

When Do AI and Emerging Technologies Shape Climate Investment?

Sean Cao, Junyoung Park, Ling Xue, and Keer Yang[†]

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Abstract

Firms apply AI and emerging technologies to address climate challenges, known as ClimateTech. We use large language model contextual functions to analyze firm press releases, identify ClimateTech investment projects, and construct a taxonomy. ClimateTech investment concentrates in two categories: multipurpose infrastructure and specialized environmental technologies. Infrastructure technologies generate financial returns but show no measurable environmental impact, while specialized environmental technologies generate neither on average. We investigate why managers invest in specialized environmental technologies and present evidence that the value of emerging technologies is not warranted but depends on how they are deployed in relation to the core business.

JEL Classification: G14, G31, Q54, O33

Key Words: Climate Solution; Climate Finance; Machine Learning; ESG; Socially Responsible Investing; AI

*Cao: University of Maryland, scao824@umd.edu. Park: Auburn University, jzp0170@auburn.edu. Xue: University of Georgia, ling.xue@uga.edu. Yang: University of California, Davis, kkeyang@ucdavis.edu

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1 Introduction

AI and emerging technologies are transforming nearly all aspects of society and the economy. The widespread adoption of these technologies has also led policymakers to consider them as a key factor shaping policymaking ([Congressional Budget Office, 2024](#)). In the finance literature, such technological advances have been extensively studied as “Fin-Tech”. For example, AI has been studied to enhance information processing ([Sheng, Sun, Yang, and Zhang, 2025](#); [Li, Rossi, Yan, and Zheng, 2025](#); [Jha, Qian, Weber, and Yang, 2024](#)) and improve household welfare ([Rossi and Utkus, 2024](#)), but may also introduce new concerns, including biased financial decision-making ([Ouyang, Yun, and Zheng, 2025](#)). These studies focus on how AI affects information and its consequences for firm value and financial decision-making. However, beyond information effects, AI can also affect corporate real investment when firms address emerging societal challenges such as climate issues ([Department of Energy, 2024](#)). Following this new line of inquiry, in this paper, we examine how AI and new technologies affect the effectiveness of corporate climate investment.

Another motivation for examining the effects of AI on firms’ real climate investment is that the use of AI in climate-related real investment is becoming an industry trend, while our understanding of its real effects remains limited. For example, in 2019, Microsoft invested in an Azure-based platform to monitor and optimize workplace energy use, resulting in energy savings of up to 25%. In 2022, Target launched its most sustainable store, which is designed to generate more renewable energy than it consumes annually. The adoption of AI and emerging technologies to address climate issues is commonly referred to in industry as ClimateTech. However, it remains unclear whether, when, and through which channels they create value, as well as the conditions under which they fail. This question is timely given the scale of AI investment and growing evidence on uneven outcomes, as most organizations fail to realize measurable benefits from AI adoption: a recent MIT report estimates that roughly 95% of firms earn no return on in-house AI investments ([Challapally, Pease, Raskar, and Chari, 2025](#)).

In this paper, we provide a systematic analysis of technology-based climate investment, or ClimateTech. We define ClimateTech as climate solutions investments that in-

corporate advanced technologies, such as AI and alternative energy, distinguishing them from broader climate initiatives that lack such features. We explore three research questions:

- 1) Taxonomy of ClimateTech: We focus on the types of technologies adopted and the purposes for which ClimateTech is used.
- 2) Overall Effectiveness and Potential Failure of ClimateTech: We examine whether ClimateTech is effective or fails based on two criteria: (a) financial value creation for shareholders and (b) measurable environmental impact for stakeholders.
- 3) When does ClimateTech work: We identify when and under what conditions ClimateTech creates value, as well as the conditions under which it fails. Our analysis focuses within the set of climate-related solutions and compares ClimateTech with more general, non-technology-oriented climate solutions.

To answer these questions, we first identify firms' ClimateTech-related investments. We focus on publicly traded firms listed in the U.S., which face both challenges and opportunities related to climate change and frequently communicate their climate-related investments to investors and other stakeholders through press releases. For example, in a January 2021 press release, Linde announced plans to build, own, and operate the world's largest Proton Exchange Membrane (PEM) electrolyzer at the Leuna Chemical Complex in Germany. The facility is expected to produce green hydrogen for Linde's industrial customers via the firm's existing pipeline network. We use information from such press releases to identify firms' ClimateTech investments. We employ an interpretable large language model (LLM) approach to analyze corporate press releases and identify firms engaged in ClimateTech investments. This approach captures word relationships with precision and meaning, ensuring that the initiatives we identify are tangible, concrete ClimateTech investments. Our analysis differs from the existing literature by focusing on technology-driven climate investments and comparing them with other climate-related activities that are often associated with greenwashing.

Using LLM to further analyze ClimateTech-related investments, we classify ClimateTech investments into two distinct categories: multipurpose infrastructure and specialized en-

environmental technologies. Multipurpose infrastructure includes environmental infrastructure technologies related to artificial intelligence (AI) and machine learning (ML), information technology (IT) infrastructure, supply chain management infrastructure, and other general-purpose infrastructure. Specialized environmental technologies include EV-related technologies, energy-related innovations, and other advanced specialized environmental solutions.

We begin by developing a taxonomy of this emerging economic phenomenon by identifying ClimateTech investments within climate-related press releases. Among 8,194 general climate-related press releases from 2010 to 2021, 23% (1,885) are classified as ClimateTech. Firms that adopt ClimateTech exhibit distinct characteristics. Early adopters of ClimateTech are led by management teams with strong technological expertise, and are typically larger firms with greater cash holdings, higher R&D intensity, and a higher concentration of AI and climate-related talent. Overall, we find that firms with the financial, technological, and human resources to adopt AI and other emerging technologies are more likely to pursue ClimateTech investments.

Beyond providing a systematic analysis of this emerging economic phenomenon and the first large-scale evidence on firms' use of technology to address climate issues, we examine the effectiveness of ClimateTech investments. This is motivated by prior work that documents that technology investments often fail to achieve desired outcomes when they are not fully integrated into firm operations ([Challapally et al., 2025](#)). We evaluate effectiveness along two dimensions: (i) financial value creation for shareholders, and (ii) measurable environmental impact for stakeholders.

To analyze financial value creation, we examine capital market responses to ClimateTech initiatives by estimating cumulative abnormal returns (CARs) around climate-related press releases. We compare the CARs of ClimateTech investments with those of other climate-related activities (ClimateNonTech) and use this comparison to evaluate the effectiveness of ClimateTech initiatives in creating financial value.¹ The average four-day abnormal return around ClimateTech investment press releases, measured from one day before to

¹Prior research emphasizes the importance of technological disruption for value creation ([Caskurlu et al., 2024](#)), suggesting that investors assess climate-related announcements based on their expected future value.

two days after the announcement, is 92 basis points. Relative to non-technology-oriented climate press releases, ClimateTech press releases generate CARs that are 56 basis points higher and statistically significant, indicating that ClimateTech initiatives, on average, meet shareholder expectations. This effect is driven by multipurpose infrastructure investments rather than specialized environmental technologies, for which press release returns are indistinguishable from those of non-technology-oriented climate initiatives. We find no evidence of post-announcement drift; abnormal returns are concentrated within the first two trading days.

The explanation for this striking difference between the financial impact of multipurpose infrastructure investments and specialized environmental technologies differs from the standard greenwashing interpretation. Our evidence from ClimateTech press releases indicates substantial real investment rather than mere image management. Given that multipurpose infrastructure ClimateTech drives the significant difference in market reaction compared with specialized environmental technologies, one interpretation is that capital markets perceive infrastructure as risk-mitigating. Such infrastructure can be applied to both environmental and non-environmental uses, whereas specialized environmental technologies serve exclusively environmental purposes.

Climate issues represent a significant externality. Shareholders may favor climate technologies because they generate financial value by mitigating risk or reducing the cost of capital through attracting sustainable investment. In such cases, financial value creation for shareholders does not necessarily benefit stakeholders, who are more concerned with tangible environmental outcomes such as pollution reduction. Therefore, we examine the effectiveness of ClimateTech investments by evaluating their measurable environmental impact for stakeholders.

To assess real environmental outcomes, we examine both MSCI environmental ratings and RepRisk climate incident data. We find no evidence of improvements in environmental outcomes, as measured by MSCI ratings or RepRisk climate incidents, following investments in either multipurpose infrastructure technologies or specialized environmental technologies. These results indicate that, on average, neither category of ClimateTech investment delivers measurable improvements in real environmental performance.

Our results provide evidence that AI and emerging technology-oriented ClimateTech investments create financial value but fail to generate real environmental impact. This divergence adds to the growing evidence on the uneven outcomes of investments in AI and emerging technologies. Given that multipurpose infrastructure ClimateTech generates financial value, it is natural for managers to invest in such technologies. In contrast, specialized environmental ClimateTech does not appear to generate either financial value or measurable environmental improvements. Why, then, do managers undertake these investments? To address this question, we identify when and under what conditions specialized environmental ClimateTech creates value and when it fails.

We examine the specific contexts in which specialized environmental ClimateTech creates value. An important observation is that many firms' investments in specialized environmental ClimateTech fall outside their core lines of business. An exploratory analysis shows that such investments create value when they are related to the firm's primary industry. Motivated by evidence from this pilot analysis, we construct a novel measure to gauge whether an investment disclosed in a press release is related to the firm's core business or to a non-core business. Specifically, Item 1 of Form 10-K provides information on a firm's core products and business activities. Accordingly, we use an LLM to assess the semantic alignment between each press release and the firm's core operations as disclosed in its 10-K, capturing whether the press release content is closely related to the core business. The model classifies a press release as core if the climate initiative is closely related to the firm's main revenue-generating activities or strategic focus, and non-core otherwise. Our methodology allows future studies to advance understanding of the nature of these events.

We find that, among press releases tied to firms' core operations, specialized environmental technology announcements are associated with an abnormal return 106 basis points higher than that of ClimateNonTech press releases. We do not observe such a difference in the non-core sample. Moreover, we document significant real environmental improvements when specialized environmental technologies are applied to core business activities. Overall, we identify that specialized environmental technology investments generate both financial value and measurable environmental outcomes when firms in-

tegrate emerging environmental technologies into their core business operations rather than confining them to peripheral or symbolic activities. These results provide evidence that the value of emerging technologies is not automatic but depends on how they are deployed in relation to firms' core business activities. Such an analysis can offer important guidance for corporate managers, especially because AI and emerging technology adoption in the climate context does not, on average, lead to satisfactory outcomes.

Because firms differ significantly in their use of state-of-the-art technology to address climate issues, one identification challenge is that the decision to adopt such technologies may be endogenous. Our empirical specification is less susceptible to this concern because we employ an event study framework focusing on short-term event windows, which are less likely to be influenced by broader factors affecting environmental technology investment. In addition, we exploit state-year variation in AI talent supply as an exogenous determinant of firms' likelihood of adopting advanced climate technologies to address endogeneity issues. Using a control function approach, we model firms' climate technology investment decisions in the first stage. The results show that a greater state-year supply of AI talent increases the likelihood that firms adopt technologies to address climate concerns, with the effect concentrated in multipurpose infrastructure ClimateTech. Based on estimation from the first stage, we include a control function in the second stage to account for omitted variables that affect both ClimateTech adoption and market reaction. We further show that the positive CAR following ClimateTech and ClimateTech Infra press releases remains robust after controlling for unobservable determinants of climate technology investment by exploiting exogenous variation in the probability of technology adoption.

Our research contributes to several strands of literature. First, our paper contributes to the emerging literature on the effectiveness of AI and emerging technology investments. While on average AI adoption does not deliver expected performance ([Challapally et al., 2025](#)), we explore when and through which channels these investments create value, as well as the conditions under which they fail. We show that the value of these technologies is not guaranteed, but instead depends on how they are deployed in the context of ClimateTech.

Second, our paper relates to the literature on climate solutions (e.g., [Larcker and Watts, 2020](#); [Klausmann et al., 2024](#); [Lu et al., 2024](#); [Sautner et al., 2023](#); [Lu et al., 2025](#); [Chiu et al., 2026](#)). A growing body of work seeks to evaluate and measure climate solutions. We provide a measure that focuses specifically on the technologies employed. Our study is therefore distinct in focusing on the underlying technologies of climate investments rather than on general climate solutions.

Lastly, the textual analysis method we develop to identify core versus non-core investments based on press releases can be applied more broadly in future studies of corporate investment press releases and patent abstract classification ([Hoberg and Manela, 2025](#); [Ma, 2025](#)). For example, when firms disclose new patent abstracts or capital expenditure announcements, our methodology can help classify these disclosures as related to the firm's core business or to a non-core business, allowing future studies to advance understanding of the nature of these events. In addition, our paper contributes to the literature by introducing an interpretable use of LLMs in this setting. Existing literature has employed textual analysis to measure diverse aspects of firm sustainability and climate-related risks (e.g., [Chiu et al., 2026](#); [Kim et al., 2023](#); [Leippold and Yu, 2026](#); [Sautner et al., 2023](#)). An advantage of using the dependency parser is that it helps alleviate concerns about the black-box nature of LLMs. Because the dependency parser is a subcomponent of the LLM, it produces observable textual and syntactic features that make the construction of our variables more transparent. By showing these intermediate features, we help readers understand how the variables are derived.

The remainder of the paper is structured as follows. [Section 2](#) reviews the related literature. [Section 3](#) presents the data. [Section 4](#) describes the empirical framework. [Section 5](#) reports the results. [Section 6](#) concludes.

2 Related Literature

This paper relates to several strands of the literature. First, we contribute to the literature on the adoption of AI and emerging technologies. Second, we extend the literature on climate solutions by examining technology-focused climate investments and developing a

taxonomy that is distinct from prior work. Third, we add to the debate on non-pecuniary ESG motives by showing how climate investments generate real environmental impact through investment channels. Finally, we contribute to the textual analysis literature in finance and accounting by employing interpretable language models to study firm disclosures.

First, our paper contributes to the literature on AI and emerging technologies. Such technological advances have been extensively studied in finance as FinTech. AI and emerging technologies are widely adopted in asset management, where they enhance information processing (Sheng et al., 2025), and improve household welfare through robo-advising (Rossi and Utkus, 2024). These technologies enable real-time investment strategies (Li et al., 2025), but they may also introduce new concerns, including biased financial decision-making (Ouyang et al., 2025). In corporate finance, AI and emerging technologies have reshaped how firms communicate with investors (Cao et al., 2023), improved managers' ability to assess the competitive landscape (Hoberg et al., 2024), and influenced corporate investment and policy decisions (Jha et al., 2024). This paper contributes to the literature examining how AI and emerging technologies shape corporate real investment. We also contribute to the emerging literature on the effectiveness of AI (Cao et al., 2025; Caplin et al., 2025) and emerging technology investments by studying their role in corporate finance and their effects on shareholder value and real environmental outcomes.

A growing body of work seeks to evaluate and measure climate solutions. For example, Lu et al. (2024) identify climate solutions that foster the transition to a low-carbon economy. Sautner et al. (2023) analyze the attention paid by earning call participants to firms' climate change exposures and capture exposures related to climate change. Skinner and Valentine (2026) utilize conference call transcripts to provide insights into how firms help investors process green innovation details. Cheng et al. (2025) use patents to measure green innovation. This differs from our approach, as we also capture activities that are not patented, recognizing that firms can engage in advanced climate technologies without necessarily holding patents. Our measure is distinct in that it emphasizes the underlying technologies of climate solutions and develops a taxonomy of these technologies.

Our paper adds to the debate on non-pecuniary ESG motives by showing how climate solutions can generate real environmental impact through investment channels. [Starks \(2023\)](#) highlights the “value versus values” debate in sustainable investment. From the shareholders’ perspective, [Barber et al. \(2021\)](#) document that investors derive nonpecuniary utility from investing in dual-objective funds, thereby sacrificing returns. [Yang and Yasuda \(2025\)](#) find that the majority of U.S. mutual funds pursue financial motives in sustainable investment. From the stakeholders’ perspective, [Duchin et al. \(2025\)](#) document that firms divest pollutive plants in response to environmental pressures, usually to buyers with weaker pressures and existing ties, yet overall pollution levels remain unchanged. [Hartzmark and Shue \(2022\)](#) find that lowering green firms’ financing costs has little effect, whereas raising brown firms’ costs produces substantial negative impacts. We add to this discussion by showing that climate solutions can operate through real investment channels that generate measurable environmental impact. In particular, we demonstrate that specialized environmental technology solutions, when applied to a firm’s core business, can fulfill the responsibility to both shareholders and stakeholders.

