10.061
Transportation	184	46	0.250	313,834	5.463	3.442
Utilities	573	331	0.578	1,227,056	17.013	13.458



Supplementary Figure A2: Model Performance relative to Training Size

Training Methodology and Model Selection

We use the labeled training set to fine-tune a GPT-3.5-turbo-1106 specialized at labeling climate solutions sentences. Fine-tuning is the process of further training a pre-trained GPT model on a specific data and involves adjusting the model's weights to better capture the language and concepts related to climate solutions. GPT algorithm is based on a neural network architecture that depends on weights, which are the parameters that are learned during training. The weights determine the strength of connections between neurons in different layers of the model. Adjusting these weights changes the way the model processes input data and generates output. Fine-tuning adjusts the model's weights so it can better understand and generate climate-specific terms and phrases, such as "renewable energy," "plant-based protein," and "cogeneration." Through this process, the model learns the contextual usage of these terms within climate-related discussions, improving its ability to generate relevant and coherent text specific to climate solutions. The fine-tuning hyperparameters for our GPT-based model are based on recommended defaults, with epochs set to 3, batch size to 7, and a learning rate multiplier of 2.

We employ 5-fold cross-validation to assess our model, optimizing the use of our labeled dataset. This method ensures comprehensive evaluation by partitioning the dataset into five subsets, where each subset serves as a test set while the remaining are used for training, iteratively. For each fold, we designate 20% of the labeled dataset as a holdout set for testing, while the remaining 80% is used to fine-tune a GPT-3.5-turbo-1106 model. The trained model is then evaluated on the held-out 20%, and this process is repeated across all five folds.

The model demonstrates an overall accuracy of 84.09%, with a standard deviation of 1.93% between folds, indicating consistency in performance across different subsets. Moreover, we report an F1 score of 79% with a standard deviation of 2% between the folds. The F1 score, being the harmonic mean of precision and recall, provides a balanced measure of the model's accuracy, particularly valuable in the context of binary classification. It is especially pertinent for evaluating performance in imbalanced datasets, where traditional accuracy metrics may not fully capture the effectiveness of the model in distinguishing between classes.

We display the GPT prompt below and the detailed model performance by industry in Supplementary Table A3.

Listing 1: GPT finetuning prompt

```
system_message = ''You are a chatbot with expertise in
   environmental regulations and climate change mitigation
   strategies. Your function is to meticulously analyze
   sections of regulatory documents, 10k filings, to identify
   the presence of proposed climate solutions. Based on the
   guidelines, assess whether the company is implementing
   specific technologies or practices contributing to a low-
   carbon economy. Look for whether there is a clear
   indication of the company's investment or future investment
    in climate solutions or the sentence implies a reduction
   in carbon emissions through the company's products or
   services. Generic, vague, or general statements about
   climate change should classified as no.''
```

Supplementary Table A3: Model Evaluation by Industry

	GPT 3.5 FT		ClimateBERT FT	
Index	**F1 Score**	**Accuracy (%)**	**F1 Score**	**Accuracy (%)**
Automobiles and Components	0.845	81.787	0.836	80.756
Utilities	0.839	81.501	0.839	80.279
Real Estate Management and Development	0.835	90.299	0.706	81.343
Energy	0.833	86.740	0.833	85.635
Food, Beverage and Tobacco	0.793	83.814	0.799	84.257
Capital Goods	0.789	84.938	0.772	82.963
Consumer Durables and Apparel	0.776	87.640	0.729	85.393
Technology Hardware and Equipment	0.727	88.608	0.646	85.443
Semiconductors and Semiconductor Equipment	0.724	76.405	0.723	75.843
Transportation	0.722	85.326	0.667	82.065
Materials	0.699	85.382	0.649	82.060
Equity Real Estate Investment Trusts	0.694	80.319	0.625	74.468
Household and Personal Products	0.636	89.041	0.528	82.877
Overall	**0.795**	**84.090**	**0.776**	**81.984**

In the process of selecting an appropriate LLM, we considered several aspects:

- **Cost:** The financial implications of model utilization vary significantly depending on the deployment strategy. For models operated on private infrastructure, the primary cost consideration involves the expenses associated with cloud services. Alternatively, when employing a proprietary model accessible via API, the cost per token becomes a pivotal factor. Opting for the latter, our strategy focused on crafting concise prompts to minimize expenses without compromising the model's effectiveness.

- **Latency:** The response time of models can range widely, influenced by factors such as model size, architectural complexity, and the computational power of the hosting environment. This variance is a critical consideration, especially in scenarios requiring rapid iterative testing and feedback. Although larger, more computationally intensive models may offer superior performance, selecting a model that balances response time and computational demands was essential for our workflow. In our approach, we utilized both, the efficiency of climateBERT to rapidly iterate over training examples and then the large context of a GPT model for the final classification.

- **Performance for Specific Tasks:** The adaptability of modern LLMs to a broad spectrum of tasks is remarkable, often eliminating the need for fine-tuning or complex prompting strategies for general applications. However, specialized tasks may necessitate tailored adjustments or fine-tuning to achieve optimal results. The trade-off between using generalized versus specialized language models for niche domains has been explored in research, such as in medicine (Nori et al., 2023) and finance (Li et al., 2023).