Lastly, this research contributes to the literature on using textual analysis, including machine learning and AI to measure firms’ sustainability and climate-related activities. Existing studies employ textual analysis to extract such measures from various firm disclosure sources. For instance, [Lu et al. \(2024\)](#) analyze business descriptions in 10-K filings to capture firms’ engagement with climate solutions using LLMs. [Leippold and Yu \(2026\)](#) develop measures of green innovation invention and adoption based on earnings conference call transcripts using transformer-based models and LLMs. [Sautner et al. \(2023\)](#) examine the attention of earnings call participants to construct firm-level exposure to climate risks using machine learning prediction models. [Chiu et al. \(2026\)](#) identify firms’ green products using trademark text data. A related and growing strand of the literature employs interpretable language models to analyze firm disclosures and extract economically meaningful signals. For example, [Cao et al. \(2025\)](#) use a deep learning model to extract fund managers’ forward-looking risk assessments from narrative disclosures. Building on the methodology proposed by [Cao et al. \(2020\)](#), we contribute to this line of work by quantifying firms’ engagement in ClimateTech using interpretable language models. Im-

portantly, our approach enhances interpretability and transparency, allowing us to link textual signals directly to economically meaningful categories of climate-related activity. Moreover, our research complements prior work on textual analysis of 10-K filings and patents to study firm operations. For instance, [Hoberg and Phillips \(2025\)](#) measure firm scope based on textual analysis on 10-K Item 1. We extend this research by leveraging LLMs to quantify the extent to which a climate-related press release pertains to a firm’s core business. That is, we extend the use of firm disclosures to measure the alignment between specific initiatives (i.e., ClimateTech investments) and existing business operations. This distinction is crucial, as the economic and environmental implications of such investments may differ depending on whether they represent peripheral adjustments or fundamental shifts in firms’ operational strategies.

3 Data and Empirical Methods

Data on Climate Press Releases We measure firms’ ClimateTech investment using firm press release from Capital IQ’s Key Developments database, which compiles structured summaries of corporate events from over 2,000 sources, including press releases, regulatory filings, earnings call transcripts, and firm websites. Each news or event item is categorized into one of more than 100 key development types, such as executive changes, M&As, and product launches. We focus on press releases classified as business expansions/reorganizations, product launches, strategic alliances, and M&As from 2010 to 2021.

To identify climate-related press releases within these categories, we employ a climate keyword list. The initial list consists of unigrams, bigrams, and trigrams related to climate change, as documented in recent literature ([Sautner et al., 2023](#)). The initial climate keyword list includes “carbon-free,” “eco-friendly,” and “renewable energy.” We then expand the initial list by identifying additional keywords from the full set of press release texts using semantic similarity based on word embeddings. Specifically, we train a Word2Vec model on the corpus of press release texts to obtain vector representations of words that capture their contextual usage. Word2Vec maps each word to a dense vector in a continuous semantic space, allowing words that appear in similar contexts to have similar vector

representations. Using these embeddings, we compute the cosine similarity between the vector representations of each candidate word in the press release corpus and the vectors of the initial seed keywords. Words with a cosine similarity score of 0.7 or higher relative to any seed keyword are considered semantically related and are added to the expanded keyword set after manual verification of their contextual relevance. Our final sample of climate press releases, identified using the expanded climate keyword list, consists of 11,935 press releases from 8,194 firms.

Data on Financial Impact We compute cumulative abnormal returns (CARs) over the event window [-1, 2] surrounding each climate press release, where day -1 is the trading day immediately before announcement date. Abnormal returns are estimated using several benchmark asset-pricing models: the CAPM, the Fama–French three-factor model, the Fama–French three-factor model with momentum, and a market-adjusted model. Expected returns are estimated over a 252 trading day window ending one day before the announcement.

Data on Environmental Impact We assess the environmental impact of each climate press release using data from MSCI and RepRisk. MSCI provides annual firm-level ratings on key ESG issues based on information from annual reports, investor presentations, and financial and regulatory filings (Kim and Yoon, 2023). We focus on the climate change theme within the MSCI ratings and measure environmental outcomes using the change in its strength rating over the two years following each press release as the MSCI impact score.

To complement this rating-based measure, we also examine environmental incident data from RepRisk. RepRisk compiles ESG-related negative incidents from media coverage, regulatory filings, and commercial documents (Li and Wu, 2020). We measure environmental outcomes using the total number of environmental incidents reported within six months and within one, two, and three years following each announcement. This measure is referred to as the RepRisk impact score.

Data on AI and Environmental Talent Following [Cao, Jiang, Yang, and Zhang \(2023\)](#) and [Cao, Liang, and Moon \(2023\)](#), we measure the supply of talent in AI, climate, and ClimateTech fields using data from the Integrated Public Use Microdata Series (IPUMS). The dataset provides information on individuals’ educational backgrounds, enabling us to identify the distribution of degree holders across U.S. states. We obtain the number of individuals aged 18–64 with undergraduate or graduate degrees in each U.S. state from 2010 to 2021. Each individual is classified as AI, climate, or ClimateTech talent based on their reported field of degree. Specifically, AI-related fields include Computer and Information Systems, Computer Science, and Statistics and Decision Science; climate-related fields include Environmental Science and Ecology; and ClimateTech-related fields include Transportation Sciences and Technologies and Environmental Engineering. Degree codes were manually reviewed to ensure accurate classification.

We construct state-year talent supply by calculating the share of graduates in each category relative to the total pool of degree holders in that state-year. These measures are denoted as Talent_AI, Talent_Climate, and Talent_ClimateTech, respectively. Finally, we match these state-level talent measures to firms based on the headquarters state of each announcing firm, obtained from Compustat, linking local talent supply to firms’ ClimateTech investment activities.

Variable definitions are provided in the Appendix, and additional data construction details are provided in the Internet Appendix.

4 Empirical Design

4.1 Identifying ClimateTech Investment Press Releases

We classify each climate press release as ClimateTech investment press release if it describes a firm’s investment in emerging technologies related to climate solutions. To identify such cases, we employ a dependency-parsing approach ([Chen and Manning, 2014](#)) that links investment-related and technology-related keywords based on their grammatical relations within the text. Dependency parsing captures syntactic relationships be-

tween words, allowing us to determine whether investment actions are directed toward specific technologies rather than simply co-occurring in the same document. Accordingly, this approach enables us to identify climate press releases that reflect concrete technological investments in climate solutions.

We employ the dependency parsing feature of LLM contextual functions, which allows direct observation of the syntactic structure of each sentence. Compared with bag-of-words approaches, this method captures context-specific relationships between words and reduces false positives arising from simple keyword co-occurrence. At the same time, dependency parsing provides greater transparency and interpretability than many black-box LLM approaches (Cao et al., 2020) because the classification is based on explicit grammatical links between investment and technology terms. For example, in the sentence “The firm reached a critical milestone in developing a carbon-free generator,” the parser connects the investment term “developing” with the technology term “carbon-free generator,” allowing us to classify the press release as ClimateTech. Our approach differs from the existing literature by focusing specifically on technological investments in climate solutions and by distinguishing ClimateTech activities from other types of climate-related corporate actions.

The dependency parser operates by taking as inputs the vector representations of the words in a sentence, their part-of-speech tags, and preliminary syntactic relations generated by a base parser. Using a deep neural network algorithm, the model produces a dependency tree that represents the grammatical structure of the sentence. The tree consists of pairs of words connected by labeled syntactic relations (e.g., verb-object or modifier). The parser is pre-trained on the Penn Treebank database, a widely used annotated linguistic dataset containing more than three million manually tagged and parsed words from sources including Wall Street Journal articles, and achieves nearly 90% out-of-sample parsing accuracy. Internet [Appendix B](#) provides more details regarding how the neural network dependency parser works.

To operationalize the classification, we construct the two keyword lists: 1) an emerging technology keyword list derived from prior literature on technological innovation (e.g., Babina et al., 2024) and further expanded using word embeddings, and 2) an investment

keyword list based on prior work on corporate investment disclosures (e.g., [Hoberg and Maksimovic, 2015](#)). A climate press release is labeled as ClimateTech if the dependency parser identifies at least one syntactic link between an investment keyword and an emerging technology keyword. We allow connections up to three dependency levels, meaning that an emerging technology term may be linked to an investment term either directly or through intermediate words within three steps in the dependency tree. If such a connection exists, the press release is classified as a ClimateTech investment announcement. A climate-related press release that are not identified as ClimateTech are classified as ClimateNonTech announcement.

Notably, ClimateNonTech press releases capture a broad range of climate-related actions that do not involve direct investment in emerging technologies. These initiatives reflect firms' engagement with climate issues but lack the technological commitment or capital investment required for ClimateTech adoption. First, philanthropic or corporate social responsibility (CSR) activities related to climate or environmental sustainability, often involving donations, partnerships, or community programs aimed at addressing environmental challenges but do not involve firms developing or investing in new technologies are included. For example, in 2019 DuPont donated energy-efficient building products, an initiative that contributes to climate mitigation through improved housing efficiency but does not reflect technological investment by the firm. Second, operational or managerial climate initiatives that do not involve technology development or investment are included. These actions often relate to environmental risk management, product related projects, or consulting services connected to climate resilience. For instance, in 2022 AECOM announced a project management initiative aimed at reducing wildfire risks. While such activities are closely related to climate adaptation and environmental risk mitigation, they primarily involve management or operational support rather than investments in new or emerging technologies. Taken together, ClimateNonTech press releases capture firms' engagement with climate issues that occurs without substantive investment in emerging technologies, lacking the technological commitment and capital allocation that characterize ClimateTech investments. As such, they provide a useful benchmark for distinguishing between general climate engagement and technology-

driven climate investment.

4.2 Identifying ClimateTech Categories (Infra vs. Env) and Subcategories

We further divide ClimateTech press releases into two technology categories. Using OpenAI’s GPT model (*gpt-4o-mini-2024-07-18*)², we classify each emerging technology keyword into one of two groups: 1) High-Tech Infrastructure (ClimateTech Infra), which includes digital innovations and IT such as AI, cloud computing, internet of things, and robotics, and 2) High-Tech in Environmental and Energy (ClimateTech Env), which includes renewable energy, alternative fuels, and other energy-related technologies.

Each ClimateTech investment press release is then assigned to a category based on the presence of category-specific keywords. ClimateTech press releases containing only infrastructure-related terms are classified as ClimateTech Infra, whereas those containing environmental or energy-related terms are classified as ClimateTech Env. When both types of keywords appear in the same press release, we assign it to the ClimateTech Env category, reflecting the closer connection between environmental and energy technologies and climate initiatives.

To provide more granular distinctions in firms’ technological investments, we further classify ClimateTech press releases within each category (i.e., Infra and Env) into more specific subcategories. We adopt a hybrid human–AI approach to define these subcategories. Specifically, we interact with ChatGPT to generate an initial set of candidate subcategories for both ClimateTech Infra and ClimateTech Env technologies. We then manually review, refine, and iteratively validate these categories through additional interactions with the model. We employ this hybrid approach because neither a purely manual classification nor a fully automated LLM-based approach is sufficient to produce categories that are both conceptually meaningful and empirically comprehensive. Human judgment ensures domain relevance and interpretability, while generative AI facilitates scalability and systematic exploration. This iterative process allows us to converge on

²Although GenAI has been increasingly used in textual analysis in finance, concerns have also been raised about the potential bias it may introduce because of biases in the training data (Yang and Yasuda, 2025). Its use in this classification task is less subject to these critiques, because we rely on it to classify well-defined topics rather than to determine whether a text is ClimateTech or not.

a set of well-defined and economically meaningful subcategories. For ClimateTech Infra press releases, we use the GPT model to assign each announcement to one of four subcategories: 1) AI / ML / Analytics, 2) General IT Infrastructure, 3) Supply Chain Management (SCM) / Logistics, and 4) Other Infrastructure Technologies. ClimateTech Env press releases are classified into three subcategories: 1) Electric Vehicles, 2) Alternative Energy / Chemicals, and 3) Other Environmental and Energy Technologies.

4.3 Identifying Core vs. Non-Core Application of ClimateTech

To assess the extent to which a climate-related press release pertains to a firm's core business, we use the GPT model (*gpt-4o-mini-2024-07-18*) to evaluate the semantic alignment between the press release and the firm's primary operations as described in Item 1 of its 10-K filing. Item 1 provides detailed information on the firm's core products, services, and strategic focus, which we use as the benchmark for defining core business activities. We prompt the model to classify each announcement as either core or non-core based on this benchmark. Specifically, the model assesses whether the climate initiative described in the press release is directly related to the firm's main revenue-generating activities or strategic priorities, as reflected in the 10-K business description, or whether it falls outside the firm's primary line of business. The model returns a binary classification of whether the press release is closely related to the firm's core business and 0 otherwise.

5 Empirical Result

5.1 Taxonomy of ClimateTech

Because ClimateTech is a new economic phenomenon, we begin by developing a taxonomy of ClimateTech. We focus on the types of technologies adopted and the purposes for which ClimateTech is used.

Table 1 Panel A presents the mean values of firm characteristics and state-level talent supply for ClimateTech adopting firms (ClimateTech, Column 1) and ClimateTech non-adopting firms (ClimateNonTech, Column 2). Firms adopting ClimateTech firms differ

systematically from ClimateNonTech firms among several dimensions. Notably, ClimateTech adopters are more likely to be among the top three firms in the industry (*Top3*, 15% versus 12%), are larger in terms of total assets (*Size*, \$39.77 billion versus \$25.27 billion) and cash/assets (*Cash*, 15% versus 14%), and are more likely to maintain a CIO position (*CIO*, 66% versus 58%). They also exhibit greater innovative capacity, as reflected in higher R&D expenditure/assets (*R&D*, 8% versus 7%) and a larger number of patents granted (*Patents*, 1.75 versus 1.66).

In addition, ClimateTech firms tend to be headquartered in states with greater supplies of relevant human capital. Specifically, their headquarters states exhibit higher proportions of AI-related talent (*Talent_AI*, 0.0115% versus 0.01119%) and climate-focused talent (*Talent_Climate*, 0.00794% versus 0.00781%).

To examine whether these differences between ClimateTech and ClimateNonTech firms are statistically significant, and to isolate the effects of time and industry trends, we regress each firm characteristic and state-level talent on ClimateTech, an indicator variable equal to one if a climate press release contains ClimateTech investment and zero otherwise. Table 1 Panel B presents the regression results for firm characteristics. The coefficients on ClimateTech are positive and statistically significant for *Top3* (0.03), *Size* (14500.61), *Cash* (0.01), *CIO* (0.08), *R&D* (0.01), and *Patents* (0.08). These results suggest that firms investing in ClimateTech tend to be larger, financially stronger, and more technologically oriented, with greater IT leadership and innovative activity.

Table 1 Panel C reports the regression results for state-level talent supply. The coefficients on ClimateTech are positive and statistically significant for *Talent_AI* (0.34) and *Talent_Climate* (0.13), indicating that firms investing in ClimateTech are more likely to be headquartered in states with greater availability of these talent pools.

[Insert Table 1 here.]

To better understand the types of emerging technologies used in climate initiatives, we classify each ClimateTech investment press release into two categories, Infra and Env, depending on whether the ClimateTech investment focuses on multipurpose infrastructure (ClimateTech Infra) or specialized environmental technologies (ClimateTech Env). Table

2 Panel A compares firms across three groups, ClimateTech Infra, ClimateTech Env, and ClimateNonTech, in terms of firm characteristics. Notably, firms investing in Infra technologies for climate initiatives exhibit stronger IT capabilities and innovation intensity than those investing in Env technologies. Specifically, ClimateTech Infra firms are more likely to have a CIO position (68% versus 57%) and allocate a higher proportion of R&D expenditures relative to total assets (9% versus 7%). ClimateTech Env technology firms showed levels of CIO positions and R&D expenditure similar to those of ClimateNonTech firms.

We further divide Infra technologies into the four subcategories and Env technologies into the three subcategories, as discussed in Section 4.2. Table 2 Panel B compares firms across these subcategories, along with ClimateNonTech firms. Among firms investing in Infra, the majority of investments are in General IT Infrastructure (70%), while 7% relate to AI / ML / Analytics and 7% to SCM / Logistics. Within the Env technology category, the largest share of investments (69%) relates to alternative Energy / Chemicals, while 16% involve Electric Vehicle technologies.

[Insert Figure 1 here.]

Word clouds in Figure 1 illustrate the most frequent words appearing in each subcategory of ClimateTech Infra and ClimateTech Env press releases. Panel A presents word cloud plots for the four ClimateTech Infra subcategories. Notable words for the AI / ML / Analytics, General IT Infrastructure, SCM / Logistics, and Other subcategories include “AI” and “data,” “network” and “solution,” “customer” and “service,” and “technology” and “product,” respectively. Panel B presents word cloud plots for the three ClimateTech Env subcategories. Notable words for the Electric Vehicle, Alt. Energy / Chemicals, and Other subcategories include “electric” and “power,” “solar” and “energy,” and “technology” and “solution,” respectively.

Notably, ClimateTech Infra category includes technology investments in data platforms and systems. AI / ML / Analytics subcategory includes press releases using predictive analytics and ML for operational optimization, AI for environmental monitoring, diagnosis, and climate-resilient resource management by processing large datasets from sources

like sensors and images, and AI / ML infrastructure that works as a backbone for managing data, training models, and scaling solutions.³ Press releases in the IT infrastructure subcategory involve software platforms for coordinating energy assets, data integration for real-time monitoring dashboards and systems to reduce carbon intensity of digital operations, and IT systems for operational efficiency. Finally, SCM / Logistics subcategory includes digital tracking and supply chain visibility technologies such as RFID, energy logistics platforms, and optimization that route energy supplies and manage supply chain nodes. These technologies are primarily data-intensive intelligence systems to optimize energy, predict environmental conditions, and improve the efficiency and sustainability of existing operations.⁴

Press releases in the ClimateTech Env category include technology investments that facilitate decarbonization, energy efficiency, and alternative fuels. The Electric Vehicle subcategory includes announcements of electrification, commercial and specialized vehicle fleets, energy storage and grid integration, and charging infrastructure improvements. The Alt. Energy / Chemicals subcategory includes press releases of low-carbon energy production and decarbonization of industrial operations. Overall, these Env technologies share a common objective of directly reducing carbon emissions and improving environmental outcomes.

Firms investing in AI / ML / Analytics within ClimateTech Infra tend to be larger, with average total assets of \$68.47 billion, and exhibit stronger IT leadership, as reflected in higher rates of CIO presence (80%) CEOs with IT background (35%). In contrast, firms investing in electric vehicle technologies within ClimateTech Env tend to be smaller, hold higher cash balances, and are more likely to have a CIO position.

Finally, Table 2 Panel C presents regression results examining whether firm characteristics are associated with the type of ClimateTech investment. Specifically, we regress firm characteristics on ClimateTech_Infra, an indicator equal to one if a ClimateTech press re-

³For example, Accenture implemented a self-learning AI-based ventilation system that reduced ventilation energy costs by 25% and cut annual CO₂ emissions by 1,800 tons.

⁴For example, press releases in the IT infrastructure subcategory involve software platforms for coordinating energy assets, data integration for real-time monitoring dashboards and systems to reduce carbon intensity of digital operations, and IT systems for operational efficiency. Finally, SCM / Logistics subcategory includes digital tracking and supply chain visibility technologies such as RFID, energy logistics platforms, and optimization that route energy supplies and manage supply chain nodes.

lease pertains to Infra technologies and zero if it pertains to Env technologies. In the regressions, we control for two-digit SIC industry fixed effects because firms across industries face very different climate-related issues, and these fixed effects absorb time-invariant industry-specific factors. The coefficients on CIO (0.08) and R&D intensity (0.01) are positive and statistically significant, indicating that firms with stronger IT leadership and greater innovation investment are more likely to pursue Infra-based ClimateTech investment.

[Insert Table 2 here.]

We also analyze the time-series trend of ClimateTech activity. Figure 2 plots the annual number of ClimateTech investment press releases, where ClimateTech investment press release refers to climate-related press releases that involve investments in emerging technologies. The figure reveals distinct temporal patterns across the two technology categories in ClimateTech. The number of Climate Env press releases remains relatively stable prior to 2019 but increases sharply after 2020. In contrast, ClimateTech Infra press releases exhibit an earlier surge in the early 2010s, followed by a decline, and then a subsequent increase beginning in 2018. The early-2010s surge likely reflects the rapid diffusion and adoption of general-purpose digital technologies, such as cloud computing and advanced data infrastructure, which firms later leveraged to support climate-related initiatives.

[Insert Figure 2 here.]

5.2 Financial Effectiveness of ClimateTech

Given the increasing deployment of AI and emerging technologies to address climate challenges, we next examine the effectiveness of ClimateTech. Despite its growing economic and societal relevance, it remains unclear whether, when, and through which channels ClimateTech creates value, as well as the conditions under which it fails. This question is especially timely given the scale of AI investment and growing evidence of uneven

outcomes, with many organizations failing to realize measurable benefits from AI adoption. We examine whether ClimateTech is effective based on two criteria: (a) financial value creation for shareholders and (b) measurable environmental impact for stakeholders.

We first examine the financial outcome of a firm's climate press release in terms of market reaction by analyzing CAR around each announcement. Specifically, we compare investor responses to ClimateTech investments, including the Infra and Env technology categories, with those to ClimateNonTech press releases.

Table 3 Panel A provides a comparison between ClimateTech and ClimateNonTech press releases. Using the Fama-French three factor model with momentum, we estimate CARs over the four-day event window [-1, 2] surrounding each climate announcement. The results show that ClimateTech press releases generate an average CAR of 92 basis points, which is statistically significant. Moreover, this return is significantly larger than CAR associated with ClimateNonTech press releases, suggesting that investors respond more favorably when firms link climate initiatives to emerging technology investments. This finding is robust to alternative risk models for estimating abnormal returns, such as the CAPM, the market-adjusted model, and the Fama-French three-factor model.

Table 3 Panel B compares the market reaction across the two ClimateTech technology categories. We find that ClimateTech Infra press releases generate an average CAR of 98 basis points, which is statistically significant and larger than the CAR associated with ClimateTech Env, which average 79 basis points. This result suggests that investors respond more strongly to climate initiatives supported by multipurpose infrastructure technologies than to those involving specialized environmental technologies. As in Panel A, the results remain consistent when CARs are constructed using alternative models.

[Insert Table 3 here.]

We next examine whether the ClimateTech initiatives generate higher financial outcomes than ClimateNonTech initiatives using regression analysis of CARs. Table 4 Panel A reports the regression results comparing ClimateTech and ClimateNonTech. In the regressions, we include industry fixed effects to account for time-invariant industry-specific

factors, as firms across industries face different climate-related issues. We also include year-quarter fixed effects to account for time-series variation in regulatory risk related to environmental issues, as the literature shows that events such as the Paris Agreement affect capital market pricing of green activities.⁵ We also control for firm characteristics that are commonly used to explain corporate actions and equity market reactions (Frank and Goyal, 2009). Across all CAR specifications using alternative asset pricing models, the coefficients on *ClimateTech* are positive and statistically significant. For example, column (1) shows that, after controlling for firm characteristics and year-quarter and industry fixed effects, a ClimateTech investment press release leads to 56 basis point higher CAR than that of a ClimateNonTech press release. This finding suggest that investors respond more favorably when climate initiatives involve emerging technology investments.

Panel B further examines whether this effect differs across the two ClimateTech categories: Infra and Env. Across all CAR specifications, the coefficients on *ClimateTech_Infra* are positive and statistically significant, while the coefficients of *ClimateTech_Env* are insignificant. For example, column (1) shows that, controlling for firm characteristics and year-quarter and industry fixed effects, a climate press release with ClimateTech Infra investment leads to 66 basis point higher CAR relative to a climateNonTech announcement, while the difference between a ClimateTech Env press release and ClimateNonTech announcement is not statistically significant. These results suggest that the positive market reaction to ClimateTech announcements is primarily driven by investments in multipurpose infrastructure technologies rather than specialized environmental technologies.

[Insert Table 4 here.]

Taken together, the results in Tables 3 and 4 indicate that ClimateTech creates financial value for shareholders, with the effect driven primarily by multipurpose infrastructure. These findings help explain firms' incentives to deploy AI- and machine learning-related infrastructure to address climate issues, as such investments may be motivated by the prospect of financial value creation. The comparison with ClimateNonTech announcements suggests that investors do not respond favorably to climate-related initia-

⁵For example, Seltzer et al. (2022) show changes in the risk assessment and pricing of corporate securities around the Paris Agreement.

tives when they lack substantive technological investment. In other words, press releases that merely signal engagement with climate issues through philanthropic activities, operational initiatives, or exploratory partnerships do not generate meaningful positive market reactions. Such investments are not viewed as producing tangible environmental outcomes, improving firms' operational efficiency in addressing climate-related challenges, or creating long-term strategic value, unlike ClimateTech press releases focused on multipurpose infrastructure. As a result, the market response to ClimateTech press releases reflects investors' expectations that technology-driven climate initiatives are more likely to translate into material operational improvements and scalable solutions to climate-related risks. Overall, these findings suggest that technology commitment plays a critical role in shaping the credibility and economic relevance of firms' climate strategies.

However, it is also possible that capital markets are overly optimistic about AI investment, so that the positive CAR is reversed over a longer horizon. To address this possibility, we further examine how financial markets incorporate ClimateTech information by testing for post-announcement return drift. Specifically, we estimate CARs over progressively longer post-event windows following the announcement date: [3, 5], [6, 10], [11, 21], [22, 63], and [64, 126] trading days. These windows allow us to assess whether abnormal returns persist after the initial announcement period.

Table 5 reports the regression results of CARs over these windows on the ClimateTech categories, ClimateTech Infra and ClimateTech Env. Columns (2)-(6) correspond to the longer post-announcement windows. We find that the coefficients on both *ClimateTech_Infra* and *ClimateTech_Env* are statistically insignificant across all post-announcement windows. The absence of systematic return drift following both ClimateTech Infra and ClimateTech Env investments provides further evidence on the financial effectiveness of ClimateTech investment. The results confirm that multipurpose infrastructure ClimateTech investment creates financial value for shareholders, as the drift analysis rules out the possibility that the positive market reaction merely reflects overoptimism about AI investment. Over the longer horizon of six months, ClimateTech investment continues to generate positive value for firms. The lack of a significant CAR for ClimateTech Env in both the short event window and the longer horizon suggests that specialized environmental technology does

not create financial value. This absence of financial value is not driven by a delayed market reaction to specialized environmental technologies.

Our evidence from ClimateTech press releases indicates that these investments reflect substantial real investment rather than mere image management. Given that multipurpose infrastructure ClimateTech drives a significant difference in market reactions relative to specialized environmental technologies, one interpretation is that capital markets perceive infrastructure investment as risk-mitigating. Such infrastructure can be applied to both environmental and non-environmental uses, whereas specialized environmental technologies serve exclusively environmental purposes.

While specialized environmental technologies appear to have only a limited financial impact, market reactions to these press releases are more heterogeneous. Consistent with this interpretation, the CAR for specialized environmental technology announcements is larger than that for ClimateNonTech press releases, but the difference is not statistically significant. This also motivates us to examine whether ClimateTech is effective in generating measurable environmental impact for stakeholders.

[Insert Table 5 here.]

5.3 Environmental Effectiveness of ClimateTech

Climate issues represent a significant externality. Shareholders may favor climate technologies because they create financial value by mitigating regulatory risk or lowering the cost of capital through greater sustainable investment. In such cases, financial value creation for shareholders does not necessarily translate into benefits for stakeholders, who are more concerned with tangible environmental outcomes such as pollution reduction. We therefore evaluate the effectiveness of ClimateTech investments by examining their measurable environmental impact on stakeholders. That is, we evaluate the actual environmental impact of ClimateTech investments. To measure real outcomes, we rely on two complementary data sources: both MSCI environmental ratings and RepRisk Climate-related incident data. While MSCI environmental ratings capture firms' exposure to environmental risks and opportunities, they are imperfect proxies for true environmental

impact, as the ratings partly reflect financial risk assessments and market perceptions rather than realized environmental outcomes. RepRisk incident data complement MSCI ratings with actual environmental impact measures.

Table 6 Panel A reports regressions examining changes in MSCI environmental ratings following ClimateTech press releases. Specifically, we measure the change in a firm's MSCI rating relative to its rating at the year of the press release. Column 1 reports the change one year after the announcement, while Column 2 reports the change two years after.

[Insert Table 6 here.]

We find no significant change in MSCI ratings one or two years after the announcement of ClimateTech Infra investments. This result is consistent with the notion that such technologies can serve both environmental and non-environmental purposes and may therefore function primarily as general risk-management tools rather than directly improving environmental performance. In contrast, we observe an increase in MSCI ratings two years after announcements of ClimateTech Env investments. This suggests that environmental technologies are more closely associated with improvements in firms' perceived environmental positioning. However, as noted above, MSCI ratings remain an imperfect measure of environmental impact. Improvements in ratings may reflect changes in perceived environmental opportunities or disclosure practices rather than genuine environmental improvements.

To address this limitation, we complement the analysis with incident-based measures of environmental outcomes using RepRisk data. Specifically, We analyze the changes in the number of RepRisk climate-related incidents following ClimateTech press releases. Because the dependent variable is a count variable, our empirical specification differs from the one used for MSCI ratings. [Cohn et al. \(2022\)](#) evaluate various econometric approaches for count-based outcome variables and show that a fixed-effects Poisson model yields satisfactory results. Accordingly, we estimate the following model:

$$\log(E(y_{i,t+k} | X_t)) = \text{ClimateTech_Infra}_{i,t} + \text{ClimateTech_Env}_{i,t} + y_{i,t-1} + \eta_j + \tau_t + \varepsilon_{i,t}$$

The sample includes all climate press releases. $ClimateTech_Infra_{i,t}$ equals one if the announcement concerns ClimateTech Infra investment and zero otherwise. $ClimateTech_Env_{i,t}$ equals one if the announcement concerns ClimateTech Env investment. The dependent variable, $y_{i,t+k}$, is the number of RepRisk climate-related incidents occurring k periods after the press release. We also include the number of incidents during the year prior to the press release to account for the firm's baseline incident propensity. Finally, we control for industry fixed effects and year-quarter fixed effects.

Table 6 Panel B reports the Poisson regression results. We find that neither ClimateTech Infra nor ClimateTech Env leads to a statistically significant reduction in climate incidents. Overall, our results show an important distinction between perceived environmental performance and realized environmental outcomes. While specialized environmental ClimateTech investments are associated with improvements in MSCI environmental ratings, they do not correspond to measurable reductions in environmental incidents. At the same time, multipurpose infrastructure ClimateTech investments show no evidence of improving either ratings or incident-based measures of environmental outcomes. These results indicate that, on average, neither category of ClimateTech generates measurable improvements in real environmental performance.

Our results provide evidence that AI- and emerging technology-oriented ClimateTech investments create financial value but fail to generate real environmental impact. This divergence adds to the growing evidence of the uneven outcomes of investments in AI and emerging technologies. As firms increasingly invest in AI and emerging technologies, shareholders may be the primary drivers of these investments, while other stakeholders, such as customers and employees, may not benefit from them. For instance, in the context of ClimateTech investments, shareholders may benefit from financial value creation, whereas employees may not experience improved environmental working conditions or fewer environmental incidents. Our results also underscore the importance of understanding when ClimateTech works.

5.4 When Does ClimateTech Work

Our results suggest that specialized environmental ClimateTech investments do not generate strong market reactions, nor do they lead to meaningful environmental improvements. This raises two related questions. First, why do these investments fail to produce measurable environmental outcomes? Second, are there forms of ClimateTech investment that can simultaneously create value for both shareholders and stakeholders? An important observation is that many firms' investments in specialized environmental ClimateTech fall outside their core lines of business. Instead, they may be side projects, experimental initiatives, or philanthropic activities that are not directly connected to the firm's primary revenue-generating activities. In this case, such investments may have limited operational impact and therefore produce neither strong financial returns nor environmental improvements. An exploratory analysis shows that such investments create value when they are related to the firm's primary industry.⁶ Motivated by evidence from this pilot analysis, we construct a novel measure to gauge whether an investment disclosed in a press release is related to the firm's core business or to a non-core business.⁷ We then examine whether the economic and environmental outcomes of ClimateTech Env investments differ across these two contexts. To implement this analysis, we focus on the subsample of climate press releases related to firms' core businesses. In Table 7 Panel A, Columns (1)–(4) report results for this core-business subsample. Columns (5)–(8) present results for the complementary set of press releases unrelated to core business activities, serving as a robustness check.

We begin by examining the CARs following ClimateTech press releases within the core-business subsample to evaluate whether specialized environmental technologies can generate value for both shareholders and stakeholders when they are integrated into firms' primary operations.

[Insert Table 7 here.]

We find that ClimateTech Env press releases tied to firms' core businesses are associ-

⁶The results are reported in Internet Appendix Tables IA1 and IA2.

⁷Infrastructure-related ClimateTech investments are not subject to this distinction, as they naturally apply to firms' overall operations.

ated with a 106-basis-point higher abnormal return than other climate announcements in core businesses. No such difference is observed within the non-core sample, suggesting that investors respond more favorably when environmental technologies are integrated into firms' primary operations.