Given these considerations, our choice of the final model was informed by a holistic assessment of primarily task-specific performance, cost, and latency. Despite ClimateBERT's suitability for our initial training needs, the superior performance, expansive knowledge, and versatility of GPT were sufficient reasons to be our choice of model for the final classification phase. Looking at the overall accuracy, the fine-tuned GPT-3.5 is at 84.09%, which is higher than that of the fine-tuned ClimateBERT's accuracy of 81.98% as seen in Supplementary Table 1C. We select the ClimateBERT model with the highest F1 score by conducting a grid search over key hyperparameters, including learning rates (5e-05, 2e-05, 1e-05, 5e-06), epsilons (1e-08, 1e-07), and dropout probabilities (0.1, 0.2, 0.3). The optimal model for which our accuracy and F1 scores are based on has a learning rate of 5e-05, epsilon of 1e-08, and dropout of 0.1.

In untabulated analysis, we also explore three alternative models, DistilRoBERTa, RoBERTa, and DeBERTa (He, Liu, Gao, & Chen, 2020; Liu et al., 2019; Sanh, Debut, Chaumond, & Wolf, 2019), with the same parameters as the ClimateBERT model. Across these models, the F1 and accuracy rates are below the ClimateBERT model, which has a performance below the fine-tuned GPT we use.

In particular, the fine-tuned GPT-3.5 outperforms the fine-tuned ClimateBERT significantly in correctly identifying climate solutions sentences in industries with fewer climate solutions, such as in Equity Real Estate Investment Trusts and Household and Personal Products. In summary, by fine-tuning GPT-3.5-turbo-1106 with a targeted training set, we achieve a balance between cost efficiency and performance.

A challenge with utilizing GPT-3.5 is its non-deterministic behavior. Non-deterministic behavior in GPT refers to the variability in its outputs even when given the same input multiple times. This behavior arises from several factors inherent to the design and operation of the model. One key factor is temperature, which controls the randomness of predictions. A higher temperature value (e.g., 1.0) produces more random outputs, while a lower temperature (e.g., 0.1) makes the output more deterministic and focused on high-probability tokens (refer to the words or sub-words that the model predicts are most likely to come next in a given sequence). Therefore, to reduce variability in predictions, we set the temperature hyper-parameter to 0.1. Additionally, to examine the potential variability in this non-deterministic behavior, we randomly selected 1,000 sentences from outside the training set and apply the fine-tuned GPT model five times. The maximum discrepancy observed between any two columns was 1 row.

Supplementary Note 2: Climate Solutions Labeling

To train our GPT climate solutions model, we label 3,508 sentences as either climate solution sentences or not. For our annotation procedure, we implement the following general rules referencing Webersinke et al. (2022). The annotators have to determine whether a sentence is related to climate solutions. Annotators are asked to apply common sense, e.g., when a given sentence might not provide all the context, but the context might seem obvious. Moreover, annotators are informed that each annotation should be a 0-1 decision. Hence, if an annotator is 70% certain, it is rounded up to 100%. Two researchers annotate the same tasks to obtain some measure of dispersion. In case of a close verdict or a tie between the annotators, the authors of this paper discuss the sentence in depth before reaching an agreement. Out of 3,508 sentences, annotators agreed on 2,905, while the remaining sentences had disagreements. To assess the degree of annotator agreement, we calculate Cohen's Kappa, which is 0.6653 with a 95% confidence interval of 0.64 to 0.6907. This indicates a substantial level of agreement in the labeling process.

We define climate solutions as products and services that develop or deploy new technologies in a transition to a low-carbon economy. As a general rule, we determine that just discussing climate change or the environment is not sufficient, the sentence should mention specific climate solutions, such as renewable energy, electrification of transportation and processes, battery technology, new agricultural practices, or plant-based protein alternatives to meat. When in doubt, we refer to the list of climate solutions technologies listed in Project Drawdown. Below, we provide some examples.

Sentence	Label	Reason
Our industry experience, the performance of our transit buses, and compelling total cost of ownership has helped make us the leader in the U.S. electric transit bus market.	1	The firm is creating electric transit bus, which, as an electric vehicle, is a climate solution.
We believe we have a responsibility and opportunity to play a role in the global economic transition to net zero emissions.	0	This is a generic statement without referencing specific products or investments, as compared to the previous sentence.
Our expanding corporate offices in Los Angeles, California are being designed and developed to qualify for LEED certification.	0	This is about their current operations, and not a product they are developing.
Many of our products meet the requirements for the awarding of LEED credits, and we are continuing to develop new products, systems and services to address market demand for products that enable construction of buildings that require fewer natural resources to build, operate and maintain.	1	This is similar to the last sentence in mentioning the LEED certification, but is used with respect to a product, and therefore qualifies.
The first class of QFs includes energy producers that generate power using renewable energy sources such as wind, solar, geothermal, hydro, biomass or waste fuels.	0	This reads as part of a regulation for Qualifying Facilities, and not a product or any indication of a company's actions.

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