We next examine whether ClimateTech Env investments within the core business subsample lead to measurable environmental improvements. Table 7 Panel B reports the impact of climate press releases on MSCI environmental ratings. We find that ClimateTech Env investments within the core subsample are followed by significant improvements in environmental ratings beginning one year after the announcement (Columns (1)-(2)). Specifically, ratings increase by 0.15 points one year after the announcement and by 0.34 points two years after. Given that the average MSCI ratings one and two years after the press release are 7.03 and 7.31, respectively, these changes correspond to increases of approximately 2.1% and 4.7%. We find consistent evidence when evaluating the impact on RepRisk environmental incidents, presented in Table 7 Panel C. Specifically, Columns (1)-(4) include only core business press releases, while Columns (5)-(8) focus on non-core business press releases. Using a Poisson regression model, we find that ClimateTech Env investments within the core sample lead to a 21% decrease in environmental incidents six months after the announcement, with the effect persisting for up to three years. In contrast, no significant changes are observed for non-core business climate press releases.

Taken together, these results suggest that specialized environmental technologies create value for both shareholders and stakeholders when integrated into firms' core business activities, but not when pursued as peripheral or non-core initiatives. Overall, we find that specialized environmental technology investments generate both financial value and measurable environmental outcomes when firms integrate these technologies into their core business operations rather than confining them to peripheral or symbolic activities. These results suggest that the value of emerging technologies is not automatic, but instead depends on how they are deployed in relation to firms' core business activities. Such an analysis can offer important guidance for corporate managers, especially because AI and emerging technology adoption in the climate context does not, on average, lead to satisfactory outcomes.

5.5 Identification Using AI Talents

Because firms differ substantially in their use of advanced technologies to address climate issues, a key identification challenge is the potential endogeneity of technology adoption. Firms that choose to invest in ClimateTech may differ systematically from those that do not, potentially confounding the relationship between ClimateTech press releases and financial outcomes. Our empirical specification mitigates this concern by using an event-study framework that focuses on short event windows around the announcement of climate announcements. By examining stock price reactions within a narrow window surrounding the announcement, the analysis isolates the incremental information conveyed by the announcement itself. While unobservable factors may influence firms' decisions to adopt ClimateTech, such factors are unlikely to drive immediate stock price movements within a short event window, as their effects typically materialize gradually over time.

We also exploit exogenous variation that affects firms' ClimateTech adoption decisions. Specifically, we use state-year variation in AI talent supply as an exogenous factor influencing firms' likelihood of adopting advanced technologies. Following [Cao et al. \(2023\)](#) and [Cao et al. \(2023\)](#), AI talent is measured as the number of people aged 18-64 with undergraduate or graduate degrees in AI-related fields, as detailed in Section 3. To exploit state-year variation in AI talent supply as an exogenous determinant of firms' likelihood of adopting advanced technologies, we use a control function approach implemented via two-stage residual inclusion ([Terza et al., 2008](#))⁸. We adopt this approach for two reasons. First, technology adoption is inherently a multistage decision process. Firms initially decide whether to invest in advanced technologies, such as AI, and subsequently determine whether to deploy these technologies in ClimateTech applications or to invest in specialized environmental technologies. Second, firms' ClimateTech investment reflects an underlying latent nonlinear decision process, with potentially varying levels of technological intensity, whereas our outcome of interest is a binary indicator rather than a continuous measure of technological intensity. Taken together, these two considerations motivate us to model firms' technology-adoption decisions explicitly and to incorporate

⁸[Wooldridge \(2015\)](#) provides a review of the use of control function methods. Control function methods have been widely used in economics and business research (e.g., [Berry et al., 1995](#); [Petrin and Train, 2010](#)).

the model-implied residual as a control variable capturing unobservable factors that may influence both ClimateTech adoption and firm outcomes. Our departure from the traditional IV approach is consistent with Angrist (2001) in that we explicitly model firms' climate investment decisions.

Accordingly, we begin by modeling the firms' first-stage ClimateTech investment decisions:

$$ClimateTechInv_{it} \mid X_{it}, Z_{it} \sim \text{Poisson}(\mu_{it})$$

with

$$\mu_{it} = E [ClimateTechInv_{it} \mid X_{it}, Z_{it}] = \exp(\beta X_{it} + \gamma Z_{it})$$

where $ClimateTechInv_{it}$ denotes the intensity of firm i 's ClimateTech investment, measured as the number of syntactic links identified within the climate press release text by the dependency parser between an investment keyword and an emerging technology keyword, including both Infra and Env technologies. Notably, our main ClimateTech indicator equals one if this link frequency is at least one, capturing whether the firm undertakes a ClimateTech investment.⁹ This latent nonlinear structure captures the underlying ClimateTech adoption decision. X_{it} captures firm characteristics, while Z_{it} denotes exogenous state-year variation in AI talent supply, measured as the log value of individuals with AI-related degrees in the firm's headquarters state-year. This variable is expected to exogenously influence firms' access to technological expertise and, therefore, their likelihood of adopting advanced technologies. In particular, greater AI talent supply is positively associated with investments in multipurpose infrastructure technologies (Infra), while being less strongly associated with investments in specialized environmental technologies (Env).

We estimate three separate first-stage regressions with alternative dependent variables: $ClimateTechInv_{it}$, $ClimateTechInv_{Infra_{it}}$, $ClimateTechInv_{Env_{it}}$, which measure total

⁹In Internet Appendix Table IA2, we show that ClimateTech Intensity is also positively associated with CARs around ClimateTech investment announcements, consistent with the evidence based on the ClimateTech indicator.

ClimateTech investment, Infra investment, and Env investment, respectively.

We define the control function as the residual from the first-stage regression,

$$\widehat{CF}_{it} = ClimateTechInv_{it} - \hat{\mu}_{it}$$

where $\hat{\mu}_{it}$ is the fitted value of μ_{it} from the Poisson regression. We also constructed three residuals, \widehat{CF}_{it} , $\widehat{CF}_{Infra_{it}}$, $\widehat{CF}_{Env_{it}}$, corresponding to the residuals from the three separately first-stage regressions explained above. These residuals capture the unobservable factors affecting firms' underlying ClimateTech investment decisions, that is, the partition of treatment variation attributed to omitted variables. We then include the corresponding control functions in the CAR regressions.

Table 8 Panel A reports the first-stage regression results. Columns (1)-(3) present the Poisson estimates, where the dependent variables are ClimateTech investment, ClimateTech infrastructure investment, and ClimateTech environmental investment, respectively. The results show that exogenous variations in state-level AI talent supply increase the likelihood of ClimateTech investment. In particular, higher AI talent supply is associated with increased adoption of ClimateTech Infra and decreased adoption of ClimateTech Env technologies. This pattern is consistent with prior literature documenting that exogenous variation in AI talent supply influences firms' technology-adoption decisions (Babina et al., 2024). We use the first-stage regressions to estimate the control functions, which capture omitted factors that may simultaneously affect firms' technology-adoption decisions and market reactions.

Table 8 Panels B and C report the second-stage regressions in which we regress CAR on the ClimateTech indicators. These specifications follow the baseline regressions in Table 4, but additionally control for the estimated control function. If the positive CAR documented in Table 4 were driven primarily by such omitted variables, the coefficient on the ClimateTech indicator should decline substantially in magnitude or lose statistical significance once the control function is included. We find little evidence consistent with this possibility. In Panel B, Column (1) shows that, after controlling for the estimated control function, a ClimateTech investment press release is associated with a 40-basis-point

higher CAR, which is comparable in magnitude to the estimate reported in Table 4 and remains statistically significant. The results remain similar when CAR is measured using alternative risk models. Overall, these findings suggest that the positive valuation effect of ClimateTech is unlikely to be driven by omitted variables related to firms' ClimateTech adoption decisions.

[Insert Table 8 here.]

We also apply the control function approach separately to ClimateTech Infra and ClimateTech Env investments, with results reported in Panel C. We find that press releases related to ClimateTech Infra investment are associated with an 85-basis-point higher CAR, and the estimate remains statistically significant. This magnitude is larger than that reported in Table 4, Panel B. In contrast, press releases related to ClimateTech Env investment do not generate a statistically significant positive CAR. In the results reported in the Internet Appendix, we also include control functions for announcement drift and real environmental impact and find that controlling for unobservable factors affecting ClimateTech investment decisions does not alter these results. Overall, these results suggest that the market impact of ClimateTech is unlikely to be driven by the endogenous nature of firms' climate-technology investment decisions.

6 Conclusion

This paper provides the first systematic evidence on how firms deploy advanced technologies to address climate challenges. By distinguishing ClimateTech from more general climate initiatives, we highlight a critical dimension of corporate climate strategy that has been largely overlooked in academic research. Our findings show that while multipurpose infrastructure investments generate significant financial returns, they fail to deliver measurable environmental benefits, thereby primarily serving shareholders. In contrast, specialized environmental technologies often yield neither financial rewards nor environmental impact. However, when integrated into firms' core operations, those environmental technologies can generate dual value for both shareholders and stakehold-

ers. Our results also add to the emerging literature on how managers respond to market feedback about emerging technologies (Cao et al., 2026).

Taken together, our study advances the literature on climate solutions, sustainable finance, and textual analysis by introducing a taxonomy of ClimateTech and demonstrating how interpretable language models can uncover the real effects of corporate climate disclosures. Looking ahead, our evidence calls for closer scrutiny of the conditions under which ClimateTech can genuinely align financial incentives with environmental responsibility, as well as for policies that encourage firms to deploy advanced technologies not only to mitigate shareholder risk but also to generate meaningful environmental impact.

References

- Angrist, J. D. (2001). Estimation of limited dependent variable models with dummy endogenous regressors: simple strategies for empirical practice. *Journal of business & economic statistics* 19(1), 2–28.
- Babina, T., A. Fedyk, A. He, and J. Hodson (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics* 151, 103745.
- Barber, B. M., A. Morse, and A. Yasuda (2021). Impact investing. *Journal of financial economics* 139(1), 162–185.
- Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica* 63(4), 841–890.
- Cao, S., J. Harris, and L. G. Lei (2025). Investing in ai: Clinical trial efficiency and market reaction. *Available at SSRN* 5691523.
- Cao, S., W. Jiang, B. Yang, and A. L. Zhang (2023). How to talk when a machine is listening: Corporate disclosure in the age of ai. *The Review of Financial Studies* 36(9), 3603–3642.
- Cao, S., Y. Kim, A. Wang, and H. Xiao (2020). Whitebox inside blackbox: Using interpretable language models to analyze financial narratives.
- Cao, S., Y. Liang, and J. Y. Moon (2023). Machine readership and financial reporting decisions. *SSRN Electronic Journal*.

- Cao, S., B. Yang, and A. L. Zhang (2025). Managerial risk assessment and fund performance: Evidence from textual disclosure. *Available at SSRN 4060307*.
- Cao, S. S., I. Goldstein, J. He, and Y. Zhao (2026). Market feedback about emerging technologies.
- Caplin, A., D. Deming, S. Li, D. Martin, P. Marx, B. Weidmann, and K. J. Ye (2025). The abcs of who benefits from working with ai: Ability, beliefs, and calibration. *Management Science*.
- Caskurlu, T., G. Hoberg, and G. M. Phillips (2024). New technology sectoral disruptions.
- Challapally, A., C. Pease, R. Raskar, and P. Chari (2025). State of ai in business 2025. Technical report, Massachusetts Institute of Technology.
- Chen, D. and C. D. Manning (2014). A fast and accurate dependency parser using neural networks. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pp. 740–750.
- Cheng, Q., A.-P. Lin, and M. Yang (2025). Green innovation and firms' financial and environmental performance: The roles of pollution prevention versus control. *Journal of Accounting and Economics* 79(1), 101706.
- Chiu, W.-C., P.-H. Hsu, K. Li, and J. T. Tong (2026). Green products. *Available at SSRN 5006863*.
- Cohn, J. B., Z. Liu, and M. I. Wardlaw (2022). Count (and count-like) data in finance. *Journal of financial economics* 146(2), 529–551.
- Congressional Budget Office (2024). Artificial intelligence and its potential effects on the economy and the federal budget. Technical Report 60774, Congressional Budget Office.
- Department of Energy (2024). Ai for energy: Opportunities for a modern grid and clean energy economy. Technical report, U.S. Department of Energy.
- Duchin, R., J. Gao, and Q. Xu (2025). Sustainability or greenwashing: Evidence from the asset market for industrial pollution. *The Journal of Finance* 80(2), 699–754.
- Frank, M. Z. and V. K. Goyal (2009). Capital structure decisions: which factors are reliably important? *Financial management* 38(1), 1–37.
- Hartzmark, S. M. and K. Shue (2022). Counterproductive sustainable investing: The impact elasticity of brown and green firms. *Available at SSRN 4359282*.

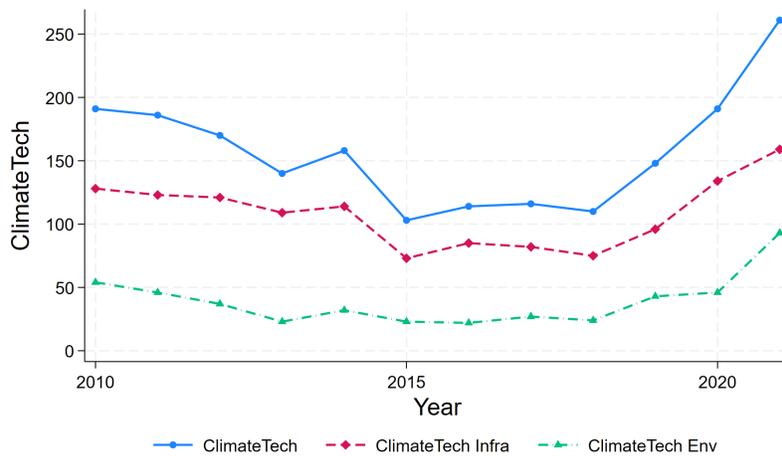
- Hoberg, G., C. Knoblock, G. Phillips, J. Pujara, Z. Qiu, and L. Raschid (2024). Using representation learning and web text to identify competitor networks. *Management Science*.
- Hoberg, G. and V. Maksimovic (2015). Redefining financial constraints: A text-based analysis. *The Review of Financial Studies* 28(5), 1312–1352.
- Hoberg, G. and A. Manela (2025). The natural language of finance. *Available at SSRN 5119322*.
- Hoberg, G. and G. M. Phillips (2025). Scope, scale, and concentration: The 21st-century firm. *The Journal of Finance* 80(1), 415–466.
- Jha, M., J. Qian, M. Weber, and B. Yang (2024). Chatgpt and corporate policies.
- Kim, A., M. Muhn, and V. Nikolaev (2023). From transcripts to insights: Uncovering corporate risks using generative ai. *arXiv preprint arXiv:2310.17721*.
- Kim, S. and A. Yoon (2023). Analyzing active fund managers' commitment to esg: Evidence from the united nations principles for responsible investment. *Management science* 69(2), 741–758.
- Klausmann, J., P. Krueger, and P. Matos (2024). The green transition: Evidence from corporate green revenues. *Available at SSRN 4850449*.
- Larcker, D. F. and E. M. Watts (2020). Where's the greenium? *Journal of Accounting and Economics* 69(2-3), 101312.
- Leippold, M. and T. Yu (2026). Firm-level green innovation beyond patents. *Review of Finance* 30(2), 423–458.
- Li, B., A. G. Rossi, X. S. Yan, and L. Zheng (2025). Machine learning from a “universe” of signals: The role of feature engineering. *Journal of Financial Economics* 172, 104138.
- Li, J. and D. Wu (2020). Do corporate social responsibility engagements lead to real environmental, social, and governance impact? *Management Science* 66(6), 2564–2588.
- Lu, S., E. Riedl, S. Xu, and G. Serafeim (2025). Climate solutions, transition risk, and stock returns. *Available at SSRN 5018767*.
- Lu, S., G. Serafeim, and S. Xu (2024). Catalysts for climate solutions: corporate responses to venture capital financing of climate-tech startups. *Available at SSRN 5018769*.
- Ma, S. (2025). Technological obsolescence. *The Review of Financial Studies*, hhaf059.
- Ouyang, S., H. Yun, and X. Zheng (2025). Ai as decision-maker: ethics and risk preferences

- of llms. *Available at SSRN 4851711*.
- Petrin, A. and K. Train (2010). A control function approach to endogeneity in consumer choice models. *Journal of marketing research* 47(1), 3–13.
- Rossi, A. G. and S. Utkus (2024). The diversification and welfare effects of robo-advising. *Journal of Financial Economics* 157, 103869.
- Sautner, Z., L. Van Lent, G. Vilkov, and R. Zhang (2023). Firm-level climate change exposure. *The Journal of Finance* 78(3), 1449–1498.
- Seltzer, L. H., L. Starks, and Q. Zhu (2022). Climate regulatory risk and corporate bonds.
- Sheng, J., Z. Sun, B. Yang, and A. L. Zhang (2025). Generative ai and asset management. *Review of Financial Studies*.
- Skinner, A. N. and K. Valentine (2026). Green patenting and voluntary innovation disclosure. *Review of Accounting Studies*, 1–42.
- Starks, L. T. (2023). Presidential address: Sustainable finance and esg issues—value versus values. *The Journal of Finance* 78(4), 1837–1872.
- Terza, J. V., A. Basu, and P. J. Rathouz (2008). Two-stage residual inclusion estimation: Addressing endogeneity in health econometric modeling. *Journal of Health Economics* 27(3), 531–543.
- Wooldridge, J. M. (2015). Control function methods in applied econometrics. *Journal of Human resources* 50(2), 420–445.
- Yang, K. and A. Yasuda (2025). Decoding sustainable investment strategies: Bridging intentions and outcomes. *Available at SSRN 4637264*.

Figure 2: Trends

This figure plots the annual trend of the number of ClimateTech press releases. A ClimateTech press release is defined as a climate press release with emerging technology investments, indicated by at least one investment keyword syntactically linked to one emerging technology keyword. A ClimateTech Infra press release is defined as a ClimateTech press release, where the focal emerging technology is classified as multipurpose infrastructure technology. A ClimateTech Env press release is defined as a ClimateTech press release, where the focal emerging technology is classified as environmental technology. Panel A presents the number of press releases in each category. Panel B focuses on climate press releases in each category from firms in environmental industries, defined firms with SIC codes 13 (Oil and Gas Extraction) and 49 (Electric, Gas, and Sanitary Services).

Panel A: Number of ClimateTech Investment Press Releases



Panel B: Number of ClimateTech Investment Press Releases in Environmental Industries

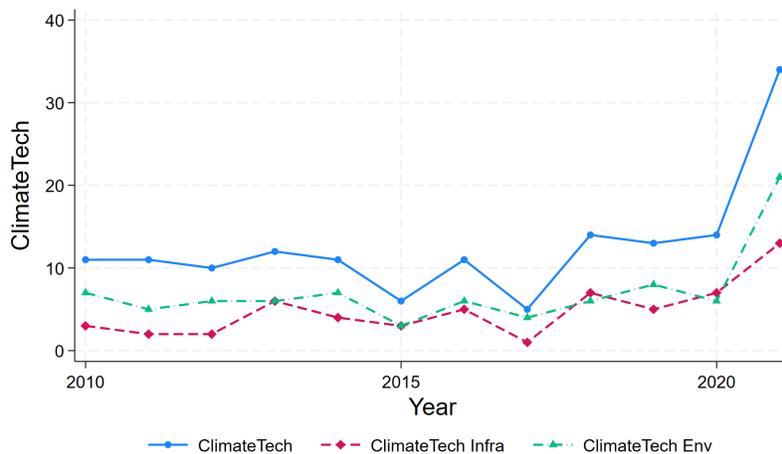


Table 1: Taxonomy of ClimateTech

This table reports the mean values of firm characteristics and state-level talent supply for ClimateTech announcing firms and ClimateNonTech announcing firms. Panel A presents the mean values of firm characteristics for ClimateTech announcing firms and ClimateNonTech announcing firms. The sample press releases are selected from Capital IQ’s Key Development database, spanning 2010 – 2021. ClimateTech sample is climate announcements about firms investing in emerging technologies to address climate challenges. ClimateNonTech sample is climate announcements about firms addressing climate challenges without applying emerging technologies. Panel B reports regression results of the firm characteristics (defined in Panel A) on ClimateTech. ClimateTech equals to 1 if a climate announcement is a ClimateTech announcement and 0 if the announcement is a ClimateNonTech announcement. t-statistics in parentheses are based on standard errors clustered by industry. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: ClimateTech versus ClimateNonTech

| Sample | (1) ClimateTech | (2) ClimateNonTech |
|--------------------|--------------------|-----------------------|
| Top3 | 0.15 | 0.12 |
| Size | 39772.25 | 25271.64 |
| Cash | 0.15 | 0.14 |
| CIO | 0.66 | 0.58 |
| CEO_IT | 0.20 | 0.18 |
| R&D | 0.08 | 0.07 |
| Patents | 1.75 | 1.66 |
| Talent_AI | 11.53 | 11.19 |
| Talent_Climate | 7.94 | 7.81 |
| Talent_ClimateTech | 5.29 | 5.23 |
| Rate_Sustain | 2.57 | 2.55 |
| Observations | 1885 | 6309 |

Table 1: continued

Panel B: Regression of Firm Characteristics on ClimateTech

| Dep. Var. | (1) Top3 | (2) Size | (3) Cash | (4) CIO | (5) CEO_IT | (6) R&D | (7) Patents | (8) Rate_Sustain |
|----------------|--------------------|------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|---------------------|
| ClimateTech | 0.03*** (3.55) | 14500.61*** (5.09) | 0.01*** (2.93) | 0.08*** (5.05) | 0.01 (1.20) | 0.01*** (2.87) | 0.08** (2.11) | 0.02 (1.14) |
| Constant | 0.12*** (28.10) | 25271.64*** (18.47) | 0.14*** (74.02) | 0.58*** (82.65) | 0.18*** (32.70) | 0.07*** (43.42) | 1.66*** (82.97) | 2.55*** (239.37) |
| Year-Qtr FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 8089 | 8083 | 7919 | 6119 | 6119 | 5723 | 4319 | 2348 |
| Adjusted R^2 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Panel C: Regressions of Talent Supplies on ClimateTech

| Dep. Var. | (1) Talent_AI | (2) Talent_Climate | (3) Talent_ClimateTech |
|----------------|----------------------|-----------------------|---------------------------|
| ClimateTech | 0.34*** (3.86) | 0.13** (2.31) | 0.06 (1.47) |
| Constant | 11.19*** (262.53) | 7.81*** (287.06) | 5.23*** (283.31) |
| Year-Qtr FE | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes |
| Observations | 7738 | 7738 | 7738 |
| Adjusted R^2 | 0.00 | 0.00 | 0.00 |

Table 2: Taxonomy of Infrastructure and Environmental ClimateTech

This table reports the mean values of firm characteristics and state-level talent supply for firms across ClimateTech categories. Panel A presents the mean values of firm characteristics for ClimateTech announcing firms, divided into Infra and Env, depending on whether the ClimateTech investment focuses on multi-purpose infrastructure (Infra) or specialized environmental technologies (Env), and ClimateNonTech announcing firms. Panel B further divides the two ClimateTech categories into subcategories. Specifically, a ClimateTech Infra press release is classified into one of the following subcategories: 1) AL/ML/Analytics, 2) IT Infrastructure, 3) SCM & Logistics, and 4) Others, and a ClimateTech Env press release into one of the following categories: 1) Electric Vehicles, 2) Alternative Energy & Chemicals, and 3) Others. Panel C reports regression results of the firm characteristics defined in Panel A. The sample is ClimateTech investment press releases. t-statistics in parentheses are based on standard errors clustered by industry. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: ClimateTech Infra and Env versus ClimateNonTech

| Sample | (1) ClimateTech Infra | (2) ClimateTech Env | (3) ClimateNonTech |
|--------------|--------------------------|------------------------|-----------------------|
| Top3 | 0.15 | 0.15 | 0.12 |
| Size | 39790.99 | 36602.06 | 25271.64 |
| Cash | 0.15 | 0.15 | 0.14 |
| CIO | 0.68 | 0.57 | 0.58 |
| CEO_IT | 0.20 | 0.20 | 0.18 |
| R&D | 0.09 | 0.07 | 0.07 |
| Patents | 1.75 | 1.66 | 1.66 |
| Rate_Sustain | 2.59 | 2.51 | 2.55 |
| Observations | 1298 | 470 | 6315 |

Table 2: continued

Panel B: Subcategories of ClimateTech Infra and Env

| Sample Sub-category | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|------------------------|---------------------|----------------|--------------|----------------|-------------------|----------------|---------------|-----------------|
| | ClimateTech - Infra | | | | ClimateTech - Env | | | Climate NonTech |
| | AI/ML | IT | SCM | Other | EV | Alt. Energy | Other | |
| Top3 | 0.16 | 0.15 | 0.18 | 0.14 | 0.14 | 0.15 | 0.16 | 0.12 |
| Size | 68474.13 | 41670.35 | 33545.46 | 21818.38 | 25140.80 | 37595.11 | 44178.60 | 25271.64 |
| Cash | 0.16 | 0.16 | 0.10 | 0.16 | 0.20 | 0.13 | 0.16 | 0.14 |
| CIO | 0.80 | 0.70 | 0.67 | 0.56 | 0.73 | 0.53 | 0.57 | 0.58 |
| CEO_IT | 0.35 | 0.21 | 0.17 | 0.10 | 0.12 | 0.21 | 0.24 | 0.18 |
| R&D | 0.09 | 0.09 | 0.06 | 0.07 | 0.09 | 0.06 | 0.08 | 0.07 |
| Patents | 1.72 | 1.79 | 1.55 | 1.70 | 1.54 | 1.69 | 1.63 | 1.66 |
| Rate_Sustain | 2.66 | 2.57 | 2.68 | 2.58 | 2.45 | 2.48 | 2.72 | 2.55 |
| Observations | 89 (6.9%) | 914 (70.4%) | 84 (6.5%) | 211 (16.3%) | 74 (15.7%) | 326 (69.3%) | 70 (14.9%) | 6315 |

Panel C: Regressions of Firm Characteristics on ClimateTech Infra

| Dep. Var. | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|-------------------|--------------------|-----------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| | Top3 | Size | Cash | CIO | CEO_IT | R&D | Patents | Rate_Sustain |
| ClimateTech_Infra | -0.00 (-0.00) | 60.44 (0.01) | 0.01 (0.88) | 0.08*** (2.74) | -0.00 (-0.10) | 0.01* (1.95) | 0.03 (0.44) | 0.06 (1.53) |
| Constant | 0.15*** (10.04) | 39730.55*** (6.53) | 0.15*** (23.11) | 0.61*** (26.14) | 0.20*** (10.21) | 0.08*** (14.18) | 1.72*** (25.50) | 2.53*** (79.19) |
| Year-Qtr FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1865 | 1864 | 1827 | 1344 | 1344 | 1411 | 1129 | 568 |
| Adjusted R^2 | -0.00 | -0.00 | -0.00 | 0.00 | -0.00 | 0.00 | -0.00 | 0.00 |

Table 3: ClimateTech Press Release Return

This table compares the CAR of ClimateTech investment press releases versus ClimateNonTech press releases. Panel A presents the mean cumulative abnormal returns (CAR) for ClimateTech and ClimateNonTech press releases. CARs are computed over the window [-1, 2] surrounding each announcement with expected returns estimated over a window of 252 trading days ending one day before the announcement. Abnormal returns are estimated using the Fama–French three-factor model with momentum (CAR_ffm_2), the market-adjusted model (CAR_madj_2), the CAPM (CAR_capm_2), and the Fama–French three-factor model (CAR_ff_2). Panel B presents the mean CAR for the separate announcement samples of the two ClimateTech categories: Infra and Env.

Panel A: ClimateTech versus ClimateNonTech

| Sample | (1) ClimateTech | (2) ClimateNonTech |
|--------------|--------------------|-----------------------|
| CAR_ffm_2 | 0.92 | 0.45 |
| CAR_madj_2 | 0.93 | 0.45 |
| CAR_capm_2 | 0.89 | 0.40 |
| CAR_ff_2 | 0.95 | 0.45 |
| Observations | 2960 | 9456 |

Panel B: ClimateTech Infra versus Env

| Sample | (1) ClimateTech Infra | (2) ClimateTech Env |
|--------------|--------------------------|------------------------|
| CAR_ffm_2 | 0.98 | 0.79 |
| CAR_madj_2 | 0.99 | 0.79 |
| CAR_capm_2 | 0.96 | 0.71 |
| CAR_ff_2 | 1.01 | 0.79 |
| Observations | 2103 | 857 |

Table 4: ClimateTech Press Release Return Regressions

This table reports the regression results of the CAR on ClimateTech (Panel A) and ClimateTech Infra and ClimateTech Env (Panel B). The sample includes all climate press releases. The dependent variables are CAR calculated using the Fama–French three-factor model with momentum (Column 1), market-adjusted model (Column 2), the CAPM (Column 3), and the Fama–French three-factor model (Column 4). In all specifications, CARs are computed over the window [-1, 2] surrounding each announcement with expected returns estimated over a window of 252 trading days ending one day before the press release. All control variables are lagged by one quarter. t-statistics in parentheses are based on standard errors clustered by industry. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Regressions of CAR on ClimateTech

| Dep. Var. | (1) CAR_ffm_2 | (2) CAR_madj_2 | (3) CAR_capm_2 | (4) CAR_ff_2 |
|-------------------|---------------------|---------------------|---------------------|---------------------|
| ClimateTech | 0.56*** (3.95) | 0.57*** (3.86) | 0.56*** (3.77) | 0.58*** (4.12) |
| MTB_lag | -0.16* (-1.90) | -0.17* (-1.97) | -0.17** (-2.06) | -0.17* (-1.91) |
| Tangibility_lag | 0.18 (0.43) | 0.29 (0.65) | 0.36 (0.82) | 0.35 (0.79) |
| Profitability_lag | -11.25* (-1.89) | -11.31* (-1.99) | -11.26* (-1.91) | -11.38* (-1.88) |
| Leverage_lag | -0.27 (-0.79) | -0.27 (-0.77) | -0.37 (-1.01) | -0.36 (-1.05) |
| lnSales_lag | -0.28*** (-3.87) | -0.27*** (-3.85) | -0.26*** (-3.65) | -0.28*** (-3.87) |
| Year-Qtr FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Observations | 11935 | 11935 | 11935 | 11935 |
| Adjusted R^2 | 0.01 | 0.02 | 0.01 | 0.02 |

Table 4: continued

Panel B: Regressions of CAR on ClimateTech Infra and Env

| | (1) | (2) | (3) | (4) |
|-------------------|---------------------|---------------------|---------------------|---------------------|
| | CAR_ffm_2 | CAR_madj_2 | CAR_capm_2 | CAR_ff_2 |
| ClimateTech_Infra | 0.66*** (2.74) | 0.68*** (2.73) | 0.69*** (2.84) | 0.70*** (2.92) |
| ClimateTech_Env | 0.31 (1.48) | 0.29 (1.33) | 0.24 (1.05) | 0.30 (1.36) |
| MTB_lag | -0.16* (-1.91) | -0.17* (-1.98) | -0.17** (-2.08) | -0.17* (-1.93) |
| Tangibility_lag | 0.21 (0.49) | 0.32 (0.72) | 0.39 (0.90) | 0.38 (0.86) |
| Profitability_lag | -11.33* (-1.88) | -11.41* (-1.98) | -11.36* (-1.91) | -11.47* (-1.88) |
| Leverage_lag | -0.27 (-0.79) | -0.27 (-0.77) | -0.37 (-1.01) | -0.36 (-1.05) |
| lnSales_lag | -0.28*** (-3.86) | -0.27*** (-3.84) | -0.26*** (-3.63) | -0.28*** (-3.86) |
| Year-Qtr FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Observations | 11935 | 11935 | 11935 | 11935 |
| Adjusted R^2 | 0.01 | 0.02 | 0.01 | 0.02 |

Table 5: ClimateTech Press Release Return Drift Regressions

This table reports the regression results of the CAR drift. The sample includes all climate press releases. The dependent variables are CAR calculated using the Fama–French three-factor model with momentum. CARs are computed over the window of [-1, 2] days (CAR_ffm_2), [3, 5] days (CAR_ffm_5), [6, 10] days (CAR_ffm_10), [11, 21] days (CAR_ffm_21), [22, 63] days (CAR_ffm_63), and [64, 126] days (CAR_ffm_126) with expected returns estimated over a window of 252 trading days ending one day before the press release. All control variables are lagged by one quarter. t-statistics in parentheses are based on standard errors clustered by industry. Asterisks denote significance levels (***=1%, **=5%, *=10%).

| Dev. Var. | (1) CAR_ffm_2 | (2) CAR_ffm_5 | (3) car_ffm_10 | (4) car_ffm_21 | (5) car_ffm_63 | (6) car_ffm_126 |
|-------------------|---------------------|--------------------|--------------------|-------------------|-------------------|--------------------|
| ClimateTech_Infra | 0.66*** (2.74) | -0.00 (-0.02) | 0.10 (0.45) | 0.00 (0.03) | -0.12 (-0.27) | 0.04 (0.06) |
| ClimateTech_Env | 0.31 (1.48) | -0.17 (-1.06) | 0.09 (0.55) | -0.33 (-0.80) | 0.50 (0.65) | -0.06 (-0.06) |
| MTB_lag | -0.16* (-1.91) | -0.02 (-1.17) | -0.10** (-2.44) | -0.00 (-0.04) | 0.01 (0.03) | 0.12 (0.37) |
| Tangibility_lag | 0.21 (0.49) | -0.16 (-0.27) | -0.88 (-1.51) | 0.61 (0.86) | 1.58 (0.52) | -0.88 (-0.18) |
| Profitability_lag | -11.33* (-1.88) | 5.26* (1.99) | 8.42 (1.47) | 9.92*** (2.69) | 10.56 (0.60) | 28.89*** (2.72) |
| Leverage_lag | -0.27 (-0.79) | 0.64** (2.60) | 0.09 (0.48) | 0.22 (1.01) | 1.60* (1.75) | 3.04** (2.03) |
| lnSales_lag | -0.28*** (-3.86) | -0.08** (-2.47) | -0.10* (-1.71) | -0.03 (-0.45) | -0.23 (-1.20) | -0.41* (-1.84) |
| Year-Qtr FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 11935 | 11935 | 11935 | 11935 | 11935 | 11883 |
| Adjusted R^2 | 0.01 | 0.01 | 0.00 | 0.00 | 0.02 | 0.03 |

Table 6: ClimateTech Environmental Impact

This table reports the regression results of the environmental impact of ClimateTech. The sample includes all climate press releases. In Panel A, the dependent variables are the change in MSCI firm strength ratings on climate change theme over the two years following each climate press release. In Panel B, the dependent variables are the number of RepRisk negative incidents in 6 months, 1 year, 2 years, and 3 years following the climate announcement date. All control variables are lagged by one quarter. t-statistics in parentheses are based on standard errors clustered by industry. Asterisks denote significance levels (**=1%, ***=5%, *=10%).

Panel A: Regressions of MSCI Rating on ClimateTech Infra and Env

| Dep. Var | (1) Δ MSCI_lead1 | (2) Δ MSCI_lead2 |
|-------------------|----------------------------|----------------------------|
| ClimateTech_Infra | -0.08 (-1.68) | -0.04 (-0.62) |
| ClimateTech_Env | 0.11 (1.61) | 0.19** (2.41) |
| MTB_lag | -0.02 (-1.15) | 0.02 (0.66) |
| Tangibility_lag | 0.07 (0.58) | -0.03 (-0.21) |
| Profitability_lag | -0.63 (-0.46) | -0.34 (-0.20) |
| Leverage_lag | 0.10 (1.14) | 0.16 (1.33) |
| lnSales_lag | 0.02 (0.95) | -0.02 (-0.65) |
| Year-Qtr FE | Yes | Yes |
| Industry FE | Yes | Yes |
| Observations | 5771 | 5562 |
| Adjusted R^2 | 0.02 | 0.03 |

Table 6: continued

Panel B: Regressions of RepRisk Incidents on ClimateTech Infra and Env

| Dep. Var. | (1) RepRisk_6m | (2) RepRisk_1y | (3) RepRisk_2y | (4) RepRisk_3y |
|-------------------|--------------------|---------------------|---------------------|---------------------|
| ClimateTech_Infra | -0.02 (-0.76) | -0.04 (-1.41) | -0.04* (-1.66) | -0.04 (-1.63) |
| ClimateTech_Env | 0.02 (0.37) | -0.00 (-0.03) | 0.01 (0.27) | 0.00 (0.14) |
| RepRisk_bf1y | 0.01*** (3.84) | 0.01*** (3.89) | 0.01*** (3.86) | 0.01*** (3.84) |
| MTB_lag | 0.12*** (5.18) | 0.13*** (5.62) | 0.15*** (6.69) | 0.16*** (7.69) |
| Tangibility_lag | -0.03 (-0.14) | 0.06 (0.24) | 0.24 (0.73) | 0.41 (0.97) |
| Profitability_lag | -4.17** (-2.44) | -4.66*** (-2.64) | -4.86*** (-2.99) | -5.13*** (-3.33) |
| Leverage_lag | -0.05 (-0.19) | -0.03 (-0.13) | -0.10 (-0.40) | -0.17 (-0.61) |
| lnSales_lag | 0.91*** (13.30) | 0.91*** (14.11) | 0.91*** (14.49) | 0.91*** (14.49) |
| Year-Qtr FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Observations | 8862 | 8862 | 8864 | 8870 |
| Pseudo R^2 | 0.78 | 0.82 | 0.85 | 0.86 |

Table 7: Further Breakdown of Environmental ClimateTech

This table reports the regression results of the CAR and the environmental impact of ClimateTech Env, comparing ClimateTech environmental investment press releases to ClimateNonTech press releases. Columns (1)-(4) present results for the Core sample, in which a climate initiative is relevant to the announcing firm's primary operations. Columns (5)-(8) present results for the Non-Core sample, in which a climate initiative is for peripheral operations rather than primary. In Panel A, the dependent variables are CAR calculated using the Fama-French three-factor model with momentum (Columns 1 and 5), the market-adjusted model (Columns 2 and 6), the CAPM (Columns 3 and 7), and the Fama-French three-factor model (Columns 4 and 8). In all specifications, CARs are computed over the window [-1, 2] surrounding each announcement. In Panel B, the dependent variables are the change in MSCI firm strength ratings on climate change theme in the next year (Columns 1 and 3) and two years (Columns 2 and 4) post each climate announcement. In Panel C, the dependent variables are the number of RepRisk negative incidents in 6 months (Columns 1 and 5), 1 year (Columns 2 and 6), 2 years (Columns 3 and 7), and 3 years (Columns 4 and 8) following the climate announcement. All control variables are lagged by one quarter. t-statistics in parentheses are based on standard errors clustered by industry. Asterisks denote significance levels (**=1%, ***=5%, *=10%).

Panel A: Regressions of CAR on ClimateTech Env by Core vs. Non-Core Samples

| Sample | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|-------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| | Core | | | | Non-Core | | | |
| Dep. Var. | CAR_ffm_2 | CAR_madj_2 | CAR_capm_2 | CAR_ff_2 | CAR_ffm_2 | CAR_madj_2 | CAR_capm_2 | CAR_ff_2 |
| ClimateTech_Env | 1.06*** (3.03) | 1.01** (2.33) | 1.00** (2.19) | 1.04*** (2.77) | 0.00 (0.00) | -0.01 (-0.04) | -0.09 (-0.34) | -0.03 (-0.10) |
| MTB_lag | -0.14 (-1.66) | -0.13 (-1.55) | -0.13 (-1.64) | -0.14* (-1.71) | -0.16* (-1.95) | -0.16** (-2.32) | -0.17** (-2.38) | -0.17** (-2.07) |
| Profitability_lag | 4.82 (1.07) | 5.15 (0.98) | 5.07 (0.99) | 4.56 (1.00) | 0.29 (0.07) | -0.42 (-0.10) | -0.01 (-0.00) | 0.31 (0.07) |
| Tangibility_lag | -0.54 (-0.61) | -0.38 (-0.44) | -0.27 (-0.32) | -0.38 (-0.44) | 1.55 (1.65) | 1.72* (1.82) | 1.75* (1.88) | 1.71* (1.82) |
| Leverage_lag | -0.14 (-0.49) | -0.17 (-0.52) | -0.40 (-1.22) | -0.24 (-0.77) | -0.21 (-0.42) | -0.17 (-0.35) | -0.22 (-0.46) | -0.27 (-0.57) |
| lnSales_lag | -0.46*** (-3.57) | -0.43*** (-3.35) | -0.41*** (-3.30) | -0.46*** (-3.64) | -0.26*** (-3.42) | -0.24*** (-2.90) | -0.24*** (-2.80) | -0.25*** (-3.28) |
| Year-Qtr FE | Yes |
| Industry FE | Yes |
| Observations | 4820 | 4820 | 4820 | 4820 | 5066 | 5066 | 5066 | 5066 |
| Adjusted R ² | 0.01 | 0.01 | 0.01 | 0.01 | 0.03 | 0.03 | 0.03 | 0.03 |

Table 7: continued

Panel B: Regressions of MSCI Rating on ClimateTech Env by Core. Non-Core Samples

| Sample | (1) | (2) | (3) | (4) |
|-------------------|---------------------|---------------------|---------------------|---------------------|
| | Core | | Non-Core | |
| Dep. Var. | Δ MSCI_lead1 | Δ MSCI_lead2 | Δ MSCI_lead1 | Δ MSCI_lead2 |
| ClimateTech_Env | 0.15 (1.65) | 0.34** (2.58) | 0.06 (0.60) | 0.08 (0.70) |
| MTB_lag | -0.03* (-1.76) | 0.00 (0.10) | -0.01 (-0.34) | 0.03 (0.84) |
| Profitability_lag | -0.05 (-0.03) | 1.14 (0.70) | -0.55 (-0.33) | -0.08 (-0.04) |
| Tangibility_lag | 0.15 (0.91) | 0.16 (0.86) | 0.10 (0.45) | -0.10 (-0.44) |
| Leverage_lag | 0.28** (2.20) | 0.17 (1.04) | -0.01 (-0.13) | 0.21 (1.12) |
| lnSales_lag | -0.01 (-0.54) | -0.04 (-1.13) | 0.04 (1.30) | 0.00 (0.12) |
| Year-Qtr FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Observations | 2300 | 2210 | 2414 | 2329 |
| Adjusted R^2 | 0.05 | 0.04 | 0.02 | 0.01 |

Table 7: continued

Panel C: Regressions of Reprisk Incidents on ClimateTech Env by Core vs Non-Core Samples

| Sample | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|-------------------|---------------------|---------------------|---------------------|---------------------|--------------------|--------------------|---------------------|---------------------|
| | Core | | | | Non-Core | | | |
| Dep. Var. | RepRisk_6m | RepRisk_1y | RepRisk_2y | RepRisk_3y | RepRisk_6m | RepRisk_1y | RepRisk_2y | RepRisk_3y |
| ClimateTech_Env | -0.21* (-1.85) | -0.21*** (-2.91) | -0.21*** (-2.72) | -0.21** (-2.41) | 0.06 (1.29) | 0.03 (0.83) | 0.04 (1.25) | 0.04 (1.30) |
| RepRisk_bfly | 0.01*** (7.00) | 0.01*** (7.39) | 0.01*** (7.15) | 0.01*** (7.18) | 0.01*** (4.60) | 0.01*** (4.61) | 0.01*** (4.53) | 0.01*** (4.51) |
| MTB_lag | 0.09** (2.39) | 0.07** (2.35) | 0.09*** (3.37) | 0.11*** (3.98) | 0.12*** (6.79) | 0.13*** (7.51) | 0.15*** (9.58) | 0.17*** (11.41) |
| Profitability_lag | -7.39*** (-5.02) | -7.45*** (-5.43) | -8.04*** (-6.21) | -8.23*** (-6.19) | -3.43* (-1.96) | -3.94** (-2.38) | -3.98*** (-2.63) | -4.24*** (-2.77) |
| Tangibility_lag | 0.13 (0.71) | -0.01 (-0.08) | 0.20 (0.84) | 0.38 (1.13) | 0.06 (0.23) | 0.24 (0.83) | 0.46 (1.16) | 0.67 (1.35) |
| Leverage_lag | 0.18* (1.66) | 0.26*** (2.58) | 0.24*** (2.58) | 0.22*** (2.60) | -0.17 (-0.61) | -0.13 (-0.49) | -0.22 (-0.74) | -0.30 (-0.93) |
| lnSales_lag | 0.92*** (16.31) | 0.90*** (17.60) | 0.91*** (17.94) | 0.93*** (18.12) | 0.85*** (13.48) | 0.85*** (14.17) | 0.85*** (15.38) | 0.84*** (15.60) |
| Year-Qtr FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Industry FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 3525 | 3533 | 3533 | 3533 | 3769 | 3784 | 3809 | 3814 |
| Pseudo R^2 | 0.76 | 0.81 | 0.85 | 0.87 | 0.79 | 0.84 | 0.86 | 0.87 |

Table 8: Causal Inference for ClimateTech

This table reports the estimates from the CAR regressions that implement a control function approach using two-stage residual inclusion, following [Terza et al. \(2008\)](#), to address endogeneity in firms' ClimateTech investment decisions. In the first stage, we estimate Poisson models of ClimateTech investment intensity, measured as the frequency count of ClimateTech-related keywords in firm disclosures. We estimate separate first-stage regressions for all ClimateTech investment announcement, ClimateTech Infra investment press release, and ClimateTech Env investment press release. The control functions are defined as the residuals from these first-stage regressions, computed as the difference between observed investment intensity and the fitted Poisson value. In the second stage, we regress CAR on indicators for ClimateTech investment and include the corresponding control function to account for unobservable factors affecting firms' underlying technology-adoption decisions. Firm-level controls are included in all specifications. Panel A reports first-stage Poisson estimates. Panel B reports second-stage results for overall ClimateTech investments. Panel C reports second-stage results separately for ClimateTech Infra and ClimateTech Env investments. t-statistics in parentheses are based on standard errors clustered by industry. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: First-Stage Model for ClimateTech

| Dep. Var. | (1) ClimateTechInv | (2) ClimateTechInv_Infra | (3) ClimateTechInv_Env |
|-------------------|-----------------------|-----------------------------|---------------------------|
| Talent_AI | 0.020* (0.011) | 0.112*** (0.040) | -0.087*** (0.027) |
| MTB_lag | 0.013** (0.006) | 0.014 (0.017) | -0.016 (0.038) |
| Tangibility_lag | -0.121 (0.117) | -0.892 (0.576) | 0.405 (0.370) |
| Profitability_lag | 0.628 (0.412) | -0.483 (0.467) | -4.323*** (1.079) |
| Leverage_lag | -0.034** (0.016) | -0.058 (0.201) | -0.056 (0.127) |
| lnSales_lag | 0.020** (0.009) | 0.117*** (0.035) | 0.073* (0.040) |
| Year-Qtr FE | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes |
| Observations | 11504 | 11504 | 11504 |
| Pseudo R^2 | 0.03 | 0.10 | 0.07 |

Table 8: continued

Panel B: Regressions of CAR on ClimateTech

| Dep. Var. | (1) CAR_ffm_2 | (2) CAR_madj_2 | (3) CAR_capm_2 | (4) CAR_ff_2 |
|-------------------|---------------------|---------------------|---------------------|---------------------|
| ClimateTech | 0.40*** (3.96) | 0.42*** (4.48) | 0.41*** (4.24) | 0.42*** (3.98) |
| PControl | 0.01 (0.90) | 0.01 (0.54) | 0.01 (0.77) | 0.01 (0.96) |
| MTB_lag | -0.11 (-1.45) | -0.12 (-1.55) | -0.12 (-1.64) | -0.12 (-1.48) |
| Tangibility_lag | 0.52 (1.09) | 0.65 (1.41) | 0.72 (1.56) | 0.70 (1.41) |
| Profitability_lag | -7.89 (-1.57) | -7.79* (-1.68) | -7.81 (-1.60) | -7.93 (-1.55) |
| Leverage_lag | -0.15 (-0.46) | -0.16 (-0.50) | -0.24 (-0.71) | -0.22 (-0.70) |
| lnSales_lag | -0.29*** (-3.62) | -0.27*** (-3.58) | -0.26*** (-3.38) | -0.28*** (-3.64) |
| Year-Qtr FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Observations | 11507 | 11507 | 11507 | 11507 |
| Adjusted R^2 | 0.02 | 0.02 | 0.02 | 0.02 |

Table 8: continued

Panel C: Regressions of CAR on ClimateTech Infra and Env

| | (1) | (2) | (3) | (4) |
|-------------------|---------------------|---------------------|---------------------|---------------------|
| | CAR_ffm_2 | CAR_madj_2 | CAR_capm_2 | CAR_ff_2 |
| ClimateTech_Infra | 0.85** (2.10) | 0.86* (1.97) | 0.90** (2.11) | 0.94** (2.23) |
| ClimateTech_Env | 0.10 (0.38) | -0.06 (-0.22) | -0.07 (-0.24) | -0.00 (-0.00) |
| PControl_Infra | -0.05* (-1.69) | -0.05 (-1.43) | -0.05 (-1.57) | -0.06* (-1.79) |
| PControl_Env | 0.04 (1.19) | 0.06* (1.68) | 0.05 (1.48) | 0.05 (1.57) |
| MTB_lag | -0.12 (-1.47) | -0.12 (-1.57) | -0.12 (-1.66) | -0.12 (-1.49) |
| Tangibility_lag | 0.59 (1.23) | 0.73 (1.55) | 0.80* (1.73) | 0.78 (1.58) |
| Profitability_lag | -7.96 (-1.59) | -7.94* (-1.72) | -7.94 (-1.63) | -8.05 (-1.58) |
| Leverage_lag | -0.15 (-0.46) | -0.16 (-0.50) | -0.25 (-0.71) | -0.23 (-0.70) |
| lnSales_lag | -0.29*** (-3.76) | -0.28*** (-3.71) | -0.27*** (-3.53) | -0.29*** (-3.79) |
| Year-Qtr FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Observations | 11507 | 11507 | 11507 | 11507 |
| Adjusted R^2 | 0.02 | 0.02 | 0.02 | 0.02 |

Appendix A Variable Definitions

Table A1: Variable Definitions

| Variable | Definition |
|---------------------------------------|--|
| ClimateTech | Indicator variable equal to one if the dependency parser identifies at least one syntactic link between an investment keyword and an emerging technology keyword, up to three dependency levels, in the climate announcement text |
| ClimateTech_Infra | Indicator variable equal to one if the ClimateTech investment announcement includes a multipurpose infrastructure technology keyword but not specialized environmental technology keyword in the announcement text |
| ClimateTech_Env | Indicator variable equal to one if the ClimateTech investment announcement includes a specialized environmental technology keyword in the announcement text |
| CAR_ffm, CAR_adj, CAR_capm, CAR_ff | Cumulative abnormal returns (CARs) with abnormal returns estimated using the Fama-French three-factor model with momentum, the market-adjusted model, the CAPM, and the Fama-French three-factor model, respectively, over an event window surrounding each climate announcement, where day 0 is the announcement date (or the next trading day if the announcement is released on a weekend or holiday) Suffixes _2, _5, _10, _21, _63, and _126 correspond to event windows of [-1, 2], [3, 5], [6, 10], [11, 21], [22, 63], and [64, 126] trading days. |
| Δ MSCI | The change in the Climate Theme Score from the MSCI database, measured one or two years after the press release, relative to the year of the press release. This compares the climate-announcing firm's score in the year after the announcement (_lead1) and two years after the announcement (_lead2) with its rating before the press release. |
| RepRisk | Number of climate-related negative incidents from RepRisk database Suffixes _bf1y, _6m, _1y, _2y, and _3y correspond to the windows of 1 year before the announcement, 6 months, 1 year, 2 years, and 3 years after the announcement. |

Table A1: continued

| Variable | Definition |
|--------------------|---|
| MTB | Ratio of market value to total assets in the announcement quarter |
| Tangibility | Fixed assets divided by total assets in the announcement quarter |
| Profitability | Operating income before depreciation divided by total assets in the announcement quarter |
| Leverage | Book debt divided by book value in the announcement quarter |
| lnSales | Natural logarithm of sales in the announcement |
| Top3 | Indicator variable equal to one if the firm's market capitalization ranks in the top three within its two-digit SIC industry in the announcement year |
| Size | Market capitalization in the announcement year |
| Cash | Cash divided by total assets in the announcement year |
| CIO | Indicator variable equal to one if the firm maintains a CIO position in the announcement year |
| CEO_IT | Indicator variable equal to one if the CEO of the firm has an IT-related background |
| R&D | R&D expenditure divided by total assets in the announcement year |
| Patents | Number of patents granted to the firm in the announcement year |
| Rate_Sustain | Sustainability ratings of funds from Morningstar Sustainability database, aggregated at the firm level using the market-value weight of the firm within each fund's portfolio in the announcement month |
| Talent_AI | Share of individuals aged 18-64 with undergraduate or graduate degrees in AI-related fields in the announcement year in the headquarter state |
| Talent_Climate | Share of individuals aged 18-64 with undergraduate or graduate degrees in climate-related fields in the announcement year in the headquarter state |
| Talent_ClimateTech | Share of individuals aged 18-64 with undergraduate or graduate degrees in ClimateTech-related fields in the announcement year in the headquarter state |

Appendix B ChatGPT Prompts

We provide the GPT prompt used in the paper in the appendix. We used the GPT model *gpt-4o-mini-2024-07-18* for all tasks.

The GPT prompt used to classify each emerging technology keyword into ClimateTech Infra or ClimateTech Env is as follows:

You are a research assistant who strictly follows instructions and provides only valid answers.

The following are a keyword related to an emerging technology and two categories of emerging technologies. Choose the relevant categories for the keyword and mark as 1. You need to choose at most one category for each keyword.

Keyword: "keyword"

Emerging Technology Categories:

- 1. High Tech Infrastructure (e.g., LLM, AI, quantum computing, cloud computing, edge computing, internet of things (IoT), robotics, augmented reality (AR), virtual reality (VR), cybersecurity, 3D printing)*
- 2. High Tech in Environmental and Energy (e.g., Renewables, Nuclear Energy, Hydrogen, Sustainable Fuels)*

Please respond in the format: "High Tech Infrastructure": 1/0, "High Tech in Environmental and Energy": 1/0.

The GPT prompt used to classify each ClimateTech Infra press release into its subcategories is as follows:

You are given a firm announcement about a climate change initiative where the firm uses high-tech infrastructure technologies to address a climate issue.

Your tasks are:

- 1. Classify the announcement into exactly one of the following subcategories, based on the main type of technology used:*

- 1) AI/ML
- 2) IT Infrastructure (e.g., cloud)
- 3) Supply Chain Management & Logistics
- 4) Other General Infra Technology

2. Provide a one-sentence summary explaining how the identified technology is being used for the climate initiative.

Rules:

- Choose only one subcategory (1, 2, 3, or 4).
- The summary must be concise (one sentence only).

Announcement: ""

Please respond in the format:

"Subcategory": 1/2/3/4, "Summary": "<one-sentence explanation>"

The GPT prompt used to classify each ClimateTech Env press release into its subcategories is as follows:

You are given a firm announcement about a climate change initiative where the firm uses high-tech environmental technologies to address a climate issue.

Your tasks are:

1. *Classify the announcement into exactly one of the following subcategories, based on the main type of technology used:*

- 1) *electric vehicles*
- 2) *alternative energy & chemicals*
- 3) *Other General environmental technology*

2. *Provide a one-sentence summary explaining how the identified technology is being used for the climate initiative.*

Rules:

- Choose only one subcategory (1, 2, 3, or 4).
- The summary must be concise (one sentence only).

Announcement: ""

Please respond in the format:

"Subcategory": 1/2/3/4, "Summary": "<one-sentence explanation>"

The GPT prompt used to classify each climate press release into Core (climate initiative related to the announcing firm's primary revenue-generating operations or strategic focus) as follows:

*You are an academic researcher specializing in corporate disclosure. Your task is to evaluate the extent to which a firm announcement pertains to the firm's **core or non-core business**.*

*- **Core business** is defined as activities, products, or services that are directly related to the company's primary revenue-generating operations or strategic focus, as described in the firm's 10-K business description.*

*- **Non-core business** refers to activities outside of these primary areas.*

*Based on the firm's announcement and the provided 10-K business description, assess whether the announcement is related to the firm's **core or non-core business**.*

*Respond **strictly in JSON format**, following this structure: "json "classification": 1 (core) or 0 (non-core), "justification": "Brief reasoning (1 sentence) explaining your classification based on the provided announcement and 10-K."*

Internet Appendices for *"When Do AI and Emerging Technologies Shape Climate Investment?"*

Internet Appendix A: Appendix Table

Internet Appendix B: Details for Dependency Parser

Internet Appendix C: Examples of ClimateTech Press Releases

Internet Appendix D: Additional Data Construction Details

Appendix A Appendix Table

Table IA1: Financial Value within Environmental Industries

This table reports the regression results of the CAR associated with ClimateTech Env investment press releases, comparing ClimateTech environmental investment press releases to ClimateNonTech press releases, for firms within environmental industries. Environmental industries firms are defined as firms with SIC codes 13 (Oil and Gas Extraction) and 49 (Electric, Gas, and Sanitary Services). The dependent variable is CAR computed over the event window [-1, 2] around each press release. CAR is estimated using the Fama–French three-factor model with momentum in Columns (1), the market-adjusted model in Columns (2), the CAPM in Columns (3), and the Fama–French three-factor model in Columns (4). All control variables are lagged by one quarter. Asterisks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

| Sample | (1) | (2) | (3) | (4) |
|-------------------|--------------------------|------------------|------------------|------------------|
| | Environmental Industries | | | |
| Dep. Var. | CAR_ffm_2 | CAR_madj_2 | CAR_capm_2 | CAR_ff_2 |
| ClimateTech_Env | 0.60 (1.50) | 0.61* (1.69) | 0.62* (1.80) | 0.53 (1.36) |
| MTB_lag | -0.23 (-0.82) | -0.30 (-1.09) | -0.28 (-0.99) | -0.32 (-1.10) |
| Profitability_lag | -0.35 (-0.34) | -0.16 (-0.16) | -0.09 (-0.09) | 0.07 (0.07) |
| Tangibility_lag | -6.21 (-0.83) | -5.44 (-0.77) | -4.79 (-0.66) | -6.88 (-0.93) |
| Leverage_lag | -0.43 (-0.47) | -0.45 (-0.47) | -0.42 (-0.43) | -0.62 (-0.68) |
| lnSales_lag | -0.17 (-1.36) | -0.14 (-1.10) | -0.14 (-1.10) | -0.19 (-1.52) |
| Year-Qtr FE | Yes | Yes | Yes | Yes |
| Observations | 895 | 895 | 895 | 895 |
| Adjusted R^2 | 0.02 | 0.00 | 0.01 | 0.02 |

Table IA2: Environmental Impact within Environmental Industries

This table reports the regression results of the environmental impact of ClimateTech Env investment press releases, comparing ClimateTech environmental investment press releases to ClimateNonTech press releases, for firms within environmental industries. Environmental industries firms are defined as firms with SIC codes 13 (Oil and Gas Extraction) and 49 (Electric, Gas, and Sanitary Services). In Panel A, the dependent variables are the change in MSCI firm strength ratings on climate change theme over the two years following each climate press release. In Panel B, the dependent variables are the number of RepRisk negative incidents in 6 months, 1 year, 2 years, and 3 years following the climate press release date. All control variables are lagged by one quarter. t-statistics in parentheses are based on standard errors clustered by industry. Asterisks denote significance levels (***)=1%, (**)=5%, (*)=10%.

Panel A: MSCI Rating

| Sample Dep. Var. | (1) | (2) |
|---------------------|---------------------|---------------------|
| | Environmental | |
| | Δ MSCI_lead1 | Δ MSCI_lead2 |
| ClimateTech_Env | 0.37 (1.62) | 0.38 (1.28) |
| MTB_lag | 0.38 (1.20) | 0.09 (0.23) |
| Profitability_lag | 1.06** (2.31) | 0.93 (1.32) |
| Tangibility_lag | 2.88 (0.48) | 10.66 (1.68) |
| Leverage_lag | 1.50** (2.50) | 1.23** (2.29) |
| lnSales_lag | 0.00 (0.02) | -0.15 (-1.30) |
| Year-Qtr FE | Yes | Yes |
| Industry FE | Yes | Yes |
| Observations | 489 | 472 |
| Adjusted R^2 | 0.12 | 0.19 |

Table IA2: continued

Panel B: RepRisk Incidents

| Dep. Var. | (1) | (2) | (3) | (4) |
|-------------------|--------------------|--------------------|--------------------|--------------------|
| | RepRisk_6m | RepRisk_1y | RepRisk_2y | RepRisk_3y |
| ClimateTech_Env | 0.01 (0.11) | -0.03 (-0.39) | 0.00 (0.02) | 0.01 (0.20) |
| RepRisk_bf1y | 0.03*** (6.02) | 0.03*** (6.41) | 0.02*** (5.89) | 0.02*** (6.30) |
| MTB_lag | 0.09 (0.55) | 0.08 (0.53) | 0.07 (0.54) | 0.11 (0.83) |
| Tangibility_lag | 0.17 (0.61) | 0.03 (0.11) | 0.16 (0.66) | 0.29 (1.24) |
| Profitability_lag | -1.56 (-0.89) | -2.65* (-1.81) | -1.87 (-1.26) | -1.40 (-1.03) |
| Leverage_lag | 0.57** (2.44) | 0.64*** (2.58) | 0.75*** (3.18) | 0.74*** (3.12) |
| lnSales_lag | 0.67*** (11.52) | 0.66*** (11.83) | 0.68*** (12.64) | 0.67*** (14.09) |
| Year-Qtr FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Observations | 771 | 771 | 771 | 771 |
| Pseudo R^2 | 0.56 | 0.61 | 0.66 | 0.70 |

Table IA3: ClimateTech Press Release Return Regressions with Continuous Measure

This table reports the regression results of the CAR on ClimateTech Intensity. The sample includes all climate press releases. ClimateTech Inv. denotes the intensity of firm *i*' ClimateTech investment, measured as the log of the number of syntactic links identified within the climate press release text by the dependency parser between an investment keyword and an emerging technology keyword, including both Infra and Env technologies. The dependent variables are CAR calculated using the CAPM (Column 1), the Fama–French three-factor model (Column 2), the Fama–French three-factor model with momentum (Column 3), and a market-adjusted model (Column 4). In all specifications, CARs are computed over the window [-1, 2] surrounding each press release with expected returns estimated over a window of 252 trading days ending one day before the announcement. All control variables are lagged by one quarter. t-statistics in parentheses are based on standard errors clustered by industry. Asterisks denote significance levels (***=1%, **=5%, *=10%).

| Dep. Var. | (1) CAR_ffm_2 | (2) CAR_madj_2 | (3) CAR_capm_2 | (4) CAR_ff_2 |
|-------------------|---------------------|---------------------|---------------------|---------------------|
| ClimateTech Inv. | 0.28* (1.91) | 0.23 (1.63) | 0.25* (1.75) | 0.28* (1.89) |
| MTB_lag | -0.17** (-2.07) | -0.17** (-2.09) | -0.18** (-2.23) | -0.17** (-2.07) |
| Tangibility_lag | 0.17 (0.80) | 0.27 (1.16) | 0.35 (1.51) | 0.34 (1.36) |
| Profitability_lag | -11.68** (-2.43) | -11.71** (-2.33) | -11.67** (-2.35) | -11.82** (-2.37) |
| Leverage_lag | -0.26 (-1.00) | -0.26 (-1.01) | -0.36 (-1.36) | -0.35 (-1.38) |
| lnSales_lag | -0.28*** (-3.84) | -0.26*** (-3.66) | -0.25*** (-3.40) | -0.27*** (-3.84) |
| Year-Qtr FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Observations | 11935 | 11935 | 11935 | 11935 |
| Adjusted R^2 | 0.01 | 0.01 | 0.01 | 0.01 |

Table IA4: Causal Inference for ClimateTech Press Release Return Drift Regressions

This table reports the regression results of the CAR drift. The sample includes all climate press releases. The dependent variables are CAR calculated using the Fama–French three-factor model with momentum. CARs are computed over the window of [-1, 2] days (CAR_ffm_2), [3, 5] days (CAR_ffm_5), [6, 10] days (CAR_ffm_10), [11, 21] days (CAR_ffm_21), [22, 63] days (CAR_ffm_63), and [64, 126] days (CAR_ffm_126) with expected returns estimated over a window of 252 trading days ending one day before the press release. The control functions, PControl_Infra and PControl_Env, constructed from the estimation in Table 8, Panel A, are included. All control variables are lagged by one quarter. t-statistics in parentheses are based on standard errors clustered by industry. Asterisks denote significance levels (***=1%, **=5%, *=10%).

| Dev. Var. | (1) CAR_ffm_2 | (2) CAR_ffm_5 | (3) car_ffm_10 | (4) car_ffm_21 | (5) car_ffm_63 | (6) car_ffm_126 |
|-------------------|---------------------|---------------------|--------------------|-------------------|-------------------|--------------------|
| ClimateTech_Infra | 0.69* (1.80) | 0.06 (0.19) | 0.43 (0.95) | -0.06 (-0.22) | -0.72 (-0.93) | 0.77 (0.76) |
| ClimateTech_Env | -0.06 (-0.23) | 0.09 (0.20) | 0.35 (0.66) | -0.67 (-0.98) | 0.91 (0.84) | 1.66 (0.80) |
| PControl_Infra | -0.03 (-1.02) | -0.01 (-0.53) | -0.04 (-1.29) | 0.01 (0.61) | 0.06 (0.98) | -0.07 (-1.31) |
| PControl_Env | 0.06* (1.94) | -0.03 (-0.70) | -0.04 (-0.65) | 0.04 (0.56) | -0.04 (-0.42) | -0.23 (-1.33) |
| MTB_lag | -0.12 (-1.48) | -0.03 (-1.54) | -0.10** (-2.42) | -0.00 (-0.02) | -0.00 (-0.01) | 0.09 (0.25) |
| Tangibility_lag | 0.58 (1.21) | -0.18 (-0.29) | -0.81 (-1.38) | 0.50 (0.70) | 1.68 (0.52) | -1.38 (-0.27) |
| Profitability_lag | -8.04 (-1.60) | 5.76** (2.17) | 8.45 (1.27) | 10.06** (2.56) | 8.48 (0.46) | 29.24** (2.40) |
| Leverage_lag | -0.15 (-0.46) | 0.65** (2.45) | 0.09 (0.50) | 0.34 (1.38) | 1.64 (1.60) | 3.11* (1.81) |
| lnSales_lag | -0.29*** (-3.72) | -0.09*** (-2.86) | -0.11* (-1.78) | -0.03 (-0.47) | -0.24 (-1.21) | -0.46* (-1.87) |
| Year-Qtr FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 11504 | 11504 | 11504 | 11504 | 11504 | 11454 |
| Adjusted R^2 | 0.02 | 0.01 | 0.00 | 0.00 | 0.02 | 0.03 |

Table IA5: Causal Inference for ClimateTech Environmental Impact

This table reports the regression results of the environmental impact of ClimateTech. The sample includes all climate press releases. In Panel A, the dependent variables are the change in MSCI firm strength ratings on climate change theme over the two years following each climate press release. In Panel B, the dependent variables are the number of RepRisk negative incidents in 6 months, 1 year, 2 years, and 3 years following the climate press release date. The control functions, PControl_Infra and PControl_Env, constructed from the estimation in Table 8, Panel A, are included. All control variables are lagged by one quarter. t-statistics in parentheses are based on standard errors clustered by industry. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Panel A: Regressions of MSCI Rating on ClimateTech Infra and Env

| Dep. Var | (1) Δ MSCI_lead1 | (2) Δ MSCI_lead2 |
|-------------------|----------------------------|----------------------------|
| ClimateTech_Infra | -0.21** (-2.36) | -0.16 (-1.23) |
| ClimateTech_Env | 0.11 (0.72) | 0.19 (0.94) |
| PControl_Infra | 0.01 (1.56) | 0.01 (1.05) |
| PControl_Env | -0.00 (-0.14) | 0.00 (0.01) |
| MTB_lag | -0.01 (-0.99) | 0.02 (0.74) |
| Tangibility_lag | 0.06 (0.43) | -0.06 (-0.40) |
| Profitability_lag | -0.34 (-0.25) | 0.06 (0.04) |
| Leverage_lag | 0.13 (1.35) | 0.19 (1.46) |
| lnSales_lag | 0.02 (1.00) | -0.02 (-0.56) |
| Year-Qtr FE | Yes | Yes |
| Industry FE | Yes | Yes |
| Observations | 5454 | 5304 |
| Adjusted R^2 | 0.02 | 0.03 |

Table IA5: continued

Panel B: Regressions of RepRisk Incidents on ClimateTech Infra and Env

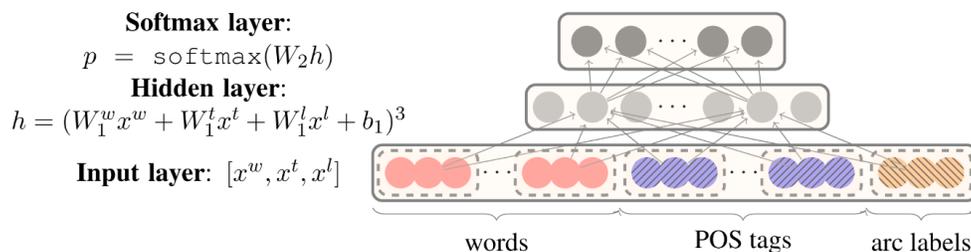
| Dep. Var. | (1) RepRisk_6m | (2) RepRisk_1y | (3) RepRisk_2y | (4) RepRisk_3y |
|-------------------|--------------------|---------------------|---------------------|---------------------|
| ClimateTech_Infra | 0.00 (0.11) | -0.03 (-0.68) | -0.05 (-1.45) | -0.05 (-1.40) |
| ClimateTech_Env | -0.03 (-0.22) | -0.02 (-0.16) | 0.01 (0.12) | 0.02 (0.17) |
| PControl_Infra | -0.00 (-0.91) | -0.00 (-0.47) | -0.00 (-0.05) | 0.00 (0.01) |
| PControl_Env | 0.01 (0.49) | 0.00 (0.20) | 0.00 (0.00) | -0.00 (-0.12) |
| RepRisk_bfly | 0.01*** (3.91) | 0.01*** (3.94) | 0.01*** (3.91) | 0.01*** (3.88) |
| MTB_lag | 0.12*** (5.39) | 0.13*** (5.76) | 0.15*** (6.88) | 0.16*** (8.02) |
| Tangibility_lag | 0.05 (0.23) | 0.14 (0.56) | 0.31 (0.96) | 0.47 (1.14) |
| Profitability_lag | -4.09** (-2.42) | -4.58*** (-2.62) | -4.74*** (-2.97) | -5.03*** (-3.32) |
| Leverage_lag | -0.08 (-0.35) | -0.07 (-0.28) | -0.14 (-0.55) | -0.21 (-0.75) |
| lnSales_lag | 0.92*** (13.50) | 0.91*** (14.22) | 0.92*** (14.67) | 0.92*** (14.74) |
| Year-Qtr FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Observations | 8553 | 8553 | 8555 | 8561 |
| Pseudo R^2 | 0.78 | 0.83 | 0.85 | 0.86 |

Appendix B Details for Dependency Parser

In this section, we describe the dependency parser methodology used to quantify firm investments in AI and emerging technologies. Unlike traditional text analysis methods, this approach represents each sentence as a tree structure, with words as nodes and directed arcs indicating specific syntactic relations. Because these identified relations are grounded in human grammatical understanding, the methodology offers high transparency. This interpretability allows researchers to explicitly trace the technology investment within press release texts, circumventing the “blackbox” nature of LLMs.

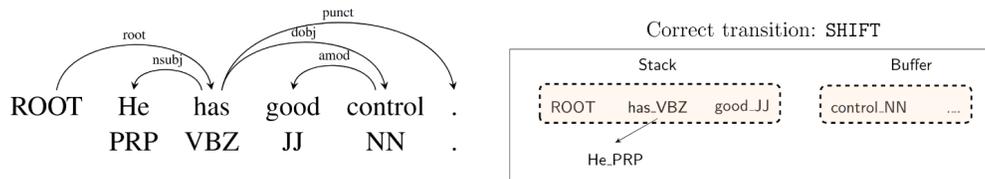
We employ the novel deep neural network algorithm developed by Chen and Manning (2014) to parse the dependency structure of sentences within our corpus. The goal is to extract the syntactic relations between words to measure ClimateTech investment. The parsing model is a three-layer feedforward neural network that predicts the subsequent transition required to construct a dependency tree. The algorithm utilizes three types of features as inputs: word embeddings, Part-of-Speech (POS) tags (derived from the Stanford POS tagger), and arc labels (derived from the Basic Stanford Parser). These features capture both semantic meanings and linguistic structures. The second layer of the parser is a fully-connected hidden layer that employs a cube activation function. The third layer is a Softmax output layer with each node representing the probability of a specific transition choice, such as SHIFT, LEFT-ARC, or RIGHT-ARC. Figure 1 illustrates the neural network architecture of the model.

Figure IA1: Neural Network Dependency Parsing Model (Source: Chen and Manning (2014))



Consistent with other transition-based parsers, this model builds a parse by performing a linear-time scan of the words in a sentence to predict a transition sequence. Figure 2 illustrates the parsing steps. At each incremental step, the parser maintains a configuration comprising a partial parse, a stack of words currently under processing, and a buffer of words yet to be processed. The parser continues applying transitions to its state, systematically moving words from the buffer to the stack and establishing dependency arcs, until its buffer is empty and the dependency graph is complete.

Figure IA2: he parsing transition steps of an example sentence (Source: Chen and Manning (2014))

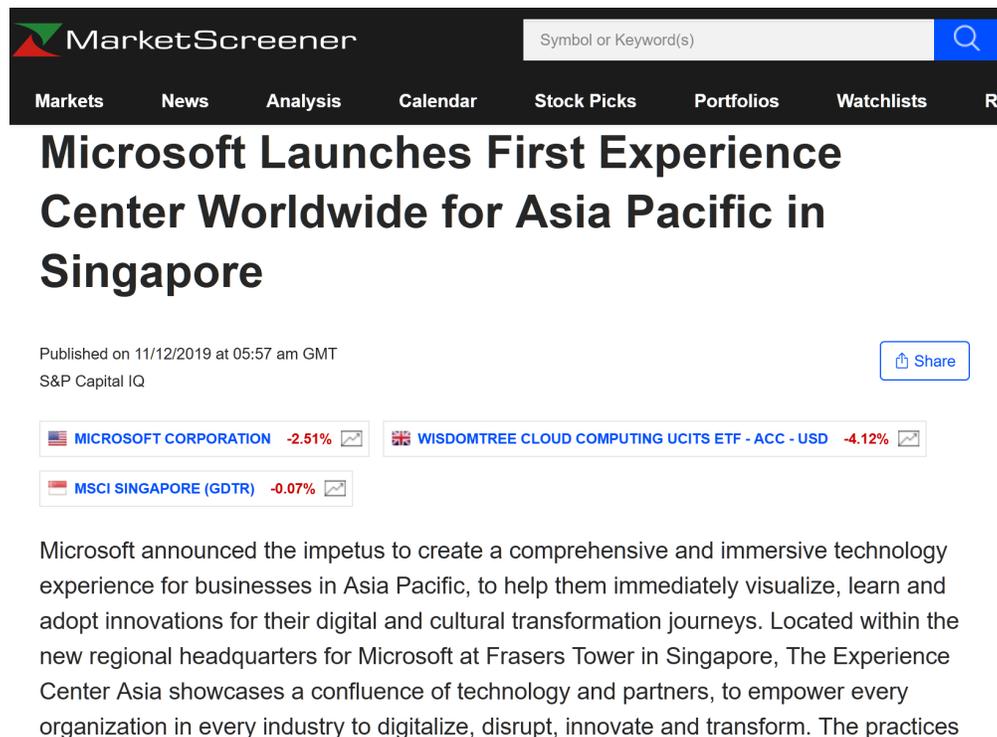


| Transition | Stack | Buffer | A |
|------------------|-------------------------|-------------------------|---|
| SHIFT | [ROOT] | [He has good control .] | \emptyset |
| SHIFT | [ROOT He] | [has good control .] | |
| LEFT-ARC (nsubj) | [ROOT He has] | [good control .] | $A \cup \text{nsubj}(\text{has}, \text{He})$ |
| SHIFT | [ROOT has] | [good control .] | |
| SHIFT | [ROOT has good] | [control .] | |
| LEFT-ARC (amod) | [ROOT has good control] | [.] | $A \cup \text{amod}(\text{control}, \text{good})$ |
| RIGHT-ARC (dobj) | [ROOT has control] | [.] | $A \cup \text{dobj}(\text{has}, \text{control})$ |
| ... | [ROOT has] | [.] | |
| ... | ... | ... | |
| RIGHT-ARC (root) | [ROOT] | [.] | $A \cup \text{root}(\text{ROOT}, \text{has})$ |

Appendix C Examples of ClimateTech Press Releases

In this section, we provide examples of identified ClimateTech investment press releases for each category.

Example 1: ClimateTech Infra In 2019, Microsoft invested in an Azure-based platform to monitor and optimize workplace energy use, resulting in energy savings of up to 25%.



The screenshot shows a news article on the MarketScreener website. The article title is "Microsoft Launches First Experience Center Worldwide for Asia Pacific in Singapore". It was published on 11/12/2019 at 05:57 am GMT by S&P Capital IQ. Below the title, there are three stock tickers: MICROSOFT CORPORATION (-2.51%), WISDOMTREE CLOUD COMPUTING UCITS ETF - ACC - USD (-4.12%), and MSCI SINGAPORE (GDTR) (-0.07%). The article text describes Microsoft's announcement to create a comprehensive and immersive technology experience for businesses in Asia Pacific, located at Frasers Tower in Singapore.

MarketScreener

Symbol or Keyword(s) [Search]

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Microsoft Launches First Experience Center Worldwide for Asia Pacific in Singapore

Published on 11/12/2019 at 05:57 am GMT
S&P Capital IQ [Share](#)

MICROSOFT CORPORATION -2.51% WISDOMTREE CLOUD COMPUTING UCITS ETF - ACC - USD -4.12%
 MSCI SINGAPORE (GDTR) -0.07%

Microsoft announced the impetus to create a comprehensive and immersive technology experience for businesses in Asia Pacific, to help them immediately visualize, learn and adopt innovations for their digital and cultural transformation journeys. Located within the new regional headquarters for Microsoft at Frasers Tower in Singapore, The Experience Center Asia showcases a confluence of technology and partners, to empower every organization in every industry to digitalize, disrupt, innovate and transform. The practices

This case is recorded in the Key Development database as follows:

Announcement ID (keydevid): 643902806

Announcing firm (gvkey): Microsoft Corp. (12141)

Announcement date (announcedate): 2019-11-12

Announcement:

Microsoft announced the impetus to create a comprehensive and immersive technology experience for businesses in Asia Pacific, to help them immediately visualize, learn and adopt innovations for their digital and cultural transformation journeys.

... 179 Bluetooth beacons in meeting rooms and 900 sensors for lighting, air quality and temperature with nearly 2100 data points from the Frasers Tower are connected to the cloud on Microsoft Azure. The sensors and telemetry monitor the facilities, energy and utilities usage to optimize space utilization, air conditioning and lighting adjustments. In future, these sensors can also monitor the carbon dioxide levels in the air, which can negatively affect work performance and neural activity, noise levels by measuring decibels, and energy usage, which can result in savings of up to 25%, as experienced in Microsoft's HQ in Redmond, Washington.

Example 2: ClimateTech Env In 2022, Target launched its most sustainable store, which is designed to generate more renewable energy than it consumes annually.

www.delimarketnews.com/well-paired/target-tests-first-ever-net-zero-energy-location-john-conlin-and-michael-fiddelke-comment/lilian-diep

Study Life GenAI4All Citadel Securities Econ NYT WSJ HBR Sloan Digital FM Technocratic 2026Move Dail

Target Tests First-Ever Net Zero Energy Location; John Conlin and Michael Fiddelke Comment

Retrofitting this location with innovations, the chain tests a first-ever format that will inform its future investments...

by [Lilian Diep](#)

MINNEAPOLIS, MN

Monday, March 21st, 2022

Regenerative and sustainability practices have taken on a higher priority for retailers and suppliers. With many taking on a greener purpose, one company standing in the spotlight recently is Target. The retail chain announced it has retrofitted one of its locations to unveil its **most sustainable store to date**.

This case is recorded in the Key Development database as follows:

Announcement ID (keydev): 1778102370

Announcing firm (gvkey): Target Corp. (3813)

Announcement date (announcedate): 2022-03-17

Announcement:

Target Corporation announced its most sustainable store to date, as the site will generate more renewable energy than it needs annually to operate and will test multiple innovations to reduce the building's emissions. The Vista, California, store's retrofit and new features will inform Target's investments in new stores and remodel programs that support its long-term growth and help guide the retailer's efforts to achieve its sustainability goals. The store will generate renewable energy through 3,420 solar panels across its roof and newly installed carport canopies. The site is expected to produce up to a 10% energy surplus each year that it can transmit back to the local power grid, and Target has applied for net zero energy certification from the International Living Future Institute. The building also features elements to further reduce emissions, such as powering its HVAC heating through rooftop solar panels, instead of natural gas. ...

Appendix D Additional Data Construction Details

We use the BoardEx database to identify CEOs' IT backgrounds and the presence of CIO positions. CEOs are identified in the individual role dataset using keywords such as "CEO" and "Chief Executive," while CIOs are identified using keywords such as "Chief Information" and "Chief IT." Interim and acting roles are included, whereas division-, field-, regional-, group-, and deputy-level roles are excluded to focus on top executive positions. CEO_IT is an indicator of whether the CEO of the firm has IT-related background, based on information from prior role description, educational history, or achievement records containing IT-related keywords such as "IT", "information technology", "AI", or "data". CIO is an indicator of whether the firm maintains a CIO position.

To measure investors' sustainability preference, we use the Morningstar Sustainability Rating, which evaluates mutual funds' ESG exposure monthly basis using Sustainalytics' ESG Risk Ratings. We construct a firm-level measure, Rate_Sustain, by aggregating fund-level sustainability ratings using the market-value weight of the firm within each fund's portfolio. For each press release, we assign the firm's aggregated sustainability rating in the announcement month.

Information on firms' patent activities is obtained from the United States Patent and Trademark Office (USPTO) and matched to Compustat using pre-processed firm names. Patents is the number of patents granted to the firm in the announcement year.

Firm-level financial characteristics are obtained from Compustat. Top3 is an indicator equal to one if the firm's market capitalization ranks in the top three firms within its two-digit SIC industry in the announcement year. Size is the market capitalization in the announcement year. Cash is the ratio of cash to total assets in the announcement year. R&D is the ratio of R&D expenditure to total assets in the announcement year. Market-To-Book is the ratio of market value (total assets plus market value of equity minus book equity) to total assets in the announcement quarter. Tangibility is calculated as fixed assets divided by total assets in the announcement quarter. Profitability is calculated as operating income before depreciation divided by total assets. Book_Leverage is book debt divided by book value. lnSales is the natural logarithm of sales.